DEMOCRITUS UNIVERSITY OF THRACE
Faculty of Social, Political and Economic Sciences
Department of Economics

ΔΗΜΟΚΡΙΤΕΙΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΘΡΑΚΗΣ

COMMEMORATIVE VOLUME FOR THE TWENTY-FIFTH ANNIVERSARY OF THE ESTABLISHMENT OF THE DEPARTMENT OF ECONOMICS

KOMOTINI
OCTOBER 2025

On the occasion 25 YEARS OF THE DEPARTMENT OF ECONOMICS

EDITORS

Ioannis Dokas
Associate Professor of Accounting

Dimitrios Dimitriou
Professor of Management, Head of the Department of Economics

PAPAZISSIS PUBLISHERS

On the occasion

25 YEARS

OF THE DEPARTMENT OF ECONOMICS

IN DEMOCRITUS UNIVERSITY OF THRACE

OCTOBER 2025

PAPAZISSIS Publishers S.A.

On the occasion
25 YEARS
OF THE DEPARTMENT OF ECONOMICS
IN DEMOCRITUS UNIVERSITY OF THRACE
Dimitrios Dimitriou, Ioannis Dokas (Editors)

ISBN: 978-960-02-4584-4

2 Nikitara str., 106 78 Athens
Tel.: 210-3822.496 210-3838.020
site: www.papazisi.gr
e-mail: papazisi@otenet.gr

Print: Grafima Advertising S.A.
Eleftherias 29 (Amfitheas), Alimos, 17455, Greece
Tel. +30 210 7251600 (int.33) ¦ Mob. +30 6942 439439
www.grafimaprint.gr

DEMOCRITUS UNIVERSITY OF THRACE
Faculty of Social, Political and Economic Sciences
Department of Economics

On the occasion
25 YEARS
OF THE DEPARTMENT OF ECONOMICS IN DEMOCRITUS UNIVERSITY OF THRACE

OCTOBER 2025

EDITORS

Dimitrios Dimitriou
Professor of Management, Head of the Department of Economics

Ioannis Dokas
Associate Professor of Accounting

PAPAZISIS PUBLISHERS
ATHENS 2025

CONTENTS

SCIENTIFIC COMMITTEE

Chionis Dionysios	*Professor, Department of Economics, Democritus University of Thrace*
Dalla Eleni	*Assistant Professor, Department of Economics, Democritus University of Thrace*
Dimitriou Dimitrios	*Professor, Department of Economics, Democritus University of Thrace*
Dokas Ioannis	*Associate Professor, Department of Economics, Democritus University of Thrace*
Drimpetas Evaggelos	*Professor, Department of Economics, Democritus University of Thrace*
Geronikolaou George	*Associate Professor, Department of Economics, Democritus University of Thrace*
Gogas Periklis	*Professor, Department of Economics, Democritus University of Thrace*
Hazakis Konstantinos	*Professor, Department of Economics, Democritus University of Thrace*
Kanakaris Venetis	*Lab Teaching Staff, Department of Economics, Democritus University of Thrace*
Karagkouni Aristi	*Assistant Professor Department of Economics, Democritus University of Thrace*
Kollias Konstantinos	*Assistant Professor Department of Economics, Democritus University of Thrace*
Koutroukis Theodoros	*Professor, Department of Economics, Democritus University of Thrace*
Papadimitriou Theofilos	*Professor, Department of Economics, Democritus University of Thrace*

Pistikou Victoria	*Associate Professor, Department of Economics, Democritus University of Thrace*
Plakandaras Vasileios	*Associate Professor, Department of Economics, Democritus University of Thrace*
Praggidis Ioannis-Chrisostomos	*Professor, Department of Economics, Democritus University of Thrace*
Rigopoulos Konstantinos	*Assistant Professor, Department of Economics, Democritus University of Thrace*
Poufinas Thomas	*Associate Professor, Department of Economics, Democritus University of Thrace*
Sarafopoulos George	*Professor, Department of Economics, Democritus University of Thrace*
Sartzetaki Maria	*Associate Professor, Department of Economics, Democritus University of Thrace*
Spyromitros Eleftherios	*Professor, Department of Economics, Democritus University of Thrace*
Stavridou Silvia	*Associate Professor, Department of Economics, Democritus University of Thrace*
Vlados Charis	*Associate Professor, Department of Economics, Democritus University of Thrace*

INTRODUCTION

This commemorative volume has been prepared to mark the twenty-fifth anniversary of the Department of Economics at Democritus University of Thrace. The aim of this volume is to highlight the research contributions of the Department's faculty members to the international literature in the field of economics. A significant portion of this effort also reflects the research conducted by the Department's doctoral candidates and postdoctoral researchers.

Over the past quarter century, the Department has gained a distinctive profile in Greek higher education, a testament to the department's faculty's, students', and researchers' unstinted dedication. Key national and international developments have reshaped the field of higher education and research, forcing the Department to continuously adapt to such reshaping. Through embracing newer trends in research, it has upgraded its undergraduate and postgraduate studies while reforming its research focus to engage with the pressing economic and social challenges of the present day.

Today, the Department of Economics is structured into two main sections: Economic Analysis and Business Administration (Management). Such a divided structure is a cornerstone of its constitution. The Division of Economic Analysis is concerned with the promotion of both theoretical and applied studies in the discipline of economics, including crucial areas such as economic growth, distributional issues, market behavior, and policy formation. On the other hand, the Division of Business Administration offers specialized training in subjects such as management, strategy, and organizational studies, thus offering insightful contributions to the operation of firms and institutions in a dynamically transforming economic environment. Both these sections foster an interdisciplinary academic environment that combines rigorous economic theory with practical perspectives on business and entrepreneurship. Such a balance strengthens both the teaching profile of the Department and its research impact.

The research endeavors of the Department are further enhanced by the presence of two specialized research laboratories. The Laboratory of Emerging Methodologies in Economics and Finance (EMEF) emphasizes the creation and utilization of cutting-edge analytical instruments, while also promoting international collaborations in research and advanced educational initiatives. In parallel, the Laboratory of Management, Governance, Business Intelligence, Strategy and Corporate Ethics in Infrastructure Operators, Networks and Supply Chain (MaGBISE) aligns with this mission through a pronounced focus on applied management, business planning, and investment policy investigations, additionally serving as part of the National Research Infrastructure (ENIRISST), which is dedicated to evaluating the socioeconomic impacts of critical infrastructure investments. Collectively, these laboratories represent the Department's dedication to enhancing knowledge, integrating theoretical insights with practical applications, and actively participating in global academic and research discussions.

It is particularly notable for the significance of the Department's academic and research staff contribution. They are themselves actively involved in heading and taking part in key national and international research initiatives, many of them sponsored by elite bodies, private sector businesses and the European Union. Their output has yielded a high volume of international journal publications in high-standing journals, serving markedly to enhance the Department's profile in the international academic world. Through their leadership in the field of research, they not only influence scholarly discourse but also inform evidence-based practice and policy, serving to strengthen the Department's position as a center of excellence in both management and in economics. An essential aspect of the Department's development deals with actions and activities internationalization. At the turn of the century, the Department undertook major initiatives in this field, introducing educational programs in English that make its curriculum available to a wider international constituency.

At the same time, it has taken advantage of the benefits of distance education, offering flexible, high-quality education available to students throughout Greece and globally. Those initiatives have increased participation, raised the profile of the Department globally, and increased the diversity of its academic environment through greater diversity. For the future, the Department is committed to building on these initiatives, furthering international collaboration, introducing new English-language curricula, and expanding its offer in distance learning. Combining tangible achievements with a forward-looking vision, the Department sustains a profile as a lively and outward-facing academic institution in close harmony with the current international trends in higher education.

This volume is both a celebration and a testament to collective achievement. We extend our sincere gratitude to the faculty members of the Department of Economics at the Democritus University of Thrace, as well as to the doctoral candidates and postdoctoral researchers whose contributions were integral to its preparation. We are equally thankful to our undergraduate and postgraduate students: their decision to pursue studies with us enriches the intellectual vitality of the Department and reinforces its esteemed reputation.

Finally, we warmly thank Papazisis Publications, and in particular Mr. Alexandros Papazisis, for generously covering the publication costs of this volume. His support represents a meaningful recognition of the Department's scholarly work and its contribution to the broader academic community.

The Volume Editors,
Ioannis Dokas,
Assoc. Professor, Faculty Member of the Department of Economics, D.U.Th
Dimitrios Dimitriou,
Professor, Chair of the Department of Economics, D.U.Th

SECTION 1

ARTICLES

INVESTMENTS IN LARGE INFRASTRUCTURE AND CLIMATE CHANGE:

RECONCILING INTERNATIONAL REGULATORY FRAMEWORK WITH ENVIRONMENTAL COMMITMENTS

Dimitrios Dimitriou

Head of the Dept. of Economics, Director of the MaGBISE Research Laboratory

Director of the MSc in Supply Chain Management Democritus University of Thrace

ddimitri@econ.duth.gr

ABSTRACT

International economic regulations, primarily governed by the World Trade Organization (WTO) and a dense network of investment treaties (BITs, MITs, and sectoral instruments such as the Energy Charter Treaty), was crafted to promote liberalisation, investor confidence, and cross-border capital mobility. In parallel, the international climate regime—centred on the UN Framework Convention on Climate Change (UNFCCC) and the Paris Agreement—seeks deep decarbonisation, climate resilience, and intergenerational equity. The intersection of these regimes is nowhere more salient than in infrastructure investments, which, while indispensable for development, are major drivers of greenhouse gas emissions and path dependency. This article examines how international economic regulatory framework interacts with climate obligations in the specific context of infrastructure development. It adopts a doctrinal and comparative methodology, evaluates WTO and ISDS case law, integrates policy analysis, and grounds proposals in ethical *frameworks of climate justice and intergenerational equity. A regional lens on the Mediterranean—including Greece, Turkey, and North African states—illustrates distributive consequences of measures such as the EU Carbon Border Adjustment Mechanism (CBAM).*

Keywords: *Investments, regulation, climate crises, decision making, managing critical infrastructure*

1. Introduction and Methodology

Infrastructure sits at the heart of the climate–economy nexus. Energy systems, transport corridors, ports, water and waste facilities, and urban construction collectively account for a dominant share of global CO_2 emissions and for long-lived capital that locks societies into particular development pathways (IEA, 2021; IPCC, 2022). This dual role—engine of growth and source of emissions—creates a central legal dilemma: how can the international economic regime, designed to facilitate cross-border investment and trade in goods and services relevant to infrastructure, accommodate the imperatives of deep decarbonisation and climate resilience?

The dilemma is acute in the Mediterranean. Greece's economy is tightly interwoven with infrastructure-intensive sectors—shipping, ports, cement, aluminium, construction for tourism—while the region is a climate hotspot facing heat extremes, water stress, and sea-level rise (IPCC, 2022). Similar dynamics characterise Turkey and several North African economies integrated into EU value chains for steel, cement, aluminium and fertilisers. These states must mobilise large-scale finance for low-carbon and resilient infrastructure while navigating WTO disciplines, investment protections, and EU climate policies such as the Emissions Trading System (ETS) and CBAM.

This article addresses the following question: How can international economic law—particularly trade and investment law—be reconciled with climate commitments in the domain of infrastructure investments, with particular reference to the Mediterranean region and Greece? To answer this, the study pursues four objectives: (1) doctrinal analysis of the relevant trade and investment rules; (2) identification of conflict zones through WTO and ISDS jurisprudence; (3) exploration of emerging synergies in treaty practice, industrial policy, and sustainable finance; and (4) articulation of legal–ethical pathways for reconciliation that foreground climate justice and intergenerational equity (Rawls, 1971; Brown Weiss, 1989; Jonas, 1984; Voigt, 2020).

We argue that reconciliation is both necessary and feasible. It requires embedding climate commitments into trade and investment agreements; clarifying the WTO legality of green subsidies and border adjustments; reforming investor–state dispute settlement (ISDS) to avoid regulatory chill; leveraging sustainable finance and ESG standards; and adopting cooperative regional mechanisms to support decarbonisation of infrastructure value chains. The Mediterranean case demonstrates how carefully designed legal tools and ethical guardrails can align infrastructure investment with a just transition.

Methodologically, the article combines doctrinal legal research with comparative assessment and policy evaluation. The doctrinal dimension reviews the structure and interpretation of WTO law (GATT 1994, SCM Agreement, GATS) and investment protections (FET, expropriation, ISDS), contrasting them with obligations and expectations under the UNFCCC and Paris Agreement. The comparative analysis focuses on EU law, given its centrality to Mediterranean economies, including the European Climate Law (Regulation (EU) 2021/1119) and the CBAM Regulation (EU 2023/956). Case law analysis examines WTO disputes—US–Shrimp (1998), Brazil–Retreaded Tyres (2007), Canada–Renewable Energy (2013)—and ISDS awards under the ECT—Vattenfall v Germany (II), Rockhopper v Italy—as well as climate rights litigation in European courts (Neubauer v Germany; KlimaSeniorinnen v Switzerland). Policy evaluation draws on IEA, IPCC, EIB, and World Bank materials on sustainable infrastructure finance. Finally, the normative analysis applies climate justice (distributive, corrective, procedural) and intergenerational equity lenses to assess the legitimacy and design of legal reforms.

2. The Normative Framework

International economic law was not designed with climate stabilisation in mind. The WTO disciplines trade in goods and services through core principles of non-discrimination—Most-Favoured Nation (MFN) and National Treatment—and constrains subsidies and quantitative restrictions. Infrastructure-related markets are directly touched by these disciplines: steel, cement and aluminium (GATT rules), logistics and energy services (GATS), and public support for infrastructure (SCM Agreement). WTO law does not prohibit environmental protection; however, measures must satisfy strict tests of necessity, proportionality, and non-discrimination, with general exceptions in GATT Article XX operating as narrow gateways (Van den Bossche & Zdouc, 2017).

The investment regime emerged in the second half of the twentieth century to shield investors from political risk. BITs and multilateral treaties such as the Energy Charter Treaty (ECT) guarantee fair and equitable treatment (FET), protection against direct and indirect expropriation, and access to ISDS. Infrastructure projects—power plants, pipelines, ports, and water concessions—are archetypal protected investments. Yet when states, responding to climate imperatives, revise energy mixes, withdraw fossil fuel licences, or reconfigure subsidy schemes, investors can invoke treaty protections to claim compensation, potentially chilling regulatory action (Tienhaara, 2018; Burger & Gundlach, 2021).

In contrast, the international climate regime articulates a trajectory to net-zero. The Paris Agreement relies on Nationally Determined Contributions (NDCs), transparency, and periodic ambition cycles to drive progressive emissions reductions. It incorporates the principle of equity and contextualises obligations through capabilities and responsibilities (UNFCCC, CBDR–RC). While the Paris Agreement does not prescribe specific infrastructure choices, its long-term temperature goal and net-zero objective have direct implications for the compatibility of new fossil fuel infrastructure with climate stability (Voigt, 2020).

The EU has internalised climate objectives through binding legislation. The European Climate Law makes climate neutrality by 2050 legally enforceable across the Union and requires alignment of EU policies and finance flows. For infrastructure inputs, the EU ETS prices carbon at source, while the CBAM aims to ensure foreign producers of carbon-intensive goods face equivalent costs when exporting to the EU market. EU sustainable finance measures (the Taxonomy and SFDR) further influence the bankability of infrastructure projects across member states, including Greece, and shape cross-border capital allocation to the wider Mediterranean.

3. Conflicts: Investment and Infrastructure vs Climate Commitments

Trade conflicts first arise around subsidies for green infrastructure. Many states rely on public support to scale renewable energy generation, grid upgrades, public transport electrification, and industrial decarbonisation. Under the SCM Agreement, however, subsidies contingent on the use of domestic content or conferring specific advantages can be actionable. In Canada–Renewable Energy, elements of Ontario's feed-in tariff were found inconsistent with WTO rules even though the measure pursued climate goals (Howse, 2013). The jurisprudence signals a narrow legal corridor for climate-oriented industrial policy unless disciplines are reinterpreted or reformed.

Second, border adjustment mechanisms such as CBAM provoke disputes over MFN, National Treatment, and the nature of permitted border charges. Critics contend that CBAM constitutes an additional import duty contrary to GATT Article II or that it discriminates against imports lacking access to equivalent decarbonised energy or carbon pricing. The EU, by contrast, frames CBAM as mirroring domestic ETS obligations and as falling within Article XX(b) and (g), provided it is administered without arbitrary discrimination (Mehling et al., 2019). The outcome of any WTO litigation will have systemic consequences for the compatibility of trade rules with decarbonisation of infrastructure supply chains.

Investment arbitration reveals perhaps the sharpest friction. In Vattenfall v Germany (II), a utility sought billions in compensation following Germany's post-Fukushima nuclear phase-out, arguing that the regulatory shift violated FET and legitimate expectations. In Rockhopper v Italy, an investor received compensation after a ban on nearshore oil exploration along the Adriatic. Spain faced multiple claims after retroactive changes to renewable subsidies. These cases, arising under the ECT framework, illustrate how investment protections can lock in carbon-intensive infrastructures and penalise policy corrections, producing a regulatory chill that deters ambitious action (Tienhaara, 2018; Burger & Gundlach, 2021).

For Mediterranean economies, the stakes are tangible. Greece's cement and aluminium producers are energy-intensive and trade-exposed; decarbonisation requires substantial capital for electrification, carbon capture, or alternative binders and smelting processes. If the state adjusts support schemes or accelerates standards, foreign investors could test the boundaries of BIT and ECT protections. Turkey and Egypt, major exporters of steel and fertilisers to the EU, may face trade frictions under CBAM while also being exposed to ISDS risks as they reconfigure energy infrastructure. The cumulative effect can be to delay or dilute the transition.

4. Emerging Synergies: Innovations in Trade, Investment and Infrastructure Governance

Despite persistent conflicts, practice is evolving toward alignment. First, the Energy Charter Treaty has come under sustained criticism for shielding fossil fuel assets. In response, multiple EU member states—France, Germany, Spain, the Netherlands—have decided to withdraw, and proposals to neutralise the sunset clause are advancing (Gazzini, 2023). An ECT exit or deep reform, coupled with new-generation investment agreements that explicitly preserve the right to regulate for climate objectives, would significantly reduce arbitration exposure for infrastructure transitions.

Second, green industrial policy has moved to centre stage. The EU's Green Deal Industrial Plan and the U.S. Inflation Reduction Act (IRA) deploy large-scale subsidies, tax credits, and public procurement to accelerate clean energy and low-carbon manufacturing. Scholars argue for revisiting the WTO's subsidy rules to differentiate climate-supportive measures from trade-distorting fossil fuel support, potentially through a 'climate waiver' or revised SCM criteria (Howse, 2013; Mavroidis & Neven, 2021; Rubini, 2015). Such reforms would provide legal certainty for grid upgrades, green hydrogen, and public transport investments.

Third, sustainable development clauses in trade agreements and environmental carve-outs in investment treaties are proliferating. Instruments like CETA and the EU–Vietnam FTA reference the Paris Agreement; some recent BITs clarify that non-discriminatory environmental and health measures do not breach FET or amount to indirect expropriation (Morgera & Kulovesi, 2019). While enforcement remains variable, these clauses help align treaty interpretation with climate goals relevant to infrastructure choices.

Fourth, sustainable finance is reshaping capital allocation. The EU Taxonomy defines technical screening criteria for activities deemed climate-aligned; the SFDR imposes disclosure duties on financial intermediaries. Multilateral development banks now screen infrastructure pipelines for Paris alignment. Private ESG integration and stewardship are exerting pressure on infrastructure sponsors to decarbonise assets and disclose climate risks (Sjåfjell & Bruner, 2022). Together, these mechanisms tilt the investment ecosystem toward low-carbon infrastructure.

Finally, corporate governance reforms and business ethics are embedding climate responsibility within firms. Boards are increasingly expected to oversee climate strategy, scenario analysis, and just transition plans for infrastructure-heavy portfolios. Embedding responsibilities for intergenerational impacts strengthens the legitimacy of difficult trade-offs and mitigates the risk that private enforcement (via ISDS) undermines public climate mandates.

5. Case Study: The EU CBAM and Infrastructure in the Mediterranean

The EU CBAM, enacted through Regulation (EU) 2023/956, introduces a border carbon pricing mechanism for imports of cement, iron and steel, aluminium, fertilisers, hydrogen, and electricity. During the transitional phase (2023–2025), importers report embedded emissions; from 2026, they must purchase CBAM certificates reflecting the EU ETS price, adjusted for any carbon price paid in the country of origin (European Commission, 2023). CBAM's logic is to prevent carbon leakage, level the playing field for EU producers already subject to ETS costs, and incentivise decarbonisation in exporting countries.

For Greece, CBAM's relevance is immediate. The domestic cement sector has long been export-oriented in the Eastern Mediterranean; firms face rising ETS costs and capital needs for clinker substitution, waste heat recovery, and carbon capture. CBAM reduces the risk of displacement by lower-cost, higher-carbon imports but also raises input costs for construction. In aluminium, Greek producers have pursued greener electricity procurement; CBAM helps shield against imports produced with coal-heavy power mixes, but simultaneously pushes for faster decarbonisation of domestic grids and smelters.

Shipping and port infrastructure, central to Greece's economy, are indirectly affected. While international shipping sits primarily under the IMO and the EU ETS extension to maritime, CBAM influences the price of steel and aluminium used for ships, cranes, and port upgrades. Greek shipyards and port authorities planning expansions must now factor the carbon cost of materials, encouraging procurement strategies that reward lower-embodied-carbon products and suppliers investing in cleaner production.

Turkey illustrates CBAM's extraterritorial pull. As a major exporter of steel and cement to the EU, Turkish manufacturers face higher market entry costs absent an equivalent domestic carbon price. Policymakers in Ankara are considering an ETS and sectoral decarbonisation roadmaps partly in response to CBAM (Erdem & Turhan, 2023). The mechanism thus functions as a legal and economic nudge toward aligning infrastructure supply chains with EU climate norms.

North African states encounter diverse effects. Morocco, with significant renewable deployment, could leverage CBAM by branding aluminium and fertiliser exports as low-carbon, attracting green infrastructure investment. Egypt, a large fertiliser exporter, may face tougher adjustments where gas feedstock and electricity are carbon-intensive. Tunisia risks marginalisation without finance for industrial upgrades. Western Balkan countries—Serbia, Bosnia-Herzegovina, North Macedonia—export electricity and materials into the EU market; CBAM pressures them to adopt ETS-compatible systems and modernise power infrastructure (Marinov, 2022).

From a WTO perspective, CBAM's legality turns on design and administration. A non-discriminatory, origin-neutral system that mirrors internal carbon pricing and allows crediting of foreign carbon costs is more likely to withstand scrutiny. The EU will likely rely on GATT Article XX(b) (protection of life and health) and XX(g) (conservation of exhaustible natural resources), aiming to satisfy the chapeau's anti-discrimination test (Mehling et al., 2019).

Ethically, CBAM raises distributive questions. EU members like Greece benefit from a protective shield that internalises carbon costs, while non-EU Mediterranean neighbours may face short-term competitiveness losses. A just approach would dedicate part of CBAM revenues to climate finance and technology transfer for affected partners, supporting clean electrification, low-carbon cement and steelmaking, and port decarbonisation across the region. Such recycling could transform CBAM from a unilateral measure into a cooperative engine of regional transition.

6. Critical Infrastructure Investments in Greece and Climate Change Mitigation Commitments

Greece's trajectory toward climate neutrality is fundamentally shaped by the future of its critical infrastructure—the energy grid, transport systems, industrial facilities, and ports—that both sustain the national economy and drive its carbon footprint. The country's National Energy and Climate Plan (NECP), aligned with the European Climate Law (Regulation 2021/1119), commits Greece to achieving a 55% reduction in greenhouse gas emissions by 2030 compared to 1990 levels and to reaching climate neutrality by 2050. Meeting these targets requires a profound transformation of infrastructure investments, which remain both an enabler and a constraint on climate policy.

The most visible shift concerns the energy sector, historically dominated by lignite-fired power plants in Western Macedonia and the Peloponnese. Greece has pledged to phase out lignite power generation entirely by 2028, with some units closing even earlier. This decision, while consistent with the Paris Agreement's net-zero objectives, necessitates massive investment in renewable energy infrastructure—solar parks in Central Greece and the islands, wind farms onshore and offshore in the Aegean, and energy storage projects to balance intermittency. The Independent Power Transmission Operator (ADMIE) is also expanding interconnections to link the islands to the mainland grid, thereby reducing reliance on oil-fired generators. These projects illustrate how critical infrastructure investment is both a mitigation tool and a means of enhancing resilience and energy security. However, they also expose Greece to ISDS risk: foreign investors in existing fossil-based infrastructure could seek compensation under investment treaties if regulatory changes diminish asset values.

Ports and maritime infrastructure represent another sector at the crossroads of economic growth and climate commitments. Greece's ports, particularly Piraeus and Thessaloniki, are critical nodes in global trade and central to the EU's Trans-European Transport Network (TEN-T). Yet port operations are energy-intensive, relying heavily on fossil fuels for shipping, logistics, and cargo handling. Under the EU's Fit for 55 package, shipping will be included in the EU ETS from 2024, and ports are required to provide shore-side electricity to vessels by 2030. This compels significant infrastructure upgrades: electrification of port equipment, installation of renewable-based shore power, and potential adaptation for alternative fuels such as LNG and green hydrogen. These investments, supported by EU cohesion funds and the Recovery and Resilience Facility, directly link Greece's critical infrastructure strategy with its climate mitigation commitments. Without them, the competitiveness of Greek ports could decline relative to Mediterranean rivals that move faster toward decarbonisation.

Transport infrastructure more broadly faces a similar challenge. Road transport is the largest emitting sector in Greece, and decarbonisation requires not only electrification of private vehicles but also large-scale investment in public transit, rail, and intermodal hubs. Projects such as the Athens Metro expansion, the electrification of key railway corridors, and the development of urban tram and bus networks are essential to shift passenger flows toward low-carbon modes. The EU's Connecting Europe Facility and NextGenerationEU funds have prioritised such investments, but their success depends on coordinated governance and long-term financing. Moreover, climate-proofing these infrastructures against rising temperatures and extreme weather is vital, as recent floods in Thessaly demonstrated the vulnerability of transport corridors to climate shocks.

Greece's industrial base, particularly cement and aluminium production, highlights the complexities of reconciling critical infrastructure with CBAM and EU ETS obligations. The cement industry, led by Titan Cement Group, and aluminium producers such as Aluminium of Greece (Mytilineos Group), are energy- and emissions-intensive but vital to both domestic construction and exports. Under CBAM, imports of cement, steel, and aluminium into the EU will be subject to carbon pricing, effectively requiring Greek producers to decarbonise in order to remain competitive. Investments in carbon capture and storage (CCS), electrification of industrial processes, and substitution with lower-carbon inputs are therefore indispensable. Titan has already piloted CCS projects, while Aluminium of Greece has pursued power purchase agreements with renewable energy providers. Nevertheless, the scale of required investment is daunting and raises questions about the balance between state support (potentially vulnerable to WTO subsidy challenges) and private finance guided by ESG criteria.

The tourism sector, which accounts for around 20% of GDP, further illustrates the intersection of critical infrastructure and climate commitments. Tourism relies on airports, hotels, coastal resorts, and water supply systems that are vulnerable to rising sea levels, droughts, and extreme heat. Investments in climate-resilient water infrastructure, sustainable building retrofits, and low-carbon transport connections to tourist regions are essential. Moreover, airports such as Athens International Airport and island facilities must prepare for EU regulations requiring sustainable aviation fuels, which demand significant fuel storage and supply chain upgrades. Without such investments, Greece risks both reputational damage in sustainable tourism markets and economic losses from climate impacts.

Taken together, these examples show that critical infrastructure investment in Greece is inseparable from climate change mitigation commitments. The energy transition, port and shipping decarbonisation, transport electrification, industrial modernisation, and tourism resilience all require capital flows on a scale unprecedented in Greece's modern history. They also expose Greece to international economic law frictions: WTO rules on subsidies may constrain state aid for clean industries; CBAM may create competitiveness pressures for neighbours; and investment treaty protections may conflict with regulatory shifts. Yet they also offer opportunities: EU sustainable finance frameworks, climate-aligned trade agreements, and ESG-driven investment trends provide mechanisms for mobilising and legitimising the transition. Greece thus exemplifies the broader Mediterranean dilemma: only by aligning critical infrastructure investments with international climate obligations can the region ensure both economic prosperity and climate resilience.

7. Pathways for Reconciliation

Treaty reform is foundational. Under WTO law, members could adopt a targeted waiver insulating climate-consistent subsidies and border adjustments from challenge, or revise the SCM Agreement to recognise the unique role of green infrastructure support. The concept of 'likeness' could explicitly incorporate production-related carbon intensity, allowing differential treatment of otherwise similar products based on embedded emissions. Such doctrinal moves would legitimise public investment in resilient grids, mass transit, and low-carbon building materials while preserving core non-discrimination constraints (Howse, 2013; Mavroidis & Neven, 2021).

Investment treaties should be modernised to embed climate carve-outs and clarify the right to regulate. Model clauses can specify that bona fide, non-discriminatory measures aimed at complying with international climate commitments do not breach FET or constitute indirect expropriation. States may also exclude fossil fuel investments from treaty coverage or adopt joint interpretive statements guiding tribunals to weigh climate imperatives. The EU's initiative for a Multilateral Investment Court could integrate public law safeguards, appellate review, and environmental expertise (European Commission, 2020).

ISDS reform should be complemented by investor obligations. Access to treaty protections could be conditioned on compliance with domestic environmental law, Paris-aligned transition plans, and robust human rights due diligence. Tribunals should be empowered to hear state counterclaims against investors for environmental harm or failure to implement agreed decarbonisation pathways. These steps would rebalance rights and responsibilities in infrastructure investment.

Ethical frameworks must guide legal design. Climate justice demands attention to distributional effects across and within countries; CBAM revenues could be earmarked for Mediterranean green infrastructure funds that co-finance clean industrial upgrades and coastal resilience. Intergenerational equity requires screening infrastructure proposals for long-term climate compatibility, avoiding stranded assets and prioritising projects—renewables, storage, efficient buildings, resilient ports—that deliver benefits over decades (Brown Weiss, 1989; Voigt, 2020). Procedural justice calls for inclusive planning that integrates affected communities into decision-making.

Sustainable finance is the implementation engine. Aligning national development banks, multilateral lenders, and private capital with the EU Taxonomy and Paris Agreement standards can unlock investment at scale. Disclosure regimes like the SFDR and emerging climate reporting requirements channel capital away from high-carbon infrastructure and toward bankable, resilient alternatives. For Greece and neighbours, blended finance vehicles—combining EU funds, MDB loans, and private equity—can de-risk first-of-a-kind projects such as green hydrogen corridors, carbon capture hubs, and zero-emission port operations.

Finally, regional cooperation in the Mediterranean can smooth CBAM frictions and accelerate transition. Options include linking carbon pricing systems, mutual recognition of robust MRV (monitoring, reporting, verification) frameworks for embedded emissions, joint technology roadmaps for low-carbon cement and steel, and coordinated procurement standards for public infrastructure that privilege low-embodied-carbon materials. Such cooperation would reduce trade tensions and build a shared market for climate-aligned infrastructure.

8. Concluding remarks

Infrastructure is the decisive arena where the trajectories of international economic law and climate governance converge. WTO disciplines and investment protections have at times impeded decarbonisation, particularly in infrastructure-intensive sectors essential to the Mediterranean economy. Yet the legal landscape is evolving: treaty withdrawals and reinterpretations, sustainable finance, corporate governance reforms, and novel trade instruments like CBAM point toward a workable reconciliation.

Greece and the wider region, the meet of success will depend on combining legal innovation with ethical commitment. Trade and investment rules must be recalibrated to protect regulatory space for climate-aligned infrastructure while maintaining fair competition. At the same time, distributive mechanisms should cushion short-term adjustment costs for neighbouring exporters and communities. If designed with justice and intergenerational stewardship, the reconciliation of international economic regulatory framework with climate commitments can deliver resilient growth, and a credible pathway towards net-zero market in the Mediterranean and beyond.

References

Brown Weiss, E. (1989) In Fairness to Future Generations. United Nations University Press.

Burger, M. and Gundlach, J. (2021) The Energy Charter Treaty and Climate Change: The Need for

Dimitriou D., Sartzetaki M., Karagkouni A. (2025). Harnessing Neuroleadership Concept for Enhancing Management Efficiency and Business Sustainability in Supply Chain: A System of System Approach, Journal of Lifestyle and SDGs Review. https://doi.org/10.47172/2965-730X.SDGsReview.v5.n06.pe06449

Dimitriou D. and M. Sartzetaki, (2022). Modified fuzzy TOPSIS assessment framework for defining large transport enterprises business value, Operational Research, Springer, DOI : https://doi.org/10.1007/s12351-022-00719-9

Dimitriou D. and Karagkouni A., (2022). Du-dilligence of transport infrastructure operators sustainability: a circular economy driven approach, Frondiers in Sustainability : Circular Economy, DOI: https://doi.org/10.3389/frsus.2022.916038

Dimitriou D., (2022). Corporate Ethics: an arbitration of philosophical concepts and market practices, CONATUS, International Journal of Philosophy, DOI: https://doi.org/10.12681/cjp.29864

Dimitrios D. and P. Zeimbekis, Appraisal modelling for FSRU greenfield energy projects, Energies 2022, 15(9), 3188; DOI: https://doi.org/10.3390/en15093188

Dimitriou D., Karagkouni, A. (2022). 'Airports' Sustainability Strategy: Evaluation framework upon environmental awareness'. Frontiers in Sustainability. https://doi.org/10.3389/frsus.2022.880718

Dimitriou D. and Karagkouni A. (2022). "Assortment of Airports' Sustainability Strategy: A Comprehensiveness Analysis Framework", International Journal: Sustainability, 14 (7): 4217. DOI: https://doi.org/10.3390/su14074217

Dimitriou D., Sartzetaki M., (2022). Assessment of socioeconomic impact diversification from transport infrastructure projects: the case of a new regional airport, Transportation Research Records (TRR), SAGA, Vol 2676, Issue 4, 2022, pp 732-745. DOI: https://doi.org/10.1177/03611981211064999

Reform. Sabin Center for Climate Change Law, Columbia University.

Epps, T. and Green, A. (2010) Reconciling Trade and Climate: How the WTO Can Help Address Climate Change. Edward Elgar.

Erdem, S. and Turhan, M. (2023) 'Turkey and the EU's Carbon Border Adjustment Mechanism: Between Compliance and Contestation', Journal of World Trade, 57(3), 401–426.

European Commission (2020) Proposal for a Multilateral Investment Court. COM(2020) 379.

European Commission (2023) Regulation (EU) 2023/956 establishing a carbon border adjustment mechanism. Official Journal of the European Union.

Gazzini, T. (2023) 'The EU Withdrawal from the Energy Charter Treaty: Legal and Policy Implications', Common Market Law Review, 60(2), 345–372.

Howse, R. (2013) 'Climate Mitigation Subsidies and the WTO Legal Framework', Journal of International Economic Law, 16(2), 469–491.

IEA (2021) Net Zero by 2050: A Roadmap for the Global Energy Sector. International Energy Agency.

IPCC (2022) AR6 Working Group II: Impacts, Adaptation and Vulnerability. Cambridge University Press.

Jonas, H. (1984) The Imperative of Responsibility. University of Chicago Press.

Karagkouni, A., Dimitriou D. (2022). 'Sustainability Performance Appraisal for Airports Serving Tourist Islands'. Sustainability, 14, no. 20: 13363. DOI: https://doi.org/10.3390/su142013363

Karagkouni, A., Dimitriou D. (2022). 'Sustainability Performance Appraisal for Airports Serving Tourist Islands'. Sustainability, 14, no. 20: 13363. DOI : https://doi.org/10.3390/su142013363

Marinov, E. (2022) 'The Western Balkans, EU ETS, and CBAM: Challenges of Alignment', Southeast European and Black Sea Studies, 22(4), 563–582.

Mavroidis, P.C. and Neven, D.J. (2021) 'Greening the WTO: The Case for Climate-Related Subsidies', World Trade Review, 20(4), 545–567.

Mehling, M., van Asselt, H., Das, K., Droege, S. and Verkuijl, C. (2019) 'Designing Border Carbon Adjustments for Enhanced Climate Action', American Journal of International Law, 113(3), 433–481.

Morgera, E. and Kulovesi, K. (2019) Research Handbook on International Climate Law. Edward Elgar.

Rawls, J. (1971) A Theory of Justice. Harvard University Press.

Rubini, L. (2015) Subsidies, Climate Change and the WTO: The Energy Sector. Cambridge University Press.

Sartzetaki, M., Moutzouri, A., Karagkouni, A., & Dimitriou, D. (2025). The Ecosystem of Ethical Decision Making: Key Drivers for Shaping the Corporate Ethical Character. Conatus - Journal of Philosophy, 10(1), 221–238. https://doi.org/10.12681/cjp.38439

Sartzetaki, M., Dimitriou, D., Karagkouni A. (2025). Assortment of the Regional Business Ecosystem Effects Driven by New Motorway Projects, Transportation Research Procedia, Volume 82, Pages 515-529, ISSN 2352-1465, https://doi.org/10.1016/j.trpro.2024.12.111.

Sjåfjell, B. and Bruner, C. (2022) The Cambridge Handbook of Corporate Law, Corporate Governance and Sustainability. Cambridge University Press.

Tienhaara, K. (2018) 'Regulatory Chill in a Warming World: The Threat to Climate Policy Posed by Investor-State Dispute Settlement', Transnational Environmental Law, 7(2), 229–250.

Tsironis, G., Karagkouni, A., Dimitriou, D., Tsagarakis, K.P., (2023). Mapping sustainable practices and concepts in the transportation ecosystem for the EU-27 coun-

tries, based on LinkedIn company profiles, Frontiers in Sustainability, 2023, 4, DOI: https://doi.org/10.3389/frsus.2023.1268575
Van den Bossche, P. and Zdouc, W. (2017) The Law and Policy of the World Trade Organization. Cambridge University Press.
Voigt, C. (2020) 'Climate Change and Intergenerational Justice', in Daly, E. and Kotzé, J. (eds.) Research Handbook on Human Rights and the Environment. Edward Elgar.

EARNINGS MANAGEMENT AND THE COST OF DEBT:

EVIDENCE FROM THE EUROPEAN CORPORATE BOND MARKET

Ioannis Dokas
Department of Economics Democritus University of Thrace
intokas@econ.duth.gr

Evaggelos Drimpetas
Department of Economics Democritus University of Thrace
edrimpet@econ.duth.gr

Konstantinos Hazakis
Department of Economics Democritus University of Thrace
kmhazaki@otenet.gr

Christos Leontidis
Department of Economics Democritus University of Thrace
cleonti@econ.duth.gr

Eleftherios Spyromitros
Department of Economics Democritus University of Thrace
espyromi@econ.duth.gr

ABSTRACT

This study examines the impact of accrual-based and real earnings management on the cost of debt in the European corporate bond market. Using a dataset of 203 publicly listed companies that issued non-convertible corporate bonds between 2013 and 2023, the analysis assesses how earnings manipulation proxies influence bond ratings and yield spreads. The findings show that firms engaging in accrual-based earnings management are consistently penalized. In essence, higher discretionary accruals are associated with lower bond ratings and, to a lesser extent, higher yield spreads. In contrast, real earnings management—captured by abnormal discretionary expenses, abnormal production costs, and abnormal cash flows—has no significant effect on ratings or spreads, potentially due to detection challenges or its alignment with legitimate business strategies. The results also reveal that firm-specific fundamentals, such as profitability, leverage, size, and audit quality, exert a stronger influence on credit assessments than the contractual terms of the bond issues. Overall, the study underscores the central role of accounting quality in debt market evaluations and offers insights for managers, investors, and regulators on the implications of earnings management for financing conditions.

Keywords: *Earnings management, financial reporting quality, bond ratings, yield spread, bond issues*

1. Introduction

Over the past decade, the European corporate bond market has expanded rapidly, becoming an increasingly important source of financing in a region traditionally dominated by bank lending. In such a market, where information asymmetries between issuers and investors can be pronounced, the quality of financial reporting plays a pivotal role in credit risk assessment and pricing. Bondholders rely heavily on publicly available accounting information to evaluate issuers' capacity to meet debt obligations, making any manipulation of reported performance—whether through accrual-based adjustments or real activity changes—potentially consequential for both ratings and yield spreads. As issuance grows and investor scrutiny intensifies, understanding how different forms of earnings management are perceived and priced in the European corporate bond market becomes increasingly relevant.

In line with other research on crucial financing events—such as IPOs, SEOs, and loan contracts (Teoh et al., 1998a, 1998b; Ducharme et al., 2001; Cohen and Zarowin, 2010; Pappas et al., 2019; Dyreng et al., 2022)—accounting scholars have examined the role of earnings management in the context of corporate bond issuances. A substantial body of evidence documents heightened earnings management activity in periods surrounding bond offerings (Liu et al., 2010; Caton et al., 2011; Demirtas and Rodgers Cornaggia, 2013; Mellado-Cid et al., 2017). Building on these insights, other studies have explored whether such practices influence the cost of debt—essentially, whether stakeholders in the bond market, including rating agencies and investors, can identify manipulation and respond by adjusting credit terms. The findings, however, remain mixed. One strand of the literature reports that income-increasing manipulation is associated with higher credit ratings or lower yield spreads, suggesting that external stakeholders do not fully recognize or penalize reduced earnings quality (Liu et al., 2010; Mellado-Cid et al., 2017). In contrast, other research finds evidence that credit market participants are able to detect poor earnings quality and incorporate it into their risk assessments, resulting in lower ratings and higher spreads (Caton et al., 2011; Ge and Kim, 2014; Crabtree et al., 2014). This divergence highlights the need for further investigation—particularly in the European corporate bond market, where institutional, regulatory, and market structures differ markedly from those in the United States.

This study examines a sample of 203 publicly listed European firms that issued non-convertible corporate bonds between 2013 and 2023. The main objective is to investigate the impact of accrual-based and real earnings management on the cost of debt, which is represented by bond ratings and yield spread. The empirical analysis reveals that accrual-based earnings management is consistently penalized in the European corporate bond market. Firms with higher discretionary accruals receive lower bond ratings and, to a lesser extent, face higher yield spreads, indicating that both rating agencies and investors incorporate financial reporting quality into their risk assessments. In contrast, proxies for real earnings management do not exhibit statistically significant effects on either ratings or spreads. This suggests that real earnings management is either more difficult to detect or is often intertwined with legitimate operational decisions, reducing its influence on debt pricing. Furthermore, the analysis shows that firm-specific fundamentals, including profitability, leverage, size, and audit quality, have a stronger influence on credit assessments than the contractual features of the bond issues.

The contribution of this study is twofold. First, it provides new empirical evidence to the ongoing debate on how financial reporting quality influences the cost of debt. Although this relationship has been widely examined, prior studies have produced mixed and sometimes contradictory results, particularly regarding the sensitivity of credit markets to different forms of earnings management. By simultaneously examining both accrual-based and real earnings management, this research offers a more comprehensive assessment of how various manipulation strategies affect credit risk evaluations. Second, whereas most previous literature has focused exclusively on U.S. bond issuers, this study shifts the perspective to the European corporate bond market. This extension is important because the European context differs markedly from the U.S. in terms of market maturity, investor composition, legal enforcement, accounting traditions, and cultural attitudes toward risk and corporate governance (Darmouni and Papoutsi, 2022). By drawing on data from a broad range of European economies, the analysis captures the influence of these institutional and economic differences, allowing for a richer understanding of whether established U.S.-based findings can be generalized across heterogeneous settings.

The remainder of this study is structured as follows: Section 2 reviews the relevant literature and introduces the research queries. Section 3 outlines the methodological framework, including sample selection, earnings management estimation methods, and the specification of baseline models. Section 4 offers an analysis and interpretation of the empirical results. Finally, Section 5 provides concluding remarks and identifies potential avenues for future inquiry.

2. Literature Review and Hypotheses Development

The accounting literature has identified a variety of conditions under which firms systematically engage in earnings management. Both equity and debt financing have been extensively examined, particularly with regard to how manipulation practices affect the cost of capital acquisition. In the context of equity financing, a substantial body of research has shown that firms frequently adopt aggressive accounting policies during periods surrounding initial public offerings (Teoh et al., 1998a; Ducharme et al., 2001; Premti and Smith, 2020) or seasoned equity offerings (Teoh et al., 1998b; DuCharme et al., 2004; Cohen and Zarowin, 2010; Kothari et al., 2016), with the explicit aim of influencing the outcomes of these transactions. Similarly, numerous studies have examined the impact of earnings management on the cost of debt associated with loan agreements. Francis et al. (2005) and Bharath et al. (2008) indicate that lenders frequently penalize firms exhibiting unusually high discretionary accruals, resulting in more stringent loan terms, such as increased interest rates, shorter maturities, and higher collateral requirements. Pappas et al. (2019) investigate real earnings management, which is alleged to be a less detectable manipulation technique compared to accrual-based practices. They demonstrated that when intervention in operating activities is revealed, lenders impose restrictive loan conditions and tighter financial covenants. Dyreng et al. (2022) suggest that when earnings management remains undisclosed to banks, firms benefit from reduced borrowing costs and long-term shareholder gains. Conversely, when covenant violations occur, banks impose sanctions, which are particularly severe for firms practicing aggressive and ineffective real earnings management. Overall, this strand of literature highlights the substantial impact of earnings management on debt costs and the contractual dynamics between firms and lenders.

While much of the prior research has concentrated on private debt arrangements, such as bank loans, the influence of earnings management is not limited to this context. Firms also engage in accounting manipulation when accessing public debt markets, particularly around corporate bond issuances. Liu et al. (2010) provide strong evidence that U.S. bond issuers engage in income-increasing accrual-based earnings management in the two years preceding a bond issue, followed by negative discretionary accruals post-issuance due to the reversal of prior adjustments. This upward manipulation around bond offerings is further supported by Caton et al. (2011), who find significant accrual-based earnings management in most bond rating groups, and by Demirtas and Rodgers Cornaggia (2013), who show that issuers primarily use short-term accruals rather than long-term adjustments to enhance their financial position. Beyond accrual-based practices, Mellado-Cid et al. (2017) document the use of real earnings management during the five quarters leading up to bond issuance. In contrast, Gottardo and Moisello (2018) find no significant evidence of accrual-based earnings management for bond issuers, suggesting that some firms prioritize maintaining high-quality financial reporting to avoid penalties from debtholders.

Beyond research on the existence of earnings management around bond issuances, subsequent studies have built on this evidence to examine how such manipulation strategies influence the cost of public debt. These studies, focusing on bond ratings and yield spread as main proxies for the cost of debt investigate whether rating agencies are capable of detecting distorted financial statements and whether their assessments are reflected in the ratings they provide. The demonstrated findings are mixed, indicating two groups of studies. The first group claims that earnings management can contribute to the improvement of the financial performance achieving higher bond ratings or decreased yield spreads. Liu et al. (2010) pointed out a negative impact of discretionary accruals on the yield spread, indicating that the yield spreads decrease when firms present an artificially enhanced performance. Demirtas and Rodgers Cornaggia (2013) used bond ratings as proxy for cost of debt, confirming that manipulations through current accruals lead to higher initial bond ratings. Alissa et al. (2013) demonstrated that deviations from expected ratings are linked to both accrual-based and real earnings management, which firms use to revert toward their expected ratings. Kim et al. (2013) found that firms increase real earnings management while limiting accrual manipulation before credit rating changes, as real activities are deemed less detectable. Similarly, Mellado-Cid et al. (2017) reported that real earnings management prior to bond issues is negatively associated with bond yield spreads, suggesting its use to reduce debt costs.

Conversely, the second group supports that bond holder and rating agencies can efficiently evaluate the financial reporting quality and the actual firm performance, reacting by adapting the cost of debt through higher spreads and lower ratings, respectively. Caton et al. (2011) found that aggressive accounting practices lead to lower initial bond ratings, suggesting that rating agencies take earnings quality into account when assessing the bond issuers. Ge and Kim (2014) investigated the relationship between real earnings management and bond issuance costs, finding that income-increasing manipulations through overproduction reduces bond ratings and increases yield spreads, while sales manipulation is also linked to higher spreads. Crabtree et al. (2014) observed that both real and accrual-based earnings management adversely impact new bond issue ratings, with excessive real earnings management resulting in higher bond yields, especially for firms attempting to meet analyst forecasts. Additionally, Pappas et al. (2019) demonstrated that real earnings management increases bond yield spreads, although it does not significantly affect maturity or collateral requirements.

The above discussion highlights the need for further investigation into the relationship between earnings management and the cost of bond issuance, as existing findings remain mixed. While much of the prior research in this area focuses on U.S. firms, extending the analysis to European markets offers a particularly compelling avenue for study. The European corporate bond market differs from its U.S. counterpart in terms of maturity, rating agency coverage, legal frameworks, and issuer composition (Darmouni and Papoutsi, 2022). Furthermore, the European bond market has expanded rapidly in recent years, with growth largely driven by smaller and riskier issuers. These structural and institutional differences provide a unique context to assess whether earnings management strategies exert a similar influence on bond ratings and yield spreads in Europe. Consequently, this study addresses the following research queries:

RQ1: Does earnings management influence the bond ratings of European bond issuers.

RQ2: Does earnings management influence the yield spread of European bond issuers.

3. Methodology

3.1 Sample selection

The sample consists of 203 publicly listed European firms that issued non-convertible corporate bonds between 2013 and 2023. In line with Liu et al. (2010), Ge and Kim (2014), and Crabtree et al. (2014), convertible bonds were excluded from the sample to eliminate potential confounding effects due to their embedded equity characteristics. Financial and bond issuance data were obtained from the Eikon and DataStream platforms (Thomson Reuters). We have used the bond issue ratings published by Moody's, because the available data from S&P and Fitch ratings led to considerably limited sample sizes. Firms operating in the financial, real estate services, and utilities sectors (SIC codes 4400-4999 and 6000-6999) were excluded due to their distinct accounting practices and the challenges associated with estimating discretionary accruals. Following Liu et al. (2010), a weighted observation approach was applied for multiple bond issues from the same issuer within a given year, and only one bond issue per issuer was retained for each five-year interval throughout the study period. To ensure accurate measurement of both real and accrual-based earnings management proxies, a minimum of seven annual firm-level observations prior to the bond issuance date was required.

Table 1 summarizes the distribution of the sample by issuing country, year of bond issuance, and industry classification. Panel A shows that the sample is concentrated in a few core European economies, with France, Germany, and the United Kingdom together accounting for more than half of the observations. Panel B reveals that bond issuance is skewed toward more recent years, particularly from 2020 to 2023, indicating a more active recent debt market. Panel C highlights industry composition, with Industrials, Consumer Cyclicals, and Technology firms being the most represented sectors, reflecting the sectors most engaged in bond financing within the sample.

Table 1: Sample distribution by nation, industry and year of issuance

A. Nation

Nation	Freq.	Percent
Austria	1	0.49
Belgium	6	2.96
Denmark	3	1.48
Finland	4	1.97
France	47	23.15
Germany	34	16.75
Ireland	9	4.43
Italy	8	3.94
Luxembourg	6	2.96
Monaco	1	0.49
Netherlands	18	8.87
Norway	4	1.97
Spain	3	1.48
Sweden	11	5.42
Switzerland	10	4.93
Turkey	6	2.96
United Kingdom	32	15.76
Total	203	100.00

B. Issue year

Issue Year	Freq.	Percent
2013	3	1.48
2014	5	2.46
2015	14	6.90
2016	16	7.88
2017	16	7.88
2018	25	12.32
2019	15	7.39
2020	27	13.30
2022	37	18.23
2023	45	22.17
Total	203	100.00

C. Industry

Industry	Freq.	Percent
Basic Materials	34	16.75
Consumer Cyclicals	41	20.20
Consumer Non-Cyclicals	27	13.30
Healthcare	17	8.37
Industrials	47	23.15
Technology	37	18.23
Total	203	100.00

Note: This table presents the distribution of the sample across issuing nations, bond issue years, and industry sectors. Panel A reports the countries of origin for the sample firms. Panel B shows the distribution of bond issues by year, covering a period from 2013 to 2023. Panel C provides the industry classification of the bond issuers based on sectoral groupings.

Table 2 presents the descriptive statistics for the variables used in the empirical analysis. The maturity (*Matur*) of bonds is relatively stable across the sample, with a mean of approximately 10 years and low variation. Dummy variables such as *Guar*, *Call*, and *Coll* indicate that a considerable proportion of bonds in the sample are callable or secured, while third-party guarantees are less frequent. The average issue size, expressed as a ratio of total debt (*Issue_debt*), displays high dispersion, suggesting significant heterogeneity in financing practices. Key financial characteristics such as profitability (*ROA*), leverage, and firm size (*Fsize*) show variation consistent with a diverse set of issuers. Notably, 88% of the firms are audited by Big Four firms (*BIG4*), reflecting generally high audit quality. The presence of loss-making firms (*Loss*) and the dispersion in market valuation (*PTBV*) further highlight cross-sectional differences in firm fundamentals relevant to bond pricing.

Table 2: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Matur	203	10.023	0.125	9.945	10.640
Guar	203	0.227	0.420	0	1
Call	203	0.650	0.478	0	1
Coll	203	0.615	0.383	0.008	1.620
Issue_debt	203	205.425	424.155	0.287	4988.519
ROA	203	0.048	0.044	-0.095	0.203
Leverage	203	0.313	0.170	0.032	1.503
Fsize	203	16.864	1.293	13.553	19.848
BIG4	203	0.882	0.324	0	1
Growth	200	0.067	0.236	-0.275	2.805
Loss	203	0.094	0.292	0	1
PTBV	203	3.249	15.043	-66.740	200.810

Note: This table reports descriptive statistics for the variables used in the analysis. *Matur* refers to the bond term in years. *Guar*, *Call*, and *Coll* are dummy variables indicating the presence of a guarantee, callability, and collateral, respectively. *Issue_debt* represents the bond issue size as a ratio of the firms' total debt. *ROA* denotes return on assets, and *Leverage* is the ratio of total debt to total assets. *Fsize* is the natural logarithm of total assets, and *BIG4* is a dummy equal to one if the firm is audited by a Big Four auditor. Growth measures the year-over-year change in sales, Loss is a dummy for loss-making firms, and *PTBV* is the price-to-book value ratio.

3.2 Earnings management level estimation

In line with prior research in accounting (Christopoulos et al., 2023; Cho and Patil, 2024), we use the modified Jones (1991) model, as refined by Dechow et al. (1995), to measure accrual-based earnings management. Our proxy for earnings management is the discretionary component of total accruals, which is derived from the residuals of the following regression model (Equation 1):

$$\frac{TA_{it}}{A_{it-1}} = \alpha_{1t}\left(\frac{1}{A_{it-1}}\right) + \alpha_{2t}\left(\frac{\Delta REV_{it} - \Delta REC_{it}}{A_{it-1}}\right) + \alpha_{3t}\left(\frac{PPE_{it}}{A_{it-1}}\right) + \varepsilon_{it} \tag{1}$$

The equation estimates total accruals (*TAi*,t) as a function of cash sales, captured by the difference between changes in revenue (*ΔREVi,t*) and accounts receivable (*ΔRECi,t*), and gross property, plant, and equipment (*PPEi,t*). Total assets are computed as earnings before extraordinary items minus operating cash flows. The cash sales term reflects non-discretionary accruals linked to current economic conditions, while PPE controls for the non-discretionary component of depreciation.

We employ three models proposed by Roychowdhury (2006) to capture earnings management through cutting discretionary expenses (e.g., R&D and SG&A), overproduction to lower *COGS*, and sales manipulation. Equation (2) presents discretionary expenses ($DISEXP_t$) as a function of lagged sales (S_{t-1}), with the residuals representing unexpected discretionary expenses as a proxy for real earnings management. Positive residuals indicate earnings reduction, while negative residuals suggest upward earnings management.

$$\frac{DISEXP_t}{A_{t-1}} = a_0 + a_1\left(\frac{1}{A_{t-1}}\right) + \beta\left(\frac{S_{t-1}}{A_{t-1}}\right) + \varepsilon_t \tag{2}$$

Equation (3) provides a regression model used to estimate a proxy for real earnings management based on abnormal production costs. Such abnormal production arises when firms overproduce to reduce the cost of goods sold (*COGS*) and artificially boost reported earnings.

$$\frac{PROD_t}{A_{t-1}} = a_0 + a_1\left(\frac{1}{A_{t-1}}\right) + \beta_1\left(\frac{S_t}{A_{t-1}}\right) + \beta_2\left(\frac{\Delta S_t}{A_{t-1}}\right) + \beta_2\left(\frac{\Delta S_{t-1}}{A_{t-1}}\right) + \varepsilon_t \tag{3}$$

$PROD_t$ denotes the production cost for the period, calculated as the sum of COGS and the change in inventories. ΔS_t represents the change in revenues from the previous period, and ΔS_{t-1} is the lagged revenue change. A positive abnormal production cost indicates income-increasing earnings management.

The third real earnings management proxy is derived from the residuals of Equation (4), where cash flows from operations (CFO_t) are regressed on sales (S_t) and changes in sales (ΔS_t). Since sales manipulation reduces cash flows, a negative residual indicates income-increasing earnings management.

$$\frac{CFO_t}{A_{t-1}} = a_0 + a_1\left(\frac{1}{A_{t-1}}\right) + \beta_1\left(\frac{S_t}{A_{t-1}}\right) + \beta_2\left(\frac{\Delta S_t}{A_{t-1}}\right) + \varepsilon_t \tag{4}$$

All variables in equations (1), (2), (3), and (4) are scaled by lagged total assets (A_{t-1}), as a means in mitigating heteroscedasticity. The models are estimated cross-sectionally by implementing regressions within firms sharing the same two-digit SIC industry code, requiring a minimum of eight annual observations per firm.

3.3 Empirical approach and variable selection

The employed methodological approach includes the following two fixed-effects regression models (Model 5 and 6), which uses bond ratings (*BR*) and yield spread (*YS*) as dependent variables.

$$BR_t = a_o + a_1|EM|_{t-1} + a_2Matur_t + a_3\text{Guar}_t + a_4\text{Call}_t + a_5\text{Col}_t + a_6\text{Issue\_debt}_t + a_7\text{ROA}_t + a_8Leverage_t + a_9Fize_t + a_{10}BIG4_t + a_{11}Growth_t + a_{12}Loss_t + a_{13}\text{PTBV}_t + \sum a_i Industry_i + \sum a_i Nation_i + \sum a_i Year_i \tag{5}$$

$$YS_t = a_o + a_1|EM|_{t-1} + a_2Matur_t + a_3\text{Guar}_t + a_4\text{Call}_t + a_5\text{Col}_t + a_6\text{Issue\_debt}_t + a_7\text{ROA}_t + a_8Leverage_t + a_9Fize_t + a_{10}BIG4_t + a_{11}Growth_t + a_{12}Loss_t + a_{13}\text{PTBV}_t + \sum a_i Industry_i + \sum a_i Nation_i + \sum a_i Year_i \tag{6}$$

In line with prior research, we converted bond ratings into numeric scores[1], with lower values indicating lower ratings (Caton et al., 2011; Demirtas and Rodgers Cornaggia, 2013). In the European context, the yield spread is defined as the difference between the corporate bond yield and the yield on a German Bund of the same maturity, which is commonly used as a risk-free benchmark in Eurozone studies. The key independent variable

1. Moody's numeric bond rating conversion: Aaa(21), Aa1(20), Aa2(19), Aa3(18), A1(17), A2(16), A3(15), Baa1(14), Baa2(13), Baa3(12), Ba1(11), Ba2(10), Ba3(9), B1(8), B2(7), B3(6), Caa1(5), Caa2(4), Caa3(3), Ca(2), C(1)

(*EM*) is defined as the absolute value of the earnings management proxies derived from regression models (1) to (4) for the year prior to the bond issuance. We use the absolute values of the earnings management proxies to capture the magnitude of manipulation rather than its direction, as positive values indicate income-increasing practices, while negative values reflect income-decreasing practices.

Models (5) and (6) also include a set of firm-level and issue-specific variables, the definitions of which are provided in Table 3. *Matur* is defined as the natural logarithm of the years to maturity of the issued bond. Ziebart and Reiter (1992) contend that longer maturities increase interest rate risk; in contrast, Ge and Kim (2014), Demirtas and Rodgers Cornaggia (2013), and Liu et al. (2010) report that longer maturities are associated with higher bond ratings and lower yield spreads. *Guar* denotes the value of property, plant, and equipment available as collateral for the bond (measured as gross property, plant, and equipment divided by total assets). *Coll* is a dummy variable indicating whether the bond issuance is guaranteed by a third-party organization (e.g., banks or insurance companies). *Call* is an indicator for callable bonds, while *Issue_debt* represents the ratio of total bond proceeds to total debt. Bonds with guarantees, whether provided by external organizations or by the company's assets, are generally regarded as lower-risk investments; accordingly, the variables Coll and Guar are expected to correlate with higher bond ratings or lower yield spreads (Kale and Meneghetti, 2011; Mellado-Cid et al., 2017). In contrast, callable bonds and those for which the proceeds constitute a significant portion of total debt are considered to entail greater risk and uncertainty. Therefore, we expect the *Call* and *Issue_debt* variables to negatively influence bond ratings and to be positively associated with yield spreads.

Moreover, the models incorporate a set of firm-level variables. *ROA* represents return on assets, capturing firm profitability, while Leverage measures financial risk as the ratio of total debt to total assets. *Fsize*, calculated as the natural logarithm of total assets, reflects firm scale and market power. *BIG4* is a dummy variable indicating audits by a Big 4 firm, serving as a proxy for audit quality. Growth measures expansion opportunities, typically via sales or asset growth, while Loss identifies firms reporting net losses. *PTBV* (price-to-book value) represents the market valuation relative to book value. Larger and more profitable firms are expected to receive higher bond ratings and lower yield spreads due to their lower perceived risk (Ogden, 1987; Denis &

Mihov, 2003; Liu et al., 2010; Crabtree et al., 2014; Ge & Kim, 2014; Mellado-Cid et al., 2017; Kim et al., 2020). In contrast, higher Leverage is anticipated to reduce ratings and widen spreads due to increased financial risk (Liu et al., 2010; Kim et al., 2013; Pappas et al., 2019). Firms audited by Big 4 firms and those with higher *PTBV* are also expected to enjoy higher ratings and lower spreads, reflecting stronger audit quality and greater market confidence.

Table 3: Variable definition

Variable	**Definition**
abnCFO	Abnormal cash flows from operations, calculated the Roychowdhury (2006) model. Used as a proxy for real earnings management.
abnProd	Abnormal production cost, calculated the Roychowdhury (2006) model. Used as a proxy for real earnings management.
BIG4	Dummy variable equal to 1 if the firm is audited by a Big Four audit firm, and 0 otherwise.
BR	Bond rating score, calculated by converting bond ratings into numerical values, with higher numbers representing higher credit quality
Call	Dummy variable equal to 1 if the bond is callable by the issuer, and 0 otherwise.
Coll	Collateral indicator; equal to 1 if the bond is secured by specific collateral, and 0 otherwise.
DACC	Discretionary accruals estimated using the Modified Jones Model (Dechow et al., 1995), used as a proxy for accrual-based earnings management.
DACC_roa	Discretionary accruals estimated using the Kothari et al. (2005) model, which adjusts for firm performance (ROA).
DiscExp	Abnormal discretionary expenses, calculated the Roychowdhury (2006) model. Used as a proxy for real earnings management.
Fsize	Firm size, measured as the natural logarithm of total assets.
Growth	Sales growth, measured as the percentage change in revenue from the previous year.
Guar	Dummy variable equal to 1 if the bond is guaranteed by a third-party, and 0 otherwise.
Issue_debt	Bond issue size expressed as a ratio of the firm's total debt.
Leverage	Financial leverage, calculated as total debt divided by total assets.
Loss	Dummy variable equal to 1 if the firm reported a net loss, and 0 otherwise.
Matur	Bond maturity, measured in years.
PTBV	Price-to-book value ratio, calculated as the market value of equity divided by book value of equity.
REM1	Composite real earnings management proxy, defined as the sum of abnormal discretionary expenses (multiplied by -1) and abnormal production costs.
REM2	Composite real earnings management proxy, defined as the sum of abnormal discretionary expenses and abnormal cash flows from operations.
ROA	Return on assets, calculated as net income divided by total assets.
YS	Yield spread, measured as the difference in yield between the corporate bond and a risk-free benchmark.

4. Results and Discussion

4.1 Main results

4.1.1. Pairwise correlations

Table 4 reports the pairwise correlations of the variables used in the regression analysis. The results indicate that *BR* is negatively associated with accrual-based earnings management (*DACC*, -0.184*) and discretionary expenses (*DiscExp*, -0.263*), suggesting that higher levels of earnings management are linked to lower bond ratings. In contrast, real earnings management proxies, such as abnormal production (*abnProd*) and abnormal cash flows from operations (*abnCFO*), exhibit no significant correlation with BR. YS also shows a negative but weak correlation with *DACC* (-0.110) and a positive correlation with *DiscExp* (0.158), reflecting mixed associations with EM proxies. Regarding bond issue characteristics, only the callability of the bond (*Call*) is significantly and negatively correlated with *BR*, indicating that callable bonds are associated with lower ratings. At the firm level, *BR* is positively correlated with *ROA* (0.307*) and firm size (0.359*), while it is negatively associated with leverage (-0.456*) and loss (-0.394*), suggesting that larger and financially healthier firms tend to achieve higher *BR*. Conversely, *YS* is negatively related to *ROA* (-0.334*) and size (-0.256*), but positively related to loss (0.351*), implying that smaller and less profitable firms have higher *YS*. Overall, the low to moderate correlations among the explanatory variables indicate that multicollinearity is not a concern for the regression analysis.

Table 4: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) BR	1.000																	
(2) YS	-0.657*	1.000																
(3) DACC	-0.184*	0.110	1.000															
(4) DiscExp	-0.263*	0.158	0.175	1.000														
(5) abnProd	-0.025	0.011	0.099	0.570*	1.000													
(6) abnCFO	-0.078	0.026	0.304*	0.232*	0.185*	1.000												
(7) Matur	-0.013	-0.010	0.072	0.040	-0.072	-0.071	1.000											
(8) Guar	-0.098	0.100	0.064	0.065	0.107	0.018	0.041	1.000										
(9) Call	-0.148*	0.079	-0.025	0.153	-0.020	0.066	0.089	0.150*	1.000									
(10) Coll	-0.123	0.130	0.052	-0.086	-0.084	-0.133	-0.072	-0.045	-0.126	1.000								
(11) Issue_debt	-0.025	0.006	0.092	-0.018	0.232*	0.036	-0.085	0.112	0.171*	-0.096	1.000							
(12) ROA	0.307*	-0.334*	0.120	-0.166	0.039	0.041	0.035	0.053	-0.027	-0.070	0.255*	1.000						
(13) Leverage	-0.456*	0.368*	0.092	0.227*	-0.105	0.015	0.056	0.042	-0.048	0.094	-0.188*	-0.201*	1.000					
(14) Fsize	0.359*	-0.256*	-0.056	-0.227*	-0.128	-0.013	0.094	-0.286*	-0.267*	-0.026	-0.436*	-0.094	-0.226*	1.000				
(15) BIG4	0.045	-0.035	0.065	-0.008	-0.038	0.027	0.053	0.089	0.115	0.024	0.030	-0.048	-0.007	-0.090	1.000			
(16) Growth	-0.016	-0.066	0.227*	0.368*	0.193*	0.309*	-0.078	0.021	0.128	-0.111	0.028	-0.013	-0.100	0.004	-0.053	1.000		
(17) Loss	-0.349*	0.351*	0.169*	0.283*	0.083	0.235*	-0.016	-0.053	0.058	0.031	-0.046	-0.512*	0.288*	-0.061	0.065	0.109	1.000	
(18) PTBV	0.033	-0.027	0.080	0.087	0.105	0.207*	-0.011	-0.004	0.051	-0.065	0.006	0.283*	0.042	-0.058	0.034	0.013	-0.007	1.000

Note: This table presents the Pearson correlation coefficients among the variables used in the analysis. Correlations marked with * are statistically significant at the 5% level.

4.1.2. Empirical results

Table 5 reports the regression results analyzing the effect of accrual-based and real earnings management on bond ratings (*BR*). Column (1) employs accrual-based earnings management (*DACC*) as the key explanatory variable, while columns (2), (3), and (4) use real earnings management proxies (*DiscExp*, *abnProd*, and *abnCFO*, respectively). All models include firm-level and bond-specific controls, as well as industry, year, and nation fixed effects.

Table 5: Regression results-The impact of earnings management on the bond ratings

Dependent variable: BR	Accruals	Real activities		
	(1)	(2)	(3)	(4)
DACC	-2.290***			
	(0.846)			
DiscExp		-0.461		
		(0.329)		
abnProd			-0.336	
			(0.268)	
abnCFO				-0.277
				(0.452)
Matur	0.028	-0.102	-0.011	-0.016
	(0.128)	(0.139)	(0.126)	(0.129)
Guar	-0.023	-0.019	-0.018	-0.027
	(0.041)	(0.067)	(0.043)	(0.042)
Call	-0.033	-0.05	-0.024	-0.019
	(0.049)	(0.061)	(0.050)	(0.048)
Coll	-0.042	-0.104	-0.043	-0.057
	(0.061)	(0.097)	(0.062)	(0.064)
Issue_debt	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	1.410**	1.147	1.128*	1.184*
	(0.581)	(0.840)	(0.659)	(0.668)
Leverage	-0.526***	-0.519**	-0.579***	-0.554***
	(0.137)	(0.223)	(0.128)	(0.136)
Fsize	0.062***	0.057**	0.062***	0.062***
	(0.016)	(0.022)	(0.017)	(0.016)
BIG4	0.145**	0.128	0.136*	0.136*
	(0.069)	(0.083)	(0.073)	(0.073)

Dependent variable: BR	Accruals	Real activities		
	(1)	(2)	(3)	(4)
Growth	0.045	-0.013	0.005	0.002
	(.075)	(.084)	(.08)	(.078)
Loss	-0.084	-0.040	-0.116	-0.114
	(0.073)	(0.102)	(0.071)	(0.077)
PTBV	0.000	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
_cons	1.353	2.807*	1.743	1.788
	(1.224)	(1.485)	(1.209)	(1.238)
Fixed effects	Included	Included	Included	Included
Observations	203	203	203	203
R-squared	0.493	0.491	0.477	0.468

This table reports the results of the regression analysis examining the effect of accrual-based and real earnings management on bond ratings (BR). Columns (1) uses accrual-based earnings management (DACC), while columns (2), (3) and (4) use real activities manipulation proxies (DiscExp, abnProd, abnCFO). All models control for bond and firm characteristics. Industry, Year and Nation Fixed effects are included. Robust standard errors are reported in parentheses. Statistical significance levels are denoted by asterisks, where coefficients marked with *** are significant at the 1% level, ** are significant at the 5% level, and those with * are significant at the 10% level. The definitions of all variables included in the analysis are provided in Table 3.

The results indicate that *DACC* has a significant negative effect on bond ratings (–2.290, significant at the 1% level), suggesting that higher accrual-based manipulation is associated with lower ratings. This finding suggests that rating agencies consider the quality of financial reporting as an integral part of their firm evaluation process. This observation aligns with prior literature indicating that aggressive accounting policies serve as warning signals to rating agencies, as they are often associated with increased financial and operational risks (Caton et al., 2011; Crabtree et al., 2014). Real earnings management proxies (*DiscExp*, *abnProd*, *abnCFO*) also display negative coefficients in relation to bond ratings but do not exhibit statistical significance. The negative sign suggests that rating agencies might perceive real earnings management activities as a risk factor; however, this interpretation cannot be made with confidence due to the lack of significance. One possible explanation is that interventions in operating activities may not solely stem from earnings management practices but could reflect broader corporate investment strategies. For example, discretionary expenses (such as R&D and marketing) or production costs often represent strategic initiatives aimed at long-term growth rather than earnings manipulation. As a result, the real earnings management proxies may contain substantial noise and fail to accurately capture opportunistic managerial behavior. A second explanation relates to the long-term consequences of real earnings management on future financial performance (e.g., reduced R&D may impair future profitability), which may not be immediately evident to rating agencies. In essence, firms issuing bonds, particularly during significant corporate events, may be reluctant to engage in aggressive real earnings management, as its detection could negatively impact their cost of debt (Vorst, 2016; Bereskin et al., 2018; Farooqi et al., 2020).

Among the controls, *ROA* (profitability), *Fsize* (firm size), and *BIG4* (audit quality) have positive and significant effects on bond ratings, while Leverage has a negative and significant impact, consistent with prior literature. It is noteworthy that the issue-level bond characteristics (such as maturity, guarantees, callability, collateral, and issue size) do not exhibit statistically significant effects on bond ratings. This suggests that, within the context of this sample, rating agencies may place greater emphasis on firm-specific fundamentals and financial reporting quality—particularly accrual-based earnings management—rather than on contractual features of the bond itself. The models show adequate explanatory power, with R-squared values ranging from 0.468 to 0.493. Robust standard errors are reported in parentheses.

Table 6 presents the regression results examining the impact of accrual-based and real earnings management on yield spreads (*YS*). Column (1) uses accrual-based earnings management (*DACC*) as the key variable, while columns (2), (3), and (4) include real earnings management proxies (*DiscExp*, *abnProd*, and *abnCFO*, respectively). All models incorporate firm- and bond-specific controls, with industry, year, and nation fixed effects included.

Table 6: Regression results-The impact of earnings management on the yield spread

Dependent variable: YS	Accruals	Real activities		
	(1)	(2)	(3)	(4)
DACC	26.683*			
	(14.798)			
DiscExp		3.824		
		(4.313)		
abnProd			-0.243	
			(3.300)	
abnCFO				5.576
				(9.642)
Matur	-0.105	3.076**	0.601	0.595
	(2.081)	(1.396)	(1.95)	(1.986)
Guar	0.875	0.205	0.976	0.919
	(1.229)	(.707)	(1.321)	(1.196)
Call	0.727	1.12	0.556	0.592
	(0.788)	(1.138)	(0.794)	(0.762)
Coll	1.864	2.167	1.998	2.087
	(1.286)	(1.488)	(1.394)	(1.412)
Issue_debt	0.001	0.001	0.001	0.001
	(0.000)	(0.001)	(0.000)	(0.000)
ROA	-27.402*	-12.087	-24.343	-25.181
	(16.276)	(12.022)	(16.26)	(16.922)
Leverage	8.755***	7.557*	8.975***	9.234***
	(2.284)	(4.464)	(2.331)	(2.299)
Fsize	-0.627**	0.071	-0.611**	-0.619**
	(0.290)	(0.329)	(0.285)	(0.290)
BIG4	-1.865**	-1.834*	-1.751*	-1.741*
	(0.895)	(1.029)	(0.887)	(0.895)
Growth	-2.572	-0.611	-1.938	-2.175
	(1.598)	(1.253)	(1.506)	(1.633)
Loss	1.93	.724	2.41	2.151
	(1.942)	(2.217)	(2.044)	(1.993)

Dependent variable: YS	Accruals	Real activities		
	(1)	(2)	(3)	(4)
PTBV	0.005	0.010	0.007	0.003
	(0.017)	(0.015)	(0.019)	(0.016)
_cons	11.86	-31.826**	4.762	4.682
	(21.734)	(13.936)	(20.387)	(20.785)
Fixed effects	Included	Included	Included	Included
Observations	203	203	203	203
R-squared	0.370	0.341	0.361	0.362

This table reports the results of the regression analysis examining the effect of accrual-based and real earnings management on yield spread (*YS*). Columns (1) uses accrual-based earnings management (*DACC*), while columns (2), (3) and (4) use real activities manipulation proxies (*DiscExp*, *abnProd*, *abnCFO*). All models control for bond and firm characteristics. Industry, Year and Nation Fixed effects are included. Robust standard errors are reported in parentheses. Statistical significance levels are denoted by asterisks, where coefficients marked with *** are significant at the 1% level, ** are significant at the 5% level, and those with * are significant at the 10% level. The definitions of all variables included in the analysis are provided in Table 3.

The results show that *DACC* has a significant positive effect on yield spreads (26.683, significant at 10%), indicating that accrual-based manipulation is associated with higher debt costs. The real earnings management proxies do not show significant effects. Regarding the controls, *ROA* negatively and significantly affects yield spreads, confirming that more profitable firms face lower borrowing costs. *Leverage* exhibits a positive and highly significant impact, reflecting the risk premium associated with higher debt levels. *Fsize* and BIG4 both have significant negative effects, suggesting that larger firms and those audited by Big 4 firms benefit from narrower spreads. The models explain a substantial portion of the variation in yield spreads, with robust standard errors reported in parentheses.

Overall, the impact of earnings management on yield spreads is weaker than its impact on bond ratings. Accrual-based earnings management (*DACC*) has a positive association with borrowing costs, but this relationship is only marginally significant. The measures of real earnings management do not show any significant effect. This means that bond investors may notice and respond to accrual-based manipulation, but its effect on yield spreads is less clear than on credit ratings. One possible reason is that yield spreads are affected by many other market factors—such as current interest rates, liquidity, and investor sentiment—which can weaken the influence of earnings management.

4.3 Robustness tests

To ensure the robustness of the baseline findings, we perform additional analyses using alternative specifications and methodologies. First, we replicate the baseline models by employing alternative earnings management proxies (Table 7), both accrual-based and real activities manipulation measures, to test whether the main results are sensitive to the choice of proxy. Second, we replace the continuous bond rating variable with a binary indicator of investment grade and estimate logistic regressions (Table 8).

4.3.1. Alternative earnings management proxies

Table 7 reports the robustness test using alternative earnings management proxies. Columns (1) and (4) use the Kothari et al. (2005) performance-adjusted discretionary accruals (*DACC_roa*), while columns (2), (3), (5), and (6) replace the main real earnings management measures with the aggregate proxies *REM1* and *REM2*.

Table 7: Robustness test using alternative earnings management proxies

Dependent variable	Bond ratings (BR)			Yield spread (YS)		
Variables	Accruals	Real activities		Accruals	Real activities	
	(1)	(2)	(3)	(4)	(5)	(6)
DACC_roa	-2.178**			25.2700*		
	(0.84)			(14.681)		
REM1		-0.104			1.143	
		(0.150)			(1.910)	
REM2			-0.264			1.930
			(0.324)			(4.048)
Matur	0.015	-0.100	-0.118	0.082	3.073**	3.204**
	(0.131)	(0.137)	(0.139)	(2.070)	(1.38)	(1.396)
Guar	-0.024	-0.006	-0.025	0.888	0.267	0.257
	(0.041)	(0.072)	(0.067)	(1.230)	(0.799)	(0.719)

Dependent variable	Bond ratings (BR)			Yield spread (YS)		
Variables	Accruals	Real activities		Accruals	Real activities	
	(1)	(2)	(3)	(4)	(5)	(6)
Call	-0.031	-0.049	-0.058	0.711	1.196	1.176
	(0.049)	(0.062)	(0.061)	(0.786)	(1.173)	(1.093)
Coll	-0.044	-0.095	-0.109	1.896	2.192	2.205
	(0.061)	(0.102)	(0.098)	(1.296)	(1.557)	(1.462)
Issue_debt	0.000	0.000	0.000	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
ROA	1.387**	1.144	1.163	-27.158*	-12.289	-12.246
	(0.583)	(0.841)	(0.842)	(16.273)	(12.252)	(12.087)
Leverage	-0.526***	-0.555**	-0.526**	8.758***	7.603*	7.638*
	(0.137)	(0.232)	(0.228)	(2.286)	(4.387)	(4.499)
Fsize	0.062***	0.066***	0.060***	-0.623**	0.052	0.046
	(0.016)	(0.022)	(0.022)	(0.290)	(0.368)	(0.318)
BIG4	0.145**	0.132	0.133	-1.867**	-1.85*	-1.872*
	(0.069)	(0.082)	(0.083)	(0.896)	(1.019)	(1.009)
Growth	0.041	-0.041	-0.022	-2.523	-0.453	-0.512
	(0.075)	(0.088)	(0.091)	(1.596)	(1.417)	(1.252)
Loss	-0.087	-0.054	-0.052	1.959	0.822	0.835
	(0.073)	(0.106)	(0.106)	(1.941)	(2.134)	(2.219)
PTBV	0.00	-0.001	-0.001	0.005	0.011	0.011
	(0.001)	(0.001)	(0.001)	(0.017)	(0.016)	(0.015)
_cons	1.491	2.641*	2.934*	9.902	-31.513**	-32.712**
	(1.257)	(1.474)	(1.513)	(21.667)	(13.916)	(13.765)
Fixed effects	Included	Included	Included	Included	Included	Included
Observations	203	203	203	203	203	203
R-squared	0.491	0.491	0.486	0.369	0.339	0.339

This table reports the results of the regression analysis examining the effect of accrual-based and real earnings management on bond ratings (*BR*) and yield spreads (*YS*). Columns (1) and (4) uses an alternative accrual-based earnings management proxy (DACC_roa), estimated using the Kothari et al. (2005) model. Columns (2), (3), (5) and (6) include real activities manipulation proxies: *REM1* combines discretionary expenses and abnormal production costs, while *REM2* aggregates discretionary expenses and abnormal CFO. All models control for bond and firm characteristics. Industry, Year, and Nation fixed effects are included. Robust standard errors are reported in parentheses. Statistical significance levels are denoted by asterisks, where coefficients marked with *** are significant at the 1% level, ** are significant at the 5% level, and * are significant at the 10% level. The definitions of all variables included in the analysis are provided in Table 3.

The results confirm the main findings. *DACC_roa* remains negative and significant for bond ratings (–2.178, column 1) and positive and significant for yield spreads (25.270, column 4), consistent with the baseline results where *DACC* had a significant impact on both outcomes (Table 5 and 6). Real earnings management proxies (*REM1* and *REM2*), similar to *DiscExp*, *abnProd*, and *abnCFO* in the main models, are not statistically significant in explaining bond ratings or yield spreads, reaffirming that real earnings management does not appear to drive debt market assessments.

The control variables display patterns comparable to the main models: *ROA* and *Fsize* positively affect bond ratings and negatively affect yield spreads, while *Leverage* remains negative for ratings and positive for spreads. *BIG4* continues to show a favorable influence on ratings (positive) and spreads (negative). These results demonstrate that the conclusions regarding accrual-based earnings management are robust to alternative measurement approaches.

4.3.1. Logistic regression using investment grade as dependent variable

Table 8 presents a robustness analysis using a logistic regression model, where the dependent variable (*Grade*) equals 1 if the bond is rated as investment grade and 0 otherwise. Column (1) employs accrual-based earnings management (*DACC*), while columns (2)–(4) use real earnings management proxies (*DiscExp, abnProd, abnCFO*).

Table 8: Robustness test using logistic regression

Dependent variable: Grade	Accruals	Real activities		
	(1)	(2)	(3)	(4)
DACC	-26.057***			
	(9.991)			
DiscExp		-6.569		
		(5.692)		
abnProd			-7.938**	
			(3.39)	
abnCFO				-11.598*
				(6.562)
Matur	-2.744	-3.860*	-3.343*	-3.318*
	(1.912)	(2.071)	(1.924)	(1.959)
Guar	-0.576	-0.949	-0.314	-0.519
	(0.519)	(1.085)	(0.545)	(0.525)

Dependent variable: Grade	Accruals	Real activities		
	(1)	(2)	(3)	(4)
Call	-0.118	-0.697	0.043	0.056
	(0.718)	(0.981)	(0.680)	(0.659)
Coll	-0.608	-2.193*	-0.345	-0.921
	(0.721)	(1.271)	(0.750)	(0.790)
Issue_debt	0.000	0.000	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
ROA	17.654*	17.815	12.256	15.131
	(9.103)	(15.518)	(10.251)	(10.11)
Leverage	-2.829	-1.685	-5.036**	-4.352*
	(2.047)	(3.338)	(2.456)	(2.410)
Fsize	0.709***	0.712**	0.778***	0.680***
	(0.192)	(0.318)	(0.202)	(0.197)
BIG4	1.269*	2.141**	1.271	1.171
	(0.749)	(1.032)	(0.774)	(0.762)
Growth	0.604	0.275	0.302	0.404
	(0.678)	(0.780)	(0.726)	(0.686)
Loss	-0.361	-0.230	-0.737	-0.281
	(0.887)	(1.157)	(0.937)	(0.927)
PTBV	0.153**	0.089	0.187**	0.148*
	(0.065)	(0.123)	(0.075)	(0.076)
_cons	16.227	27.192	21.058	22.900
	(18.958)	(20.978)	(19.397)	(19.531)
Fixed effects	Included	Included	Included	Included
Observations	302	302	302	302
Pseudo R^2	0.321	0.322	0.331	0.304

This table reports the results of a robustness analysis using a logit model where the dependent variable is a dummy equal to 1 if the bond is rated as investment grade, and zero otherwise. Columns (1) uses accrual-based earnings management (DACC), while columns (2), (3) and (4) use real activities manipulation proxies (DiscExp, abnProd, abnCFO). All models control for bond and firm characteristics. Industry, Year and Nation Fixed effects are included. Robust standard errors are reported in parentheses. Statistical significance levels are denoted by asterisks, where coefficients marked with *** are significant at the 1% level, ** are significant at the 5% level, and those with * are significant at the 10% level. The definitions of all variables included in the analysis are provided in Table 3.

The findings are consistent with the main results from Table 5 and Table 6: *DACC* has a significant negative effect (–26.057, 1% level), confirming that higher accrual-based earnings management reduces the likelihood of a bond being classified as investment grade. In contrast, the real earnings management proxies (DiscExp, abnProd, abnCFO) remain statistically insignificant, reaffirming that real activities manipulation is not a key determinant of credit quality.

Control variables such as *ROA* (positive and significant) and *Leverage* (negative and significant) maintain their expected directions, as seen in the baseline models. *Fsize* and *BIG4* continue to exert positive effects, while *Matur* shows a mixed but weak relationship. The Pseudo R^2 values (0.321–0.364) indicate a good fit for the logistic models.

5. Conclusion

This study analyzes how the quality of financial reporting affects the cost of debt for European corporate bonds, focusing on bond ratings and yield spreads. Based on a sample of 203 listed European firms that issued non-convertible corporate bonds between 2013 and 2023, the findings show clear evidence that credit rating agencies and bond investors penalize accrual-based earnings management. Firms with higher discretionary accruals tend to receive lower bond ratings and, to a lesser degree, face higher yield spreads. In contrast, real earnings management does not have a significant effect on either bond ratings or yield spreads. This could be because such practices are less favored by issuers, who fear the potential negative consequences if these actions are uncovered, or because real earnings management is harder to distinguish from legitimate business activities. The results also indicate that firm-specific factors—such as profitability, leverage, size, and audit quality—have a greater impact on credit assessments than specific bond contract features. This highlights the importance of accounting quality as a key component of risk evaluation in the European bond market.

The findings have severe implications for various stakeholders. For managers, the evidence underscores the importance of maintaining transparent and high-quality financial reporting, as aggressive accrual-based manipulation can directly increase borrowing costs and negatively impact credit ratings. For investors and credit rating agencies, the results underline the need to refine analytical tools to better identify real earnings management, which may currently pass undetected. For regulators and standard-setters, the evidence provides empirical support for ongoing initiatives aimed at strengthening disclosure requirements and enhancing earnings transparency to improve debt market efficiency.

Future research could build on these results by exploring cross-country differences within Europe to examine how institutional environments—such as legal enforcement, investor protection, and capital market sophistication—affect the debt market's sensitivity to earnings management. It could also investigate whether macroeconomic and monetary conditions influence the pricing of such practices in expansionary versus contractionary periods. Further, incorporating measures of analyst coverage, institutional ownership, or ESG disclosures could shed light on whether broader information environments mitigate or amplify the effects documented here. Finally, examining the post-issuance performance of bonds issued by high-earnings-management firms would deepen understanding of the long-term consequences of reporting quality for debt markets.

References

Alissa, W., Bonsall Iv, S.B., Koharki, K., & Penn Jr, M.W. 2013. Firms' use of accounting discretion to influence their credit ratings. Journal of Accounting and Economics 55, 129-147. https://doi.org/10.1016/j.jacceco.2013.01.001.

Bereskin, F.L., Hsu, P.H. & Rotenberg, W. 2018. The real effects of real earnings management: Evidence from innovation. Contemporary Accounting Research 35, 525-557. https://doi.org/10.1111/1911-3846.12376.

Bharath, S.T., Sunder, J. & Sunder, S.V. 2008. Accounting quality and debt contracting. The accounting review 83, 1-28. https://doi.org/10.2308/accr.2008.83.1.1.

Caton, G.L., Chiyachantana, C.N., Chua, C.T. & Goh, J. 2011. Earnings management surrounding seasoned bond offerings: Do managers mislead ratings agencies and the bond market?. Journal of Financial and Quantitative Analysis. 46, 687-708. https://doi.org/10.1017/S0022109011000147.

Cho, K.H. and Patil, B., 2025. Does macroeconomic uncertainty (really) influence managers' earnings management?. Journal of Corporate Accounting & Finance, 36(1), pp.185-197. https://doi.org/10.1002/jcaf.22748

Christopoulos, A., Dokas, I., Leontidis, C. & Spyromitros, E. 2023. The effect of corruption on the level of real and accrual earnings management in cases of target firms. EuroMed Journal of Business, 18, 575-603. https://doi.org/10.1108/EMJB-03-2022-0055.

Cohen, D.A. & Zarowin, P. 2010. Accrual-based and real earnings management activities around seasoned equity offerings. Journal of accounting and Economics, 50, 2-19. https://doi.org/10.1016/j.jacceco.2010.01.002.

Crabtree, A., Maher, J.J. & Wan, H. 2014. New debt issues and earnings management. Advances in Accounting, 30, 116-127. https://doi.org/10.1016/j.adiac.2014.04.005.

Darmouni, O. & Papoutsi, M. 2022. The Rise of Bond Financing in Europe. ECB, Working Paper No. 2022/2663, Available at SSRN: https://ssrn.com/abstract=4115175 or http://dx.doi.org/10.2139/ssrn.4115175

Dechow, P.M., Sloan, R.G. & Sweeney, A.P. 1995. Detecting earnings management. Accounting review, 70, 193-225. https://doi.org/10.1002/9781119204763.ch4.

Demirtas, K.O. & Rodgers Cornaggia. K. 2013. Initial credit ratings and earnings management. Review of Financial Economics, 22, 135-145. https://doi.org/10.1016/j.rfe.2013.05.003.

Denis, D.J. and Mihov, V.T., 2003. The choice among bank debt, non-bank private debt, and public debt: evidence from new corporate borrowings. Journal of financial Economics, 70(1), pp.3-28. https://doi.org/10.1016/S0304-405X(03)00140-5

DuCharme, L.L., Malatesta, P.H. & Sefcik, S.E. 2001. Earnings management: IPO valuation and subsequent performance. Journal of Accounting, Auditing & Finance, 16, 369-396. https://doi.org/10.1177/0148558X0101600409.

Dyreng, S.D., Hillegeist, S.A. & Penalva, F. 2022. Earnings management to avoid debt covenant violations and future performance. European Accounting Review, 31, 311-343. https://doi.org/10.1080/09638180.2020.1826337.

Farooqi, J., Jory, S.R. and Ngo, T.N., 2020. Target firm earnings management, acquisition premium, and shareholder gains. The International Journal of Accounting, 55(02), p.2050009. https://doi.org/10.1142/S1094406020500092

Francis, J., LaFond, R., Olsson, P. & Schipper, K. 2005. The market pricing of accruals quality. Journal of accounting and economics, 39, 295-327. https://doi.org/10.1016/j.jacceco.2004.06.003.

Frankfurt, Ger

Ge, W. & Kim, J.B. 2014. Real earnings management and the cost of new corporate bonds. Journal of Business Research, 67, 641-647. https://doi.org/10.1016/j.jbusres.2013.01.021.

Gottardo, P. & Moisello, A.M. 2018. Capital Structure, Earnings Management, and Risk of Financial Distress: A Comparative Analysis of Family and Non-family Firms. Springer.

Jones, J.J. 1991. Earnings management during import relief investigations. Journal of accounting research, 29, 193-228. https://doi.org/10.2307/2491047.

Kale, J.R. & Meneghetti, C., 2011. The choice between public and private debt: A survey. IIMB Management Review, 23(1), pp.5-14. https://doi.org/10.1016/j.iimb.2010.12.001

Kim, Y.S., Kim, Y. & Song, K.R. 2013. Credit rating changes and earnings management. Asia-Pacific Journal of Financial Studies, 42, 109-140. https://doi.org/10.1111/ajfs.12007.

Kothari, S.P., Mizik, N. & Roychowdhury, S. 2016. Managing for the moment: The role of earnings management via real activities versus accruals in SEO valuation. The Accounting Review, 91, 559-586. https://doi.org/10.2308/accr-51153.

Liu, Y., Ning, Y. & Davidson III, W.N. 2010. Earnings management surrounding new debt issues. Financial Review, 45, 659-681. https://doi.org/10.1111/j.1540-6288.2010.00265.x.

Mellado-Cid, C., Jory, S.R. & Ngo, T. 2017. Real earnings management activities prior to bond issuance. BRQ Business Research Quarterly, 20, 164-177. https://doi.org/10.1016/j.brq.2017.04.004.

Ogden, J.P., 1987. Determinants of the ratings and yields on corporate bonds: Tests of the contingent claims model. Journal of Financial Research, 10(4), pp.329-340. https://doi.org/10.1111/j.1475-6803.1987.tb00506.x

Pappas, K., Walsh, E. & Xu, A.L. 2019. Real earnings management and Loan Contract terms. The British Accounting Review, 51, 373-401. https://doi.org/10.1016/j.bar.2019.03.002.

Roychowdhury, S. 2006. Earnings management through real activities manipulation. Journal of accounting and economics 42: 335-370. https://doi.org/10.1016/j.jacceco.2006.01.002.

Teoh, S.H., Welch, I. & Wong, T.J. 1998. Earnings management and the long-run market performance of initial public offerings. The journal of finance, 53, 1935-1974. https://doi.org/10.1111/0022-1082.00079.

Vorst, P. 2016. Real earnings management and long-term operating performance: The role of reversals in discretionary investment cuts. The Accounting Review, 91, 1219-1256. https://doi.org/10.2308/accr-51281.

Ziebart, D.A. & Reiter, S.A. 1992. Bond ratings, bond yields and financial information. Contemporary Accounting Research, 9, 252-282. https://doi.org/10.1111/j.1911-3846.1992.tb00879.x.

IDENTIFYING INVESTMENT-READY SMES WITH AI

Gogas Periklis,* Papadimitriou Theofilos, Goumenidis Panagiotis, Kontos Andreas and Giannakis Nikolaos

Department of Economics, Democritus University of Thrace, 69100 Komotini, Greece

ABSTRACT

Small and medium-sized businesses (SMEs) are vital for our economy, driving growth, innovation, and jobs. But they often hit a wall when trying to get funding. This usually happens because investors see them as risky or don't have enough clear information. To help with this, our study introduces a new way to predict if an SME is truly "investment-ready" using machine learning. We've taken a huge amount of data from the European Central Bank's survey on how businesses access finance (called SAFE) and put it through its paces. We tested nine different machine learning models, like Gradient Boosting, Random Forest, and Logistic Regression. What we found is that these advanced tools are really good at spotting which SMEs are ready for investment. In particular, the Gradient Boosting model was the standout, correctly identifying investment-ready companies about 75% of the time. This research offers valuable insights for everyone involved:

For policymakers: *It provides clear information on where to focus efforts and design programs that truly help SMEs get the funding they need.*

For investors: *It gives them a smart, data-driven way to find promising SMEs, helping them make better investment decisions.*

* Correspondence: pgkogkas@econ.duth.gr

For the economy as a whole: *By making it easier for deserving SMEs to get capital, we can boost economic growth, create more jobs, and ensure our financial resources are used as effectively as possible.*
Ultimately, we believe machine learning can play a big role in closing the funding gap for SMEs, leading to a stronger, more dynamic economy.

Keywords: *SMEs; investment readiness; machine learning; SAFE dataset; equity financing; economic resilience; gradient boosting; random forest; logistic regression; SVC; VIM*

1. Introduction and Literature Review

Small and medium-sized enterprises are defined as enterprises with fewer than 250 employees, having an annual turnover less than 50 million €and/or an annual balance sheet total less than = 43 million € (Commission of the European Communities, 2003/361/EC). They play a crucial role in economic growth, employment, and innovation. They account for approximately 90% of all businesses globally, providing over half of the total employment and significantly contributing to GDP across various economies (World Bank, 2023). Despite their crucial role, SMEs frequently struggle to secure adequate external financing, limiting their potential for growth and innovation. This issue is particularly acute in emerging markets, where about 40% of formal SMEs report unmet financing needs (World Bank, 2023). The financing gap faced by SMEs is often due to information asymmetries and the perception of higher risk, causing lenders and investors to be cautious when considering investments in smaller firms. As traditional financial institutions generally rely on established credit histories and collateral—requirements, many SMEs cannot meet—these enterprises often resort to internal funding or informal finance sources (Mason & Harrison, 2001, Douglas & Shepherd, 2002).

Investment readiness—the ability of an SME to attract and secure external funding—has emerged as an important concept to bridge the financing gap. A firm that is "investment ready" typically demonstrates a sound and viable business model, credible financial reporting, clear growth potential, and an effective management team capable of communicating these strengths to potential investors (Douglas & Shepherd, 2002). Yet, previous research consistently finds a mismatch between SMEs' self-assessments of readiness and investors' evaluations, resulting in many firms being overlooked despite having solid business foundations (Fellnhofer, 2015).

Traditional approaches for evaluating SME investment readiness, such as financial ratios, scoring systems and qualitative assessments, have significant limitations. These methods often overlook complex, non-linear relationships within the data and rely heavily on past financial performance, potentially disregarding other vital aspects like managerial capability or innovation (Mullainathan & Spiess, 2017; Dumitrescu et al., 2021). In response, machine learning (ML) techniques have begun to gain prominence due to their ability to analyze large, multidimensional datasets and identify complex, predictive patterns that traditional econometric methods might miss (Dumitrescu et al., 2021).

Given these challenges and opportunities, this paper applies advanced ML methods to assess the investment readiness of SMEs, using the European Central Bank's (ECB) Survey on Access to Finance of Enterprises (SAFE) dataset. This large-scale, cross-national dataset offers extensive qualitative and quantitative information on SMEs' financial conditions, their market positions, innovation activities, and management capabilities—factors critical for assessing investment readiness.

Investment Readiness and SME Financing

Investment readiness is a multidimensional concept reflecting an enterprise's capacity to understand and satisfy investor expectations as captured through business planning, financial transparency, growth prospects and managerial competence. Mason and Harrison (2001) emphasized that simply increasing the availability of venture capital without ensuring SMEs are investment-ready is insufficient to address funding gaps. Many entrepreneurs are often perceived by investors as "not ready" due to weak financial documentation, unrealistic growth expectations or an aversion to equity dilution. Douglas and Shepherd (2002), similarly, found discrepancies in perceptions of investment readiness between entrepreneurs and investors highlighting the importance of clear communication and alignment of expectations to improve SMEs' chances of securing financing.

Investment readiness programs have been developed globally to bridge these gaps by providing targeted training and support to SMEs, improving their business plans, enhance financial transparency and overall investability (Cusolito, Dautovic, & McKenzie, 2021). However, despite their importance, such programs typically yield only modest improvements and may not fully resolve systemic issues such as informational asymmetries and entrenched investor biases (Owen et al., 2023).

Recent studies have shown that machine learning (ML) methods significantly outperform traditional econometric models in forecasting complex financial market behavior. ML models, unlike traditional approaches, can handle vast and multidimensional datasets, uncovering and capturing complex and intricate relationships and interactions between variables (Du & Rada, 2010; Khan et al., 2023). For instance, Dumitrescu et al. (2021) demonstrated how hybrid ML-econometric models significantly improve credit scoring by combining predictive accuracy with interpretability.

Despite the promising potential of ML approaches, existing research on their application specifically to SME investment readiness remains limited. Most studies focus on broader financial forecasting contexts or specific applications such as credit risk or stock market prediction, leaving a notable research gap regarding the application of ML in predicting SME investment readiness.

Additionally, while investment readiness programs have been implemented globally to support SMEs, their effectiveness in addressing structural financing gaps remains minimal, suggesting the need for more sophisticated, data-driven assessment tools (Cusolito, Dautovic, & McKenzie, 2021; Owen et al., 2023).

From a venture capital perspective, enhancing screening efficiency to identify promising SMEs remains a challenge. The potential for ML to significantly streamline this screening process, reducing biases and enhancing deal-flow quality, has not yet been thoroughly examined in academic research (Zana & Barnard, 2019). From a venture capital perspective, investment readiness screening is essential due to the high-risk nature of early-stage financing. Venture capitalists often reject many SMEs at early screening stages due to insufficient preparedness in terms of management capabilities, realistic financial projections, and business viability (Mason & Kwok, 2010; Zana & Barnard, 2019). While human judgment remains essential, integrating machine learning that is independent of related human biases and misjudgments into the venture screening process could significantly streamline identification efforts, reducing biases and expanding the search for investment ready SMEs beyond personal networks (Zana & Barnard, 2019).

Our research directly addresses these gaps by empirically evaluating multiple advanced ML algorithms, i.e., Gradient Boosting, Logistic Regression, Random Forest, and ensemble methods, using a comprehensive and robust dataset provided by the European Central Bank's Survey on Access to Finance of Enterprises (SAFE). By explicitly linking managerial competencies, innovation, and openness to equity financing to SME investment readiness through ML techniques, this study contributes both methodologically and substantively to the entrepreneurial finance literature. It does not only advance predictive accuracy, but also offers actionable insights for SMEs, investors, and policymakers, ultimately aiming to enhance resource allocation efficiency and support broader economic growth and innovation.

2. Data and Research Methodology

2.1. Data Collection and Pre-Processing

The dataset was collected from the European Central Bank Data Portal and contains anonymous qualitative responses from micro, small, medium and large companies across Europe. The dataset provides insights into the financing conditions faced by these companies.

The dataset was thoroughly cleaned by removing duplicates, non-SME entries, sparse features, and variables closely tied to the target to ensure data relevance and prevent leakage and contamination. After cleaning, the final dataset contained 10937 SME entries (rows) each described by 59 variables (columns). The dataset is heavily imbalanced with 12% of entries belonging to class 1 (investment ready class) and the remaining 88% to class 0 (non-investment ready class). Categorical variables were converted to numerical format using dummy encoding, creating binary columns to represent each category.

The binary target variable takes the value of 1 when the SME is investment ready, and 0 in the opposite case. We define an SME as investment ready (IR) when it is:

- **Innovative:** these are the firms that have reported new developments, such as introducing a new product or service to the market, implementing a new production process or method, adopting new management practices, or exploring new ways of selling goods or services.
- **Fast growing:** these are the cases where the annual turnover increases by more than 20%.
- **Open to equity financing:** whether it reported equity as either a relevant funding source or one used in the past six months.

2.2. Machine Learning Algorithms

Machine learning (ML) enables algorithms to learn from data and improve predictive performance without explicit programming (Norvig & Russel, 2020). Supervised learning, a common form, trains models on labeled data to generalize predictions for new inputs.

Logistic Regression models the probability of a categorical outcome using a logistic function applied to a linear combination of features. It offers interpretability via coefficient signs, though translating coefficients into probabilities requires additional steps. Regularization methods (L1, L2, ElasticNet) prevent overfitting (Cox, 1958).

K-Nearest Neighbors (K-NN) predicts the class of a data point based on the labels of its nearest neighbors, using distance metrics like Euclidean distance. Small k risks overfitting; large k can cause underfitting (Cover & Hart, 1967).

Random Forest is an ensemble of decision trees trained on bootstrapped data subsets, selecting random feature subsets at splits to reduce overfitting. It predicts by majority voting and offers feature importance measures (Breiman, 2001).

Support Vector Machines (SVM) classify by finding the hyperplane that maximizes margin between classes. When data is not linearly separable, kernel functions (e.g., radial basis function) map data to higher-dimensional spaces. Regularization balances model complexity and generalization (Cortes & Vapnik, 1995).

Naïve Bayes classifiers use Bayes' theorem, assuming feature independence, to calculate posterior probabilities and classify instances by the most probable class (Manning et al., 2008).

AdaBoost sequentially trains weak classifiers, emphasizing misclassified samples by increasing their weights, and combines their predictions with weighted voting to form a strong classifier (Freund & Schapire, 1995).

Easy Ensemble combats class imbalance by creating balanced subsets via under-sampling and training multiple AdaBoost models, aggregating them with voting to improve minority class recognition (Liu et al., 2009).

Balanced Bagging is similar, combining balanced bootstrap samples with bagging to reduce bias in imbalanced classification through majority voting (Breiman, 1996).

Gradient Boosting builds additive models by sequentially training decision trees to correct previous errors (residuals), improving predictions iteratively to minimize loss (Friedman, 2001).

2.3. Cross Validation

Before training, we split the data into a training set for model fitting and hyperparameter tuning, and a separate validation set to assess performance on unseen data. Managing overfitting and underfitting is crucial: underfitting happens when a model is too simple and performs poorly on all data, while overfitting occurs when a model fits training data too closely, leading to poor generalization. To balance this, we used stratified 5-fold cross-validation on the training set, ensuring each fold reflects the original class distribution (12% minority class). In each iteration, four folds train the model while one tests it, cycling through all folds. We average performance across folds to select the best model, ensuring robust evaluation despite class imbalance.

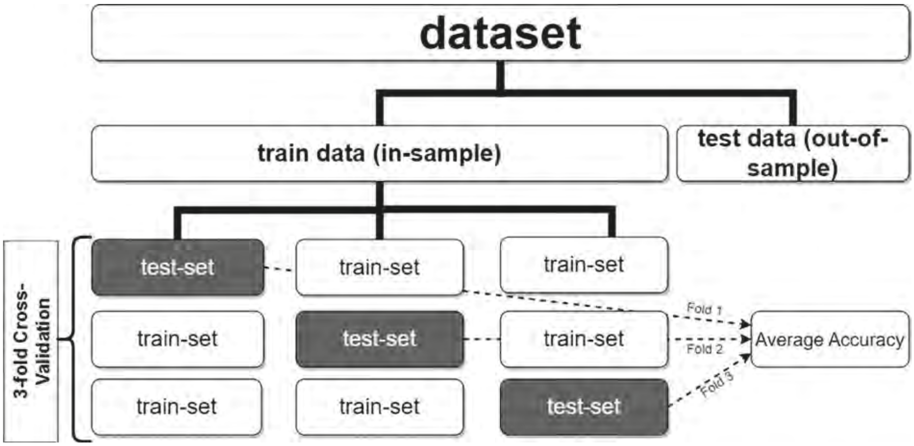


Figure 1. A graphical representation of a 3-fold cross validation process. A graphical representation of a 3-fold cross validation process. For every set of hyperparameters test, each fold serves as a test sample, while the remaining folds are used to train the model. The average performance for each set of parameters over the k test folds was used to identify the best model. (Gogas et al., 2019).

2.4. Model Selection

For our analysis, we employed nine classification algorithms. We optimized each algorithm's performance through grid search, systematically testing various hyperparameter combinations. The best settings for each model were determined by selecting those that yielded the highest average performance during a stratified 5-fold cross-validation process on the training data. The algorithms used were:

1. Logistic Regression
2. K-Nearest Neighbor
3. Random Forest
4. Support Vector Machines with RBF and linear kernel
5. Naïve Bayes Classifier
6. AdaBoost
7. Easy Ensemble
8. Balanced Bagging Classifier
9. Gradient Boosting Trees

2.5. Data Imbalance

To address the issue of the imbalanced dependent variable, the models were trained using balanced class weights. This approach involves assigning higher weights to the underrepresented class (class 1 – Is Investment Ready) and lower weights to overrepresented class (class 0 – Is Not Investment Ready) during the training process. By doing this, the model is penalized more for misclassifying the minority class observations, encouraging it to pay more attention to the less frequent instances.

2.6. Forecasting Performance Metrics

In a binary classification problem, normally, a confusion matrix is created to visually summarize the models' performance. The confusion matrix consists of four values as below:

- True Positives (TP): The number of instances that the model correctly predicts the positive class (in our case the SME to be predicted as investment-ready, class 1).
- True Negatives (TN): The number of instances that the model correctly predicts the negative class (in our case the SME to be predicted as non-investment-ready, class 0).
- False Positives (FP): The number of instances that the model incorrectly predicts the positive class when the actual class is negative.
- False Negatives (FN): The number of instances that the model incorrectly predicts the negative class when the actual is positive.

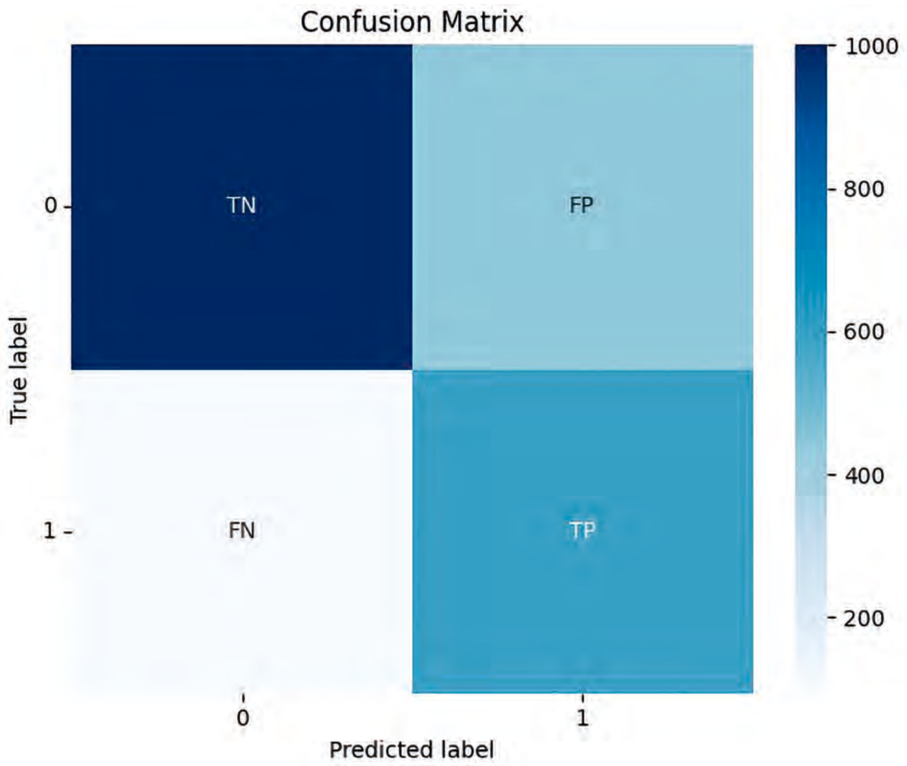


Figure 2. Confusion Matrix.

From these values above, various metrics are being defined and have been used to evaluate our models as below:

Precision

Measures the reliability of positive predictions for each class:

Class 0 (not investment-ready):

It counts the proportion of companies forecasted as "not investment-ready" that are truly non-investment-ready. High precision indicates high confidence in negative predictions.

$$Precision(0) = \frac{TN}{TN + FN} \tag{1}$$

Class 1 (investment ready):

In this case, the precision measures the proportion of companies predicted as "investment-ready" that are truly investment-ready. High precision reduces false positives (e.g., mislabeling non-investment-ready companies as investment-ready).

$$Precision(1) = \frac{TP}{TP + FP} \tag{2}$$

Recall (Sensitivity/Specificity)

Measures the models' ability to identify all relevant instances of a class:

Class 0 Recall (Specificity):

Recall of class 0 counts the ability of the model to correctly identify non-investment-ready companies.

$$Recall(0) = \frac{TN}{TN + FP} \tag{3}$$

Class 1 Recall (Sensitivity):

Recall of class 1 counts the ability of the model to correctly identify investment-ready companies.

$$Recall(1) = \frac{TP}{TP + FN} \tag{4}$$

F1-Score

Balances precision and recall using their harmonic mean. A high F1-Score indicates strong performance in both precision and recall for a class. It is critical for evaluating the investment-ready (minority) class, where both false positives (costly misallocations) and false negatives (missed opportunities) are consequential.

$$F1\,Score = \frac{TP}{TP + \frac{1}{2(FP + FN)}} \tag{5}$$

or alternatively,

$$F1\,Score = \frac{2\ x\ \text{Pre}\,cision\ x\,Recall}{\text{Pre}\,cision + Recall} \tag{6}$$

Balanced Accuracy

While accuracy is the standard metric for evaluating classification models on balanced datasets, it becomes less informative in the presence of class imbalance, as in our case. In such data, the balanced accuracy measure is preferred. Defined as the average recall (sensitivity) across all classes, balanced accuracy offers a more reliable assessment of model performance by accounting for sensitivity in each class explicitly. Balanced accuracy can also be interpreted as class-wise accuracy weighted by class prevalence in the dataset (Brodersen, Ong et al., 2010).

$$Balanced\ Accuracy = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \tag{7}$$

Receiver Operating Characteristic Area Under Curve (ROC-AUC)

The ROC-AUC measures a model's ability to distinguish between classes by plotting the true positive rate against the false positive rate at different thresholds. Its value ranges from 0.5 (random guessing) to 1 (perfect discrimination).

Each metric serves a purpose: high precision for Class 0 filters out non-investment-ready firms accurately; high recall for Class 1 ensures investment-ready firms are identified; and precision for Class 1 reduces costly false positives. The F1-score and balanced accuracy summarize these trade-offs into a single metric, which is especially important for imbalanced datasets.

2.7. Variable Importance Measure (VIM)

In tree-based models, the VIM is used to assess and rank the contribution of each variable to the model's predictive performance. During the construction of a decision tree, the algorithm selects variables at each split based on how well they improve the model's ability to distinguish between classes.

This is typically done by minimizing a metric known as impurity (e.g. Gini impurity or entropy). Variables that consistently result in greater reductions of impurity across the tree are considered more important. The VIM reflects this by aggregating the impurity reductions attributed to each variable over the entire tree (or forest, in ensemble models like Random Forest), helping to identify which features have the most influence on the model's decisions.

3. Empirical Results

Because most companies in our dataset are not investment-ready (88% fall into this category versus only 12% that are), simply looking at overall "accuracy" can be misleading. Imagine a very basic system that just guesses "not investment-ready" for every company; it would appear 88% accurate, even though it completely fails to identify any actual investment-ready firms. That's why we use balanced accuracy. This metric provides a fairer picture by giving equal weight to how well the model identifies both types of companies – those that are investment-ready and those that aren't – regardless of how many there are in each group. By using balanced accuracy, we get a reliable way to compare and choose the best-performing model.

We looked at a range of models, and their "balanced accuracy" scores varied quite a bit, from around 55% to a high of 75.4%. The Gradient Boosting model truly shined, coming out on top with a balanced accuracy of 75.4%. Right on its heels was Logistic Regression at 75%. When we dive into the details (you can see all the charts in Figures 3 to 5), it's clear that Gradient Boosting isn't just slightly better; it's the overall best performer across key measures like Balanced Accuracy and ROC-AUC. Now, if we zoom in on identifying just the investment-ready companies (what we call 'Class 1'), Gradient Boosting still did incredibly well. It was only a tiny bit behind the best models in terms of finding all the investment-ready companies (Recall, where Logistic Regression did slightly better) or avoiding false alarms (Precision, where Random Forest had a slight edge). But here's the crucial point: Gradient Boosting had the best F1-score for Class 1. This means it found the best balance between correctly identifying investment-ready companies and not flagging too many false positives. Essentially, it's the most well-rounded model for helping us spot those truly promising SMEs.

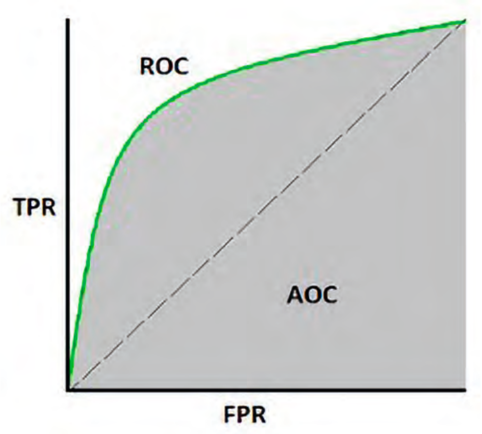


Figure 3. ROC AUC Curve.

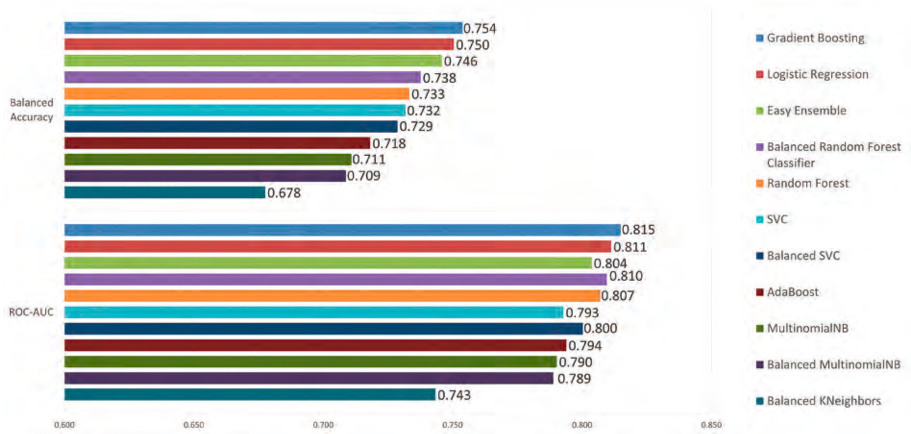


Figure 4. Balanced Accuracy and ROC-AUC.

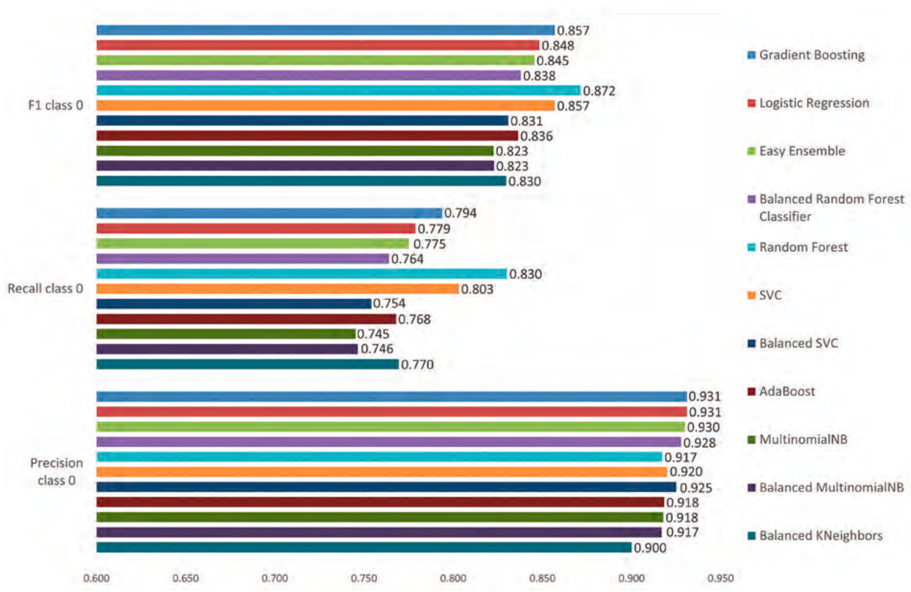


Figure 5. Class 0 Metrics.

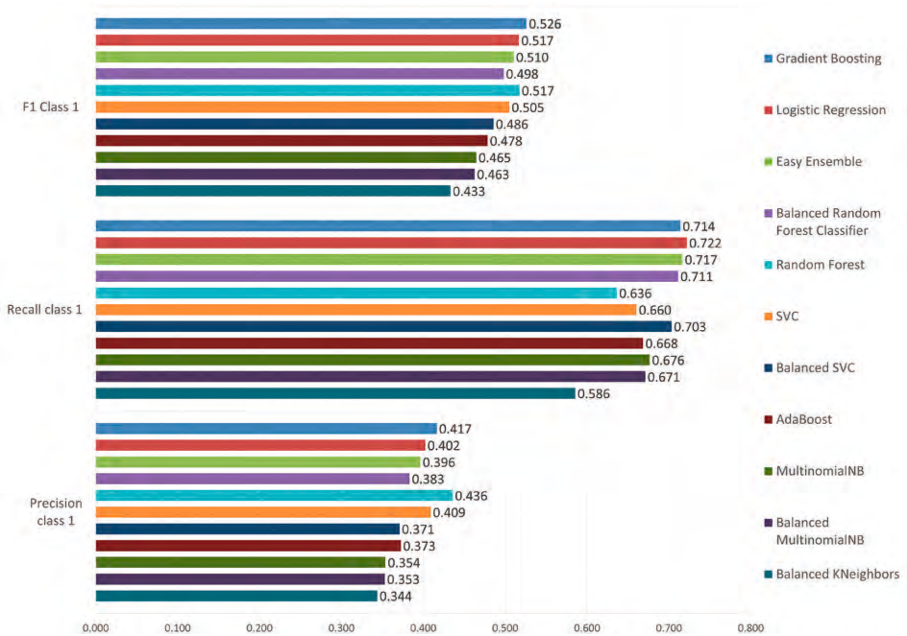


Figure 6. Class 1 Metrics.

Moreover, in Figure 7 below, we present the ROC Curve for the Gradient Boosting model.

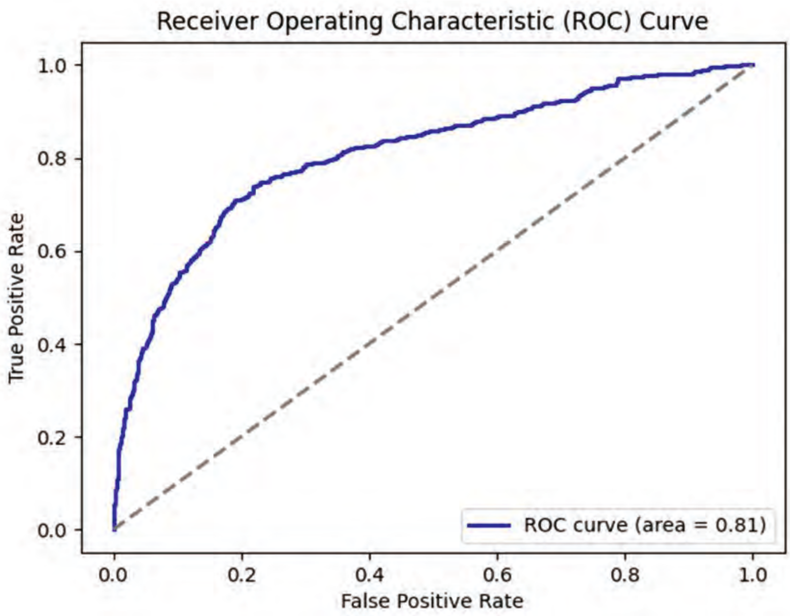


Figure 7. Gradient Boosting ROC Curve.

Despite its algorithmic simplicity, the Logistic Regression has demonstrated a remarkable performance, particularly in class 1 recall reaching 0.722; the highest of all models. The Logistic Regression had a balanced accuracy of 0.750 and an ROC-AUC score of 0.811, which are second only to Gradient Boosting. Easy ensemble shows consistent performance across metrics. While not leading in any metric, with a balanced accuracy of 0.746, a precision of 0.396 and a recall of 0.717, its consistent performance suggests robustness in its capabilities. With an F1-score of 0.510 and ROC-AUC of 0.804, it performs only slightly worse than the two leading models. Finally, the Balanced Random Forest had the third highest ROC-AUC score of 0.810, only marginally worse than Logistic Regression and had a competitive recall rate of 0.711. Nonetheless, it has the lowest balanced accuracy (0.738) and precision (0.383) among the top models.

Considering Precision, Recall, and F1, Gradient Boosting appears to outperform most of the competition for class 0, exhibiting some of the top values across all evaluation metrics. The model achieved the best overall precision of 0.931, with the second highest overall Recall score of 0.794 and the second highest F1-score of 0.857 only falling behind the Random Forest, which had a recall score of 0.830 and an F1 score of 0.872.

Precision remains consistent across all models with a limited variability (Precision variance of models is 0.031). The same is not true for Recall (Recall variance of models is 0.128). All models achieve exceptional Class 0 precision (>90%) with Gradient Boosting offering the optimal performance.

Overall, Gradient Boosting is the optimal model for predicting SME investment readiness and is the recommended model in terms of creating a balanced predictive strategy. There are however models that excel at specific metrics, like the Logistic Regression in terms of class 1 Recall or Random Forest in terms of class 0 Recall. Classifying the majority class proved to be an easy task for all of the models, having achieved very high levels of both precision and F1-scores. This indicates that the algorithms were effective at filtering out non-investment-ready firms. On the other hand, predicting the minority class proved to be a challenge. This is made evident by the overall lower F1-scores all of the models, which peaked at 0.526 and low precision levels. This highlights the challenge in avoiding false positives.

In Figures 8 and 9 below, we present the confusion matrix and the normalized confusion matrix respectively for the best model, the Gradient Boosting. It achieved:

- 267 TP predictions (investment-ready) out of 374, or 71.3%.
- 1440 TN predictions (not-investment-ready) out of 1814 or 79.3%.
- 374 FP predictions (predicted as investment-ready but are not) or 20.6%
- 107 FN predictions (predicted as not-investment-ready but are not) or 28.6%.

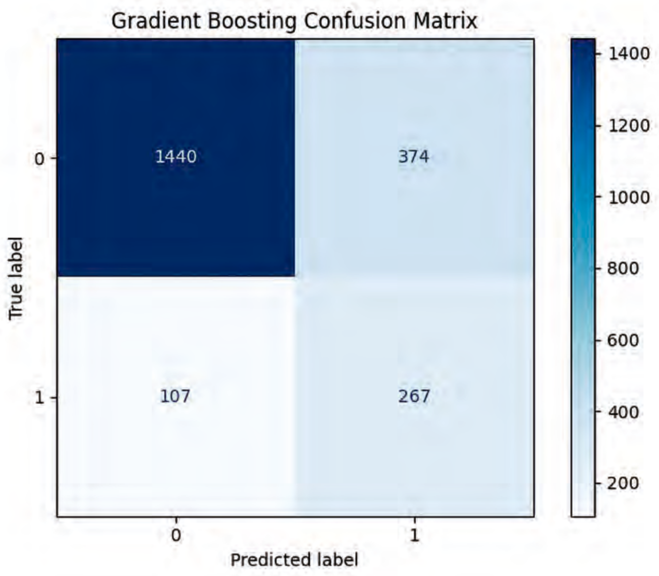


Figure 8. Gradient Boosting Confusion Matrix.

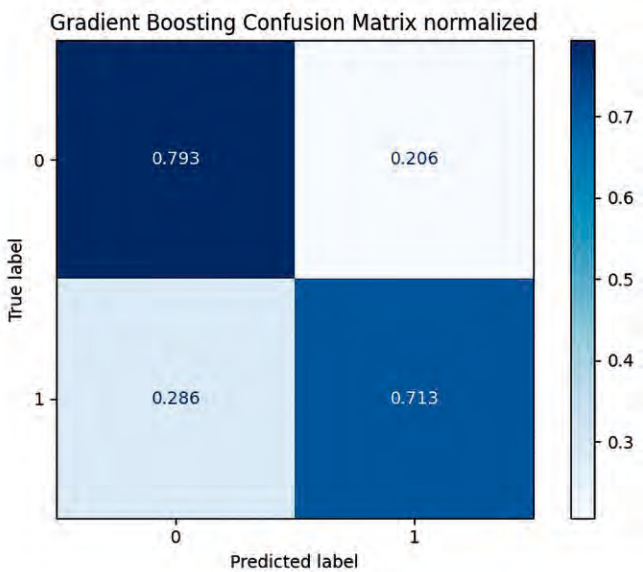


Figure 9. Gradient Boosting Confusion Matrix normalized.

The confusion matrices for the other models are provided in the Appendix. Using the Variable Importance Measure (VIM) on our best model, Gradient Boosting, Figure 10 shows the top 10 most influential variables. The first six stand out as especially important.The strongest predictor is the firm's confidence in negotiating with equity investors or venture capitalists, reflecting preparation and business strength vital for attracting investment. Next is financing growth, highlighting the role of active financial planning and scaling. Third, future financing plans indicate investors favor firms with clear strategies for securing finance ahead. External financing factors, like market conditions and access to funding channels, also impact predictions. The autonomous organization type suggests more agile, innovative firms attract investors. Lastly, investor willingness to invest reflects market sentiment towards the firm. Overall, these variables reveal key traits that drive investment readiness in SMEs.

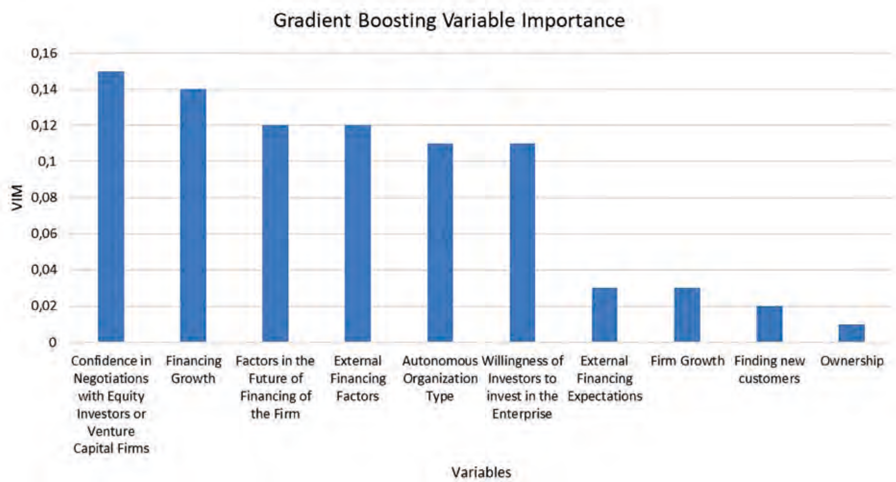


Figure 10. Gradient Boosting Variable Importance Plot.

These six variables summarize the importance of both a) internal factors such as confidence, growth, future outlook, and the firm's autonomy and flexibility and b) external factors such as market conditions, availability of financing and the overall sentiment of the investors' towards investing in a firm.

4. Conclusions

This study shows how advanced machine learning techniques can effectively predict which small and medium-sized enterprises (SMEs) are ready to attract external investment. Using a large and detailed European dataset, we tested several models, with Gradient Boosting performing best by accurately identifying investment-ready SMEs nearly 75% of the time. Notably, simpler models like Logistic Regression also performed well, offering easy interpretability and fast deployment—important considerations for practical use.

Our findings highlight key factors that influence a company's investment readiness: strong managerial confidence, active innovation, openness to equity funding, and positive investor sentiment. Understanding these can help SMEs focus their efforts on the areas that truly matter to investors.

For investors and financial institutions, these predictive models offer a powerful tool to identify promising SMEs more reliably and reduce costly misjudgments. Regulators and policymakers can leverage these insights to design targeted programs that support SME growth and optimize the impact of public funds.

Importantly, when financial consequences of misclassifications are considered, selecting the best predictive model depends not just on accuracy but on the relative cost of missing good investment opportunities versus wrongly approving weaker firms. This cost-sensitive approach helps align model choice with real-world priorities and risk tolerance.

By adopting these data-driven approaches, all stakeholders can foster a more efficient allocation of capital, ultimately enabling SMEs to thrive and contribute more effectively to economic growth and job creation.

Executive Summary - Using Machine Learning to Identify Investment-Ready SMEs

Small and medium-sized enterprises (SMEs) are crucial to economic growth but often struggle to access external funding. Our study applies advanced machine learning (ML) techniques to predict which SMEs are investment-ready, using comprehensive European survey data. Among several models tested, Gradient Boosting achieved the highest accuracy, identifying promising SMEs with nearly 75% balanced accuracy.

Key drivers of investment readiness include managerial confidence, innovation, proactive financial planning, and investor interest. These insights help investors and funders focus on businesses with the strongest potential, reducing costly mistakes in funding decisions.

Importantly, while complex ML models perform best, simpler models like Logistic Regression also deliver strong results with easier interpretation, enabling rapid adoption by financial institutions and policymakers alike.

By adopting these data-driven tools, investors can improve portfolio selection, businesses can better prepare for funding, and policymakers can design targeted support programs to foster SME growth—ultimately promoting more efficient capital markets and stronger economies.

Policy Brief

SMEs face significant barriers in accessing external financing despite their vital role in innovation and job creation. Accurate assessment of investment readiness remains a challenge, often resulting in misallocation of scarce financial resources.

Key Findings

- Our research demonstrates that machine learning algorithms, especially Gradient Boosting, significantly improve the ability to identify SMEs ready for external investment.
- Important factors influencing investment readiness are managerial confidence, innovation, and clear financial strategies.
- Simpler models also prove effective, offering transparent and actionable tools for broader use.

Policy Implications

- Targeted Support: Use ML-based assessments to prioritize SMEs that show genuine readiness, ensuring public funds and assistance programs deliver maximum impact.
- Capacity Building: Encourage SMEs to strengthen key areas such as business planning, innovation, and investor communication to increase their investment attractiveness.

- Risk Management: Implement cost-sensitive evaluation frameworks that balance the risks of missing opportunities against funding less-prepared firms.

Recommendations

- Integrate ML tools into public finance agencies and SME development programs for data-driven decision-making.
- Promote training initiatives to improve SME "investment readiness," focusing on the traits identified as most predictive.
- Foster collaboration between financial institutions and policymakers to adopt transparent models supporting equitable access to finance.

Note: The research project is implemented in the framework of H.F.R.I call "Basic Research Financing (Horizontal support of all Sciences)" under the National Recovery and Resilience Plan "Greece 2.0" funded by the European Union – NextGenerationEU (H.F.R.I. Project Number: 16856).

H.F.R.I. Hellenic Foundation for Research & Innovation
Greece 2.0 NATIONAL RECOVERY AND RESILIENCE PLAN
Funded by the European Union NextGenerationEU

Appendix

Table A1. Confusion Matrix Metrics for all models.

Model	TN	FP	FN	TP
Gradient Boosting	1440	374	107	267
Logistic Regression	1413	401	104	270
Easy Ensemble Classifier	1406	408	106	268
Balanced Random Forest Classifier	1386	428	108	266
Random Forest	1506	308	136	238
SVC	1457	357	127	247
Balanced SVC	1368	446	111	263
AdaBoost	1393	421	124	250
MultinomialNB	1352	462	121	253
Balanced MultinomialNB	1354	460	123	251
Balanced KNeighbors	1396	418	155	219
KNeighbors	1745	69	321	53

Table A2. Balanced Accuracy and ROC-AUC score for all models.

Model	Balanced Accuracy	ROC-AUC
Gradient Boosting	0.754	0.815
Logistic Regression	0.750	0.811
Easy Ensemble Classifier	0.746	0.804
Balanced Random Forest Classifier	0.738	0.810
Random Forest	0.733	0.807
SVC	0.732	0.793
Balanced SVC	0.729	0.800
AdaBoost	0.718	0.794
MultinomialNB	0.711	0.790
Balanced MultinomialNB	0.709	0.789
Balanced KNeighbors	0.678	0.743
KNeighbors	0.552	0.640

Table A3. Precision, Recall and F1 score for all models.

Model	Precision Class 0	Recall Class 0	F1 Class 0	Precision Class 1	Recall Class 1	F1 Class 1
Gradient Boosting	0.931	0.794	0.857	0.417	0.714	0.526
Logistic Regression	0.931	0.779	0.848	0.402	0.722	0.517
Easy Ensemble Classifier	0.930	0.775	0.845	0.396	0.717	0.510
Balanced Random Forest Classifier	0.928	0.764	0.838	0.383	0.711	0.498
Random Forest	0.917	0.830	0.872	0.436	0.636	0.517
SVC	0.920	0.803	0.858	0.409	0.660	0.505
Balanced SVC	0.925	0.754	0.831	0.371	0.703	0.486
AdaBoost	0.918	0.768	0.836	0.373	0.668	0.478
MultinomialNB	0.918	0.745	0.823	0.354	0.676	0.465
Balanced MultinomialNB	0.917	0.746	0.823	0.353	0.671	0.463
Balanced KNeighbors	0.900	0.770	0.830	0.344	0.586	0.433
KNeighbors	0.845	0.962	0.899	0.434	0.142	0.214

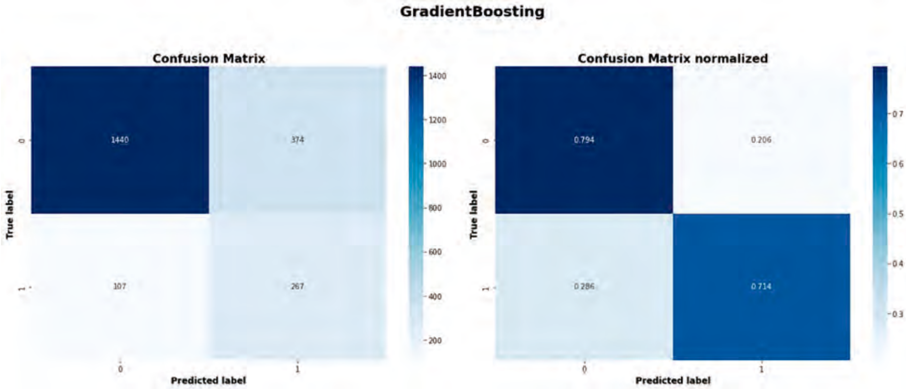


Figure A1. Gradient Boosting confusion matrices.

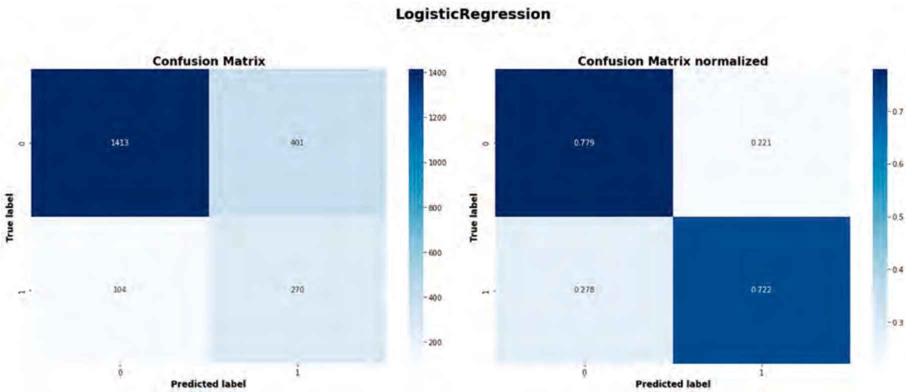


Figure A2. Logistic Regression model confusion matrices.

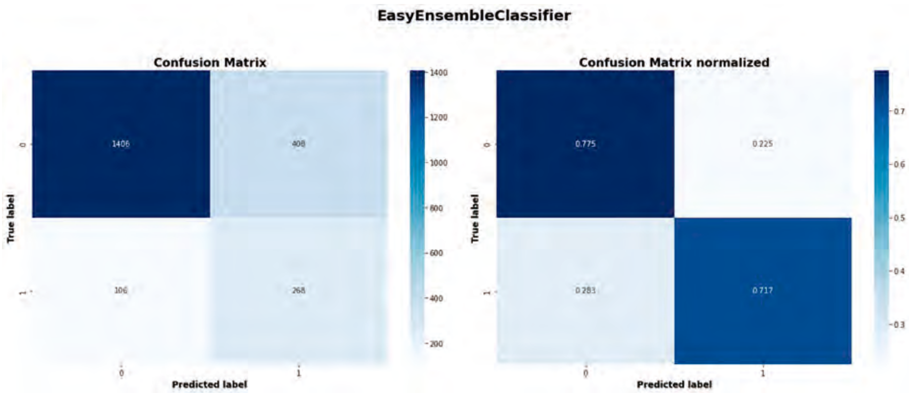


Figure A3. Easy Ensemble Classifier model confusion matrices.

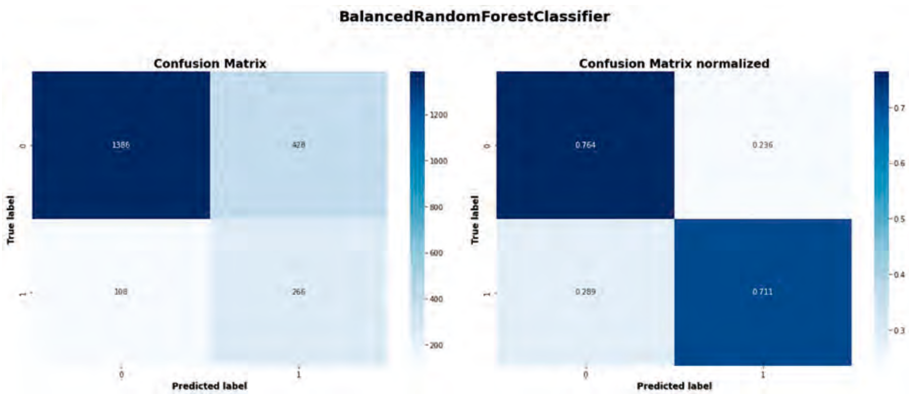


Figure A4. Balanced Random Forest model confusion matrices.

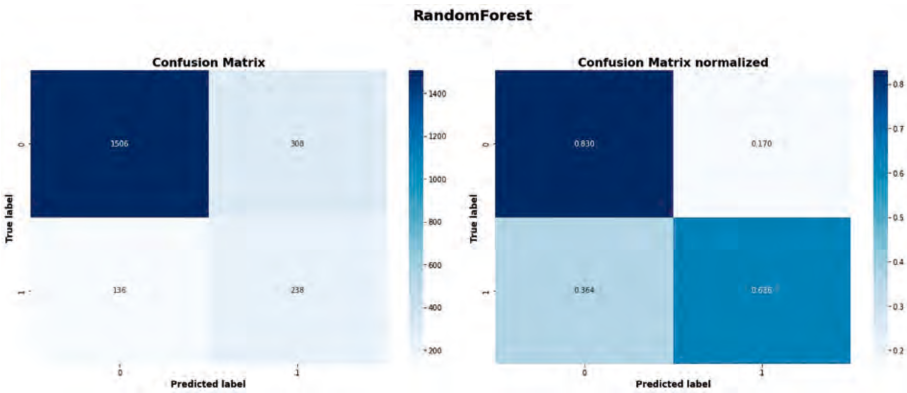


Figure A5. Random Forest model confusion matrices.

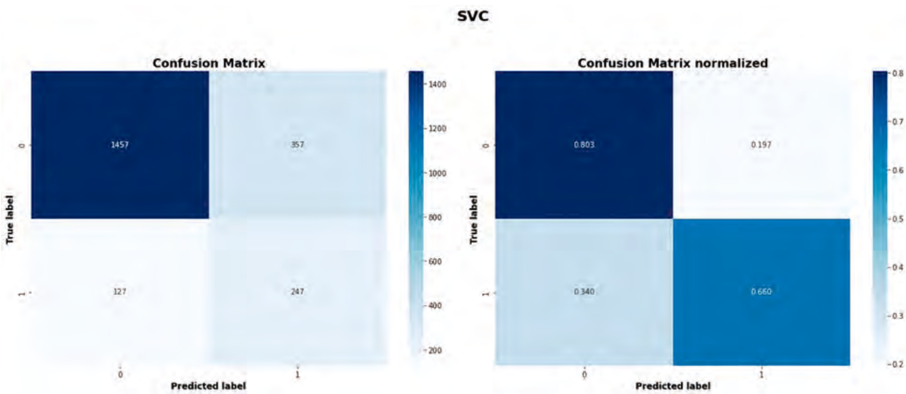


Figure A6. SVC model confusion matrices.

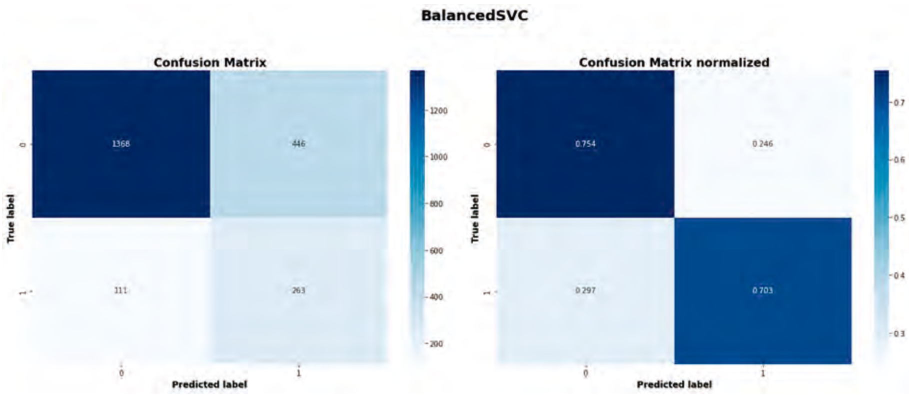


Figure A7. Balanced Bagging SVC model confusion matrices.

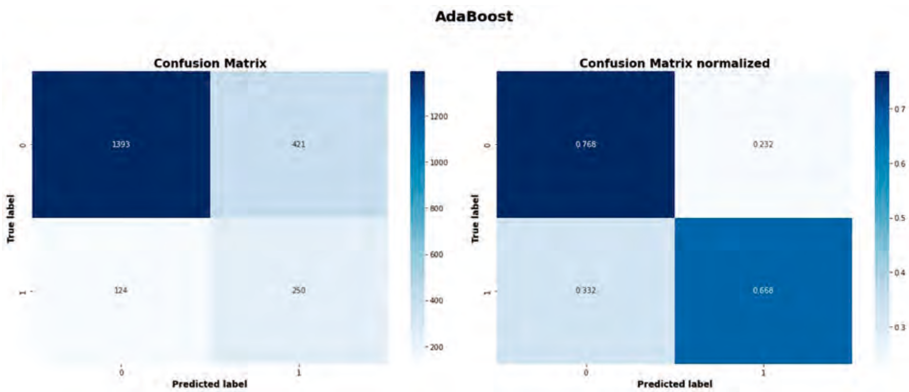


Figure A8. Adaboost model confusion matrices.

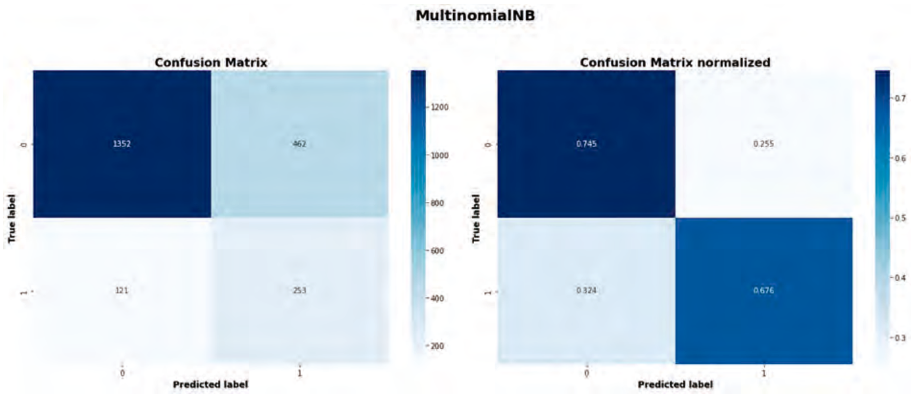


Figure A9. MultinomialNB model confusion matrices.

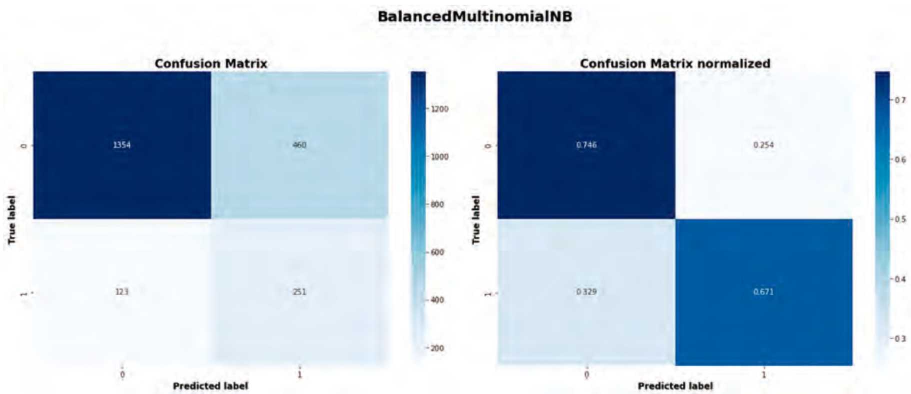


Figure A10. Balanced Bagging MultinomialNB model confusion matrices.

References

Commission Recommendation of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises (notified under document number C(2003) 1422), *Official Journal L 124 , 20/05/2003 P. 0036 – 0041,* https://eur-lex.europa.eu/eli/reco/2003/361/oj

Chonsawat, N., & Sopadang, A. (2020). Defining SMEs' 4.0 Readiness Indicators. *Applied Sciences, 10*(24), 8998. https://doi.org/10.3390/app10248998

Cusolito, A. P., Dautovic, E., & McKenzie, D. (2021). Can government intervention make firms more investment-ready? A randomized experiment in the Western Balkans. *Review of Economics and Statistics, 103*(3), 428–442. https://doi.org/10.1162/rest_a_00882

Douglas, E. J., & Shepherd, D. A. (2002). Exploring investor readiness: Assessments by entrepreneurs and investors in Australia. *Venture Capital, 4*(3), 219–236. https://doi.org/10.1080/13691060213713

Du, J., & Rada, R. (2010). Machine learning and financial investing. In *Handbook of Research on Machine Learning Applications and Trends: Algorithms, Methods, and Techniques* (pp. 375–398). IGI Global. https://doi.org/10.4018/978-1-60566-766-9.ch017

Dumitrescu, E., Hué, S., Hurlin, C., & Tokpavi, S. (2021). Machine learning or econometrics for credit scoring: Let's get the best of both worlds. *HAL Working Paper hal-02507499*. Available at: https://hal.archives-ouvertes.fr/hal-02507499

European Central Bank (ECB) (2023). *Survey on the Access to Finance of Enterprises (SAFE) Dataset*. Retrieved from https://www.ecb.europa.eu/stats/ecb_surveys/safe/html/data.en.html

Fellnhofer, K. (2015). Literature review: Investment readiness level of small and medium-sized companies. *International Journal of Managerial and Financial Accounting, 7*(3/4), 268–284. https://doi.org/10.1504/IJMFA.2015.074904

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics, 29*(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

Friedman, J. H. (1999). Stochastic Gradient Boosting. *Technical Report*. Stanford University.

Khan, A. H., Shah, A., Ali, A., Shahid, R., Zahid, Z. U., Sharif, M. U., Jan, T., & Zafar, M. H. (2023). A performance comparison of machine learning models for stock market prediction with novel investment strategy. *PLOS ONE, 18*(9), e0286362. https://doi.org/10.1371/journal.pone.0286362

Li, M. (2023). Financial investment risk prediction under the application of information interaction Firefly Algorithm combined with Graph Convolutional Network. *PLOS ONE, 18*(9), e0291510. https://doi.org/10.1371/journal.pone.0291510

Mason, C. M., & Harrison, R. T. (2001). "Investment readiness": A critique of government proposals to increase the demand for venture capital. *Regional Studies, 35*(7), 663–668. https://doi.org/10.1080/00343400120075939

Mason, C. M., & Kwok, J. (2010). Investment readiness programmes and access to finance: A critical review of design issues. Working Paper 10-03, Hunter Centre for Entrepreneurship, University of Strathclyde.

Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives, 31*(2), 87–106. https://doi.org/10.1257/jep.31.2.87

Okfalisa, et al. (2021). Measuring the effects of different factors influencing the readiness of SMEs towards digitalization: A multiple perspectives design of decision support system. *Decision Science Letters, 10*, 425–442. https://doi.org/10.5267/j.dsl.2021.1.002

Owen, R., Botelho, T., Hussain, J., & Anwar, O. (2023). Solving the SME finance puzzle: An examination of demand and supply failure in the UK. *Venture Capital, 25*(1), 31–63. https://doi.org/10.1080/13691066.2022.2135468

Pirola, F., Cimini, C., & Pinto, R. (2020). Digital readiness assessment of Italian SMEs: a case-study research. *Journal of Manufacturing Technology Management, 31*(5), 1045–1083. https://doi.org/10.1108/JMTM-09-2018-0305

Shobana, G., & Umamaheswari, K. (2021). Forecasting by machine learning techniques and econometrics: A review. In *Proceedings of the Sixth International Conference on Inventive Computation Technologies (ICICT 2021)*. IEEE Xplore.

Vasilescu, L. G. (2009). 'Investment readiness'—aligning capital demand and supply. [Details needed from original publication].

World Bank (2023). Small and Medium Enterprises (SMEs) Finance – Improving SMEs' access to finance and finding innovative solutions to unlock sources of capital. Retrieved from: https://www.worldbank.org

Zana, D., & Barnard, B. (2019). Venture capital and entrepreneurship: The cost and resolution of investment readiness. *SSRN Electronic Journal*. Available at SSRN: https://doi.org/10.2139/ssrn.3351938

Norvig, Russel (2020). Artificial Intelligence. A Modern Approach (4rth Edition) Pearson Series.

Cover, T.M., & Hart, P.E. (1967). Nearest neighbor pattern classification. IEEE Trans. Inf. Theory, 13, 21-27.

L. Breiman. (2001) Random Forests, Machine Learning, 45(1), 5-32.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273–297.

Cox, D.R. (1958) The regression analysis of binary sequences. Journal of the Royal Statistical Society: Series B (Methodological), 20(2), pp.215–232.

Freund, Y., & Schapire, R.E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. European Conference on Computational Learning Theory.

Liu, X., Wu, J., & Zhou, Z. (2009). Exploratory Undersampling for Class-Imbalance Learning. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 39, 539-550.

Breiman, L. (1996). Bagging predictors. Machine Learning, 24(2), 123–140.

C.D. Manning, P. Raghavan and H. Schuetze (2008). Introduction to Information Retrieval. Cambridge University Press, pp. 234-265.

Brodersen, K.H.; Ong, C.S.; Stephan, K.E.; Buhmann, J.M. (2010). The balanced accuracy and its posterior distribution. Proceedings of the 20th International Conference on Pattern Recognition, 3121-24.

Gogas, P.; Papadimitriou, T.; Sofianos, E. (2019) Money Neutrality, Monetary Aggregates and Machine Learning. Algorithms, 12,137.

Peykani, P., Peymany Foroushany, M., Tanasescu, C., Sargolzaei, M., & Kamyabfar, H. (2025). Evaluation of Cost-Sensitive Learning Models in Forecasting Business Failure of Capital Market Firms. *Mathematics*, *13*(3), 368. https://doi.org/10.3390/math13030368

ECB Data References:

- European Central Bank (2023). Survey on the Access to Finance of Enterprises (SAFE). Retrieved from: https://www.ecb.europa.eu/stats/ecb_surveys/safe/html/data.en.html
- ECB (2023). SAFE Methodology Documentation. Retrieved from: https://data.ecb.europa.eu/data/datasets/SAFE/structure
- ECB (2023). Dataset Structure Documentation. Retrieved from: https://data.ecb.europa.eu/data/datasets/SAFE/structure
- ECB (2023). SAFE Data Information. Retrieved from: https://data.ecb.europa.eu/data/datasets/SAFE/data-information

TESTING INDUSTRIAL POLICY IN TIMES OF CRISIS:

THE CASE OF GREECE (2008–2024)

Dionysios Chionis
Department of Economics,Democritus University of Thrace
dchionis@ierd.duth.gr

Fotios Mitropoulos
Department of Economics,Democritus University of Thrace
fmitropo@econ.duth.gr.

Antonios Sarantidis
Department of Management Science and Technology University of the Peloponnese
asarantidis@yahoo.com

ABSTRACT

In the aftermath of prolonged economic crises and successive shocks—including the sovereign debt crisis, the COVID-19 pandemic, and the energy crisis triggered by geopolitical instability—Greece stands at a pivotal juncture. This paper examines the evolution of Greek industrial policy and the policies implemented to target economic transformation, synthesising empirical data and policy analysis. We explore the country's industrial stagnation, the limitations of prior growth models, and the potential for transformation through the Recovery and Resilience Facility (RRF). Our findings underscore the urgency of shifting towards a new production paradigm grounded in sectoral policy, *competitiveness, innovation, and sustainability. Through econometric evidence and policy evaluation, we provide actionable insights for reshaping Greece's industrial landscape to align with EU priorities and global realities.*

JEL: *E61, L52, O25*

Keywords: *Industrial Policy, Economic Transformation, Structural Reforms, Recovery and Resilience Facility (RRF)*

Introduction

The Great Recession, which began in 2009, led the financial and economic system of Greece into a period of long-term distress. The adverse effects were evident in both the financial area and in the entrepreneurship activities. During that turbulent period and the implementation of three adjustment programs in Greece (2010-2018), the government imposed significant fiscal measures (in response to the losses incurred in accessing financing in the financial market and the deep recession, characterised by rising unemployment rates. After more than ten years, the national economy and businesses have been able to withstand the effects of the crisis and enter the phase of economic recovery.

The period of economic recovery did not last long, as the COVID-19 pandemic emerged at the end of 2019. COVID-19 has had a significant impact on the economy and entrepreneurial activities, leading to the closure of national borders and forcing citizens to stay at home. Furthermore, the pandemic has harmed the global supply chain and contributed to the worldwide supply chain crisis of 2021. The expansive fiscal policies implemented during that period, combined with unexpected demand for specific goods, led Greece to face higher inflation rates. The pandemic crisis led to an increase in the inflation rate and played a significant role in the current energy crisis. Later, the mentioned supply chain crisis and the current Russia-Ukraine crisis have deepened the energy crisis, leading the economy and business activities into a new period of distress.

As already mentioned, these shocks have affected the demand and supply side (Blanchard, 2020). The pandemic crisis and the subsequent Ukraine invasion have cost Greece's economy, and more specifically, its industrial sector. In response to that and at the beginning of Covid-19, the European Commission presented the New Industrial Strategy for Europe (EC, 2020), which aimed to address the two biggest challenges, namely, the transition of the industry to climate neutrality with zero emissions by the year 2050 and on the other hand, its digital transformation. Haussman et al. (2021, quoted in Haussman, 2021) stated that "The EU Recovery and Resilience Facility (RRF), as the centrepiece of the Next Generation EU (NGEU) programme started 07/2020, enshrines the twin priorities the green transition and the digital transformation, aiming on increasing the EU's potential growth, helping for long-term fiscal consolidation, and boosting economic convergence across the EU, Greece will receive up to 30.5 billion euros from the EU RRF funds, of which 17.8 billion euros are in grants and 12.7 billion euros in loans, with availability until the end of 2026".

The three basic frameworks

Over the preceding quinquennium, efforts have been made to effect an economic transformation through the implementation of a structured intervention framework, organised around three fundamental pillars. The Growth Plan for the Greek economy, otherwise referred to as the Pissarides Report (2020), the Green Growth Plan 2021-2025, the transition to the circular economy, and finally, the Digital Transformation Programme 2021-2027. All these attempts were undertaken under the auspices of the European Commission, part of the new Industrial Strategy for Europe (EC, 2020), which aimed for a green transition, a shift in industrial production to zero pollution by 2050, and a digital transition.

The overarching objective of these initiatives was to contribute to the country's economic transformation and enhance competitiveness. The Pissarides report specifically referenced the anticipated 'strong' productivity growth. A comparison of the effectiveness of these interventions with actual macroeconomic performance is necessary to determine whether, after five years, the desired productive transformation of the economy and improvement in competitiveness have been achieved. The answer to that lies in the performance of the trade balance and competitiveness indicators.

The research documents the industrial landscape of Greece and offers significant recommendations for a new functional industrial policy. That is achieved through the combination of theoretical and quantitative analysis. Specifically,

- It records the current landscape and the rigidities of Greece's latest industrial policy.
- It collects various variables associated with recent turbulent periods to analyse econometrically the impact they have on the industrial sector and economic growth.
- It analyses the recommendations derived from theoretical and quantitative analysis and provides accurate and specific policy recommendations.

Literature Review

During turbulent periods, the industrial sector has played a crucial role in the economic recovery of many European countries. On the one hand, the financial and economic crises have shifted interventions from the national level to a more common EU policy; however, industrial policy in Europe is still largely carried out at the national level (Terzi et al., 2022; Hodge et al., 2024). On the other hand, however, any "one size fits all" policy is very difficult to implement in countries suffering from diverse idiosyncrasies, including those at the regional and sub-national levels (Benner, 2019).

A genuine European industrial policy is necessary if Europe wants to be a manufacturing powerhouse in the following decades (Franco-German Manifesto, 2019). In this sense, European countries should learn from the success of the "Asian Miracles". Many economists and policymakers argue that the recipe for a better industrial sector is a combination of several factors, including openness to trade, ease of doing business, macroeconomic stability, and financial deepening. The State and the markets must thus play their roles in implementing Technology and Innovation policies (Cherif & Hasanov, 2019). Some authors (Mazzucato, 2013; Wade, 2018) argue that the State plays a significant role in promoting innovation and growth. These stand in contrast to other approaches, which argue that a free-market policy should be the primary vehicle for industrial growth (see, e.g., Monnery, 2017).

From the onset of the 2007-2008 economic downturn, the industrial sector played a pivotal role in the economic recovery of European countries. It is worth noting that the financial and economic crises have led to a shift in interventions from the national level to a more common policy of the European Union. On the other hand, the "one size fits all" policy is very difficult to implement in countries with diverse cultural and social characteristics. The need to "reindustrialise" countries has been advocated by several international programs and reports, as a genuine European industrial policy is necessary if Europe wants to be a manufacturing powerhouse in the following decades (Franco-German Manifesto, 2019) [3].

The recent pandemic crisis has disrupted global value chains, causing economic disturbances, significant shortages, and delays in goods and services, which have resulted in a rapid increase in final prices. The initial period of restrictions and modest spending by households and enterprises, due to the disruption of international trade flows, led to increased demand for various goods. Moreover, a sharp expansion of the e-commerce sector was observed. This was driven by the loose fiscal policy implemented by countries to address the consequences of the pandemic, including a reduction in imports and an increase in social expenditures to alleviate the impact on citizens.

As the pandemic seems to be receding and the global supply chains restructured, Russia's invasion of Ukraine is already causing new major shocks and affecting the economy of Greece (Kapopoulos et al., 2024). The intensity of that shock depends on both the duration and the outcome of that conflict. Despite these unforeseen circumstances, Greek economic production rebounded and ultimately returned to its pre-pandemic level in 2021, thanks to an expansive policy mix and significant EU economic support (IMF, 2022).

This research focuses on the Renaissance of Greek industrial policy and the impact that structural reforms and the COVID-19 pandemic crisis could have. The conclusions drawn from the theoretical and empirical approach regarding industrial policy are important. It assesses the extent to which industrial policy is affected and provides policy recommendations to address these issues and enhance the economy during turbulent times.

---

3. A Franco-German Manifesto for a European industrial policy fit for the 21st Century, (2019), https://www.bmwi.de/Redaktion/DE/Downloads/F/franco-german-manifesto-for-a-european-industrial-policy.pdf?__blob=publicationFile&v=2

Industrial Policy: EU and Greece

The context of industrial policy is complex as it encompasses tools ranging from innovation to foreign direct investment (FDI). Pack and Saggi (2006) define it as a form of government intervention that can take various shapes and sizes, and whose goal is to transform and channel production to sectors that are expected to perform better economically with such interventions than without them.

Two core elements stand out: first, there are some preferred sectors for production, and second, governments should create the circumstances to enhance and improve the production process in these preferred sectors (Terzi et al., 2022). Stiglitz (2017) defines the primary purpose of industrial policies as "to affect the economy's sectoral allocation or choice of technique to address market failures that do not lead to an efficient allocation of resources among the different sectors".

Industrial policy has returned to the agenda of countries and organisations around the world. According to Landesmann and Stollinger (2020), concerns in the EU about a potential de-industrialisation tendency, the changing global circumstances as well as the enduring disparities among regions and the impact of the financial crisis of 2008, that not unevenly the member states, lead to a rethinking of the industrial policy after the stagnant period of 1990s and 2000s. In particular, the persistent effects of the financial crisis have taken their toll on labour markets. At the same time, low growth development, especially within the eurozone, and the decline in employment shares in manufacturing have posed serious concerns. At the same time, the growing competition from China and the current trend of Industry 4.0 have necessitated the rethinking and reconsideration of industry policies worldwide (Aiginger & Rodrik, 2020). Almost all major global economies, including the United States, Japan, and China, are developing plans for their industrial policies (Cimoli et al., 2009).

Traditionally, typical European industrial policy combines both horizontal and sector-specific measures- the mix varying according to several circumstances (Landesmann & Stollinger, 2020). However, a purely horizontal approach is neither sufficient nor feasible, as several sectors are favoured by horizontal interventions (Rodrik, 2009).

In the EU, industrial policy aims to enhance the competitiveness of European countries and continue its role as a driving force for sustainable development. It lies, however, mainly in the hands of national governments, which are responsible for developing policies and tools that primarily support small and medium-sized enterprises (SMEs). As such, the specific role and characteristics of industrial policy vary according to each national context (Johnstone et al., 2021). This strong government involvement in the economy was reinforced further during the 2008 financial crisis and the more recent COVID-19 pandemic. In both cases, governments intervened to support the economy and reduce the impact of both crises. Despite some sectoral industrial interventions and measures even since the creation of the European and Steel Community, there was not the expected progress on creating a standard industrial policy after the formation of the European Economic Community; only some policy framework refinement, which led to a more standardised policy, away from just specific national interventions, has been observed. (Szczepański and Zachariadis, 2019).

The industrial policy in the EU aims to improve the competitiveness of European countries, taking into account sustainability and enhancing employment. However, in today's landscape, economies are still on the road to recovery from the socio-economic crisis brought on by the COVID-19 pandemic. Moreover, events such as the Russian invasion of Ukraine alter the global landscape in sectors like the economy, energy, and technology, rapidly transforming the production process. Climate change poses a severe threat, and the EU's industrial policy faces various challenges in creating a sustainable future.

Lamdesmann and Stollinger (2020) identify four main challenges that the revived interest in European industrial policy should address, including technology and the green transition. These challenges or goals should not be viewed individually, but rather as interdependent and mutually reliant on one another. For instance, Aghion et al. (2016) have demonstrated that industrial policy can link technological innovation and a green transition, thereby pushing the former in the direction of the latter. Keeping up with the competition is also essential, primarily by tilting innovation development towards a direction closer to the country's original comparative advantage, which could stem from the green transition (Rodrik, 2014; Aghion et al., 2021). Having a proactive role and being a "first-mover" as a government can ensure a national competitive advantage. Simultaneously, the EU needs to maintain the dynamic function of the Single Market while "pushing" European companies, through its industrial policy, towards directions that could grant their nations a competitive advantage.

In this sense, the EU must balance numerous factors as it navigates the ever-changing global context. The challenges presented underscore the fact that addressing them at a supranational level can be more effective, as no individual member state can meet these challenges independently. The Industrial policy in Europe has changed over the last decades, towards a more horizontal and standardised policy away from targeted national industrial support. On the other hand, inequalities persist, and the imbalances are more pronounced during turbulent periods. These imbalances come to the forefront in times of shock, such as the current Russian invasion of Ukraine, where decisions are initially national-oriented.

Data and Methodology

The dataset contains variables for the Number of new firms launched, the Number of Businesses that were obliged to stop their activities, GDP growth, Foreign Direct Investment (FDI), the Current account deficit (% of GDP), the Real Effective Exchange Rate Index, the unemployment rate, and the Turnover of Businesses. Data are collected for Greece, using quarterly time series observations. The period spans the years from the first quarter of 2008 (Q1) to the fourth quarter of 2024 (Q4). This period contains three significant events: the economic crisis of 2007/2008, the COVID-19 pandemic and the energy crisis. To deal with that, we included in the analysis three dummy variables: a) an economic crisis dummy (2008q1-2012q4), b) a COVID-19 dummy (2020q1-2021q4) and c) an energy crisis dummy (2021q1-2024q4) - data on GDP growth, FDI and unemployment rates are obtained from the World Bank's World Development Indicators (WDI). Data on the Number of Businesses, business turnover, the Number of Businesses that were obliged to stop their activities, and the Current account deficit (as a percentage of GDP) are obtained from the European Commission Dataset and the Hellenic Statistical Authority. The Real Effective Exchange Rate Index is obtained from the Bank of Greece database. Table 1 presents the variables used in the analysis, and Table 2 provides the summary statistics.

Table 1: Variables

Name	Interpretation	Period
GDP	Gross Domestic Product (% change)	2008-2024
FDI	Foreign Direct Investments (% of GDP)	2008-2024
UNEMPL	Unemployment rate (% change)	2008-2024
NB	Number of Businesses (% change)	2008-2024
TURNOVER	Turnover of businesses	2008-2024
CLOSEB	Close of Businesses (% change)	2008-2024
CAD	Current account deficit (% of GDP)	2008-2024
REER	Real Effective Exchange Rate Index	2008-2024
D_CRISIS	Dummy variable for the economic crisis period 2009-2012	2008-2024
D_COVID	Dummy variable for the COVID-19 period 2019-2021	2008-2024
D_ENERGY	Dummy variable for the energy crisis period 2021-today	2008-2024

Table 2: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
GDP	92	-0.94	4.96	-10.15	8.30
UNEMPL	92	17.51	6.37	7.76	27.47
FDI	92	1.40	0.66	0.18	2.44
NB	92	1.52	11.78	-8.69	44.61
TURNOVER	92	0.52	4.34	-7.60	6.92
CLOSEB	92	-2.48	32.64	-67.30	67.68
D_crisis	92	0.24	0.44	0.00	1.00
D_covid	92	0.29	0.47	0.00	1.00
E_crisis	92	0.24	0.44	0.00	1.00
REER	92	-5.89	4.41	-15.37	-0.88
CAD	92	-0.04	0.56	-1.20	0.90

In the empirical section, we investigate the potential impact of the economic crisis, the COVID-19 pandemic and the energy crisis on Greece's macroeconomic variables and entrepreneurial activities (new business creation and business closures). The macroeconomic variables reveal the impact that the three crisis periods could have on Greece's overall economy, while the entrepreneurial variables indicate the effect they may have on overall business activities. We use as dependent variables the Number of new Businesses and the Number of Business that closed. Welch's mean-comparison tests are first employed to determine the possible average level of each variable change during crisis periods. Then, the autoregressive distributed-lag time-series regressions are employed for each of the dependent variables used in the analysis, where the dummy variables are used as independent variables in the model.

The Welch mean-comparison test specification, where the dummy variables are employed as dependent takes the following form:

$$Y_t = a_0 + \beta_1 D\_CRISIS_{it} + \varepsilon_{it} \tag{1}$$

Where Y denotes the variables except the dummies, D_CRISIS denotes the dummy variables period, and ε denotes an error term.

Next, the autoregressive distributed lag time series regression takes the following form:

$$Y_t = a_0 + a_1 Y_{t-1} + \beta_1 X_t + \varepsilon_{it}, \qquad \varepsilon_{it} \sim \mathrm{HAC}(1) \tag{2}$$

Where Y denotes the dependent variables of NB and CLOSEB, X_t denotes the independent variables and ε denotes an error term.

Before estimating the above models, we test for possible correlations among the variables, and no significant correlations are found. The correlation technique has been widely used in econometric literature and will not be presented in this section.

Empirical Results

In this section of the paper, the Welch mean-comparison tests and the autoregressive distributed lag time-series regressions results for the period from 2008 to 2024 are presented. The Welch mean-comparison test results for the economic crisis dummy are presented in Table 3. The table provides evidence that the variables are negatively influenced by the crisis dummy and the results are statistically significant except for the TURNOVER. Specifically, GDP growth (-5.38), the FDI (-0.77), NB (-1.69), REER (-5.70) and CAD (-5.72) decrease while UNEMPL (5.87) and CLOSEB (0.78). Table 4 shows the results for the COVID-19 dummy variable. That table provides evidence that GDP growth (5.54), CLOSEB (1.08) and NB (-0.59) are negatively influenced while the FDI (0.87) shows positive results.

Table 3. Economic crisis dummy results

Variable	Mean when 0	Mean when 1	Δ Mean (1-0)	t	p-value
GDP	1.19	-4.19	**-5.38**	5.09	0.0017 **
FDI	1.56	0.79	**-0.77**	3.83	0.0003 **
UNEMPL	14.96	20.83	**5.87**	6.18	0.001**
NB	3.50	1.80	**-1.69**	2.93	0.004**
TURNOVER	0.60	-0.05	-0.65	0.22	0.84
CLOSEB	1.42	2.20	**0.78**	2.87	0.005**
REER	-4.99	-8.81	-5.70	1.72	0.14
CAD	0.02	-0.23	-0.25	0.66	0.55

The economic crisis negatively impacted the GDP growth, FDI, Unemployment rate, New Businesses and the number of businesses that closed. Other variables show no statistically significant results.

Table 4. COVID-19 crisis dummy results

Variable	Mean when 0	Mean when 1	Δ Mean (1-0)	t	p-value
GDP	-0.23	-5.77	**-5.54**	4.22	0.001**
FDI	1.15	2.02	**0.87**	3.12	0.002**
CLOSEB	1.52	2.59	**1.08**	4.54	0.001**
NB	3.07	2.49	**-0.59**	1.97	0.052+
UNEMPL	17.8	17.2	-0.6	0.40	0.69

During the pandemic years, GDP growth decreases, FDI increases, business closures increases and New Businesses decrease, signalling stress in the entrepreneurial ecosystem.

The effects that the energy crisis had on the variables are presented in Table 5. The table shows that during the period, GDP (5.21), the FDI (1.12), NB (1.29), REER (5.50) and CAD (2.72) were positively affected. Unemployment is negatively affected by 8.19 while the CLOSEB shows also negative results (-1.13). The results indicate that business activity declined significantly during the economic and COVID-19 crises but showed signs of recovery during the energy crisis. The recovery of businesses is also due to the RRF and the expansionary fiscal programs implemented by the Greek government, with the ultimate goal of addressing the negative effects.

Table 5. Energy crisis dummy results

Variable	Mean when 0	Mean when 1	Δ Mean (1-0)	t	p-value
GDP	-1.78	3.43	**5.21**	4.79	0.001**
FDI	1.05	2.17	**1.12**	4.22	0.001**
UNEMPL	19.96	11.77	**-8.19**	7.46	0.001**
NB	2.61	3.89	**1.29**	3.26	0.002**
CLOSEB	2.32	1.19	**-1.13**	3.79	0.001**
REER	96.6	102.1	**5.5**	3.47	0.001**
CAD	-7.80	-5.08	**2.72**	2.16	0.034*

The energy crisis period impacted all the variables in the table with the New Businesses variable to be positively influenced and the Close Businesses variable negatively.

The autoregressive distributed lag time series regressions for NB and CLOSEB, as dependent variables, are presented in the following tables. Table 6 presents the estimation results for the NB variable, where the NB lagged value is positive and significant (0.473). Similarly, the GDP growth (43.71) and the energy crisis dummy (2.812) exhibit positive effects, whereas the economic crisis dummy (-3.087), the COVID-19 dummy (-1.548) and the Unemployment variable show adverse effects on NB. Table 7 shows the CLOSEB regression results, where the lagged value of CLOSEB is positive (0.517).Similar, the Unemployment (1.327), the D_CRISIS (20.912), the D_ COVID (28.327) and the TURNOVER (4.769) variables are also positive and significant. Adverse effects on CLOSEB have the NB (-0.246) and E_CRISIS (-14.789) variables. The estimation results indicate that NB improves with past values, but declines during the economic and COVID-19 crises, as well as with rising unemployment. CLOSEB increases during crises and with higher unemployment and turnover but decreases when NB is stronger and during the energy crisis—indicating that better business conditions reduce closures.

Table 6. NB is the dependent variable for time series regression

Variable	Coef	Std. Err	t	p-value
NB_lag1	**0.473****	0.152	3.12	0.002
GDP	**43.710***	17.83	2.45	0.017
UNEMPL	**-0.782+**	0.399	-1.96	0.054
TURNOVER	1.153	0.752	1.53	0.129
CLOSEB	0.061	0.045	1.34	0.184
D_crisis	**-3.087***	1.388	-2.22	0.030
D_covid	**-1.548***	0.719	-2.15	0.034
E_crisis	**2.812****	0.935	3.01	0.004
const	**4.265***	1.944	2.19	0.032
R-squared	0.853			
Adj. R^2	0801			

Table 7. CLOSEB is the dependent variable for time series regression

Variable	Coef	Std. Err	t	p-value
CLOSEB_lag1	**0.517****	0.136	3.81	0.001
GDP	**-7.945**	5.228	-1.52	0.132
UNEMPL	**1.327***	0.576	2.30	0.024
TURNOVER	**4.769+**	2.412	1.98	0.052
NB	**-0.246***	0.115	-2.15	0.034
D_crisis	**20.912****	6.184	3.38	0.001
D_covid	**28.327****	9.664	2.93	0.005
E_crisis	**-14.789****	4.908	-3.01	0.004
const	-6.127	12.073	-0.51	0.512
R-squared	0.829			
Adj. R^2	0.769			

Based on the above econometric analysis, we conclude that the dummy variables, namely D_CRISIS, D_COVID, and E_CRISIS, are affecting the macroeconomic and entrepreneurial variables of Greece. The effects vary across the dependent variables we employed, with most being statistically significant.

Policy Recommendations and Proposals

In the theatrical representation of the novella Così è (se vi pare-1917), Nobel Prize-winning author Luigi Pirandello focuses on the impossibility of understanding reality, where everyone offers their interpretation that coincides with their desires. This results in social confusion, leading to an illusion and an inability to understand reality. We believe that the lessons of this three-act play about Italian society in the interwar period are also relevant to us in Greece, as they could help us reduce the significant gap in public opinion. That would enable everyone to offer their explanations for the problematic State of the above macroeconomic variables. Recently, we have begun discussing changes to the production model and the implementation of sectoral policies. However, we have realised, albeit belatedly, that none of these frameworks has been able to bring about the significant change expected. Let us therefore leave utopias behind and adopt a sectoral industrial policy to change the growth model by identifying industries and sectors where:

- There is a comparative advantage.
- They play a key role in self-sufficiency
- They produce intermediate industrial goods.
- Moreover, finally, they must have a significant contribution to the import substitution.

As stated in the Draghi report (2024), the persistent reluctance to adopt this new production model is driven by the objective of securing funding from EU resources. That is a prerequisite for initiating the process. However, the availability of these resources remains ambiguous. From an economic perspective, it is evident that establishing a complete monetary union necessitates a sufficiently large budget with the capacity to issue common debt. That was made in the context of European states' deliberations on economic and political integration. Notable instances include the Werner Report in 1970, the MacDougall Report in 1977, the Delors Report in 1989, the Five

Presidents' Report in 2015, the Juncker Plan in 2019 (which resulted in the creation of millions of new jobs and 1,039,000 new businesses), and most recently, the Draghi Report. The reality of the situation is that the necessary funding for a substantial alteration to the prevailing growth model will never materialise, due to a paucity of available funding.

The transition from the crisis period of the financial debt crisis to a stable investment environment is closely linked to the Greek economy's ability to create the necessary opportunities for its industrial sector. The goal for the manufacturing sector is to regain its lost share of the GDP. This is directly related to the economy's openness, the utilisation of all factors of production, as well as its ability to innovate, develop new technologies, and increase productivity.

The new paradigm, known as the “New Industrial Policy" of Greece, should introduce a new culture that permeates the entire administration in terms of planning and implementing policies. Moreover, it should promote the coordination and complementarity of policy initiatives and build, through institutions, procedures and relationships of trust and co-responsibility among the industry sector and the State. The crucial issue is establishing effective rules for industrial policy governance at various levels.

Through the theoretical and econometric/quantitative analysis, the policy recommendations for the “New Industrial Policy” of Greece are mentioned below,

- To focus on economic activities that enhance Greece's competitive advantage and export performance, highlighting industries, sectors, and geographical regions with clear prospects for international markets of high-income levels.
- To increase the contribution of the industry to 13% of GDP within five years and to 15% towards 2030 compared to 10.7% today. There is also a plan to increase the employee-to-company ratio from 8.2% to 12% over a five-year horizon and to 14% by 2030.
- The financial sector should support and finance the enterprises. Especially today, there is a massive increase in deposits due to COVID-19, despite zero interest rates. However, average interest rates on both new and existing loans in Greece remain at high levels, twice the eurozone average.

Conclusions

This paper examines the impact of various crises, including the financial crisis, the COVID-19 pandemic, and the energy crisis on business activities and consequently on the Greek economy. It examines how these external shocks have impacted macroeconomic stability, industrial competitiveness, and the potential for structural transformation of Greece. Our empirical findings highlight several key insights. First, crisis periods have had statistically significant and divergent impacts on key economic indicators. The economic crisis and COVID-19 pandemic severely undermined business activity; however, it placed significant pressure on the business ecosystem, as evidenced by increased business closures and unemployment. The energy crisis, though damaging in broader geopolitical terms, correlated surprisingly with positive short-term changes in business activity, driven by fiscal stimulus and temporary adjustments in trade balances.

Second, the structural weaknesses of the Greek economy remain entrenched. Despite marginal gains in investment and modest improvements in the industrial sector's contribution to GDP, Greece has not achieved a meaningful transformation of its production model. Indicators such as the persistently high current account deficit, the dominance of non-tradable sectors, the stagnation in gross value added from manufacturing, and the low technological content of exports suggest that competitive challenges are structural, not cyclical. Third, our analysis indicates that existing policy frameworks—despite being aligned with broader EU objectives on green and digital transitions—have fallen short in catalysing a deep, sector-driven reindustrialisation. The lack of a coherent sectoral strategy has allowed transient policy themes to dominate the agenda. At the same time, long-standing issues such as weak inter-sectoral linkages and limited production of intermediate goods remain unresolved.

In this context, the Recovery and Resilience Facility (RRF) represents a critical but time-bound opportunity. For it to yield long-term benefits, Greece must adopt a New Industrial Policy that is not merely reactive but strategic, grounded in comparative advantages, focused on self-sufficiency and import substitution, and designed to support sectors with high value-added potential. Ultimately, successful industrial transformation in Greece will depend not only on the availability of funding but also on effective governance. This includes coordinated planning, institutional trust, and performance-based collaboration between the public and private sectors. Without these structural changes, Greece risks continuing a growth path overly dependent on consumption and external borrowing, rather than innovation, exports, and productive investment.

References

Aiginger, K. & Rodrik, D. (2020). "Rebirth of Industrial Policy and an Agenda for the Twenty-First Century" Journal of Industry Competition and Trade, 20, pp. 187-207.

Aghion, P., Antonin, C., & Bunel, S. (2021). The Power of Creative Destruction. Belknap Press.

Aghion, P., Dechezlaprêtre, A., Hémous, D., Martin, R., and Van Reenen, J. (2016). "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry", Journal of Political Economy, 124(1), pp. 1-51.

Benner, M. (2019). Industrial Policy in the EU and Its Neighbourhood: Learning from Policy Experimentation. *Economies*, *7*(2), 44.

Blanchard, O. (2020). "The COVID economic crisis". Additional chapter for ``Macroeconomics, 8th edition.

Cacciatore, M., Duval, R., Fiori, G. and Ghironi, F. (2016). "Short-term pain for long-term gain: Market deregulation and monetary policy in small", Journal of International Money and Finance, Vol. 68, pp. 358-385.

Cimoli, M., Dosi, G., & Stieglitz, J. (2009). Industrial Policy and Development. Oxford University Press.

Dias da Silva, A., Givone, A. & Sondermann, D. (2017). "When Do Countries Implement Structural Reforms?" ECB mimeo.

Draghi. M. (2024). "The future of European competitiveness", European Commission.

Duval, R. & Elmeskov, J. (2006). "The effects of EMU on structural reforms in labour and product markets". OECD mimeo.

European Commission (2020). "A new Industrial Strategy for a globally competitive, green and digital Europe", March 2020. European Commission.

Hodge, A., Piazza, R. Hasanov, F., Li, X., Vaziri, M, Weller, A. and Wong, Y.C. (2024). "Industrial Policy in Europe: A Single Market Perspective", IMF Working Papers 2024, 249 (2024).

IMF (2022). Greece: Staff Concluding Statement of the 2022 Article IV Consultation Mission, https://www.imf.org/en/News/Articles/2022/03/31/greece-staff-concluding-statement-of-the-2022-article-iv-consultation-mission

Johnstone, P., Rogge, K.S., Kivimaa, P., Fratini, C. F. and Primmer, E. (2021). "Exploring the re-emergence of industrial policy: Perceptions regarding low-carbon energy transitions in Germany, the United Kingdom and Denmark". Energy Research & Social Science, 74(2021), pp. 1–15.

Kapopoulos, P., Marinopoulou, E., & Mitropoulos, F. (2024). "Experiencing Energy Shocks in Greece: Inflation, Public Finances and Investment Dynamics" Alpha Bank, Insights April

Landesmann, M. & Stollinger, R. (2020). "The European Union's industrial policy: what are the main challenges?" The Vienna Institute for International Economic Studies, Policy Notes and Reports 36.

Mazzucato, M., (2013). "The Entrepreneurial State: Debunking Public vs. Private Sector Myths". New York: Public Affairs.

Monnery, N. (2017). "Architect of Prosperity: Sir John Cowperthwaite and the Making of Hong Kong". London: London Publishing Partnership.

Pack, H. & Saggi, K. (2006). "Is there a case for industrial policy? A critical survey". The World Bank Research Observer, 21(2), pp. 267–297.

PBO (2022). Report 4th Quarter 2021, Hellenic Parliamentary Budget Office, 15th March, in Greek

Pissarides et al. (2020). "Growth Plan for Greek Economy", in Greek, https://docs.google.com/viewerng/viewer?url=https://government.gov.gr/wp-content/uploads/2020/11/growth_plan_2020-11-23_1021.pdf&hl=en

Rodrik, D. (2009). "Industrial policy: Do not ask why, ask how", Middle East Development Journal, 1(1), pp.1–29.

Rodrik, D. (2014). "Green industrial policy", Oxford Review of Economic Policy, 30(3), pp.469–491.

Stiglitz, J. E. (2017). Industrial policy, learning and development. In: Page, J. and Tarp, F. (eds) The practice of industrial policy. Oxford University Press.

Szczpanski M. and Zachariadis I. (2019). "EU industrial policy at the crossroads: Current state of affairs, challenges and way forward", European Parliament, December 2019.

Terzi, A., Singh, A. And Sherwood, M. (2022) "Industrial policy for the 21st century: lessons from the past". European Commission Directorate-General for Economic and Financial Affairs, Discussion Paper 157.

Wade, R. (2018). "The Development State: Dead or Alive?" Development and Change 49(2): 518–46.

BIG DATA AND ECONOMIC PRINCIPLES:
REVISITING ESTABLISHED CONCEPTS THROUGH A NEW LENS

Vasileios Plakandaras
Department of Economics, Democritus University of Thrace
vplakand@econ.duth.gr

ABSTRACT

This concise paper explores the applicability of big data within the financial sector, viewed through the advancements in Artificial Intelligence (AI) and Machine Learning (ML). Initially, we delineate the distinctions in objectives, methodologies, and frameworks between the ML literature and conventional econometric and statistical approaches to utilizing big data. Subsequently, we broaden our scope to assess the efficacy of integrating these innovative statistical techniques into finance and the consequent transformations they have introduced. Our analysis spans from conventional fundamental and technical analyses to other estimation methods that can enhance our comprehension of market dynamics. Finally, we underscore significant policy implications arising from the evolution of methodological approaches within the field.

Keywords: *Big data, finance, Artificial intelligence, machine learning*

Key insights:

- The financial landscape has been profoundly altered by AI financial technology.
- Novel trading instruments offer increased profitability while reducing personnel requirements.
- Emerging AI applications, such as high-speed trading, are forging new avenues in finance.
- This new suite of tools is implicated in heightened volatility, instability, and diminished interpretability.
- The regulatory framework faces considerable challenges.

A widely accepted economic tenet posits that technological advancement serves as a primary catalyst for growth. This is attributed to technology's capacity to reduce the marginal cost of production, reconfigure labor markets, expand the consumer base, and reshape our understanding of economic activity. The rapid pace of technological progress has introduced various terms into common discourse, including "big data," "artificial intelligence," "machine learning," and "data analytics."

This "explosion of information," as it's often called, has fundamentally transformed the financial sector. It has opened new avenues for active asset management, risk mitigation, and the introduction of innovative financial instruments such as high-speed trading and automated investment. Consequently, the swift progress in harnessing data sources through machine learning techniques in finance has yielded significantly more accurate price forecasting compared to traditional econometric methods, thereby reshaping financial research. The deployment of vast information resources continues to evolve the financial domain, creating fresh opportunities to re-evaluate established financial norms. Examples include the hypothesis concerning the delayed diffusion of information between industries (Hou, 2007) and the cornerstone of modern finance, the market efficiency hypothesis (Fama, 1970). Nevertheless, while artificial intelligence demonstrates substantial potential in predictive tasks, it often struggles to offer causal explanations for the functional structure of the financial market and to generate explicit policy recommendations.

The application of Machine Learning (ML) is not a recent phenomenon within financial literature. ML methodologies such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Recurrent Neural Networks (RNNs)—particularly Long Short-Term Memory (LSTM) networks—and Convolutional Neural Networks (CNNs) have proven to be powerful instruments for financial time series forecasting (Lara-Benítez et al., 2021). In a recent comprehensive review, Nti et al. (2020) concluded that machine learning techniques generally surpass most of their econometric counterparts in predicting financial time series based on both fundamental and technical analysis methods. However, while ML methods have garnered considerable attention in the relevant literature, the advent of Artificial Intelligence (AI) applications, such as robot trading, has established a novel approach to managing financial processes. The OECD (2022) defines AI as follows: "Artificial Intelligence (AI) is a general-purpose technology that has the potential to improve the welfare and well-being of people, to contribute to positive sustainable global economic activity, to increase innovation and productivity, and to help respond to key global challenges. It is deployed in many sectors ranging from production, finance and transport to healthcare and security." This definition encompasses all facets of human endeavor and addresses a multitude of contemporary challenges, offering a comprehensive description of AI. Should one attempt to differentiate AI from ML, a plausible distinction would be that ML provides the mathematical foundation for identifying a set of rules derived from data, thereby shaping the policy decisions of AI procedures. In essence, ML can be viewed as a tool that quantifies and establishes the rules for the suggestions and decisions that constitute an AI-driven policy implementation scheme.

A distinct aspect of the rapid technological evolution of information-based platforms, such as the Internet of Things (IoT), financial digitalization tools, and social media, is the generation of an immense volume of data. This data manifests in diverse formats, is continuously updated, and significantly impacts financial markets. The incessant creation of a large body of data in various forms (text, audio, video, raw numerical data, etc.), often referred to as "big data," necessitates advanced data processing methods. This, in turn, propels the development of "data analytics" and frequently the ML research domain. The superiority of ML methods in forecasting financial series can be attributed to their capacity to extract information from diverse sources, unlike their econometric counterparts. The evolution of AI-based methods to derive sentiment from text, video, and audio, and the automated quantification of these outputs without requiring human annotation, can provide timely market sentiment that can be leveraged in modeling. Based on product reviews, images, text messages, blogs, social media posts, newsletters, and official firm announcements, ML methods extract the sentiment of market participants and assess its predictive power for the market. Specifically, CNNs, an ML technique prominent in computer vision, can provide accurate and cost-effective classification of large samples of news texts into sentiment categories (Algaba et al., 2020).

In the seminal work by Gu et al. (2020), the authors integrated a variety of ML methods with a collection of potential determinants proposed by contemporary empirical asset pricing research to uncover the dynamics of market risk premia for stock returns. Their findings indicate that ML enhances the description of expected returns, and when applied to portfolio diversification, performance improvements are most pronounced among the more sophisticated models, while classical trend indicators are the primary drivers of predictability. The potential reason for this superiority over classical literature is largely due to the allowance for non-linear predictor interactions that simpler methods overlook. Non-linear interactions among covariates play a substantial role in several studies and are more impactful than non-linearities in single characteristics (Bianchi et al., 2021), although this view is not universally accepted (Kozak et al., 2020). Indeed, in certain instances, new patterns have been identified in specific applications thanks to ML. For example, high-frequency stock returns are largely influenced by industry factors, contrasting with traditional characteristics-based factors. A nascent body of literature on variable selection for financial forecasting suggests that beyond choosing the variables fed into the ML model, one could construct or instrument factor loadings to condense their information content (Kelly et al., 2019) or integrate ML structure with economic restrictions (Lettau and Pelger, 2020) to mitigate discouraging issues affecting traditional models (Giglio and Xiu, 2021).

A significant concern in the application of ML literature is that even though forecasting algorithms may be effective, their performance is heavily dependent on fine-tuning and adaptation to effectively address the specific problems traders are interested in. The most notable drawback of all ML algorithms is their lack of an intrinsic structure representation capability; they must be carefully modified to account for causal relationship representations, endogeneity, and data structures (such as panel data), or the presence of credible restrictions motivated by economic theory, such as the monotonicity of demand with respect to prices or other shape constraints (Mullainathan and Spiess, 2017). Furthermore, ML algorithms predominantly leverage past patterns to predict future ones, placing excessive emphasis on historical price trends (Gentzkow and Taddy, 2019). Thus, while AI is likely to substitute human prediction, it still necessitates human skills, such as judgment, to organize ML applications within a business-specific framework.

Another apprehension concerning the use of big data in finance is that information extraction can become a self-fulfilling prophecy, inducing traders to rely on others' information rather than producing their own analysis based on actual data. In other words, in a big data analytics environment, the emphasis shifts to faster and more efficient information collection and analysis using complex models that lack tangible physical interpretation and testable predictions, rather than genuine financial analysis of asset values and financial risk. Instead of examining a firm's business model or forecasting its profitability, the new trend in analytics advocates for mining order flow data and developing algorithms to profit from patterns in others' trades, seeking what is termed "dumb money." As the big data trend permeates the financial sector, price trends gain prominence, and fundamentals lose their predictive value, leading to a potential disconnect between the financial sector and the real economy. This could potentially result in significant market crashes when financial speculation does not align with economic evolution. Consequently, technological change can account for a market-wide shift in data collection, and new data-intensive trading strategies have been implicated in market volatility, illiquidity, and inefficiency.

Finally, echoing general concerns about the adverse effects of new technologies on the labor market, many market participants suggest that numerous finance jobs involving repetitive, routine, or optimization tasks will be diminished and supplanted by AI applications. The relevant literature indicates that due to AI, demand will shift towards AI experts, with workers in the 90th wage percentile being most susceptible to AI substitution (Webb et al., 2020). Conversely, Acemoglu et al. (2020) document that AI exposure is linked to a decline in previously sought-after skills in job vacancies and the emergence of new skills, implying that AI is altering the task structure of jobs. However, there is no discernible AI effect on wages at the occupation or industry level, suggesting that AI is not yet having detectable aggregate labor market consequences.

The era of AI and big data in finance has undeniably begun and is irreversibly transforming the sector. The new analytical tools, leveraging a wealth of novel information, provide a fresh arena that shapes trading strategies with enhanced profitability, increased speed, and potentially without the need for human intervention, thereby revealing new trends and possibly a different mode of operation. This emerging era of financial trading is characterized by personnel highly proficient in AI and ML tools, leading to the creation of new instruments such as high-speed trading and robot trading applications. Nevertheless, this new era is not without its perils. This novel trading environment is more intricate than before, as the new tools are more complex than their econometric predecessors and lack tangible physical interpretation. Hence, this shift in emphasis towards the tools rather than the asset's characteristics poses significant risks of a potential divergence between the markets and the actual economy, as price trends become more important than value, and speculative bubbles could form. Lastly, in this evolving environment, policymakers face unprecedented challenges in navigating the new complex and rapidly changing market and in bridging the gap between policy and enforcement concerning the ability to ascertain human involvement where machines or algorithms are at play. The absence of natural representation, the inability to scrutinize the immense volume of data to prevent market manipulation, and the difficulty in adapting the legal and policy framework to the continuously evolving landscape of new AI applications will constitute the primary issues for the regulatory framework.

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2020). AI and jobs: Evidence from online vacancies (No. w28257).

Algaba, A., Ardia, D., Bluteau, K., Borms, S., & Boudt, K. (2020).

Bianchi,D., Büchner,M.,& Tamoni, A. (2021). Bond risk premiums with machine learning. The Review of Financial Studies, 34(2), 1046–1089.

Developing a deep learning framework with two-stage feature selection for multivariate financial time series forecasting.

Econometrics meets sentiment: An overview of methodology and applications. Journal of Economic Surveys, 34(3), 512-547.

Expert Systems with Applications, 148, 113237.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The journal of Finance, 25(2), 383-417.

Farboodi, M., and Veldkamp L. (2020). Long-Run Growth of Financial Data Technology. American Economic Review, 110 (8): 2485-2523.

Gentzkow, M., Kelly, B., & Taddy, M. (2019). Text as data. Journal of Economic Literature, 57(3), 535-74.

Giglio, S., & Xiu, D. (2021). Asset pricing with omitted factors. Journal of Political Economy, 129(7), 1947–1990.

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, 33(5), 2223-2273.

Hou, K. (2007). Industry information diffusion and the lead-lag effect in stock returns. The review of financial studies, 20(4), 1113-1138.

International Journal of Neural Systems, 31(03), 2130001.

International Journal of Sociology and Social Policy, 40(9/10), 1005-1019.

Journal of Financial Economics, 134(3), 501–524.

Kelly, B. T., Pruitt, S., & Su, Y. (2019). Characteristics are covariances: A unified model of risk and return.

Khaled O., Kuntara P., (2022), A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news, Journal of Financial Economics, 144(1), 273-297,

Kozak, S., Nagel, S., & Santosh, S. (2020). Shrinking the cross-section. Journal of Financial Economics, 135(2), 271–292.

Lara-Benítez, P., Carranza-García, M., & Riquelme, J. C. (2021). An experimental review on deep learning architectures for time series forecasting.

Lettau, M., and Pelger, M. (2020). Factors that fit the time series and cross-section of stock returns.

Mullainathan, S., & Spiess, J. (2017). Machine learning: an applied econometric approach. Journal of Economic Perspectives, 31(2), 87-106.

National Bureau of Economic Research.

Niu, T., Wang, J., Lu, H., Yang, W., & Du, P. (2020).

OECD (2022), Recommendation of the Council on Artificial Intelligence, OECD/LEGAL/0449

The Review of Financial Studies, 33(5), 2274–2325.

Webb, A., McQuaid, R., & Rand, S. (2020). Employment in the informal economy: implications of the COVID-19 pandemic.

CORPORATE GOVERNANCE IN TRANSITION:
FROM COMPLIANCE TO THE CORPORATE CULTURE FOOTPRINT THROUGH AI AND NEUROLEADERSHIP

Maria Sartzetaki
Department of Economics, Democritus University of Thrace
MaGBISE Research Laboratory
msartze@econon.duth.gr

ABSTRACT

Corporate governance is transforming from its emphasis on compliance and regulatory management, as complexity, ethics, and stakeholder expectations escalate. The chapter examines the integration of Artificial Intelligence (AI) and neuroleadership as foundational frameworks for systems of governance that blend technological foresight with human cognitive and ethical competencies. AI extends decision-making through predictive insights, risk assessment, and time-based monitoring, while neuroleadership extends to cognitive bias correction, stress resilience, and board-level ethical judgment. Concurrently, the Corporate Culture Footprint (CCF) concept is introduced as a measurable axis of organizational culture, capturing inclusivity, trust, and adaptability as sources of strategy. Collectively, a model in transformative stages—one that transitions from compliance-based constructs to culture-based systems of adaptability and ethical guardianship is introduced. Its value proposition is that governance is reconceptualized not as fixed oversight, but as an adaptive systems alignment between technology, leadership, and culture to provide sustainable competitiveness.

Keywords: *Corporate Governance; Artificial Intelligence; Neuroleadership; Corporate Culture Footprint; Compliance; Ethical Decision-Making; Organizational Culture; Stakeholder Trust; Adaptive Governance*

1. Introduction

Good corporate governance has always been the hallmark of complex businesses, delivering accountability, disclosure, and sustainable value creation. Earlier models of governance were founded upon regulatory compliance, financial management, and the fiduciary responsibility of boards of directors. But in a world where technological change is exponential, geopolitical events are turbulent, and societal expectations for inclusivity and ethically disciplined behaviour are growing, the conventional models of governance are no longer sufficient. Today's boards are faced with complex challenges that lie beyond their finance performance, such as understanding organisational culture, stakeholder confidence, and adaptive decision-making.

Artificial Intelligence (AI) is one of the most transformative forces rewriting corporate worldscapes. From predictive analytics in risk management to algorithmic advisors in strategy planning, AI offers boards unprecedented opportunities to enhance their decision-making capacity. But these opportunities are shadowed by profound ethical and governance challenges: how transparent are AI-decisions, who is responsible for algorithmic outputs, and how can boards integrate AI insights without diluting human judgment? The integration of AI in governance is as much about technology as about revolutionizing power distribution, accountability, and trust in corporations.

Concurrent with these advances in technology, the emergence of neuroleadership—the use of neuroscience knowledge to inform leadership and organizational behavior—has provided a new perspective on how leaders cognitively process, how to manage stress effectively, and how to engender trust. Decision-making under ambiguity, emotional regulation, and biases are important themes in neuroscientific research that can inform boards in dealing with complex and ambiguous contexts. Incorporating neuroleadership into boardrooms can improve the level of board interaction, increase resilience, as well as enable more human-centered decision-making. At the crossroads between AI and neuroleadership is the imperative to rethink how governing boards capture the intangible yet vital aspect of corporate culture. Whereas Environmental, Social, and Governance (ESG) frameworks have gone mainstream in assessing corporate performance, these tend to disregard the “corporate culture footprint”—the quantifiable effect of organizational values, behaviors, and inclusivity on stakeholders. Culture decides the way strategies are executed, risks are assessed, and innovation flourishes. In this day and age where employee well-being, diversity, and ethical orientation define competitiveness head-on, disregard for cultural impact is no longer tenable.

This essay advocates for the redrafting of corporate governance as the convergence of AI, neuroleadership, and the corporate culture footprint. Through the integration of data-intelligent thinking, neuroscience-based leadership, and cultural outcome measurement, we can possibly emerge with a new type of governance that transcends compliance to resilience, adaptability, and ethical custodianship. Through this process, rather than just maintaining governance as a tool for control, we can reconceptualize it as a future-strategic benefit to the corporations of tomorrow.

2. AI in Business Governance

Artificial intelligence (AI) is rapidly altering the way that boards of directors approach decision-making, governance, and accountability. Traditionally, governance has relied on human knowledge, experience, and intuition supplemented by formal systems of compliance reporting. But the volume, velocity, and complexity of today’s corporate data are all in excess of human understanding. Here, AI has unparalleled potential to supplement the process of governance by facilitating in-the-moment insight, predictive capability, and enhanced transparency (Hilbe et al., 2020).

Boards are being asked to assess complex risks as diverse as cybersecurity attack risks to climate change-related disclosure risks. AI systems can analyze large datasets and model numerous scenarios, so directors can predict outcomes more precisely. For example, AI-based analytics can flag early warning signs of financial stress, fraud, or reputational risk (Hagendorff, 2020). But use of AI creates the question of responsibility: when an algorithm recommends a strategy direction, to what degree should boards rely on machine-driven insight or human judgment?

The concept of "algorithmic advisors" has become popular in practice as well as in theory. Some companies are experimenting with AI as quasi-board members, who provide disciplined recommendations in the heat of meetings (Holmström et al., 2020). Though these advisors may increase efficiency as well as reduce human biases, their application also transgresses conventional norms of governing. Fiduciary duty concerns emerge here: can directors be held to have fulfilled their duty if they rely on decisions made by algorithms whose rationale is unknown to them? This "black box governing" challenge underlines the need for new norms of AI explainability and transparency.

Risk management is one of the board's primary roles. AI can assist by detecting anomalies, predicting systemic vulnerabilities, and monitoring compliance in real time. Banks, for example, use machine learning to detect fraudulent payments more consistently than the traditional systems. Just as supply disruptions can be replicated with AI to test resilience under changing geopolitical or environmental stress scenarios (Ivanov & Dolgui, 2020), analogous insights can become part of governance by infusing such findings. To accomplish this task, though, directors will have to acquire new abilities in the form of data literacy as well as algorithmic responsibility (Vaio et al., 2020).

The application of AI in government brings with it great ethical challenges. Firstly, biased AI systems can entrench structural injustices, with corporate social responsibility and inclusion implications. Secondly, the question of liability gets muddled: if an AI software suggests taking a particular course of action that leads to harm, is that the fault of the board, developers, or algorithm? Thirdly, we have overdependence: directors may forego sound thinking through blind faith in outputs that are purely data-driven. This presents the curious phenomenon that AI enhances as much as undermines the integrity of government (Gupta et al., 2021).

Besides internal decision-making, AI is also altering the nature of corporations' relationship with their stakeholders. Sentiment analysis and natural language processing can track stakeholder attitudes through social media, newspapers, as well as investors' reports, giving boards a timely "dashboard" of corporate reputation (Butcher et al., 2019). Technologies like these allow directors to forecast shifts in stakeholders' trust levels and adapt their governance strategy in advance. But they also raise questions about privacy and surveillance that boards will have to address in order to stay legitimate.

Implications for Governance Models Seeking to infuse AI into government entails more than adoption in the technical sense—it entails the reconceptualization of the very systems of governance themselves. Traditional models prize independence, responsibility, and disclosure, yet AI brings new axes of explainability, algorithmic ethics, and digital fluency. Boards will therefore need to evolve hybrid arrangements of governance whereby human directors remain ultimately accountable but are supplemented by transparent, ethical, and explainable AI systems. The hybrid form is that from that of governance as a type of oversight to that of adaptive intelligence.

3. Neuroleadership and governance

Whereas Artificial Intelligence (AI) brings sophisticated tools to manage complexity, neuroleadership addresses how human leaders, especially those in governing positions, can improve their decision-making, manage emotions, and build trust in their organization through the application of neuroscience insights. Launched in the early years of the 2000s, neuroleadership applies brain science to the study of leadership, decision-making, and organizational behavior (Dimitriou, 2022). Within corporate governing contexts, it provides important points of view on how boards operate in environments of uncertainty, stress, and ethics.

Boards of directors are generally faced with situations of ambiguity and incomplete knowledge. Neuroscience research has highlighted that decision-making is less than completely rational and is significantly influenced by emotions, biases, and deficits in thinking (Sartzetaki et al., 2025a). For governing, this means that previous models of rational oversight may not reflect reality in boardrooms. Neuroleadership helps boards become more mindful about thinking traps (e.g., confirmation bias, groupthink) and teaches practices such as systematic reflection and scenario thinking to help stem them.

Directors are under growing pressure from shareholders, authorities, and media attention. Neuroscientific research indicates that chronic stress damages the prefrontal cortex, diminishing executive function, empathy, and imagination (McEwen & Morrison, 2013). Practices in neuroleadership like mindfulness, emotional management, and resilience training help directors remain composed and exercise good judgement even in high-stakes situations. By integrating these kinds of practices into governing body training, boards can enhance individual performance as well as group performance (Dimitriou et al., 2024).

Corporate governance is entirely based on trust—among boards, executives, workers, and outsiders. Neuroscience identifies oxytocin and other neurochemical mechanisms as being involved in trust and cooperation (Sartzetaki et al., 2025a). However, neuroleadership stresses open communication through empathy and perspective-taking, abilities that are ever more essential in multicultural, multinational workplaces. Aboard-created trust in the neurological domain can increase the level of governance legitimacy as well as deepen stakeholder interaction. Governance misconduct usually arises not from lack of knowledge but from cognitive biases and unconscious distortions. Neuroscience can reveal how unconscious patterns inform ethical decision-making (Greene & Paxton, 2009). For boards, this requires ethics education to go beyond formal codes of behaviour to educating about awareness of brain mechanisms that distort judgement. Neuroleadership models offer instruments for raising the level of ethical sensitivity and responsibility in governing practice.

Governance is teamwork. Current studies on "collective intelligence" indicate that teams with higher emotional intelligence and inclusive communication styles are better decision makers than teams with technical expertise alone (Woolley et al., 2010). Neuroleadership interventions like enhancing active listening, managing group emotions, and encouraging psychological safety can improve board cohesion and decision-making. This has immediate application to corporate boards, where dysfunctional dynamics are particularly problematic in poor oversight.

Though neuroleadership has commonly been deployed in the managerial or leader domain, use in boards is still in ascendance. A few companies now incorporate neuroscience-informed training in director development initiatives, including the reduction of biases, resilience, and ethical thinking (Ringleb & Rock, 2008). The integration of neuroleadership into governing mechanisms can change boards from reactive compliance panels to proactive, adaptive, and human-focused decision systems (Sartzetaki et al., 2025b).

4. Methodology - The Synergy Model: Redesigning Corporate Governance

Defining the Corporate Culture Footprint(CCF)

Though Artificial Intelligence (AI) and neuroleadership give potent tools to enhance decision-making and resilience in the board room, their long-term benefit is dependent on the measurement and management of corporate culture. Culture—the commonly held values, beliefs, and behaviors in an organization—has long been acknowledged as one that drives performance. However, as is the case with financial metrics or ESG indicators, culture is still hard to quantify and regulate. To bridge this gap, we propose the idea of the "Corporate Culture Footprint" (CCF): a measurable framework to evaluate the ethical, social, and behavioral influence that corporate culture has on stakeholders. History's most significant corporate scandals (e.g., Enron, Volkswagen's emissions scandal, Wells Fargo's phony accounts) show that governance failures are usually culture failures. A poisonous culture corrodes compliance, innovation, and trust even when formal systems are in good order Effective cultures that are inclusive and values-based build competitive advantage by driving employee engagement, innovation, and stakeholder trust (Groysberg, et al., 2018). Boards thus require robust means to assess as well as monitor culture—not as "soft" stuff, but as a priority in governance.

The Corporate Culture Footprint broadens traditional ESG metrics to examine the extent to which organisational culture is transparently impacting stakeholders. Key dimensions are depicted in Figure 1. These signs all together create a "footprint" that indicates the reach and depth that a corporation's culture has.

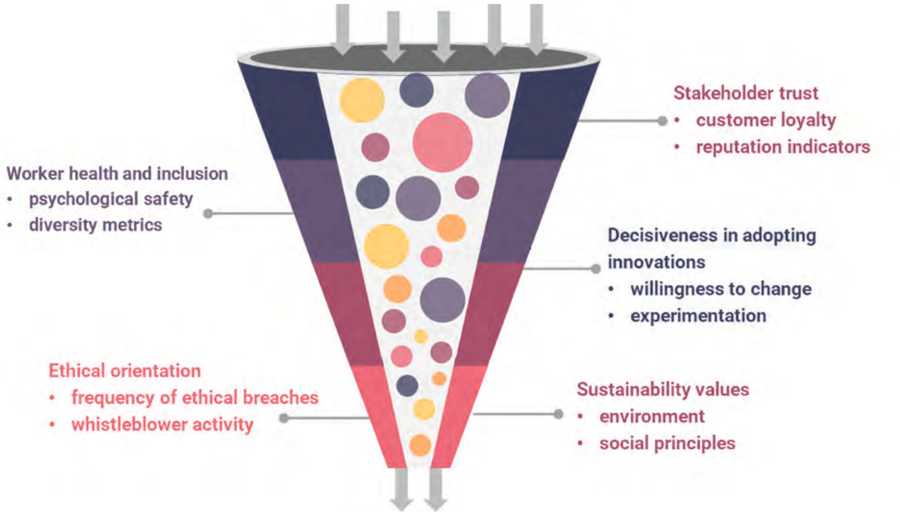


Figure 1. Key dimensions of Corporate Culture Footprint (CCF)

Perhaps the greatest challenge in the measurement of culture has been the lack of reliable data. AI technologies now enable boards to monitor organisational culture through advanced analytics:

- Employee survey, email, and digital communication sentiment analysis.
- Behavioral analytics for collaboration, innovation networks, and inclusion.
- Predictive systems that warn about the possibility of misconduct or disengagement.

AI then presents a scalable means to measure previously invisible qualities of culture, bringing culture as much into the realm of governance as idealism (Huang & Rust, 2021).

Whereas culture can be quantified by AI, neuroleadership offers the tools to form and maintain culture. Neuroscience demonstrates that culture is embedded through habitual encounter that shapes brain pathways to affect behavior and decision-making (Rock & Schwartz, 2006). Boards and leaders who use the principles of neuroleadership can instill desired cultural values like inclusivity, resilience, and adherence to ethics by fostering environments that reinforce empathy, fairness, and innovation. Through this mechanism, neuroleadership serves as the human counterpart to AI-based measurement.

CCF as a Governance Metric

Inscribing the Corporate Culture Footprint into governing arrangements obliges boards to incorporate cultural responsibility alongside financial and ESG mandates. Some practical interventions are as follows:

- Assigning board committees that are expressly.
- Reporting CCF metrics in annual disclosures to enhance transparency.
- Linking pay to executives to culture-driven performance indicators.
- Benchmarking CCF across industries to enable comparison.

It places culture not as a "soft matter" but as a strategic asset open to tough scrutiny.

By institutionalizing the Corporate Culture Footprint, boards can transition from compliance-based to adaptive and resilient governance. Culture-strong corporations are less vulnerable to crises, more capable of attracting the best talent, and capable of sustainable innovation. Shared cultures, as noted, are characteristic of companies that are consistently top-performing in finance as well as resilience. Measuring and governing culture thus becomes both an ethics imperative as well as a long-term source of competitiveness.

Previous sections explained how AI can complement board-level decision-making, how neuroleadership brings the human touch of resilience and moral judgment, and how the Corporate Culture Footprint (CCF) can provide metrics to capture the intangible performance drivers. But how do these three spheres intersect to redefine corporate governance? The research question remains: how do these three dimensions interact to reshape corporate governance? This interaction generates a new governance model—a one that moves beyond compliance and number-crunching to adoption of adaptability, inclusiveness, and ethical custodianship

From Compliance to Adaptive Governance

Traditional corporate governance has relied on compliance: rule adherence, monitoring management, and maintaining shareholder value. But compliance is reactive and insufficient in the environment of global crises, technological revolution, and social transition.

AI introduces adaptive intelligence: boards are given predictive analytics in addition to in-the-moment tracking. Neuroleadership ensures that directors can process complexity without succumbing to stress or bias. CCF provides cultural adaptability and inclusion measures. They merge into adaptive governance—a framework capable not only of conforming to, but adapting to ambiguity.

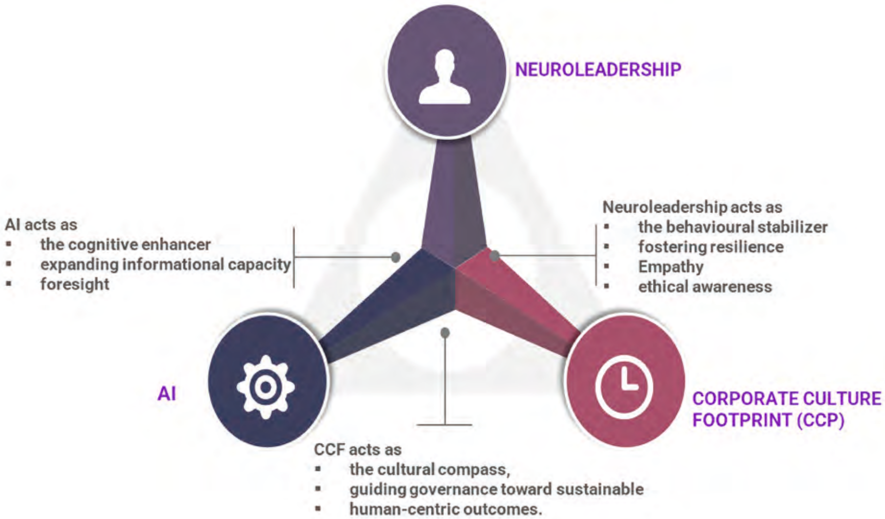


Figure 2. The proposed Triadic Framework for Corporate Governance

The triadic framework proposed includes the three dimensions as analytically depicted in Figure 2. AI acts as the cognitive enhancer, expanding informational capacity and foresight. Neuroleadership acts as the behavioural stabilizer, fostering resilience, empathy, and ethical awareness. CCF acts as the cultural compass, guiding governance toward sustainable and human-centric outcomes. In this model, governance is no longer viewed as a static structure but as a dynamic ecosystem, balancing technological, human, and cultural dimension.

The synergy model transforms board operation as depicted in Figure 3. This convergent approach avoids "black box governance" (AI-centricity) or "human bias governance" (exclusive dependence on instincts). What is encouraged instead is hybrid governance—a human intellect enhanced by tech and based on culture.

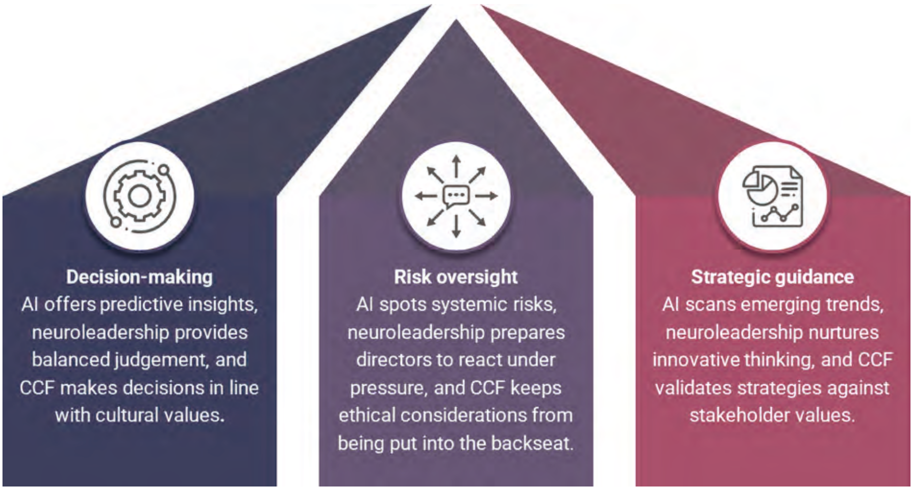


Figure 3. Synergy model's transformation principles for Boards governance

To incorporate the synergy model into practice, businesses need to undergo structural changes:

- Boards will not only have to be educated in finance and in law but also in AI literacy and in neuroleadership practices.
- Mandates to the board should specifically state overseeing corporate culture, through CCF indicators.
- Algorithmic decision-making ethics, explainability, and responsibility must be ingrained in governing codes.
- Reports should report culture footprint metrics in addition to financial and ESG performance.

These institutional arrangements guarantee that the synergy model is not idealistic but practical. Governances that integrate AI, neuroleadership, and CCF give their organizations their competitive advantage:

- Resilience: The capacity to predict crises and respond.
- Legitimacy: Greater trust among stakeholders from open and accountable governing.
- Capacity for innovation: Balanced risk cultures to experiment.
- Attracting talent: Next-generation workers favor companies with inclusive values-based cultures that are policed in the upper echelons.

Such advantages reposition governance not as a "cost of compliance" but as a driver of competitive advantage.

The synergy model identifies a paradigm shift: government as an ecosystem balancing technology, neuroscience, and culture. It defies the dichotomy between "hard" financial regulation vs. "soft" cultural management by illustrating that culture can be measured, that technology can be governed, and that human judgment can be trained. Ultimately, this model hopes to produce organizations that are profitable as well as ethical, adaptive, and human-centered—the hallmarks of sustainable competitiveness in the era.

Future Outlooks

The coming decade will define the future of corporate governance. The coming together of Artificial Intelligence (AI), neuroleadership, and the Corporate Culture Footprint (CCF) will cease to remain on the periphery but will become integral to how businesses preserve their legitimization, competitiveness, and moral authority. Focusing on 2030–2040, transformative trends that can be anticipated are as depicted in Figure 4.

Boards will, by 2030, run in AI-based governing environments in which the regulatory, financial, and social environments are constantly read by machine learning. Dashboards that provide predictive analyses of risks, stakeholder opinion, and performance parameters will be accessed by directors instead of quarterly reports. The chances are: Greater foresight, less information asymmetry, and increased proactive supervision. The risks are: Dependence on algorithmic output and the possibility of "black box governance" due to the lack of enforceable transparency and accountability.

The next board member will not only be held to the standard of financial acumen or knowledge of laws, but to the standard of neurocognitive abilities. Education in emotional management, detection of biases, and resilience to stress will become the norm in director education. Governance bodies may even mandatorily subject their directors to neuroscience-aware tests to check their psychological fitness for high-stakes decision-making. This trend reflects a shift from governance as a purely rational exercise to governance as a neurocognitive discipline.

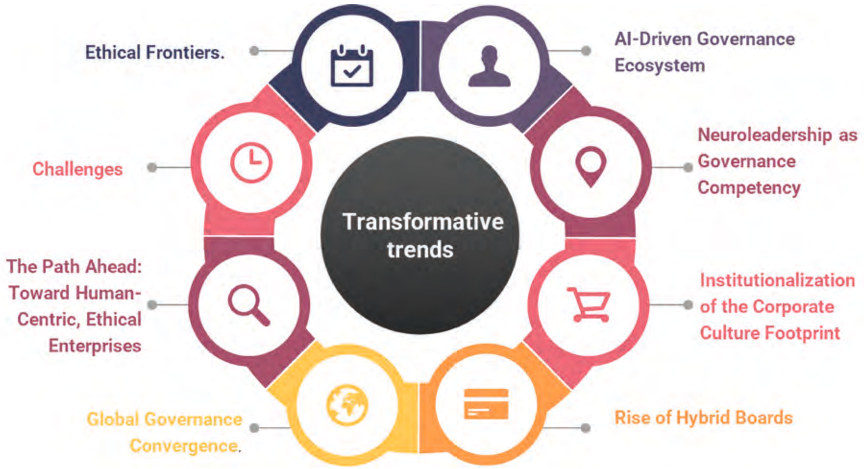


Figure 4. Transformative future outlook trends anticipated in Corporate Governance

Just as ESG reporting became mainstream in the 2020s and 2010s, the Corporate Culture Footprint can possibly become a disclosure requirement in the 2030s. There is increased pressure from stakeholders, investors, and regulators to increase disclosure in the area of inclusion, well-being, as well as ethically. Annual reports can provide "Culture Scores" in addition to financial and ESG metrics. Executive compensation can possibly be related to CCF performance. Global standard setters (e.g., ISSB, OECD) can provide CCF reporting frameworks. It makes culture measurable, controllable, and comparable between industries.

Future boards can become hybrid arrangements, made up of human directors who are complemented by algorithmic advisors and neurocognitive perspectives. Here, while human members remain under fiduciary duty, AI tools can remain as non-voting advisory members to inform deliberation without taking away responsibility. The hybrid structure strikes a balance between technological capability and human judgment and cultural supervision.

While AI goes global, regulatory frameworks will have to conform worldwide. Global corporations will insist on uniformity in AI ethics, cultural reporting, as well as in neuroleadership education across jurisdictions. The convergence may yield worldwide AI and culture governance standards similar to the way that IFRS standardized accounting approaches.

The future is not free from challenges:

- AI Governance Issues: Whose responsibility is AI-driven board decision-making?
- Privacy and Surveillance: Culture measuring tools may blur boundaries between surveillance and intrusiveness.
- Neuroethics: Its application in leader evaluation raises morality issues involving autonomy, consent, and fairness.
- Inequality Risks: Wealthy corporations may adopt advanced AI and neuroleadership training, widening the gap with smaller firms.

Boards will need ethics-by-design governing frameworks to control these risks.

Despite the obstacles, integrating AI, neuroleadership, and CCF is an unprecedented opportunity to rethink governance. The future organization will no longer just quantify profits, but rather neurocognitive readiness as well as cultural sustainability. The successful embedding of this synergy will likely benefit that organization that manage to accomplish this. Those organizations that succeed in embedding this synergy will likely enjoy:

- Higher resilience to crises,
- Further stakeholder trust,
- Increased innovative capacity,
- Stronger legitimization in an era of increased ethical responsibility.
- The trend is towards a tech-savvy future that is culture-focused, government-centered, and human-centered—a model that is more capable of handling the complexities of the 21st century.

5. Case Studies and Emerging Practices

The theory underpinning Artificial Intelligence (AI), neuroleadership, and the Corporate Culture Footprint (CCF) can be further elucidated through reference to how global businesses are already innovating these components in practice. Case studies give tangible confirmation of how governance is being transformed across sectors and enable us to notice sectoral patterns as well as the trends in commonality in the approach to transformation. The examples that follow—DBS Bank, Microsoft, and CVS Health—together show how finance, technology, and health corporations are integrating AI tools, neuroleadership practices, and culture measurement into their frameworks of governance. Overall, these cases document a worldwide change in corporate governance: from compliance-based oversight to adaptive, culture-focused governance.

Case Study 1: DBS Bank (Financial Sector)

DBS Bank in Singapore has been named among the most innovative banks in the world. Working in a highly regulated world, the bank created AI-driven board displays that give board members current information on compliance, risk, and stakeholder sentiment in real time. The predictive tool helped DBS to move from hindsight reporting to forward-looking governance, giving the board the insight to act ahead of upcoming challenges.

To leverage these tools most effectively, DBS worked with the NeuroLeadership Institute to develop director education in the recognition of bias, management of stress, and empathetic decision-making. These initiatives allowed board members to read AI output critically while displaying human-focused and ethically appropriate oversight. DBS also embedded a Corporate Culture Index, to be reviewed every quarter by the board, that monitors employee well-being, adaptability to innovation, ethical behaviour, and trust in stakeholders. Collectively, these practices put in play the Corporate Culture Footprint as a board priority (NeuroLeadership Institute, 2020). The bank improved decision-making, gained resilience in the COVID-19 pandemic crisis, and enhanced trust by reporting culture-related metrics publicly (Choudhury, 2020).

Case Study 2: Microsoft (Technology Industry)

Microsoft's renewal under CEO Satya Nadella is one of the most closely examined cases of culture-based renewal. Traditionally faulted for being too formalistic in culture, Microsoft undertook a transition in governance that integrated AI-enabled monitoring with neuroleadership-informed leadership styles (Groysberg et al., 2018) At the governance level, the company's board oversees the AI Ethics and Society Committee, which employs AI to monitor algorithmic bias, privacy risks, and regulatory challenges. This embeds AI not only as a product but as a governance mechanism ensuring accountability and ethical oversight.

At the same time, Microsoft adopted the principles of neuroleadership—most notably the growth mindset and empathy-based leadership—instilling them into leadership and board development (Neuroleadership Institute, 2019). These helped infuse higher levels of inclusion, flexibility, and resilience. The board also tracks cultural KPIs like diversity and inclusion metrics, employee engagement, psychological safety, and AI ethics performance. Although Microsoft doesn't refer to "Corporate Culture Footprint" in writing, this concept is already embedded in their board reporting on governance (Microsoft, 2022). The company reignited product innovation (cloud computing, AI), gained credibility with investors and regulators, and fashioned an inclusive, enduring organizational culture.

Case Study 3: CVS Health (Industry - Healthcare)

CVS Health, the most prominent American healthcare provider, has gone through strategic redefinition after buying Aetna. To redefine itself as the provider for healthcare innovation, the organization has combined AI analytics, inclusion projects inspired by neuroleadership, and metrics for cultural governance. Artificial intelligence is applied to provide governance oversight by identifying fraud in insurance claims, tracking patient information, and predicting community health outcomes. These are predictive indicators that give the board more than financial risk to manage, including trust and patient outcomes (CVS Health, 2022).

CVS collaborated with the NeuroLeadership Institute to instill inclusion habits among its 300,000 workers, with a focus on reducing biases and empathy-based leadership practices. This is in line with neuroleadership principles of forming habits, emotional regulation, and inclusive culture creation (NeuroLeadership Institute, 2022). At the board level, CVS Health's Healthy 2030 Impact Strategy requires the Nominating and Corporate Governance Committee to oversee cultural and social performance, with metrics that include workforce diversity, worker health, trust among patients, and community health performance. All these are part of a Corporate Culture Footprint that is grounded in strategy as well as in governance (CVS Health, 2023). CVS Health moved the governance from compliance to culture and community responsibility, fortified employee as well as patient trust, and increased legitimacy by integrating cultural performance into the board level.

Though each of the three cases displays sectoral methods of infusing AI, neuroleadership, and culture metrics into governance, comparison brings into focus both distinct strategies as well as similar trajectories. The table 1 compares the practices from DBS Bank, Microsoft, and CVS Health, illustrating how companies in finance, technology, and health are all trending towards similar innovations in governance. This comparison overview is clear that, in spite of contrasts in regulatory contexts as well as organizing contexts, all three companies are breaking free from compliance into models of governance based in the Corporate Culture Footprint.

Table 1. From Compliance to Culture: Comparative Evidence from DBS Bank, Microsoft, and CVS Health

Dimension	DBS Bank (Financial Sector)	Microsoft (Technology Sector)	CVS Health (Healthcare Sector)
Context	Leading Asian bank; regulated; focus on digital resilience.	Global tech giant; cultural renewal under Nadella.	U.S. healthcare leader; post-merger repositioning.
AI in Governance	Real-time dashboards for predictive oversight.	AI Ethics & Society Committee, AI for algorithmic bias/privacy/regulation.	AI for fraud detection, patient data, community health forecasting.
Neuroleadership	Board training with NLI on bias, resilience, empathy.	Growth mindset, empathy, resilience integrated in leadership.	NLI partnership for inclusion habits across workforce.
Culture Metrics (CCF)	Corporate Culture Index: well-being, ethics, adaptability, trust.	Cultural KPIs: diversity, engagement, psychological safety, ethical AI.	Healthy 2030 metrics: diversity, well-being, patient trust, community outcomes.
Impact	Predictive governance, strong crisis response, stakeholder trust.	Innovation revival, enhanced legitimacy, inclusive and resilient culture.	Governance shifted to culture/community accountability; enhanced legitimacy.
Key Lesson	AI and neuroleadership enable adaptive governance.	AI and neuroleadership drive cultural renewal and ethics.	AI and neuroleadership converge to embed inclusion and community culture into governance.

The examples from DBS Bank, Microsoft, and CVS Health show that while sectoral variation exists, companies are heading in the same direction in their approach to governance in which AI complements foresight, neuroleadership reinforces ethical decision-making, and cultural metrics inscribe responsibility. DBS exemplifies predictive governance in the banking sector, Microsoft presents culture-based renewal in the tech sector, while CVS represents the integration of community impact in healthcare. Overall, these cases affirm that the Corporate Culture Footprint is not sector-specific but is rather a cross-industry aspect of governance redesign.

6. Concluding remarks

This chapter has discussed how corporate governance is in the process of radical change, from compliance and financial supervision to encompass technological vision, neurocognitive sensitivity, and cultural responsibility. The comingling of Artificial Intelligence (AI), neuroleadership, and the Corporate Culture Footprint (CCF) shows that rather than as a fixed instrument of control, governance is becoming a dynamic ecosystem that reconciles technology, human discretion, and organisational values. The chapter demonstrated that AI improves governance through predictive insights, real-time tracking, and sophisticated risk analytics. However, technology is insufficient to address the ethical challenges and human frailties that boards encounter. Neuroleadership fills in the blanks for AI by giving directors resilience, emotional understanding, and mental sharpness, so that in even data-driven decision making, human-centricity is preserved. Meanwhile, the CCF redrafts culture as one measurable dimension of governance, grounding performance in inclusivity, health, ethical conduct, and stakeholder trust. The CVS Health, Microsoft, and DBS Bank case studies again confirmed that these principles are not philosophical constructs but budding practices in very distinct sectors. Whether in health, tech, or finance, corporations are embedding AI into oversight systems, adopting neuroscience-grounded leadership education, and monitoring culture as a strategic asset. The methodologies diverge—DBS in predictive dashboards, Microsoft in cultural rejuvenation, CVS in community outcomes—the cases all embody the same trend: adaptive, human-oriented, responsive-to-society governing. The repercussions are significant. For boards of directors, this revolution calls for a rewiring of competencies. Financial literacy and legal knowledge are still essential, but these are now to be supplemented by AI literacy, neurocognitive understanding, and cultural oversight abilities. For regulators and policymakers, this implies that codes of governance are to be expanded to encompass standards for algorithmic visibility, board education on awareness of biases, and disclosure of cultural footprint indicators. For researchers, this presents new transdisciplinary research possibilities between governance, technology, neuroscience, and organisational behaviour.

Long term, the future of government will depend on how effectively these three legs are consolidated into a working model. Compliance is still required, but in and of itself, it is not enough. The move towards culture as measurable footprints is not a rejection of compliance, but rather broadening the responsibility for government to meet the reality of a complicated, rapidly changing world. Through the redesigning of governance in the intersection between AI, neuroleadership, and cultural responsibility, companies can accomplish something more than regulatory compliance—they can provide resilience, ethical management, as well as sustainable competitiveness. This chapter therefore advocates for a paradigm in which the governance is neither constraint nor weakness, giving corporations the capacity to reconcile technological innovation, human capability, as well as cultural values in their quest for legitimacy as well as long-term success.

References

Butcher, J., & Beridze, I. (2019). What is the state of artificial intelligence governance globally? *RUSI Journal, 164*(5–6), 88–96. https://doi.org/10.1080/03071847.2019.1694260

Choudhury, P. (2020). *DBS Bank: Digital transformation to a digital native* (Case No. 9-620-031). Harvard Business School.

CVS Health. (2022). *ESG Report 2022: Healthy 2030 Impact Strategy*. Retrieved from https://www.cvshealth.com

CVS Health. (2023). *Healthy 2030 Impact Report Appendix*. Retrieved from https://www.cvshealth.com/content/dam/enterprise/cvs-enterprise/pdfs/2023/Healthy-2030-Impact-Report-Appendix.pdf

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research, 121*, 283–314. https://doi.org/10.1016/j.jbusres.2020.08.019

Dimitriou, D. (2022). Corporate ethics: An arbitration of philosophical concepts and market practices. *Conatus: Journal of Philosophy, 7*(2), 81–99. https://doi.org/10.12681/cjp.29864

Dimitriou, D. J., Sartzetaki, M. F., & Karagkouni, A. G. (2024). Chapter Eleven – Navigating digital transformation challenges and ethical considerations. In D. J. Dimitriou, M. F. Sartzetaki, & A. G. Karagkouni (Eds.), *Managing airport corporate performance* (pp. 279–303). Elsevier. https://doi.org/10.1016/B978-0-443-29109-8.00010-4

Greene, J. D., & Paxton, J. M. (2009). Patterns of neural activity associated with honest and dishonest moral decisions. *Proceedings of the National Academy of Sciences, 106*(30), 12506–12511. https://doi.org/10.1073/pnas.0900152106

Groysberg, B., Lee, J., Price, J., & Cheng, J. (2018). The leader's guide to corporate culture. *Harvard Business Review, 96*(1), 44–52.

Hagendorff, T. (2020). The ethics of AI ethics: An evaluation of guidelines. *Minds and Machines, 30*(1), 99–120. https://doi.org/10.1007/s11023-020-09517-8

Hilb, M. (2020). Toward artificial governance? The role of artificial intelligence in shaping the future of corporate governance. *Journal of Management & Governance, 24*(4), 851–870. https://doi.org/10.1007/s10997-020-09519-9

Holmström, J., & Hällgren, M. (2022). AI management beyond the hype: Exploring the co-constitution of AI and organizational context. *AI & Society, 37*(4), 1575–1585. https://doi.org/10.1007/s00146-021-01249-2

Huang, M.-H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research, 24*(1), 3–20. https://doi.org/10.1177/1094670520902266

Ivanov, D., & Dolgui, A. (2020). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control, 32*(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450

McEwen, B. S., & Morrison, J. H. (2013). The brain on stress: Vulnerability and plasticity of the prefrontal cortex over the life course. *Neuron, 79*(1), 16–29. https://doi.org/10.1016/j.neuron.2013.06.028

Microsoft. (2022). *Global Diversity & Inclusion Report*. Retrieved from https://www.microsoft.com/en-us/diversity/inside-microsoft/annual-report

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

NeuroLeadership Institute. (2020). *How DBS Bank builds better leaders with neuroscience*. Retrieved from https://neuroleadership.com

NeuroLeadership Institute. (2022, July 19). *CVS Health harnesses the power of companywide inclusion*. Retrieved from https://neuroleadership.com/your-brain-at-work/cvs-health-harnesses-the-power-of-companywide-inclusion/

NeuroLeadership Institute. (2019). *Neuroleadership and the growth mindset at Microsoft*. NeuroLeadership Institute. Retrieved from https://neuroleadership.com

Ringleb, A., & Rock, D. (2008). The emerging field of neuroleadership. *NeuroLeadership Journal, 1*(1), 1–7.

Sartzetaki, M., Dimitriou, D., & Karagkouni, A. (2025a). Harnessing neuroleadership concept for enhancing management efficiency and business sustainability in supply chain: A system of system approach. *Journal of Lifestyle and SDGs Review, 5*(6), 649–662. https://doi.org/10.47172/2965-730X.SDGsReview.v5.n06.pe06449

Sartzetaki, M., Moutzouri, A., Karagkouni, A., & Dimitriou, D. (2025b). The ecosystem of ethical decision making: Key drivers for shaping the corporate ethical character. *Conatus: Journal of Philosophy, 10*(1), 221–238. https://doi.org/10.12681/cjp.38439

Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., & Malone, T. W. (2010). Evidence for a collective intelligence factor in the performance of human groups. *Science, 330*(6004), 686–688. https://doi.org/10.1126/science.1193147

CHAOS CONTROL ON A DUOPOLY GAME WITH NONLINEAR AND ASYMMETRIC COST FUNCTIONS

Kosmas Papadopoulos
Department of Economics, Democritus University of Thrace
kpapa@econ.duth.gr

Despoina Terzopoulou
Department of Economics, Democritus University of Thrace
dterzopo@econ.duth.gr

George Sarafopoulos
Department of Economics, Democritus University of Thrace
gsarafop@econ.duth.gr

ABSTRACT

This article investigates a Cournot-type duopoly game with differentiated products, where both companies use nonlinear cost functions. The cost functions are asymmetric and specifically the first company follows a quadratic and the second a cubic cost function. The companies care about the maximization of an objective function (relative profit function) that contains not only their own profits, but also a percentage of the rival's profits. The two players (companies) are homogeneous, and they are characterized as bounded rational players. The Nash equilibrium position is calculated, and its local stability is studied focusing on the speed of adjustment that both players use on their decisions. It is shown that when the parameter k (speed of adjustment) takes large values outside its stability region, then *the system behaves chaotically and becomes sensitive on the selection of its initial conditions. The delayed feedback method is applied to control the chaotic behavior of the system. A new control parameter m manages to keep the Nash equilibrium locally asymptotically stable even if the parameter k moves outside the local stability space.*

Keywords: *Cournot oligopoly, Discrete dynamical system, Nash equilibrium, Local stability, Chaotic attractor, Lyapunov numbers, Nonlinear costs, Asymmetric costs, Chaos control.*

1. Introduction

The Cournot duopoly framework (1963) remains a foundational model in industrial organization and Game Theory, offering insights into strategic interactions between firms operating in markets with imperfect competition. Traditionally, Cournot models assume that firms produce homogeneous goods, possess symmetric information, and are endowed with unbounded rationality – enabling them to instantaneously compute optimal strategies. However, such assumptions, while analytically convenient, often fail to capture the complexities of real-world markets where firms differ in cost structures, produce differentiated products, and operate under cognitive or informational constraints. This paper extends the classical Cournot framework by exploring a duopoly game under more realistic conditions: homogeneous expectations, differentiated products, asymmetric cost functions, bounded rational players, and relative profit maximization.

In our model, two firms compete à la Cournot by choosing output quantities rather than prices. Unlike the classical homogeneous goods scenario, we assume differentiation – capturing the idea that while firms may serve the same market, their outputs are not perfect substitutes. This aspect introduces strategic nuances in the demand side, allowing firms to exert a degree of market power even when their rivals produce. Simultaneously, we incorporate asymmetric cost functions (Singh & Vives, 1984, Onozaki, 2018, Sarafopoulos & Papadopoulos, 2019), recognizing that real-world firms often differ in production technologies, scale efficiencies, or access to inputs.

Asymmetry in cost introduces heterogeneity in firms' incentives and strategic behavior, shaping the resulting equilibrium outcomes in nontrivial ways.

A key feature of our analysis lies in the behavioral assumption of bounded rationality. Instead of assuming that firms possess perfect foresight or engage in fully rational optimization, we consider firms as boundedly rational agents who adjust their output decisions over time using local or adaptive rules. These rules might reflect partial knowledge of market conditions, computational limitations, or reliance on past experience rather than full optimization. Specifically, we assume that firms iteratively adjust their quantities based on marginal profit signals (Baumol & Quandt, 1964, Puu, 1995, Bischi et al., 1999, Bischi & Naimzada, 2000, Naimzada & Ricchiuti, 2008, Askar, 2013, 2014), a behavior consistent with gradient dynamics or best-response learning models. This evolutionary approach allows us to study the stability and convergence properties of the dynamic adjustment process, offering a richer understanding of how firms might reach (or fail to reach) a Cournot-Nash equilibrium.

Many authors have made approaches with heterogeneous expectations of players (Den Haan, 2001, Agiza & Elsadany, 2003, 2004, Hommes, 2006, Tramontana, 2010, Fanti & Gori, 2012, Sarafopoulos, 2015, Sarafopoulos & Papadopoulos, 2017, Sarafopoulos & Terzopoulou, 2023, Sarafopoulos et al., 2024, 2025). On the other hand homogeneous expectations (Kopel, 1996, Puu, 1998, Agiza, 1999, Bishi & Kopel, 2001, Agiza et al., 2002, Agliari et al., 2005, 2006, Sarafopoulos, 2015, Sarafopoulos & Papadopoulos, 2019), in this context, refer to firms holding the same beliefs about market conditions – such as demand functions or rival behavior – even though they may differ in cost structures and strategic capabilities. This assumption allows us to isolate the effects of rationality bounds and cost asymmetries on market outcomes without introducing belief heterogeneity as an additional layer of complexity.

An additional assumption in our model is the concept of relative profit maximization. Rather than striving for absolute profit maximization, each firm in the duopoly seeks to maximize its profit relative to its competitor's profit. This assumption is motivated by the understanding that, in many real-world markets, firms are not solely concerned with their own profit levels but also with maintaining a competitive edge over their rivals. Relative profit maximization captures this behavior, where firms make strategic decisions based on the competitive outcomes they expect relative to their rival, instead of focusing on independent, standalone profits. This introduces a layer of competitive intensity and rivalry that further shapes market dynamics and equilibrium stability. The concept has been discussed in prior work by Satoh & Tanaka (2014), Li & Ma (2015), Elsadany (2017), Sarafopoulos & Papadopoulos (2019), Wei et al. (2023), who demonstrate that relative profit maximization can lead to different strategic outcomes than traditional profit-maximizing behavior, particularly in oligopolistic settings where firms are highly interdependent.

This paper contributes to the literature by synthesizing these elements – bounded rationality, product differentiation, cost asymmetry, and homogeneous expectations – within a unified Cournot duopoly framework. By doing so, we aim to bridge the gap between idealized economic models and observed market behavior. Our analysis offers both theoretical insights into the dynamics of strategic competition and practical implications for industries characterized by differentiated products and uneven cost conditions. Moreover, the incorporation of bounded rationality sheds light on potential instabilities, cyclical behaviors, or convergence failures that are often ignored in static models but are highly relevant in dynamic and imperfectly competitive markets.

Authors such as Agiza (1999), Du et al. (2009), Holyst & Urbanowicz (2000), Ding et al. (2012), Elabbasy et al. (2009), Pu & Ma (2013) have presented methods to control chaotic trajectories on their oligopoly models. To address the potential for chaotic behavior arising when firms' speed of adjustment lie outside the stability region, we incorporate a delayed feedback control mechanism into our model. This method, inspired by techniques in nonlinear dynamics and control theory, stabilizes otherwise unstable or chaotic trajectories by introducing a time-delayed component into the adjustment process. Specifically, each firm's output update includes a correction term based on the discrepancy between its current and past outputs, effectively damping oscillations and guiding the system back toward equilibrium. The delayed feedback method (Pyragas, 1992, Agiza et al., 2013, Kotsios, 2023, Wei et al., 2023) does not require full information about the system's dynamics, making it particularly well-suited for boundedly rational settings where firms operate with limited computational capacity. By implementing this control strategy, we are able to explore the conditions under which locally stable equilibria can be restored or maintained, offering a robust framework for managing instability in real-world duopolistic markets. This addition not only enriches the model's realism but also provides valuable insights into policy or strategic interventions that firms or regulators might employ to mitigate erratic market behavior.

2. The Game

The players (companies) decide their productions at discrete time periods t = 1, 2, … In this game the following inverse demand functions for two players are considered:

$$p_1 = \alpha - q_1 - d \cdot q_2 \text{ and } p_2 = \alpha - q_2 - d \cdot q_1 \tag{1}$$

where the positive parameter $\alpha > 0$ expresses the market size, $d \in (-1,1)$ is the differentiation degree of two products, p_i is the product price and q_i is the production quantity of each i company $(i \in \{1,2\})$.

The authors assume that the first firm (player) uses a nonlinear and quadratic cost function in the production process. Its cost function is given by the following equation:

$$C_1(q_1) = c_1 \cdot q_1^2 + c_2 \cdot q_1 + c_3 \tag{2}$$

with $c_1 > 0, c_2 \geq 0, c_3 \geq 0 \text{ and } c_2^2 \leq 4c_1 \cdot c_3$.

Also, the second firm follows a nonlinear polynomial cost function but of the third degree (cubic) that is given as follows:

$$C_2(q_2) = c_4 \cdot q_2^3 + c_5 \cdot q_2^2 + c_6 \cdot q_2 + c_7 \tag{3}$$

with $c_4 \geq 0, c_5 \leq 0, c_7 \geq 0 \text{ and } c_5^2 \leq 3c_4 \cdot c_6$.

This assumption of cubic cost function is widely used in energy sector (Theerthamalai & Maheswarapu, 2010, Durai et al., 2015, Mahdi et al., 2019, Hassan et al., 2022).

Under these assumptions the profit functions of two players are calculated as follows:

$$\Pi_1(q_1, q_2) = (\alpha - q_1 - d \cdot q_2) \cdot q_1 - c_1 \cdot q_1^2 - c_2 \cdot q_1 - c_3 \tag{4}$$

and

$$\Pi_2(q_1, q_2) = (\alpha - q_2 - d \cdot q_1) \cdot q_2 - c_4 \cdot q_2^3 - c_5 \cdot q_2^2 - c_6 \cdot q_2 - c_7 \tag{5}$$

The partial derivatives of profits are calculated:

$\frac{\partial \Pi_1}{\partial q_1} = \alpha - c_2 - 2(1 + c_1) \cdot q_1 - d \cdot q_2$ and $\frac{\partial \Pi_1}{\partial q_2} = -d \cdot q_1$

$\frac{\partial \Pi_2}{\partial q_1} = -d \cdot q_2$ and $\frac{\partial \Pi_2}{\partial q_2} = \alpha - c_6 - d \cdot q_1 - 2(1 + c_5) \cdot q_2 - 3c_4 \cdot q_2^2$

As it is noticed each i company cares about the maximization of an objective function U_i (relative profits) that contains a percentage of $(1 - \mu) \cdot 100\%$ of its own profits Π_i and a percentage of $\mu \cdot 100\%$ of the profit difference $\Pi_i - \Pi_j$. The objective function U_i is given by the following equation:

$$U_i = (1 - \mu) \cdot \Pi_i - \mu \cdot (\Pi_i - \Pi_j) \Rightarrow U_i = \Pi_i - \mu \cdot \Pi_j \text{ for } i \neq j \text{ and } i, j \in \{1,2\} \tag{6}$$

with partial derivative:

$$\frac{\partial U_i}{\partial q_i} = \frac{\partial \Pi_i}{\partial q_i} - \mu \cdot \frac{\partial \Pi_j}{\partial q_i} \tag{7}$$

resulting in the following partial derivatives for each i player:

$$\frac{\partial U_1}{\partial q_1} = \alpha - c_2 - 2(1 + c_1) \cdot q_1 + d \cdot (\mu - 1) \cdot q_2 \tag{8}$$

and

$$\frac{\partial U_2}{\partial q_2} = \alpha - c_6 + d \cdot (\mu - 1) \cdot q_1 - 2(1 + c_5) \cdot q_2 - 3c_4 \cdot q_2^2 \tag{9}$$

The next step to constructing the discrete dynamical system is to describe the strategies that two players follow. Both players are characterized as bounded rational players and based on the existing literature it means that each player decides his production level using the following mechanism:

$$\frac{q_i(t+1) - q_i(t)}{q_i(t)} = k \cdot q_i(t) \cdot \frac{\partial U_i}{\partial q_i} \tag{10}$$

where $k > 0$ is the positive parameter that expresses the speed of adjustment of two players. Under this mechanism, the i player increases (decreases) his level adaptation when the marginal objective function is positive (negative). The discrete dynamical system of duopoly is given as follows:

$$\begin{cases} q_1(t+1) = q_1(t) + k \cdot q_1(t) \cdot \dfrac{\partial U_1}{\partial q_1} \\ q_2(t+1) = q_2(t) + k \cdot q_2(t) \cdot \dfrac{\partial U_2}{\partial q_2} \end{cases} \tag{11}$$

The effect of the parameter k (speed of adjustment) and d (differentiation degree) over the local stability of Nash equilibrium of the system of Eq.(11) will be studied.

3. The Dynamical Analysis

3.1 The Nash equilibrium position

The Nash equilibrium of the static game that is:

$$\begin{cases} \dfrac{\partial U_1}{\partial q_1} = 0 \\ \dfrac{\partial U_2}{\partial q_2} = 0 \end{cases} \tag{12}$$

is the Nash equilibrium E_* of the discrete dynamical system of Eq.(11). The coordinates of E_* are the nonnegative common solutions of the following equations:

$$q_1^* = \frac{\alpha - c_2 + d \cdot (\mu - 1) \cdot q_2}{2(1 + c_1)} \tag{13}$$

and

$$\begin{aligned} &6c_4 \cdot (1 + c_1) \cdot (q_2^*)^2 + [4(1 + c_1) \cdot (1 + c_5) - d^2 \cdot (\mu - 1)^2] \cdot q_2^* - \\ &-2(\alpha - c_6) \cdot (1 + c_1) - d \cdot (\mu - 1) \cdot (\alpha - c_2) = 0 \end{aligned} \tag{14}$$

3.2 The local stability conditions

To study the local stability of the Nash equilibrium of the system of Eq.(11) the Jacobian matrix of the system is needed, and it is given by:

$$J(q_1, q_2) = \begin{bmatrix} 1 + k \cdot \left(\frac{\partial U_1}{\partial q_1} + q_1 \cdot \frac{\partial^2 U_1}{\partial q_1^2} \right) & k \cdot q_1 \cdot \frac{\partial^2 U_1}{\partial q_1 \, \partial q_2} \\ k \cdot q_2 \cdot \frac{\partial^2 U_2}{\partial q_2 \, \partial q_1} & 1 + k \cdot \left(\frac{\partial U_2}{\partial q_2} + q_2 \cdot \frac{\partial^2 U_2}{\partial q_2^2} \right) \end{bmatrix} \tag{15}$$

And for the position of E_* it becomes:

$$\begin{aligned} J(E_*) &= \begin{bmatrix} 1 + k \cdot q_1^* \cdot \frac{\partial^2 U_1}{\partial q_1^2} & k \cdot q_1^* \cdot \frac{\partial^2 U_1}{\partial q_1 \, \partial q_2} \\ k \cdot q_2^* \cdot \frac{\partial^2 U_2}{\partial q_2 \, \partial q_1} & 1 + k \cdot q_2^* \cdot \frac{\partial^2 U_2}{\partial q_2^2} \end{bmatrix} = \\ &= \begin{bmatrix} 1 - 2k \cdot (1 + c_1) \cdot q_1^* & k \cdot d \cdot (\mu - 1) \cdot q_1^* \\ k \cdot d \cdot (\mu - 1) \cdot q_2^* & 1 - 2k \cdot (1 + c_5) \cdot q_2^* - 6k \cdot c_4 \cdot (q_2^*)^2 \end{bmatrix} \end{aligned} \tag{16}$$

with trace:

$$Tr(J) = 2 - 2k \cdot (1 + c_1) \cdot q_1^* - 2k \cdot (1 + c_5) \cdot q_2^* - 6k \cdot c_4 \cdot (q_2^*)^2 \tag{17}$$

and determinant:

$$Det(J) = 1 - 2k \cdot (1 + c_1) \cdot q_1^* - 2k \cdot (1 + c_5) \cdot q_2^* - 6k \cdot c_4 \cdot (q_2^*)^2 +$$

$$+k^2 \cdot [4(1+c_1)\cdot(1+c_5) - d^2 \cdot (\mu - 1)^2] \cdot q_1^* \cdot q_2^* +$$
$$+12k^2 \cdot c_4 \cdot (1+c_1) \cdot q_1^* \cdot (q_2^*)^2 \tag{18}$$

Proposition 1:

The Nash equilibrium position E_* of the discrete dynamical system of Eq.(11) is locally asymptotically stable if:

$$k \cdot [4(1+c_1)\cdot(1+c_5) - d^2 \cdot (\mu-1)^2] \cdot q_1^* \cdot q_2^* + 12k \cdot c_4 \cdot (1+c_1) \cdot q_1^* \cdot (q_2^*)^2$$
$$-2(1+c_1)\cdot q_1^* - 2(1+c_5)\cdot q_2^* - 6c_4 \cdot (q_2^*)^2 < 0 \tag{19}$$

and

$$k^2 \cdot [4(1+c_1)\cdot(1+c_5) - d^2 \cdot (\mu-1)^2] \cdot q_1^* \cdot q_2^* + 12k^2 \cdot c_4 \cdot (1+c_1) \cdot q_1^* \cdot (q_2^*)^2 -$$
$$-4k \cdot [(1+c_1)\cdot q_1^* + (1+c_5)\cdot q_2^* + 3 \cdot c_4 \cdot (q_2^*)^2] + 4 > 0 \tag{20}$$

Proof:

The Nash equilibrium of the system of Eq.(11) is locally asymptotically stable if the following three inequalities (Kulenovic & Merino, 2002) are satisfied simultaneously:

$$\begin{aligned}
&\text{(i)} \quad 1 - \mathrm{Det}(J) > 0\\
&\text{(ii)} \quad 1 - \mathrm{Tr}(J) + \mathrm{Det}(J) > 0\\
&\text{(iii)} \quad 1 + \mathrm{Tr}(J) + \mathrm{Det}(J) > 0
\end{aligned} \tag{21}$$

The first inequality (i) becomes:

$$1 - \mathrm{Det}(J) > 0 \Leftrightarrow$$
$$k \cdot [4(1+c_1)\cdot(1+c_5) - d^2 \cdot (\mu-1)^2] \cdot q_1^* \cdot q_2^* + 12k \cdot c_4 \cdot (1+c_1) \cdot q_1^* \cdot (q_2^*)^2$$
$$-2(1+c_1)\cdot q_1^* - 2(1+c_5)\cdot q_2^* - 6c_4 \cdot (q_2^*)^2 < 0$$

and this is the first local stability condition.

The second inequality (ii) becomes as follows:

$$1 - Tr(J) + Det(J) > 0 \Leftrightarrow$$
$$k \cdot [4(1+c_1)\cdot(1+c_5) - d^2\cdot(\mu-1)^2]\cdot q_1^* \cdot q_2^* + 12k \cdot c_4 \cdot (1+c_1) \cdot q_1^* \cdot (q_2^*)^2 > 0$$

and it's always satisfying.

The third inequality (iii) gives:

$$1 + Tr(J) + Det(J) > 0 \Leftrightarrow$$
$$k^2 \cdot [4(1+c_1)\cdot(1+c_5) - d^2\cdot(\mu-1)^2]\cdot q_1^* \cdot q_2^* + 12k^2 \cdot c_4 \cdot (1+c_1) \cdot q_1^* \cdot (q_2^*)^2 -$$
$$-4k\cdot(1+c_1)\cdot q_1^* - 4k\cdot(1+c_5)\cdot q_2^* - 12k\cdot c_4\cdot(q_2^*)^2 + 4 > 0$$

that is the second local stability condition. □

3.3 Numerical simulations focusing on the parameter k

In this subsection, the algebraic results of Proposition 1 are verified through numerical simulations of the system of Eq.(11) focusing on the effect of the speed of adjustment (parameter k). For this reason, it is necessary to set specific values to the game's parameters such as e.g.:
$\alpha = 5, d = 0.50, \mu = 0.70, c_1 = 1, c_2 = 0.50, c_3 = 0.50, c_4 = 1, c_5 = -0.50,\ c_6 = 0.50, c_7 = 1.$

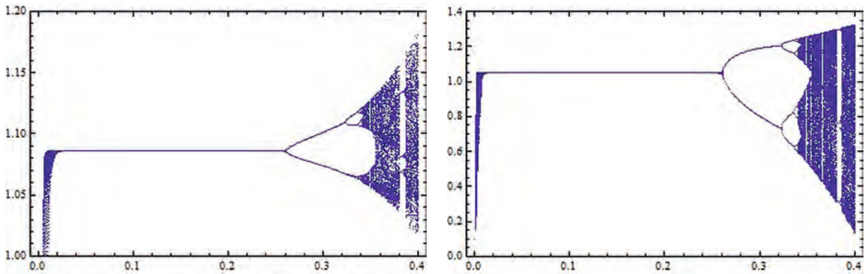
For these values of the parameters, the coordinates of the Nash equilibrium E_* are calculated as the nonnegative solutions of the algebraic system of Eq.(13-14) as follows:

$$q_1^* \cong 1.09 \text{ and } q_2^* \cong 1.05 \Longrightarrow E_* = (1.09, 1.05) \tag{22}$$

Also, the local stability conditions of Eq.(19-20) have the following common solutions focusing on the parameter k:

$$k \in (0, 0.26) \tag{23}$$

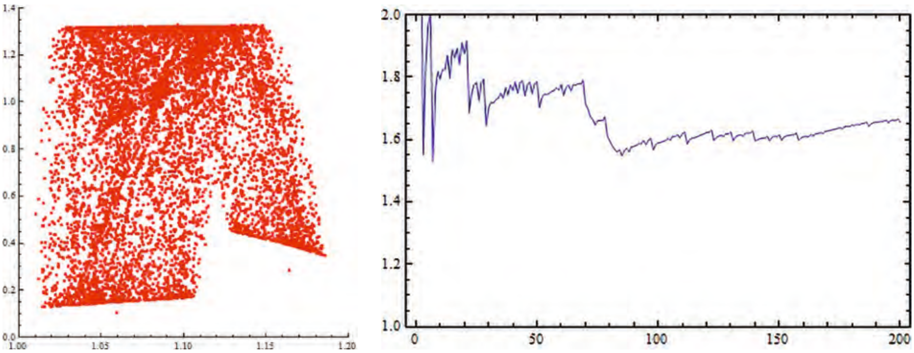
The coordinates of the Nash equilibrium position and the local stability interval focusing on the parameter can be verified by the bifurcation diagrams of production quantities q_1 (Fig. 1.a) and q_2 (Fig. 1.b) with respect to the parameter k (horizontal axis). As it seems until the value of 0.26 for the parameter k, the Nash equilibrium is locally asymptotically stable. For values larger than 0.26, doubling period bifurcations make their appearance. The two inequalities of Eq.(21) which lead too the local stability conditions are: $1 - \mathrm{Det}(J) > 0$ and $1 + \mathrm{Tr}(J) + \mathrm{Det}(J) > 0$. These conditions lead the system of Eq.(11) to destabilize the Nash equilibrium through Niemark-Sacker bifurcations $(1 - \mathrm{Det}(J) > 0)$ or through period-doubling bifurcations $(1 + \mathrm{Tr}(J) + \mathrm{Det}(J) > 0)$. For these values of the parameters, the first local stability condition Eq.(19) gives the solutions into interval $k \in (0{,}0.36)$ and the second of Eq.(20) gives $k \in (0{,}0.26) \cup (0.46, +\infty)$. It seems that when the parameter k takes values larger than 0.26, firstly the condition $1 + \mathrm{Tr}(J) + \mathrm{Det}(J) > 0$ is disturbed, while the condition is still satisfied, and as a result the unstable Nash equilibrium appears through period-doubling bifurcations.



(a) (b)

Figure 1: Bifurcation diagrams with respect to the speed of adjustment (horizontal axis) with 400 iterations of the map of Eq.(11) for
$\alpha = 5, d = 0.50, \mu = 0.70, c_1 = 1, c_2 = 0.50, c_3 = 0.50, c_4 = 1, c_5 = -0.50, c_6 = 0.50, c_7 = 1$:
(a) against the production q_1; (b) against the production q_2;

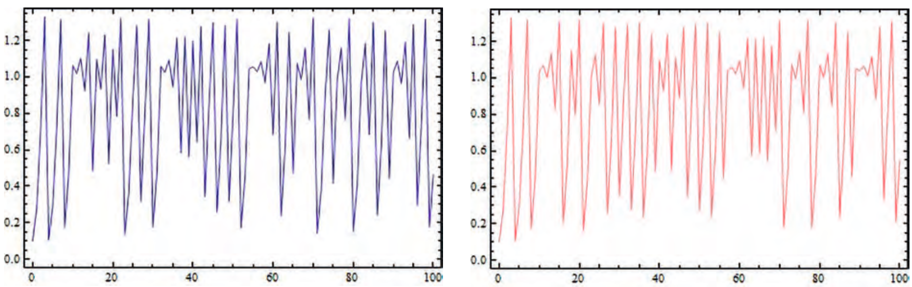
For large values of the parameter k e.g. k = 0.40, the system of Eq.(11) starts to behave chaotically. As evidence for this chaotic behavior, a chaotic attractor (Fig. 2.a) and Lyapunov numbers larger than 1 (Fig. 2.b) are plotted.



(a) (b)

Figure 2: (a): Phase portrait (chaotic attractor) with 8000 iterations and (b): Lyapunov numbers graph as numerical simulations of the orbit of (0.1,0.1) of the map of Eq.(11) for $\alpha = 5, d = 0.50, \mu = 0.70, c_1 = 1, c_2 = 0.50, c_3 = 0.50, c_4 = 1, c_5 = -0.50,$ $c_6 = 0.50,\ c_7 = 1$ and $k = 0.40$.

The chaotic dynamical systems are sensitive to the selection of their initial conditions. In Figures 3.a and 3.b the time series of the coordinate q_1 of the orbit of Eq.(11) are presented selecting two different initial conditions (0.1,0.1) (Fig. 3.a) and (0.101,0.1) (Fig. 3.b). It seems that at the first iterations the time series are identical but some iterations later, the time series begin to differentiate from each other.



(a) (b)

Figure 3: (a): Phase portrait (chaotic attractor) with 8000 iterations and (b): Lyapunov numbers graph as numerical simulations of the orbit of (0.1,0.1) of the map of Eq.(11) for $\alpha = 5, d = 0.50, \mu = 0.70, c_1 = 1, c_2 = 0.50, c_3 = 0.50, c_4 = 1, c_5 = -0.50,$ $c_6 = 0.50,\ c_7 = 1$ and $k = 0.40$.

4. Chaos Control

4.1 Applying the delayed feedback control method

In this subsection we apply delayed feedback control method to control the chaotic behavior is created for values of the speed of adjustment outside of the local stability interval. Through the delayed feedback method, a new control parameter $m \in [0,1]$ is introduced in the discrete dynamical system of Eq.(11) adding to each i-difference equation (i-player) the following control signal:

$$r_i(t) = m \cdot [q_i(t + 1 - \tau) - q_i(t + 1)] \tag{24}$$

We choose to apply this control signal for $\tau = 1$ and it becomes:

$$r_i(t) = m \cdot [q_i(t) - q_i(t + 1)] \tag{25}$$

This means that the production decision of each i-player is described by the following difference equation:

$$q_i(t+1) = q_i(t) + k \cdot q_i(t) \cdot \frac{\partial U_i}{\partial q_i} + r_i(t) \Rightarrow q_i(t+1) = q_i(t) + \frac{k}{1+m} \cdot q_i(t) \cdot \frac{\partial U_i}{\partial q_i} \tag{26}$$

As a result, the new discrete dynamical system which contains the new control parameter m is described as follows:

$$\begin{cases} q_1(t+1) = q_1(t) + \dfrac{k}{1+m} \cdot q_1(t) \cdot \dfrac{\partial U_1}{\partial q_1} \\ q_2(t+1) = q_2(t) + \dfrac{k}{1+m} \cdot q_2(t) \cdot \dfrac{\partial U_2}{\partial q_2} \end{cases} \tag{27}$$

4.2 New local stability conditions

Proposition 2:

The Nash equilibrium position E_* of the discrete dynamical system of Eq.(27) is locally asymptotically stable if:

$$k \cdot [4(1+c_1)\cdot(1+c_5) - d^2\cdot(\mu-1)^2]\cdot q_1^* \cdot q_2^* + 12k\cdot c_4\cdot(1+c_1)\cdot q_1^*\cdot(q_2^*)^2 -$$
$$-2(1+m)\cdot[(1+c_1)\cdot q_1^* + (1+c_5)\cdot q_2^* + 3c_4\cdot(q_2^*)^2] < 0 \tag{28}$$

and

$$k^2 \cdot [4(1+c_1)\cdot(1+c_5) - d^2\cdot(\mu-1)^2]\cdot q_1^* \cdot q_2^* + 12k^2\cdot c_4\cdot(1+c_1)\cdot q_1^*\cdot(q_2^*)^2 -$$
$$-4k\cdot(1+m)\cdot[(1+c_1)\cdot q_1^* + (1+c_5)\cdot q_2^* + 3c_4\cdot(q_2^*)^2] + 4(1+m)^2 > 0 \tag{29}$$

Proof:

The Jacobian matrix of the system of Eq.(27) is given by the following matrix:

$$J(q_1,q_2) = \begin{bmatrix} 1 + \frac{k}{1+m}\cdot\left(\frac{\partial U_1}{\partial q_1} + q_1\cdot\frac{\partial^2 U_1}{\partial q_1^2}\right) & \frac{k}{1+m}\cdot q_1\cdot\frac{\partial^2 U_1}{\partial q_1\,\partial q_2} \\ \frac{k}{1+m}\cdot q_2\cdot\frac{\partial^2 U_2}{\partial q_2\,\partial q_1} & 1 + \frac{k}{1+m}\cdot\left(\frac{\partial U_2}{\partial q_2} + q_2\cdot\frac{\partial^2 U_2}{\partial q_2^2}\right) \end{bmatrix} \tag{30}$$

And for the position of E_* it becomes:

$$J(E_*) = \begin{bmatrix} 1 + \frac{k}{1+m}\cdot q_1^*\cdot\frac{\partial^2 U_1}{\partial q_1^2} & \frac{k}{1+m}\cdot q_1^*\cdot\frac{\partial^2 U_1}{\partial q_1\,\partial q_2} \\ \frac{k}{1+m}\cdot q_2^*\cdot\frac{\partial^2 U_2}{\partial q_2\,\partial q_1} & 1 + \frac{k}{1+m}\cdot q_2^*\cdot\frac{\partial^2 U_2}{\partial q_2^2} \end{bmatrix} =$$
$$= \begin{bmatrix} 1 - 2(1+c_1)\cdot q_1^*\cdot\frac{k}{1+m} & d\cdot(\mu-1)\cdot q_1^*\cdot\frac{k}{1+m} \\ d\cdot(\mu-1)\cdot q_2^*\cdot\frac{k}{1+m} & 1 - 2\frac{k}{1+m}\cdot(1+c_5)\cdot q_2^* - 6\frac{k}{1+m}\cdot c_4\cdot(q_2^*)^2 \end{bmatrix} \tag{31}$$

with trace:

$$Tr(J) = 2 - 2k\cdot(1+c_1)\cdot q_1^* - 2k\cdot(1+c_5)\cdot q_2^* - 6k\cdot c_4\cdot(q_2^*)^2 \tag{32}$$

and determinant:

$$Det(J) = 1 - 2k\cdot(1+c_1)\cdot q_1^* - 2k\cdot(1+c_5)\cdot q_2^* - 6k\cdot c_4\cdot(q_2^*)^2 +$$
$$+k^2\cdot[4(1+c_1)\cdot(1+c_5) - d^2\cdot(\mu-1)^2]\cdot q_1^*\cdot q_2^* +$$
$$+12k^2\cdot c_4\cdot(1+c_1)\cdot q_1^*\cdot(q_2^*)^2 \tag{33}$$

The Nash equilibrium of the system of Eq.(27) is locally asymptotically stable if the inequalities of Eq.(21) are satisfied simultaneously.

The first inequality (i) becomes follows:

$$1-\mathrm{Det}(J)>0 \Leftrightarrow$$
$$k\cdot[4(1+c_1)\cdot(1+c_5)-d^2\cdot(\mu-1)^2]\cdot q_1^*\cdot q_2^*+12k\cdot c_4\cdot(1+c_1)\cdot q_1^*\cdot(q_2^*)^2-$$
$$-2(1+m)\cdot[(1+c_1)\cdot q_1^*+(1+c_5)\cdot q_2^*+3c_4\cdot(q_2^*)^2]<0$$

and this is the first local stability condition.

The second inequality (ii) becomes as follows:

$$1-\mathrm{Tr}(J)+\mathrm{Det}(J)>0 \Leftrightarrow$$
$$\frac{k}{1+m}\cdot[4(1+c_1)\cdot(1+c_5)-d^2\cdot(\mu-1)^2]\cdot q_1^*\cdot q_2^*+12k\cdot c_4\cdot(1+c_1)\cdot q_1^*\cdot(q_2^*)^2>0$$

which is always satisfying.

The third inequality (iii) gives:

$$1+\mathrm{Tr}(J)+\mathrm{Det}(J)>0 \Leftrightarrow$$
$$k^2\cdot[4(1+c_1)\cdot(1+c_5)-d^2\cdot(\mu-1)^2]\cdot q_1^*\cdot q_2^*+12k^2\cdot c_4\cdot(1+c_1)\cdot q_1^*\cdot(q_2^*)^2-$$
$$-4k\cdot(1+m)\cdot[(1+c_1)\cdot q_1^*+(1+c_5)\cdot q_2^*+3c_4\cdot(q_2^*)^2]+4(1+m)^2>0$$

which is the second local stability condition. □

4.3 Numerical simulations focusing on the control parameter

Setting specific values for the parameters $\alpha=5, d=0.50, \mu=0.70, c_1=1$, $c_2=0.50, c_3=0.50, c_4=1, c_5=-0.50,\ c_6=0.50, c_7=1$, the stability conditions of Eq.(28-29) take the following form:

$$\mathrm{Eq.}(28)\Longrightarrow 33.06\cdot k-11.96\cdot(1+m)<0 \tag{34}$$

and

$$\text{Eq.}\,(29) \Rightarrow 33.06 \cdot k^2 - 23.93 \cdot k \cdot (1+m) + 4 \cdot (1+m)^2 > 0 < 0 \quad (35)$$

The common solutions of Eq.(34-35) are plotted with a two-dimensional graph in Figure 4.

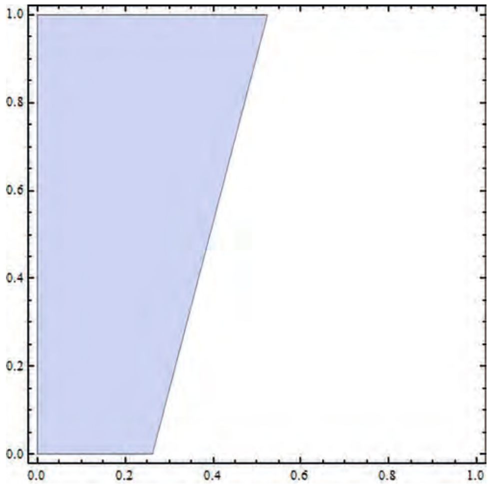
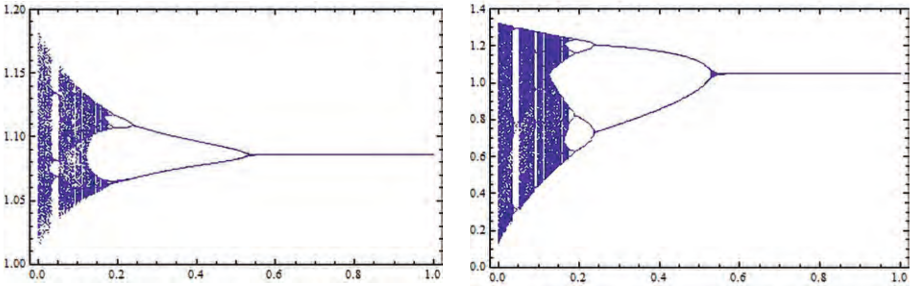


Figure 4: Two-dimensional local stability region of speed of adjustment (horizontal axis) and control parameter (vertical axis) for $\alpha = 5, d = 0.50, \mu = 0.70, c_1 = 1,$. $c_2 = 0.50, c_3 = 0.50, c_4 = 1, c_5 = -0.50, c_6 = 0.50, c_7 = 1$

Also, the local stability conditions of Eq.(34-35) setting additionally $k = 0.40$ (a value outside the local stability interval) have the following common solutions focusing on the parameter m:

$$m \in (0.54, 1] \quad (36)$$

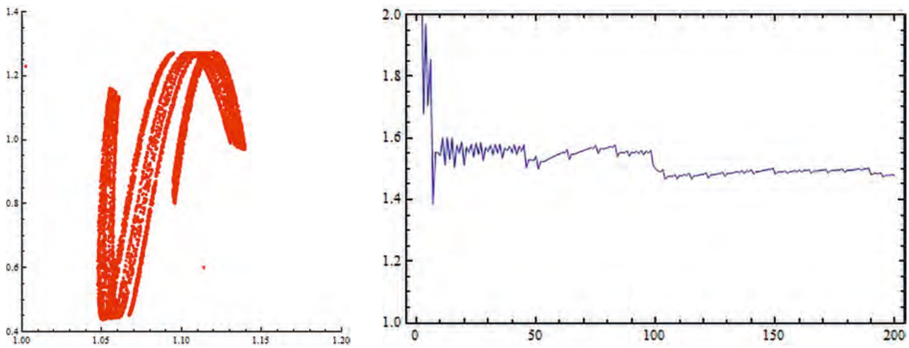
This result is verified by the Figure 4 and the bifurcation diagrams of production quantities q_1 (Fig. 5.a) and q_2 (Fig. 5.b) with respect to the parameter m (horizontal axis). It is shown that while the control parameter m is taking values larger than 0.54 the Nash equilibrium position is locally asymptotically stable. This means that the parameter m creates an interval for local asymptotic stability for the Nash equilibrium for values of the parameter k outside the local stability space.



(a) (b)

Figure 5: Bifurcation diagrams with respect to the speed of adjustment (horizontal axis) with 400 iterations of the map of Eq.(27) for $\alpha = 5, d = 0.50, \mu = 0.70, c_1 = 1, c_2 = 0.50, c_3 = 0.50, c_4 = 1, c_5 = -0.50,$ $c_6 = 0.50, c_7 = 1$ and $k = 0.40$: (a) against the production q_1; (b) against the production q_2;

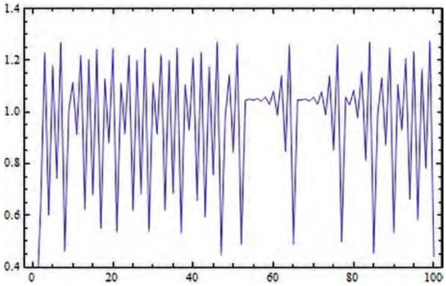
For small values of the parameter m e.g. $m = 0.10$, the orbit of Eq.(27) behaves chaotically. Some evidence for this is the chaotic attractors that appear (Fig. 6.a) and Lyapunov numbers graph with values larger than 1 (Fig. 6.b).



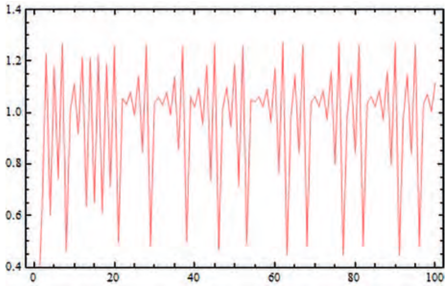
(a) (b)

Figure 6: (a): Phase portrait (chaotic attractor) with 8000 iterations and (b): Lyapunov numbers graph as numerical simulations of the orbit of (0.1,0.1) of the map of Eq.(27) for $\alpha = 5, d = 0.50, \mu = 0.70, c_1 = 1, c_2 = 0.50, c_3 = 0.50, c_4 = 1, c_5 = -0.50,$ $c_6 = 0.50,\ c_7 = 1, k = 0.40$ and $m = 0.10$.

Finally, it is shown that the dynamical system of Eq.(27) is sensitive on the selection of the initial conditions. In Figures 6.a and 6.b the time series of production q_1 of the system of Eq.(27) for initial conditions (0.1,0.1) and (0.101,0.1) are presented respectively, it seems that only a small change on the coordinates of the initial conditions of system is able to change completely the system's behavior and toy make it chaotic and unpredictable.



(a)



(b)

Figure 7: (a): Phase portrait (chaotic attractor) with 8000 iterations and (b): Lyapunov numbers graph as numerical simulations of the orbit of (0.1,0.1) of the map of Eq.(27) for $\alpha = 5, d = 0.50, \mu = 0.70, c_1 = 1, c_2 = 0.50, c_3 = 0.50, c_4 = 1, c_5 = -0.50, c_6 = 0.50, c_7 = 1, k = 0.40$ and $m = 0.10$.

5. Conclusions

This study investigated a Cournot duopoly game where two firms produce differentiated goods under asymmetric and nonlinear cost functions. Specifically, the first firm produces using a quadratic cost function while the second firm uses a cubic cost function. Both players (firms) decide their productions under the strategy of bounded rationality following a mechanism with the same speed of adjustment (parameter k) at discrete time periods. They care about the maximization of an objective function that contains not only their own profits, but also a percentage of their rival's profits (relative profit maximization).

The Nash equilibrium of the discrete dynamical system that arises is found and its local stability is studied. It is proven that the Nash equilibrium is locally asymptotically stable when two inequalities (local stability conditions) are satisfied simultaneously. Under certain circumstances (specific values of exogenous variables), it is shown that large values of the speed of adjustment destabilize the Nash equilibrium through period doubling bifurcations and may cause chaotic behavior for the system making it unpredictable and sensitive on its initial conditions. These results are verified through some numerical simulations e.g. plotting bifurcation diagrams, phase portrait (chaotic attractors), Lyapunov numbers graph, sensitive dependence on initial conditions.

Finally, the delayed feedback method is applied to this duopoly model to control the chaotic behavior that appears when the speed of adjustment takes values outside the local stability region. A new control parameter is introduced in the original discrete dynamical system. The new system has the same Nash equilibrium as the original. The local stability region between the speed of adjustment and the new control parameter is presented formulating a proposition. It seems that there is an interval of the control parameter which return the Nash equilibrium on local stability even if the speed of adjustment moves outside its local stability region.

References

Agiza, H.N. (1999). On the analysis of stability, bifurcation, chaos and chaos control of Kopel map. *Chaos, Solitons & Fractals*, *10*(11), 1909-1916, DOI: https://doi.org/10.1016/S0960-0779(98)00210-0

Agiza, H.N., & Elsadany, A.A. (2003). Nonlinear dynamics in the Cournot duopoly game with heterogeneous players. *Physica A: Statistical Mechanics and its Applications*, *320*, 512-524, DOI: https://doi.org/10.1016/S0378-4371(02)01648-5

Agiza, H.N., & Elsadany, A.A. (2004). Chaotic dynamics in nonlinear duopoly game with heterogeneous players. *Applied Mathematics and Computation*, *149*(3), 843-860, DOI: https://doi.org/10.1016/S0096-3003(03)00190-5

Agiza, H.N., Elsadany, A.A., & El-Dessoky, M.M. (2013). On a new Cournot duopoly game. *Journal of Chaos, 1*, 487803, DOI: https://doi.org/10.1155/2013/487803

Agiza, H.N., Hegazi, A.S., & Elsadany, A.A. (2002). Complex dynamics and synchronization of duopoly game with bounded rationality. *Mathematics and Computers in Simulations, 58*(2), 133-146, DOI: https://doi.org/10.1016/S0378-4754(01)00347-0

Agliari, A., Gardini, L., & Puu, T. (2005). Some global bifurcations related to the appearance of closed invariant curves. *Mathematics and Computers in Simulation*, *68*(3), 201-219, DOI: https://doi.org/10.1016/j.matcom.2004.12.003

Agliari, A., Gardini, L., & Puu T. (2006). Global bifurcations in duopoly when the Cournot point is destabilized via a subcritical Neimark bifurcation. *International Game Theory Review*, *8*(1), 1-20, DOI: https://doi.org/10.1142/S0219198906000758

Askar, S.S. (2013). On complex dynamics of monopoly market. *Economic Modelling*, *31*, 586-589, DOI: https://doi.org/10.1016/j.econmod.2012.12.025

Askar, S.S. (2014). Complex dynamics properties of Cournot duopoly games with convex and log-concave demand function. *Operations Research Letters*, *42*, 85-90, DOI: https://doi.org/10.1016/j.orl.2013.12.006

Baumol, W.J., & Quandt, R.E. (1964). Rules of thumb and optimally imperfect decisions. *American Economic Review*, *54*, 23-46, DOI: https://www.jstor.org/stable/1810896

Bischi, G.I., Gallegati, M., & Naimzada, A. (1999). Symmetry-breaking bifurcations and representative firm in dynamic duopoly games. *Annals of Operations Research*, *89*, 253-272, DOI: https://doi.org/10.1023/A:1018931824853

Bishi, G.I., & Kopel, M. (2001). Equilibrium selection in a nonlinear duopoly game with adaptive expectations. *Journal of Economic Behavior & Organization*, *46*(1), 73-100, DOI: https://doi.org/10.1016/S0167-2681(01)00188-3

Bischi, G.I., & Naimzada, A. (2000). Global Analysis of a Dynamic Duopoly Game with Bounded Rationality. In: Filar, J.A., Gaitsgory, V. & Mizukami, K. (eds), *Advances in Dynamic Games and Applications*. Annals of the International Society of Dynamic Games, vol 5. Birkhäuser, Boston, MA., DOI: https://doi.org/10.1007/978-1-4612-1336-9_20

Cournot, A.A. (1963). *Researches into the mathematical principles of the theory of wealth*. Homewood (IL): Irwin.

Den Haan, W.J. (2001). The importance of the number of different agents in a heterogeneous asset – pricing model. *Journal of Economic Dynamics and Control*, *25*(5), 721-746, DOI: https://doi.org/10.1016/S0165-1889(00)00038-5

Ding, J., Mei, Q., & Yao, H. (2012). Dynamics and adaptive control of a duopoly advertising model based on heterogeneous expectations. *Nonlinear Dynamics, 67*, 129-138, DOI: https://doi.org/10.1007/s11071-011-9964-y

Du, J., Huang, T., & Sheng, Z. (2009). Analysis of decision-making in economic chaos control. *Nonlinear Analysis: Real World Applications*, *10*, 2493-2501, DOI: https://doi.org/10.1016/j.nonrwa.2008.05.007

Durai, S., Subramanian, S., & Ganesan, S. (2015). Improved parameters for economic dispatch problems by teaching learning optimization. *International Journal* *of Electrical Power & Energy Systems*, *67*, 11-24, DOI: https://doi.org/10.1016/j.ijepes.2014.11.010

Elabbasy, E.M., Agiza, H.N., & Elsadany, A.A. (2009). Analysis of nonlinear triopoly game with heterogeneous players. *Computers & Mathematics with Applications, 57*, 488-499, DOI: https://doi.org/10.1016/j.camwa.2008.09.046

Elsadany, A.A. (2017). Dynamics of a Cournot duopoly game with bounded rationality based on relative profit maximization. *Applied Mathematics and Computation*, 294, 253-263, DOI: https://doi.org/10.1016/j.amc.2016.09.018

Fanti, L., & Gori, L. (2012). The dynamics of a differentiated duopoly with quantity competition. *Economic Modelling*, *29*, 421-427, DOI: https://doi.org/10.1016/j.econmod.2011.11.010

Hassan, M. H., Yousri, D., Kamel, S., & Rahmann, C. (2022). Amodified Marine predators algorithm for solving single-and multi-objective combined economic emission dispatch problems. *Computers & Industrial Engineering, 164*, 107906, DOI: https://doi.org/10.1016/j.cie.2021.107906

Holyst, J., & Urbanowicz, K. (2000). Chaos control in economical model by time-delayed feedback method. *Physica A: Statistical Mechanics and Its Applications, 287*, 587-598, DOI: https://doi.org/10.1016/S0378-4371(00)00395-2

Hommes, C.H. (2006). Heterogeneous agents models in economics and finance. In L. Tesfatsion & K.L. Judd (Eds.), *Handbook of Computational Economics: Agent – Based Computational Economics*, *2*, Elsevier Science B.V.: 1109-1186, DOI: https://doi.org/10.1016/S1574-0021(05)02023-X

Kopel, M. (1996). Simple and complex adjustment dynamics in Cournot duopoly models. *Chaos, Solitons & Fractals*, *7*(12), 2031-2048, DOI: https://doi.org/10.1016/S0960-0779(96)00070-7

Kotsios, S. (2023). Feedback Control Techniques for a Discrete Dynamic Macroeconomic Model with Extra Taxation: An Algebraic Algorithm Approach. *Mathematics, 11*, 4213, DOI: https://doi.org/10.3390/math11194213

Kulenovic, M. & Merino, O. (2002). *Discrete Dynamical Systems and Difference Equations with Mathematica*. Chapman & Hall/Crc.

Li, T., & Ma, J. (2015). Complexity analysis of dual-channel game model with different managers' business objectives. *Communications in Nonlinear Science and Numerical Simulations, 20*(1), 199-208, DOI: https://doi.org/10.1016/j.cnsns.2014.05.012

Mahdi, F. P., Vasant, P., Abdullah-Al-Wadud, M., Kallimani, V., & Watada, J. (2019). Quantum-behaved bat algorithm for many-objective combined economic emission dispatch problem using cubic criterion function. *Neural Computing and Applications, 31*, 5857-5869, DOI: https://doi.org/10.1007/s00521-018-3399-z

Naimzada, A.K., & Ricchiuti, G. (2008). Complex dynamics in a monopoly with a rule of thumb. *Applied Mathematics and Computation*, *203*, 921-925, DOI: https://doi.org/10.1016/j.amc.2008.04.020

Naimzada, A.K., & Sbragia, L. (2006). Oligopoly games with nonlinear demand and cost functions: Two boundedly rational adjustment processes. *Chaos, Solitons & Fractals*, *29*, 707-722, DOI: https://doi.org/10.1016/j.chaos.2005.08.103

Onozaki, T. (2018). *Nonlinearity, Bounded Rationality, and Heterogeneity*. Springer Tokyo, DOI: https://doi.org/10.1007/978-4-431-54971-0

Pu, X., & Ma, J. (2013). Complex dynamics and chaos control in nonlinear four-oligopolist game with different expectations. *International Journal of Bifurcation and Chaos, 23*, 1350053, DOI: https://doi.org/10.1142/S0218127413500533

Puu, T. (1995). The chaotic monopolist. *Chaos, Solitons & Fractals*, *5*, 35-44, DOI: https://doi.org/10.1016/0960-0779(94)00206-6

Puu, T. (1998). The chaotic duopolists revisited. *Journal of Economic Behavior & Organization*, *33*, 385-394, DOI: https://doi.org/10.1016/S0167-2681(97)00064-4

Pyragas, K. (1992). Continuous control of chaos by self-controlling feedback. *Physics Letters*, *170*, 421-428, DOI: https://doi.org/10.1016/0375-9601(92)90745-8

Sarafopoulos, G. (2015). Complexity in a duopoly game with homogeneous players, convex, log linear demand and quadratic cost functions. *Procedia Economics and Finance*, *33*, 366-385, DOI: https://doi.org/10.1016/S2212-5671(15)01720-7

Sarafopoulos, G. (2015). On the dynamics of a duopoly game with differentiated goods. *Procedia Economics and Finance*, *19*, 146-153, DOI: https://doi.org/10.1016/S2212-5671(15)00016-7

Sarafopoulos, G., & Papadopoulos, K. (2017). On a Cournot duopoly game with differentiated goods, heterogeneous expectations and a cost function including emission costs. *Scientific Bulletin – Economic Sciences*, *1*, 11-22, DOI: http://economic.upit.ro/RePEc/pdf/2017_1_2.pdf

Sarafopoulos, G., & Papadopoulos K. (2019). Chaos in oligopoly models. *International Journal of Productivity Management and Assessment Technologies*, *7*(1), 50-76, DOI: https://doi.org/10.4018/IJPMAT.2019010104

Sarafopoulos, G., & Papadopoulos, K. (2019). Dynamics of a Cournot game with differentiated goods and asymmetric cost functions based on relative profit maximization. *European Journal of Interdisciplinary Studies, 2*, 41-56, DOI: http://dx.doi.org/10.24818/ejis.2019.08

Sarafopoulos, G., Papadopoulos, K., & Terzopoulou, D. (2024). Dynamics of a Cournot Game with Differentiated Goods and Asymmetric Information. In C.H. Skiadas, Y. Dimotikalis, (Eds) *16th Chaotic Modeling and Simulation International Confer-*

ence. CHAOS 2023. Springer Proceedings in Complexity. Springer. DOI: https://doi.org/10.1007/978-3-031-60907-7_41

Sarafopoulos, G. & Terzopoulou, D. (2023). On the Dynamics of a Heterogeneous Duopoly Game in R&D Efforts. In N. Persiani, I.E. Vannini, M. Giusti, A. Karasavvoglou, P. Polychronidou, (Eds) *Global, Regional and Local Perspectives on the Economies of Southeastern Europe. EBEEC 2022*. Springer Proceedings in Business and Economics. Springer. DOI: https://doi.org/10.1007/978-3-031-34059-8_13

Sarafopoulos, G. & Terzopoulou, D. (2023). On the Dynamics of a Heterogeneous Duopoly Game Participating in Nitrogen Emission Reduction. In C.H. Skiadas, Y. Dimotikalis, (Eds) *15th Chaotic Modeling and Simulation International Conference. CHAOS 2022*. Springer Proceedings in Complexity. Springer. DOI: https://doi.org/10.1007/978-3-031-27082-6_22

Sarafopoulos, G., Terzopoulou, D. & Papadopoulos, K. (2024). Dynamics of a Duopoly Game in R&D Efforts with Asymmetric Information. In M. Mavri, P. Ikouta Mazza, A. Karasavvoglou, P. Polychronidou, (Eds) *Economic Growth, Prosperity and Sustainability in the Economies of the Balkans and Eastern European Countries. EBEEC 2023*. Springer Proceedings in Business and Economics. Springer. DOI: https://doi.org/10.1007/978-3-031-58437-4_7

Tramontana, F. (2010). Heterogeneous duopoly with isoelastic demand function. *Economic Modelling*, *27*, 350-357, DOI: https://doi.org/10.1016/j.econmod.2009.09.014

Satoh, A., & Tanaka, Y. (2014). Relative profit maximization and equivalence of Cournot and Bertrand equilibria in asymmetric differentiated duopoly. *Economic Bulletin*, *34*, 819-827, DOI: https://mpra.ub.uni-muenchen.de/55895/1/MPRA_paper_55895.pdf

Singh, N., & Vives, X. (1984). Price and quantity competition in a differentiated duopoly. *The RAND Journal of Economics, 15*(4), 546-554, DOI: https://doi.org/10.2307/2555525

Theerthamalai, A., & Maheswarapu, S. (2010). An effective non-iterative "λ-logic based" algorithm for economic dispatch of generators with cubic fuel cost function. *Electrical Power and Energy Systems, 32*(5), 539-542, DOI: http://dx.doi.org/10.1016/j.ijepes.2009.11.002

Wei, Z., Tan, W., Elsadany, A.A., & Moroz, I. (2023). Complexity and chaos control in a Cournot duopoly model based on bounded rationality and relative profit maximizations. *Nonlinear Dynamics*, *111*, 17561-17589, DOI: https://doi.org/10.1007/s11071-023-08782-3

PROFIT MAXIMIZATION IN LOTTERIES:
A REVIEW OF THEORETICAL APPROACHES

George Geronikolaou
Department of Economics Democritus University of Thrace
ggeronik@econ.duth.gr

Vasilios Plakandaras
Department of Economics Democritus University of Thrace
vplakand@econ.duth.gr

ABSTRACT

The academic literature on gambling behavior has consistently focused on constructing models to analyze the determinants of lottery participation. This paper offers an examination of the main theoretical frameworks in the field: the effective price model and the jackpot model. For each framework, we formally derive the corresponding profit-maximization conditions, as established in the literature, and evaluate their implications for lottery design, pricing, and operator strategy. Particular emphasis is placed on the interdependence among different gambles, a factor that complicates the direct application of standard optimization rules. In addition to these approaches, the paper reviews theoretical models that extend the analysis by treating demand for lottery bets as a function of higher-order moments of the prize distribution, including variance and skewness. These perspectives provide a more nuanced account of risk preferences and yield insights into gamblers' behavior that cannot be explained solely by price or jackpot considerations.

Keywords: *effective price; jackpot; gambling; lotteries; statistical moments*

1. Introduction

The early literature on the lottery industry adopts a standard framework, whereby maximum lottery profits occur when marginal revenue equals marginal cost. A common assumption is that variable costs are negligible, implying that the provision of an additional bet entails virtually zero marginal cost for the operator (Geronikolaou and Papachristou, 2016). This is a critical assumption that distinguishes the lottery business model from traditional manufacturing or service industries. The cost of printing an extra ticket or processing one more digital transaction is extremely low, especially when compared to the potential revenue. Therefore, the total cost of running a lottery business is largely composed of fixed costs, such as marketing, infrastructure, and administration, rather than variable costs associated with each individual sale. Therefore, profit maximization effectively converges with revenue maximization, implying that optimal lottery pricing corresponds to a demand elasticity of minus one (Cook and Clotfelter, 1993; Gulley and Scott, 1993; Mason et al., 1997; Farrell et al., 1999; Forrest et al., 2002). This principle is derived directly from the inverse elasticity rule of monopoly pricing, adapted to the distinctive cost structure of lottery markets. Our paper presents analytically the main theoretical approaches, namely the *effective price* model and the *jackpot* model and derives the profit maximizing rule for each of the two cases, as presented in the literature. We also examine approaches based on *multi-moment* lottery demand, as well as those that account for interdependence among lotteries.

Within this context, pricing strategy is commonly framed around the concept of the effective price, defined as the expected net cost of a bet to the player. Put differently, the effective price is calculated as the nominal ticket price minus the bettor's expected winnings (Farrell et al., 1999; Díaz and Pérez, 2021). From the operator's perspective, this framework is particularly useful because it highlights the levers through which bettors' demand can be influenced. The effective price can be altered either directly, by changing the nominal cost of a ticket, or indirectly, through modifications to the rules that determine expected earnings. In pari-mutuel lottery systems - where major prizes are funded as a fraction of total ticket sales - these adjustments typically concern parameters such as the payout ratio, i.e., the share of sales allocated to the prize pool, or the probability structure that determines the odds of winning. By altering these elements, operators can influence both the attractiveness of the game and the elasticity of demand.

The effective price framework offers a tractable means of linking lottery design and pricing strategy to consumer behavior. However, it abstracts from broader behavioral dimensions, including the appeal of skewed prize distributions and the disproportionate role of big jackpots in driving gambling behavior. Analyzing demand based solely on effective price implicitly assumes that participants focus only on the mean of the distribution, disregarding risk aversion or preferences for skewness and other higher statistical moments. Another strand of the literature argues that lottery participation is driven not only by the mean value of expected earnings but also by higher moments of the prize distribution, particularly skewness (Garrett and Sobel, 1999; Walker and Young, 2001; Wang et al., 2006). Within this framework, risk-averse bettors may accept unfavorable bets if they are compensated by a sufficiently large positive skewness, which captures the appeal of rare but substantial prizes. Consequently, demand functions for lottery products should incorporate higher-order moments in addition to expected value. However, extending the analysis in this way complicates theoretical inference because the inclusion of higher moments makes it less straightforward to determine whether operators should design games to be more or less generous in order to maximize profits.

The study of preferences over higher order statistical moments of the prize distribution has a long and well-established tradition in economics. In an early contribution, Tsiang (1972) highlighted that agents' risk attitudes are not fully captured by mean-variance considerations alone. Instead, the shape of the entire distribution - including skewness - plays a crucial role in decision-making. Tsiang (1972) further noted that such preferences for skewness are not confined to gambling. Instead, under standard assumptions, it is a general characteristic of all agents. A closely related concept is prudence - agents' tendency toward precautionary behavior - as defined by Kimball (1990), which likewise requires a preference for skewness and highlights the broader economic relevance of third-order risk preferences beyond gambling (Eeckhoudt and Schlesinger, 2008).

In the domain of gambling behavior, Golec and Tamarkin (1998) and Garrett and Sobel (1999) found that risk-averse gamblers exhibit a systematic preference for positively skewed outcomes, indicating that the prospect of a low-probability, high-payoff win can outweigh expected losses. In other words, skewness itself has an intrinsic appeal beyond expected value considerations. Further empirical evidence supports this claim: using data from the UK National Lottery, Walker and Young (2001) demonstrated that lottery demand responds not only to the mean returns but also to higher-order distributional features. Specifically, ticket sales increase with expected returns, decrease with variance (reflecting risk aversion), and rise with skewness, confirming that the allure of infrequent large jackpots is a powerful determinant of lottery participation.

From a formal perspective, a preference for positive skewness is captured mathematically by a positive third derivative of the gambler's utility function, which indicates that the marginal utility of wealth increases at an increasing rate. This relationship is often illustrated using a Taylor-series approximation of expected utility up to the third-order term. Taken together, this body of research underscores the importance of incorporating higher-order moments into models of lottery demand. By recognizing that bettors respond not only to expected returns but also to skewness and related distributional features, these models offer a more realistic and nuanced understanding of gambling behavior, while also highlighting the limitations of approaches that rely solely on mean-variance analysis.

However, several studies extend the analysis beyond skewness by examining investor behavior with respect to even higher-order moments. Brockett and Garven (1998) argue that truncating the Taylor-series expansion of the utility function at the third term is arbitrary, and that higher-order terms should be included to more accurately capture agents' preferences. The literature indicates that agents generally exhibit kurtosis aversion, and that risk-averse agents generally prefer distributions with lower kurtosis. (Eeckhoudt et al., 1996; Eeckhoudt and Schlesinger, 2008; Chow et al., 2023).

Forrest et al. (2002) proposed the *jackpot model*, which assumes that bettors purchase lottery tickets primarily in pursuit of the grand jackpot, while smaller prizes play a negligible role in driving overall lottery demand. By emphasizing the dominant influence of the top prize, the model bridges the effective price framework and the higher-moments approach. Specifically, the grand jackpot represents both the main source of a ticket's expected value and its positive skewness, each of which is a key determinant of gambling participation (Walker and Young, 2001). Within this framework, operators' profits are maximized when the payout ratio equals the jackpot elasticity of demand (Papachristou, 2006). Because the jackpot strongly influences both expected returns and the appeal of extreme outcomes, adjusting the payout ratio provides operators with a mechanism to shape demand. This approach highlights how lottery design can be strategically aligned with participants' preference for high-payoff, low-probability outcomes, while offering a tractable method for profit optimization.

Another line of research investigates how the substitutability or complementarity among different gambling games influences lottery pricing and profit maximization (Forrest et al., 2007; Forrest and McHale, 2007; Lin and Lai, 2006; Forrest et al., 2010; Pérez and Forrest, 2011; Pérez and Humphreys, 2013; Geronikolaou and Papachristou, 2016). In such contexts, profit maximization becomes more complex due to the interdependent demand structures across games. Notably, Pérez and Forrest (2011) highlight that when an operator offers multiple games whose demands are interrelated, the conventional unit-elasticity rule of the effective price framework must be adjusted. Building on this insight, Geronikolaou and Papachristou (2016) develop a profit-maximization model based on the effective price approach that explicitly accounts for substitutability or complementarity among bets offered by the same operator. In particular, when two lotteries function as substitutes, they argue that the operator should protect the larger (relatively most profitable) lottery by setting a sufficiently high effective price on the smaller one, thereby preventing cannibalization and safeguarding overall profitability. Extending this perspective, Geronikolaou (2018) adapts the jackpot model to incorporate interdependencies among lottery bets, providing a more comprehensive framework for understanding profit optimization in multi-game environments.

The paper is organized as follows: first we present the theoretical background of the *effective price*, the *multi-moment* and the *jackpot* model. We then discuss extensions that incorporate substitutability or complementarity among gambling products and we end the paper with the conclusions.

2. Theoretical Approaches

2.1 Effective Price Approach

The effective price framework assesses the net expected return per wager, taking into account both the ticket price and the expected earnings. The calculation subtracts expected prize values from the nominal ticket cost, adjusting for probabilities of success and rollover contributions (previous draw unwon jackpot that is added to the big prize of the subsequent draw). The resulting formula, as outlined by Cook and Clotfelter (1993) (see also Geronikolaou and Papachristou, 2016), provides a benchmark for assessing demand elasticity with respect to pricing. Effective price is thus:

$$P = C - p(J+R)\frac{(1-e^{-pB})}{pB} \tag{1}$$

where C is the nominal price of a bet, *p* is the probability of winning the big prize, *J* is the jackpot, *R* represents the rollover amount, defined as the unclaimed prize from the previous draw that is carried forward to the current lottery draw, *B* is the number of bets, and the last term is the bettor's expected share over the big prize, approximated via a Poisson distribution which essentially depends on the expected number of winners. Typically, profit maximization in this context consists in setting the price elasticity of lottery demand equal to minus 1 (-1) assuming that the operator has relatively small marginal costs. Thus, the profit maximization rule coincides with that of revenue maximization in a standard monopoly setting.

2.2 Higher Moments Approach

Beyond mean values, demand modeling often incorporates higher-order statistical moments such as variance and skewness. A Taylor series expansion of the bettor's utility function illustrates how these moments influence expected utility. Preference for skewness motivates bettors to favor lottery bets that exhibit positively skewed distributions of prizes. Incorporating such factors into demand estimation introduces complexity, notably the endogeneity between the demand for bets and earnings statistical moments. Endogeneity stems from the fact that all earnings moments are a function of bets themselves.

Typically, the literature assumes that one can truncate a Taylor series approximation of the bettor's utility at the third term (Golec and Tamarkin, 1998) although one can assume a generalization of this approach and present a Taylor-series approximation of the bettor's utility function to include higher terms. A standard utility function expansion up to the third term is

$$U(X) = U(\mu) + U^{(1)}(\mu)(X-\mu) + \frac{U^{(2)}(\mu)}{2!}(X-\mu)^2 + \frac{U^{(3)}(\mu)}{3!}(X-\mu)^3 \qquad (2)$$

where $U(X)$ denotes the gambler's utility function, μ is the mean, and superscripts denote derivatives. Applying the expectation operator to both sides of 2, we get

$$E[U] = U(\mu) + \frac{U^{(2)}(\mu)}{2!}\sigma^2 + \frac{U^{(3)}(\mu)}{3!}s \qquad (3)$$

where σ^2 and s are the variance and skewness of the earnings distribution respectively. In that sense, any modelling of bettor's demand must also account for higher moments which create complications in the empirical analysis of lottery demand.

2.3 Jackpot Approach

The jackpot model unifies effective price considerations with the moments-based perspective. This framework posits that bettors are primarily motivated by the pursuit of the grand jackpot, interpreted as "buying a dream" (Forrest et al. 2002). Here, lottery demand depends heavily on jackpot size, which encapsulates both skewness and expected value (Walker and Young, 2001). Within this paradigm, operator profits are maximized when the payout ratio equals the elasticity of demand with respect to jackpot size (Papachristou, 2006). This formulation reinforces the interchangeability of revenue and profit maximization when marginal costs remain negligible.

Any lottery rule that affects the expected earnings of a bet will also affect the earnings' moments. In this section we focus on the payout ratio of the game. Assume that players care mainly about the big jackpot of the lottery game and not for the other prizes. Then, a lottery operator's profit is

$$\Pi = S(J) - Q \qquad (3)$$

where sales *S* are a function of total jackpot *J*. Jackpot is the sum of current prize *Q* plus any rollover *R* from previous unwon prizes that are added to the next draw (*J*=*Q*+*R*). Maximizing (3) w.r.t. to current prize Q gives

$$\frac{\partial S(J)}{\partial J}\frac{\partial J}{\partial Q} = 1 \tag{4}$$

where $\frac{\partial J}{\partial Q} = 1$. Multiplying both parts with *J/S* gives

$$\frac{\partial S}{\partial J}\frac{\partial J}{\partial S} = \frac{J}{S} \tag{5}$$

which implies that

$$\frac{Q}{S} = \frac{\partial S}{\partial J}\frac{\partial J}{\partial S} - \frac{R}{S} \tag{6}$$

Therefore, equation 6 indicates that the payout ratio *Q/S* must be equal to the jackpot elasticity ($\frac{\partial S}{\partial J}\frac{\partial J}{\partial S}$) minus a term *R/S* which is the size of rollovers as a percentage of sales. Notice that treating rollovers *R* as exogenous and maximizing w.r.t. to *Q* instead of *J* implies that that the payout ratio (*Q/S*) must be equal to the current prize elasticity $\frac{\partial S}{\partial Q}\frac{\partial Q}{\partial S}$.

2.4 Interdependent lotteries

In this section, we provide a brief presentation of the model developed by Geronikolaou and Papachristou (2016), which investigates the profit-maximizing pricing rule in the context of interdependent lotteries. Consider an operator who functions as a multiproduct monopolist and offers two lottery games, denoted as *i* and *j*. The operator's profit function is expressed as follows:

$$\Pi = B_i(P_i,P_j)P_i + B_j(P_i,P_j)P_j - \gamma_i B_i(P_i,P_j)F_i - \gamma_j B_j(P_i,P_j)F_j \quad (7)$$

Here, $B_i(P_i, P_j)$ represents the number of bets placed on lottery *i*, which depends on the effective prices P_i and P_j. The parameter γ denotes the probability of winning a fixed prize, while *F* refers to the value of the corresponding prize. The first two terms in Equation (7) capture sales revenue associated with the grand (pari-mutuel) prizes, whereas the latter two terms represent the operator's expected variable cost arising from obligations to pay fixed, smaller prizes.

Effective prices are defined as the net expected gains per bet derived exclusively from the jackpot, with the formula for effective price given by formula 1. In the model, fixed prizes are assumed to exert no influence on demand. Accordingly, while they contribute to the operator's costs, they do not alter consumer behavior. This modeling choice, though a simplification, is consistent with both empirical evidence and theoretical reasoning. Specifically, prior studies demonstrate that bettors' demand for lottery tickets is largely driven by skewness of the payoff distribution along with expected returns (Golec and Tamarkin, 1998; Garrett and Sobel, 1999) where skewness is overwhelmingly generated by the size of the jackpot rather than by smaller prizes (Walker and Young, 2001). Moreover, this treatment is justified by the nature of rollover dynamics: variability in the effective price is exogenously determined by jackpot rollovers (Farrell et al., 1999), whereas fixed prizes remain constant and therefore do not induce shifts along the demand curve.

Maximizing the profit function 7 with respect to P_i together with some algebraic calculations yields:

$$E_i = \frac{P_i}{P_i - MC_i} + E_{i,j}\frac{(P_j - MC_j)B_j}{(P_i - MC_i)B_i} \quad (8)$$

where E_i denotes the own-price elasticity of lottery *i*, $E_{i,j} = (\partial B_j P_i)/(\partial P_i B_j)$ is the cross-price elasticity between lotteries *i* and *j*, and *MC* is the marginal cost of a bet, defined as the expected extra liability of fixed-prize payments.

Equation 8 reveals that when two lotteries are substitutes, a greater relative contribution of game *j* to profits (represented by the last fraction in 8), is associated with a higher own-price elasticity E_i and, consequently, a higher optimal effective price of lottery *i*. Therefore, in the case of substitutable products, the operator's optimal strategy entails setting a higher effective price for the less profitable lottery so as to shield the more profitable game from demand erosion. Conversely, in the case of complements, the opposite holds: stronger relative profitability reduces the optimal effective price of the associated game in order to encourage joint demand. Overall, the model illustrates a central strategic principle: in markets characterized by interdependent demand, a monopoly operator will structure its pricing policy so as to prioritize the protection and reinforcement of its more profitable products.

3. Conclusions

This paper has revisited and synthesized the two common frameworks in the economics of lottery pricing - the *effective price* model and the *jackpot* model - while also addressing extensions that account for interdependence among games. The effective price approach, grounded in the inverse elasticity rule, emphasizes revenue maximization under the assumption of negligible marginal costs. Although analytically tractable, this model abstracts from bettor preferences for distributional characteristics beyond expected value. In contrast, the jackpot model incorporates behavioral insights, particularly the role of skewness and the salience of the grand prize, thereby offering a richer explanation of observed lottery demand. We also discuss the concept of multi-moment lottery demand, which arises from approximating bettors' utility through a Taylor-series expansion up to the third-order term.

The consideration of interdependence among games introduces additional layers of complexity. As shown by various papers, substitutability and complementarity among lottery products fundamentally alter optimal pricing strategies. In such contexts, operators must not only maximize revenue from individual games but also strategically allocate profitability across their portfolio, protecting larger and more lucrative lotteries while calibrating smaller ones to avoid cannibalization or, conversely, to foster complementarities.

Taken together, these insights highlight that the problem of lottery profit maximizing is not reducible to a single pricing rule but must instead be understood as a multidimensional optimization problem shaped by demand interrelations, jackpot dynamics, and bettor preferences for higher moments of the payoff distribution. Future research should focus on addressing the empirical challenges posed by endogeneity in higher-moment demand models, as well as on developing robust instruments that capture the behavioral drivers of lottery participation. By advancing these lines of research, scholars can enhance both the theoretical understanding of lottery markets and the practical design of pricing strategies in state-controlled and private lottery games alike.

References

Brockett, P.L., Garven, J.R., 1998. A Reexamination of the Relationship Between Preferences and Moment Orderings by Rational Risk-Averse Investors. The Geneva Papers on Risk and Insurance Theory, 23(2), 127–137.

Chow, K.V., Li, B., Wang, Z., 2023. Swap variance hedging and efficiency: The role of high moments. The Journal of Financial Research, 46(3), 681-709.Cleveland, W.S., Devlin, S.J., 1988. Locally-Weighted Regression: An Approach to Regression Analysis by Local Fitting. Journal of the American Statistical Association, 83 (403), 596–610.

Cook, P.J., Clotfelter, C.T., 1993. The Peculiar Scale Economies of Lotto. American Economic Review, 83, 634-643.

Díaz, A., Pérez, L. 2021. Setting the Odds of Winning the Jackpot: On the Economics of (Re) Designing Lottery Games." Contemporary Economic Policy, 39 (1), 168–187.

Eeckhoudt, L., Gollier, C., Schlesinger, H., 1996. Changes in Background Risk and Risk Taking Behavior. Econometrica, 64(3), 683–689.

Eeckhoudt, L., Schlesinger, H., 2008. Changes in risk and the demand for saving, Journal of Monetary Economics, 55(7), 1329-1336.

Farrell, L, Morgenroth, E, Walker, I. 1999. A time-series analysis of UK lottery sales: long and short run price elasticities. Oxford Bulletin of Economics and Statistics 61: 513–526.

Forrest, D., Simmons, R., Chesters, N., 2002. Buying a Dream: Alternative Models of Demand for Lotto. Economic Inquiry, 40, 485-496.

Forrest, D, Gulley, O, Simmons, R., 2007. Substitution between games in the UK national Lottery. Applied Economics 36, 645-651.

Forrest, D., McHale, I., 2007. The relationship between a national and a multistate lotto game. The Journal of Gambling Business and Economics, 1, 207–216.

Forrest, D., Gulley, O., Simmons, R., 2010. The relationship between betting and lottery play. Economic Inquiry 48, 26–38.

Garrett, T.A., Sobel, R.S., 1999. Gamblers favor skewness, not risk: Further evidence from United States' lottery games. Economics Letters, 63(1), 85-90.

Geronikolaou, G., Papachristou, G., 2016. State Lotteries as a Multiproduct Monopoly. Managerial and Decision Economics 37(3), 208-212.

Geronikolaou, G., 2018. Interdependent lotteries and the jackpot model of lottery demand. The Journal of Gambling Business and Economics 12(2), 37-43.

Golec, J., Tamarkin, M., 1998. Bettors love skewness, not risk, at the horse track. Journal of Political Economy, 106(1), 205-225

Gulley, O, Scott, F. 1993. The demand for wagering in State-operated lottery games. National Tax Journal 45: 13-22.

Kimball, M.S., 1990. Precautionary savings in the small and in the large, Econometrica, 58, 53-73.

Lin, C, Lai, C. 2006. Substitute effects between Lotto and Big Lotto in Taiwan. Applied Economics Letters 13, 655-658.

Mason, P.M., Steagal, J.W., Fabritius, M.M., 1997. The elasticity of demand for Lotto tickets and the corresponding welfare effects. Public Finance Review 25: 474-490.

Papachristou, G., 2006. Is lottery demand elasticity a reliable marketing tool? Evidence from a game innovation in Greece. International Review of Economics, 53, 627-640

Perez, L, Forrest, D., 2011. Own- and cross-price elasticities for games within a state lottery portfolio. Contemporary Economic Policy 29, 536–549.

Perez, L., Humphreys, B., 2013. The 'who and why'of lottery: Empirical highlights from the seminal economic literature. Journal of Economic Surveys, 27(5), 915-940.

Tsiang, S.C., 1972. The Rationale of the Mean-Standard Deviation Analysis, Skewness Preference, and the Demand for Money. American Economic Review, 62(3), 354-371.

Walker, I., Young, J. 2001. An economist's guide to lottery design. The Economic Journal, 111, 700–722.

Wang, J.H., Tzeng, L.Y. and Tien, J., 2006. Willingness to pay and the demand for lotto. Applied Economics 38, 1207–1216

A MULTIDIMENSIONAL EVALUATION FRAMEWORK FOR SUPPLY CHAIN CORPORATE PERFORMANCE

Aristi Karagkouni
Department of Economics, Democritus University of Thrace
MaGBISE Research Laboratory
arkaragk@econ.duth.gr

ABSTRACT

This paper proposes a multidimensional evaluation framework for assessing the contribution of supply chain performance to overall corporate performance. Traditional supply chain metrics often focus narrowly on operational efficiency or cost, failing to capture the broader strategic and stakeholder-oriented outcomes that modern supply chains influence. Drawing on the resource-based view, systems theory, stakeholder theory, and contingency theory, this study develops a conceptual model integrating five key dimensions: operational efficiency, financial contribution, customer value and responsiveness, strategic alignment and agility, and sustainability and ESG performance. The framework provides a structured yet adaptable tool that enables organizations to evaluate performance across interdependent domains, account for trade-offs, and align supply chain capabilities with long-term strategic goals. The paper contributes to both theory and practice by offering a comprehensive approach to performance measurement that reflects the evolving role of supply chains in creating corporate value.

Keywords: *Supply Chain Management, Corporate Performance, Multidimensional Framework, Performance Evaluation*

1. Introduction

The changing dynamics of global market demand, rapid technological advances, and increased expectations by the stakeholders have all together transformed supply chain management (SCM) from a subservient operational function to a central component of corporate strategy and performance. Against the backdrop of a highly competitive globalized market, the companies are no longer judged on the basis of quarterly earnings anymore, but by their ability to deliver lean, flexible, and sustainable supply chains (Christopher, 2016; Ivanov et al., Karagkouni and Dimitriou, 2025). Besides, the effectiveness of supply chains has gotten deeply linked with corporate performance at the highest level, covering the domains of financial, strategic, environmental, and social. Despite growing recognition of the problem, the assessment of supply chain performance remains fragmented. Traditional metrics almost always focus on operational measures like cost effectiveness, material movements, and lead times, therefore providing a narrow view of performance that ignores wider organizational goals (Beamon, 1999; Gunasekaran et al., 2004). Corporate performance models, by comparison, usually favor monetary results or shareholder value, possibly to the detriment of the crucial role that supply chains provide in either supporting or hindering strategic objectives (Kaplan & Norton, 1996; Hitt et al., 2007).

Several frameworks have attempted to address different facets of the problem (Karagkouni and Dimitriou, 2025). For example, the Supply Chain Operations Reference (SCOR) model allows for standardized analysis of supply chains, while the Balanced Scorecard allows for a multi-faceted view of organizational performance (Kaplan & Norton, 1996). However, the overwhelming majority of the above frameworks do so in isolation or focus on a single dimension, without simultaneously evaluating the operational, financial, strategic, and sustainable impact of the supply chain on corporate performance.

This paper presents an evaluation framework intended to link supply chain performance with general corporate performance appraisal. The framework interweaves key performance dimensions into an integrated model. It further considers the relationships between different dimensions, as well as the feedforward mechanisms inherent in the dimensions, thus taking cognizance of the systemic nature of modern supply chains and its impingement upon corporate performance. Through the linkage of supply chain metrics with wider organizational goals, the framework here puts forward a coherent process of performance appraisal that has a valid theoretical base as well as practical utility. This study offers three key contributions. It initially reviews and evaluates the literature of the supply chains and corporate performance evaluation, highlighting the need for an integrated methodology.

2. Literature Background

2.1. Overview of Supply Chain Performance Metrics

Evaluation of supply chain performance has traditionally depended upon operational paradigms that emphasize process effectiveness, minimizing expense, and serviceability. Historically, prior work has focused mainly on internal logistics as well as in-house manufacturing-related metrics, such as inventory turns, order fulfillment time, use of capacity, and delivery reliability (Beamon, 1999; Gunasekaran et al., 2004). While important, they tend to indicate a model that has largely process-centric, transaction-centric focus with no strategic direction. Beamon (1999) argued in favor of a broader, integrative system of supply chain performance measurement, dividing it into three general categories: resources (costs, utilization, etc.), outputs (product quality, customer satisfaction, etc.), and flexibility (capacity to change in response to demand variation or disruptions). Consistent with that view, Gunasekaran et al. (2004) developed a systematic system of metrics that extend across strategic, tactical, and operational scopes, thus linking supply chain efforts with broader organizational goals.

In the modern debate, the concept of supply chain performance has progressed to cover collaboration, transparency of information, and digital flexibility, in response to the growing inclusion of breakthroughs in technologies like the Internet of Things (IoT), artificial intelligence (AI), and blockchain in supply chains (Choi et al., 2018; Büyüközkan & Göçer, 2018). Besides, sustainability metrics are increasingly important, driven by regulatory requirements as well as social pressure in favor of corporate social responsibility. These are the indicators of greenhouse gas (GHG) emissions, water use, workforce labor standards of the supplier base, and waste reduction in the whole value chain (Ahi & Searcy, 2013; Brandenburg et al., 2014).

2.2. Key Dimensions of Corporate Performance

Historically, corporate performance evaluation has depended on financial indicators, mainly geared toward increasing the value of shareholders. Widely used gauges include return on assets (ROA), return on equity (ROE), earnings per share (EPS), and market capitalization (Kaplan & Norton, 1996; Hitt et al., 2007). Although such gauges provide essential information regarding short-term financial health, they often don't sufficiently represent long-term value creation, especially in innovation, supply chains, or social license to operate industries. The drawbacks inherent in the exclusive use of a single monoeconomic gauge have triggered the evolution of balanced performance portfolios. The Balanced Scorecard (Kaplan & Norton, 1996) has been central in this evolution, outlining four interacting views: financial, customer, internal business processes, and learning and growth. By complementing leading indicators through the use of lagging indicators, the Balanced Scorecard allows for a balanced view of how organizational competencies are transformed into value.

A notable development in the area of corporate performance appraisal is summarized in the framework of the Triple Bottom Line (TBL) (Elkington, 1997), that companies must be judged across three areas: economic, environmental, and social performance. TBL enables a broader notion of value that moves beyond profit, considering ecological, as well as social, well-being. Although TBL has had considerable conceptual impact, however, it has often been criticized in terms of the shortcomings of its operationalization, as well as the specificity of the metrics (Norman & MacDonald, 2004). More recently, the development of Environmental, Social, and Governance (ESG) standards of reporting has entrenched the inclusion of non-financial indicators of performance within corporate appraisal (Sartzetaki et al., 2025). These standards require companies to quantitatively express, and publicly disclose, their carbon emission, diversity, inclusion, board independence, as well as the ethics in the supply chain. In addition, modern performance models focus on stakeholder value instead of shareholder value, similarly embracing the principles of stakeholder theory (Freeman, 1984).

2.3. Existing Frameworks and Gaps

A variety of different frameworks have been developed to evaluate supply chains or organizational performance in seclusion. Among the most commonly cited models in the supply chain literature, the Supply Chain Operations Reference (SCOR) model, developed by the Supply-Chain Council, outlines standardized metrics of performance in five core processes: Plan, Source, Make, Deliver, and Return. The SCOR model supplies process-centric, all-inclusive metrics like order cycle time, perfect order fulfillment, and supply chains spent. However, its chief focus almost always remains at the operational level, ignoring wider strategic, environmental, or social factors. The Balanced Scorecard (Kaplan & Norton, 1996) and Triple Bottom Line (Elkington, 1997) frameworks are early attempts at widening the corporate performance evaluation by including non-financial factors. Both, however, struggle in communicating the cross-functional or trans-organizational nature of supply chains effectively.

Modern concepts in Sustainable Supply Chain Management (SSCM) aim to redress the imbalance by aligning social, environmental, and economic considerations in supply chains (Seuring & Müller, 2008; Pagell & Wu, 2009). These concepts, however, often favor sustainability at the expense of other strategic priorities, such as innovation, flexibility, and customer focus. In addition, software that values the integration of multi-criteria decision-making (MCDM) techniques with systems thinking paradigms in the assessment of performance (Bai & Sarkis, 2010; Azevedo et al., 2011) holds important promise for navigating complexity by simultaneously achieving trade-off balance. These, however, often find difficulty in the scale or need much data, thus constraining further use in larger organizational contexts.

In sum, the literature reveals three key limitations:

- Siloed frameworks: Most existing models focus on either supply chain performance or corporate performance, rarely addressing the intersection of the two.
- Unidimensional metrics: Frameworks tend to prioritize either operational, financial, or sustainability metrics without integrating them into a cohesive system.
- Lack of strategic alignment: Few models explicitly connect supply chain activities to long-term corporate goals, stakeholder value creation, or enterprise risk management.

These limitations underscore the need for a multidimensional evaluation framework that can: (1) capture the breadth of supply chain contributions to corporate performance, (2) facilitate strategic alignment, and (3) accommodate multiple performance domains, including operational efficiency, financial impact, innovation, resilience, and sustainability.

3. Conceptual Foundations

3.1. Theoretical Underpinnings

Resource-Based Perspective, as outlined by Barney (1991), asserts that a sustained advantage can be obtained by the acquirement, development, and utilization of resources that are VRIN (valuable, rare, inimitable, and non-substitutable). Supply chain capability, consisting of agility, integration, information exchange, and supplier collaboration, can be treated as strategic resources if they are ingrained in the routines of the organization and tailored to the organization-specific environment of the firm (Wong et al., 2011; Dyer & Singh, 1998). According to this perspective, the effectiveness of the supply chain transcends functional significance, crosses the boundaries of strategic significance, and becomes an important predictor of firm-level outcomes like product innovation, speed of operation, and market position. Systems theory provides an integrated framework for the analysis of organizations as complex, dynamic systems of interconnected subsystems (Mentzer et al., 2001). The supply system operates within the broader framework of the enterprise; thus, its effectiveness has to be appraised in terms of its contribution to achieving organizational goals.

According to Freeman (1984) stakeholder theory, corporate success is achieved based on the ability to create and maintain value for multiple, diverse groups of stakeholders, not merely the shareholders. These linkages of the supply chains are between the communities, the customers, the employees, the regulatory agencies, and the suppliers. Thus, supply chain performance must be measured based on the parameters that represent stakeholder results, such as ethical sourcing, fair employment practices, environmental impact, as well as the ability to respond to the demands of the customers (Harrison et al., 2010). The lens of analysis thus broadens from mere economic efficacy to social and environmental responsibility.

Contingency theory asserts that no organizational design or system of performance appraisal works in all situations, but that the organization finds success through the congruence of internal resources with external environmental variables (Lawrence & Lorsch, 1967). Theory supports the view that the metrics, such as benchmarks, employed in the appraisal of supply chain performance are based in the specific attributes of the industry, market diversity, regulatory environment, and strategic priorities. The diversity of the different theoretical orientations calls for the development of an integrative framework that ties all the different activities of the supply system together in order to maximize organizational performance.

3.2. Linking Supply Chain Performance to Corporate Outcomes

Operational effectiveness works as the key link between supply chains' efficacy and organisational performance. Effective logistics, improved inventory management, and reduced lead times generate prompt cost reduction and improved asset utilisation, thus increasing profitability (Christopher, 2016; Chopra & Meindl, 2019). For companies that are focused on cost leadership, the efficacy of their supply chains lies at the centre of achieving, as well as sustaining, competitive advantage. Shorter order fulfillment cycles, higher service levels, and customization capabilities contribute to customer loyalty and market share growth (Lee, 2004; Sartzetaki et al, 2025). These outcomes are especially vital in industries where customer experience is a key differentiator. Thus, customer-focused supply chain metrics are directly linked to top-line corporate performance.

Effective supply chains are important in supporting organizational agility, covering the ability to sense and respond quickly to changes in the market, disruptions, or new opportunities. Agile supply chains support firms' innovation efforts by allowing fast product launches, the consideration of different sourcing options, and flexibility in responding to changing consumer tastes (Swafford et al., 2006; Yusuf et al., 2014). During times of turmoil, this agility can be a key enabler of long-term survival and profitability. Sustainable supply chains influence corporate performance through the reduction of regulatory risk, appealing to consumerism based on ethics, and corporate reputation enhancement. Carbon emission-related factors, ethical sourcing, and circular economy actions contribute to non-financial performance indicators, such as the ESG score, as well as brand equity (Pagell & Wu, 2009; Seuring & Müller, 2008).

Supply chain effectiveness greatly facilitates the attributes related to corporate risk management. Resilient supply chains are central to maintaining functional continuities and protecting shareholders' value (Pettit et al., 2010). Performance in this sector that can be measured includes supply redundancy, lead time variation, and disruption response time, all of which are associated with long-term strategic stability. A multidimensional evaluation framework must therefore reflect this complexity, providing a structured means of assessing how supply chain activities align with and support strategic organizational goal.

4. Multidimensional Evaluation Framework development

This section presents a comprehensive evaluation framework designed to capture the multifaceted nature of supply chain performance and its contribution to overall corporate performance, including operational efficiency, financial outcomes, customer responsiveness, strategic agility, and sustainability. Each dimension is articulated below with corresponding performance constructs and theoretical rationale. The key dimensions as well as their corresponding performance indicators are analytically depicted in Figure 1.

Figure 1: Dimensions of the Multidimensional Supply Chain Performance Framework

4.1. Operational Efficiency

Operational efficiency is a primary focus of supply chain performance appraisal. It refers to the ability of the supply chain to convert inputs into outputs in a timely, cost-effective, and reliable fashion. These are often key metrics associated with this concept of operation: inventory turn, order fulfillment lead time, perfect order percentage, forecast accuracy, and transportation or logistics unit cost (Beamon, 1999; Gunasekaran et al., 2004). These are crucial in daily appraisal of operational effectiveness, assisting in the detection of bottlenecks, redundancies, and waste in the supply chain. Historically, supply chain metric appraisal has largely focused on such operational norms in the contexts of lean philosophy and Six Sigma techniques (Chopra & Meindl, 2019). Although operational effectiveness can enhance monetary results, however, there is an increasingly accepted awareness that this reflects merely one part of value creation. Overemphasis on efficacy, as witnessed by the example of the just-in-time system, may sacrifice adaptability and robustness in the face of disruptions (Karagkouni and Dimitriou, 2025). Thus, operational metrics need to be contextualized in terms of other systemic and strategic results.

4.2. Financial Contribution

Financial contribution of supply chain extend further than direct cost savings; they also extend to its impact on profitability, return on assets, working capital management, and shareholder value. For this purpose, key performance metrics (KPIs) of the supply chain consist of the supply chain cost in terms of percentage of sales, procurement savings, margin enhancement contributions, and improvements in cash-to-cash cycle time (Kaplan & Norton, 1996; Hitt et al., 2007). By adding financial gauges, the supply chain falls no longer in the class of secondary, ancillary functions, but rather, as a key revenue generating function of the organization in terms of value creation. Financial additions often result from other functional improvements, like better customer satisfaction, quicker flexibility of the operation, or better ESG performance, that indicate the integrative function of this area. However, some benefits need not materialize in immediate terms of the accounts. It therefore requires the use of leading as well as of lagging gauges to follow the short-term as well as the long-term terms of the supply chain strategies on the finances (Kaplan & Norton, 2004).

4.3. Customer Value and Responsiveness

This dimension focuses on how the supply chain can support improved customer satisfaction, loyalty, and retention by offering service reliability, product availability, and flexibility in service adaptation to changing consumer tastes. With intense competition and constant change being the norm, the ability to meet or exceed the expectations of the customer has become a key differentiator. Performance metrics can include the percentage of on-time deliveries, order correctness, the ability to accept special requests, service lead times, and customer satisfaction metrics like the Net Promoter Score (NPS) (Lee, 2004; Hult et al., 2007). The delivery of customer value in the supply chain ties directly into the idea of a demand-driven supply chain, where the focus remains on responsiveness, visibility, and real-time market alignment. Improved responsiveness can result in better customer retention, increased revenues, and better brand equity (Choi et al., 2018).

4.4. Strategic Alignment and Agility

Strategic alignment refers to how well the supply chain can accommodate and maintain the broader business strategy. Agility, by contrast, refers to the supply chain's ability to respond to environmental changes, disruptions, and new opportunities. These are the key competencies in VUCA (volatile, uncertain, complex, ambiguous) environments. Appropriate metrics can include the timescales involved in the introduction of new products, the flexibility of the supply chain, the integration of new technologies by the supplier base, and the digital maturity level (Swafford et al., 2006; Yusuf et al., 2014). The concept of flexibility has its origin in the concept of the dynamic capabilities framework, highlighting sensing and transforming changes. Supply chains that are flexible, able to change sourcing, manufacturing, and logistics configurations are better at mitigating risk and capitalizing on new opportunity sooner than less flexible supply chains. Strategic alignment ensures that the flexibility competencies are applied in ways that are aligned with organizational priorities, such as market entry, service differentiation, or the achievement of sustainable growth.

4.5. Sustainability and ESG Performance

Sustainability and ESG performance concepts moved from the periphery of corporate thinking to central positions in corporate strategy and stakeholder engagement. The supply chain plays a key role in the attainment of ESG goals, particularly through its influence on upstream and downstream partners. Key metrics of consideration are Scope 3 carbon emissions, energy and water consumption, the percentage of recycled or sustainably sourced materials, supply chain labor standards, and the percentage of supplier non-compliance in terms of ESG (Ahi & Searcy, 2013; Seuring & Müller, 2008). This dimension captures the principles of stakeholder theory (Freeman, 1984), whose ideas suggest that corporate achievements must be judged on the basis of their positive impact on all the various stakeholders instead of shareholders only. The use of the ESG criteria in the evaluation of the supply chains aligns with investor expectations, enhances brand credibility, and reduces regulatory as well as reputational risk (Mixafenti et al., 2025).

4.6. Interrelationships and Trade-Offs Among Dimensions

These five dimensions, outlined above, are intertwined and can generate synergies as well as trade-offs. Digital investments in the supply chains can, by contrast, enhance agility, customer responsiveness, as well as ESG transparency simultaneously, generating positive effects in several dimensions. It is crucial to recognize and deal with such interdependences. A framework of systems thinking emphasizes that all modifications in one area of the supply chains will transform others. Thus, companies should evaluate the performance by an integrated dashboard that supports the thorough analysis and strategic consistency. Techniques of trade-off analysis, scenario modeling, and multi-criteria decision-making can help in the process (Bai & Sarkis, 2010; Azevedo et al., 2011).

The developed model outlines a conceptually valid and operationally practical framework for assessing the influence of supply chain performance on organizational results. With the integration of five core dimensions, the framework breaks through the limitations inherent in simplistic or unidimensional formulations. It embodies a macro perspective that considers the voluntary and systemic nature of contemporary supply chains yet pays considerable attention to the paramount importance of value creation..

5. Evaluation Methodology and Assessment Approach

This section elaborates on each of these methodological elements, establishing how the framework can be implemented within a practical yet theoretically informed evaluation system. The key steps in implementing the proposed evaluation framework are analytically depicted in Figure 2 below.

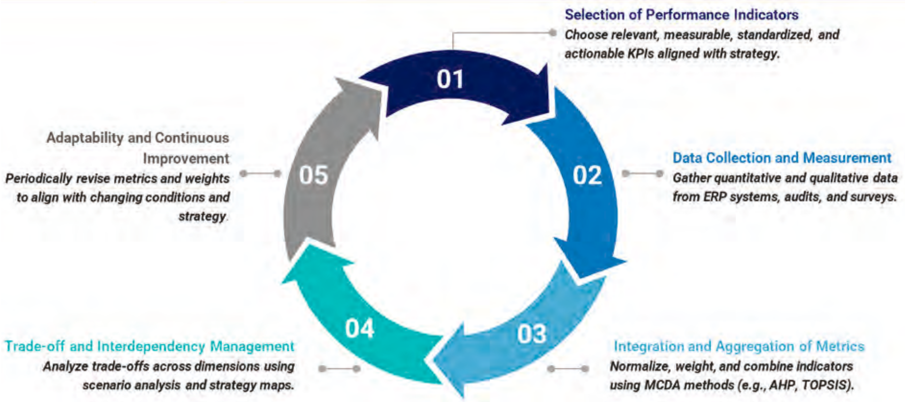


Figure 2: Methodological Steps in Implementing the Evaluation Framework

5.1. Selection of Performance Indicators

The selection of performance indicators is a foundational step in applying the multidimensional framework. Each dimension requires context-specific indicators that reflect the organization's strategic objectives. As noted by Neely et al. (2002), effective performance indicators must be strategically relevant, measurable, and actionable. Gunasekaran et al. (2004) emphasize that indicators should capture both tactical operations and strategic impacts, linking supply chain metrics to corporate-level goals. Relevance ensures that each metric contributes meaningfully to decision-making and aligns with stakeholder expectations. Measurability requires that data be obtainable and reliably quantifiable. Standardization, where feasible, promotes comparability across time and organizational units. Ultimately, the selected indicators must provide a comprehensive yet manageable representation of performance, supporting a balanced view across the five dimensions while avoiding metric overload.

5.2. Data Collection and Measurement Techniques

The effectiveness of the evaluation process largely depends on the quality and the extensiveness of the data utilized. Data gathering needs to cover data from internal systems alongside external sources to provide a complete review of the supply chain function. Quantified data can be obtained from enterprise systems, such as Enterprise Resource Planning (ERP), Warehouse Management System (WMS), and Customer Relationship Management (CRM) systems. These systems provide real-time as well as historical data of the levels of stocks, order fulfillment, the structures of the costs, as well as the services delivered to the customers (Choi et al., 2018).

Besides quantitative data, qualitative data are equally important, if not often more important, in evaluating factors such as customer value, strategic fit, and ESG performance. Qualitative data can be obtained from solicited sources, unsolicited sources, such as stakeholder surveys, supplier ratings, external audits, and observations by virtue of the ESG disclosures. For example, sustainability performance can be gauged by using data from reports issued by the Carbon Disclosure Project (CDP) or by supplier self-assessments. To assure the validity, consistency, and comparability of the gaugings, the use of standardized survey instruments and auditing processes is advisable (Ahi & Searcy, 2013). When appropriate, text mining, sentiment analysis, or other analytic software may be systematically applied in evaluating qualitative data.

5.3. Integration and Aggregation of Performance Metrics

Following the data gathering process, the next challenge involves the integration of performance from different dimensions, without oversimplifying the complexities inherent in supply chains. An efficient integration process allows the conversion of dispersed data into a unified performance profile. One commonly used process involves the development of composite indices. The process involves the normalizing of unit statistics (e.g., normalizing values within the range of 0 to 1), the assigning of weights based on importance, and the aggregation of the statistics to produce composite statistics for every dimension, and a further composite performance index where necessary.

Multi-Criteria Decision Analysis (MCDA) techniques, such as the Analytic Hierarchy Process (AHP) (Saaty, 1980) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Bai & Sarkis, 2010), offer formalized structures for evaluating and aggregating multiple criteria. These techniques allow decision-makers to factor in expert judgments and strategic thinking in the process of determining weights applied to individual metrics. The choice of a weighting approach requires the aggregation process to be marked by transparency, theoretical support, and continual review to keep in tune with the evolving priorities of the organization.

5.4. Trade-Offs and Performance Interdependencies

A key methodological challenge in multidimensional evaluation is managing trade-offs among performance dimensions. In complex supply chains, actions that improve one area may have unintended consequences in another. For example, increasing delivery speed might enhance customer satisfaction but lead to higher transportation costs and carbon emissions. Similarly, cost-cutting measures in procurement may reduce operational expenses but jeopardize supplier relationships or ESG compliance.

A deeper comprehension and management of such interdependencies require the use of a systems-thinking perspective, in addition to simulation software that can model performance within several assumption sets. Scenario analysis and what-if modeling allow for the predictive forecast of trade-offs, thus supporting companies in making choices based on risk-return analysis (Shapiro, 2001). When applied in the framework of the Balanced Scorecard (Kaplan & Norton, 2004), strategy maps are useful in representing cause-and-effects relations among several dimensions, hence supporting dialogue between corporate strategists and supply chain executives. The analysis of the associated trade-offs involves not only the technical difficulties but also the governance-related issues that need cooperation between several parties, respecting the principles of ethics and sustainability.

5.5. Adaptability and Continuous Improvement

Finally, the evaluation framework must be adaptable in the face of organizational transformations, external disruptions, and strategic evolution. It reflects the idea of contingency theory, where systems of performance must be congruent with their environmental and organizational settings (Lawrence & Lorsch, 1967). When new risks emerge, technologies change, or the expectations of the stake-holders change, prioritization and importance of the performance indicators must be recalibrated.

To support adaptability, organizations should embed the evaluation process within a continuous improvement cycle. Regular reviews, quarterly or annually, should assess the validity of selected indicators, recalibrate weights, and incorporate new data sources. Performance feedback loops can support learning and organizational alignment, while methods such as the Plan-Do-Check-Act (PDCA) or Define-Measure-Analyze-Improve-Control (DMAIC) cycles can institutionalize performance enhancement routines. Moreover, technological advancements such as business intelligence dashboards and AI-driven analytics can improve the timeliness and precision of performance evaluation, enabling more responsive and forward-looking decision-making.

6. Discussion

The five-dimensional evaluation framework outlined in this article presents an integrated view of the organizational performance impact of supply chains. It remedied a shortcoming in extant literature, since supply chain performance has often been evaluated in a restrictive way in the past, focusing mainly on the operational dimension of supply chains at the expense of wider strategic, financial, and sustainability-related dimensions (Hahn and Figge, 2004). With the integration of five key dimensions, this framework comprehensively covers the entire gamut of supply chain value creation in contemporary organizations.

This framework underscores the proposition that supply chains are not merely separate technical systems, but they are social and strategic integrations that impact, as well as are impacted by, their external environments. From a managerial perspective, the application of the proposed framework requires companies to move away from the typical service- or cost-related metrics to a broader assessment of supply chain performance that corresponds with broader corporate goals (Dimitriou et al., 2025; Chae, 2009). In addition, the framework can aid in the development of common performance dashboards, support decision making through trade-off analysis, and facilitate dialogue among supply chain professionals, accounting departments, and sustainability members. Against the backdrop of growing supply disruptions, growing expectations by the stakeholder community, and increasing regulatory attention, the integrative perspective enables companies to determine what matters most, both internally in process-related factors within the company and externally in outcome-related factors (Dimitriou et al., 2024).

While the framework has strong backing in existing theories and commonly accepted metrics of performance, its use in practical contexts will require the organization to make contextually specific adaptations, data collection, and governance provisions. Another complicating factor inherent in the framework's multi-dimensional nature, although attractive at the theoretical level, has practical drawbacks. Organizations that are fragmented in information systems, resource-constrained, or lacking in analytical talent might find the framework unworkable. Extreme care must be exercised in the balance between thoroughness and user-friendliness. Extremity in either direction must be strictly avoided.

Furthermore, the rapidly changing landscape of supply chain management, influenced by technological change, geopolitical tensions, and climactic change, requires that any system of evaluating performance be able to adapt longitudinally. The reliance of the framework on contingency reasoning and dynamic capabilities allows for adaptability, yet its utility remains in direct relation to the organization's efforts at institutionalizing the review of performances, refinement of indicators, and investment in necessary data infrastructure. Thus, the framework must not be thought of as a frozen checklist, yet as an evolving tool meant to move in tandem with the strategic landscape of the firm.

7. Concluding Remarks

This paper presents a multidimensional evaluation framework designed to bridge the gap between supply chain performance measurement and holistic corporate performance assessment. Differently from the typical methods that stick mainly to functional or monetary variables in a piecewise fashion, the new framework embrace five related dimensions of performance: operational efficiency, monetary influence, consumer value and responsiveness, strategic alignment and dynamism, as well as sustainability and ESG performance. Conceptually based on developed theoretical frameworks, the framework considers the growing sophistication of modern supply chains and their increased value creation within organizational boundaries as well as in the broader frame of wider stakeholder networks. By converging multiple definitions of performance, the existing framework affords the organization a fairer and broader tool for strategic choices, performance observation, as well as ongoing improvement. Additionally, the framework guarantees that the methods of evaluating the supply chains are compatible with modern-day demands like agility, innovation, environmental friendliness, as well as stakeholder engagement.

Future research should strive to test the proposition in a variety of industries, regions, and supply chain settings. Survey work may investigate how much the prioritizing of supply chain dimensions varies in the face of variables like firm size, market, environment, regulatory, or the persistent organisational consequences of implementing such frameworks. And, again, there remains the need for studies directed at creating instruments that can support real-time multi-dimensional supply chains' measurement, visualization, and simulation, especially in organisations enabled by digital technologies.

Convergence of supply chain evaluation with ESG factors and digital change represents a considerably promising direction for potential research undertakings. With increasing expectations among businesses for transparence, ethics, and sustainability, the systems of performance measurement need to change to accommodate inclusion of such factors not only as secondary concerns but as primary attributes of sustained value creation. Similarly, the integration of data analytics, artificial intelligence, and decision-support technologies within the process of performance management holds much potential for increasing the responsiveness and strategic efficacy of the systems.

References

Ahi, P., & Searcy, C. (2013). A comparative literature analysis of definitions for green and sustainable supply chain management. Journal of Cleaner Production, 52, 329–341. https://doi.org/10.1016/j.jclepro.2013.02.018

Azevedo, S. G., Carvalho, H., & Machado, V. C. (2011). The influence of green practices on supply chain performance: A case study approach. Transportation Research Part E: Logistics and Transportation Review, 47(6), 850–871. https://doi.org/10.1016/j.tre.2011.05.017

Bai, C., & Sarkis, J. (2010). Integrating sustainability into supplier selection with grey system and rough set methodologies. International Journal of Production Economics, 124(1), 252–264. https://doi.org/10.1016/j.ijpe.2009.11.023

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Beamon, B. M. (1999). Measuring supply chain performance. International Journal of Operations & Production Management, 19(3), 275–292. https://doi.org/10.1108/01443579910249714

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. European Journal of Operational Research, 233(2), 299–312. https://doi.org/10.1016/j.ejor.2013.09.032

Büyüközkan, G., & Göçer, F. (2018). Digital supply chain: Literature review and a proposed framework for future research. Computers in Industry, 97, 157–177. https://doi.org/10.1016/j.compind.2018.02.010

Chae, B. (2009). Developing key performance indicators for supply chain: An industry perspective. Supply Chain Management: An International Journal, 14(6), 422–428. https://doi.org/10.1108/13598540910995192

Choi, T. M., Wallace, S. W., & Wang, Y. (2018). Big Data analytics in operations management. Production and Operations Management, 27(10), 1868–1889. https://doi.org/10.1111/poms.12838

Chopra, S., & Meindl, P. (2019). Supply chain management: Strategy, planning, and operation (7th ed.). Pearson.

Christopher, M. (2016). Logistics & supply chain management (5th ed.). Pearson UK.

Dimitriou D., Sartzetaki M., Karagkouni A. (2025). Harnessing Neuroleadership Concept for Enhancing Management Efficiency and Business Sustainability in Supply Chain: A System of System Approach, Journal of Lifestyle and SDGs Review. https://doi.org/10.47172/2965-730X.SDGsReview.v5.n06.pe06449

Dimitriou, D., Sartzetaki, M., Karagkouni, A. (2024). Managing Airport Corporate Performance: Leveraging Business Intelligence and Sustainable Transition. Elsevier. ISBN: 978-0-443-29109-8. pp. 1-328. https://doi.org/10.1016/C2023-0-51427-2

Dyer, J. H., & Singh, H. (1998). The relational view: Cooperative strategy and sources of interorganizational competitive advantage. Academy of Management Review, 23(4), 660–679. https://doi.org/10.5465/amr.1998.1255632

Elkington, J. (1997). Cannibals with forks: The triple bottom line of 21st century business. Capstone Publishing.

Freeman, R. E. (1984). Strategic management: A stakeholder approach. Pitman.

Gunasekaran, A., Patel, C., & McGaughey, R. E. (2004). A framework for supply chain performance measurement. International Journal of Production Economics, 87(3), 333–347. https://doi.org/10.1016/j.ijpe.2003.08.003

Hahn, T., & Figge, F. (2011). Beyond the bounded instrumentality in current corporate sustainability research: Toward an inclusive notion of profitability. Journal of Business Ethics, 104(3), 325–345. https://doi.org/10.1007/s10551-011-0911-0

Harrison, J. S., Bosse, D. A., & Phillips, R. A. (2010). Managing for stakeholders, stakeholder utility functions, and competitive advantage. Strategic Management Journal, 31(1), 58–74. https://doi.org/10.1002/smj.801

Hitt, M. A., Ireland, R. D., & Hoskisson, R. E. (2007). Strategic management: Competitiveness and globalization (7th ed.). Cengage Learning.

Kaplan, R. S., & Norton, D. P. (1996). The balanced scorecard: Translating strategy into action. Harvard Business School Press.

Kaplan, R. S., & Norton, D. P. (2004). Strategy maps: Converting intangible assets into tangible outcomes. Harvard Business School Press.

Karagkouni, A. & Dimitriou, D. (2025). Supply Chain Disruptions and Business Resilience: A Strategic Framework for Corporate Performance. In M. Efthymiopoulos & A. Masouras (Eds.), Security and Strategy Models for Key-Solving Institutional Frameworks (pp. 171-202). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-5583-1.ch008

Karagkouni, A.; Dimitriou, D. (2025). The Overton Window in Smart City Governance: The Methodology and Results for Mediterranean Cities. Smart Cities 2025, 8, 98. https://doi.org/10.3390/smartcities8030098

Lawrence, P. R., & Lorsch, J. W. (1967). Organization and environment: Managing differentiation and integration. Harvard Business School Press.

Lee, H. L. (2004). The triple-A supply chain. Harvard Business Review, 82(10), 102–112.

Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining supply chain management. Journal of Business Logistics, 22(2), 1–25. https://doi.org/10.1002/j.2158-1592.2001.tb00001.x

Mixafenti, S.; Moutzouri, A.; Karagkouni, A.; Sartzetaki, M.; Dimitriou, D. (2025). Assessment of Occupational Health and Safety Management: Implications for Corporate Performance in the Secondary Sector. Safety 2025, 11, 44. https://doi.org/10.3390/safety11020044

Neely, A., Gregory, M., Platts, K. (2005). Performance measurement system design: A literature review and research agenda. International Journal of Operations & Production Management. 25. 1228-1263. https://doi,org/10.1108/01443570510633639.

Norman, W., & MacDonald, C. (2004). Getting to the bottom of "Triple Bottom Line." Business Ethics Quarterly, 14(2), 243–262. https://doi.org/10.5840/beq200414211

Pagell, M., & Wu, Z. (2009). Building a more complete theory of sustainable supply chain management using case studies of 10 exemplars. Journal of Supply Chain Management, 45(2), 37–56. https://doi.org/10.1111/j.1745-493X.2009.03162.x

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring supply chain resilience: Development of a conceptual framework. Journal of Business Logistics, 31(1), 1–21. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x

Saaty, T. L. (1980). The analytic hierarchy process. McGraw-Hill.

Sartzetaki M., Karampini T., Karagkouni A., Drimpetas E. and Dimitriou D. (2025) Circular economy strategies in supply chain management: an evaluation framework for airport operators. Front. Sustain. 6:1558706. https://doi.org/10.3389/frsus.2025.1558706

Sartzetaki, M., Karagkouni, A., & Dimitriou, D. (2025). Enterprise Strategic Management Upon Sustainable Value Creation: A Fuzzy Topis Evaluation Tool for Transport and Supply Chain Enterprises. Sustainability, 17(11), 5011. https://doi.org/10.3390/su17115011

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. Journal of Cleaner Production, 16(15), 1699–1710. https://doi.org/10.1016/j.jclepro.2008.04.020

Shapiro, J. F. (2001). Modeling the supply chain. Duxbury.

Swafford, P. M., Ghosh, S., & Murthy, N. (2006). The antecedents of supply chain agility of a firm: Scale development and model testing. Journal of Operations Management, 24(2), 170–188. https://doi.org/10.1016/j.jom.2005.05.002

Wong, C. Y., Boon-itt, S., & Wong, C. W. Y. (2011). The contingency effects of environmental uncertainty on the relationship between supply chain integration and operational performance. Journal of Operations Management, 29(6), 604–615. https://doi.org/10.1016/j.jom.2011.01.003

Yusuf, Y. Y., Gunasekaran, A., Musa, A., Dauda, M., El-Berishy, N. M., & Cang, S. (2014). A relational study of supply chain agility, competitiveness and business performance in the oil and gas industry. International Journal of Production Economics, 147, 531–543. https://doi.org/10.1016/j.ijpe.2012.10.009

STRIKING FIRST, STRIKING HARD:

A COMMUNICATION STRATEGY FOR SOCIAL MEDIA STORMS

Konstantinos Rigopoulos
Department of Economics, Democritus University of Thrace
krigopou@econ.duth.gr

ABSTRACT

The lack of Corporate social Responsibility (CSR) and deceptive "greenwashing" practices increasingly erode public trust, amplified by the swift and pervasive nature of social media. This paper investigates effective crisis communication strategies during social media storms (SMS), arguing for a "strike first-strike hard" proactive approach over traditional, often ineffective, post-crisis corporate social responsibility (CSR) initiatives. Utilizing a vignette-based role-playing methodology with executive education students in an oil and gas context, the study identifies six critical themes: the influence of pre-existing reputational anchors, the significance of empathetic and prepared real-time engagement, the power of transparency and information provision for de-escalation, the necessity of strategic avoidance of trolls, the lingering impact on public trust, and the foundational role of organizational preparedness. Findings reveal that proactive, empathetic, and transparent engagement, coupled with strategic disengagement from toxic commentary, is paramount for mitigating reputational damage and fostering long-term trust in the volatile social media landscape.

Keywords: *Social Media Storms, Crisis Management, Corporate Social Responsibility (CSR), Greenwashing, Proactive Communication, Reputation Management, Transparency, Empathy, Organizational Preparedness.*

Introduction

In today's rapidly evolving business landscape, corporate misconduct has become a persistent issue, leading to significant reputational damage and severe financial consequences for organizations (Hadani, 2024; Jain & Zaman, 2020; Kim & Rim, 2023). From historical financial scandals like Enron and WorldCom to more recent environmental controversies involving BP and Amazon, a consistent pattern emerges: corporate social irresponsibility inevitably draws stakeholder condemnation, jeopardizing a firm's value (Nardella et al., 2023). This persistent prevalence of such irresponsibility demands a critical examination of how companies communicate and manage their image, especially given the heightened scrutiny in the digital age. The phenomenon known as a 'social media storm' (SMS), becomes increasingly common and it refers to instances where consumers collectively and suddenly rise against companies on social media platforms (Rydén, Kottika, Hossain, Skare, & Morrison, 2020).

A major driver of public distrust, particularly among younger, environmentally conscious consumers, is the deceptive practice known as "greenwashing" (TerraChoice, 2010). While green advertising aims to resonate with consumers concerned about sustainability (Kao & Du, 2020), a significant portion of these communications lack substantive information. This fuels widespread skepticism regarding corporate environmental claims (Carlson, Grove, & Kangun, 1993; Guix, Ollé, & Font, 2022; Lyon & Montgomery, 2015). Research has extensively documented the misleading nature of green advertising claims (Carlson, Grove, & Kangun, 1993; Matthes, 2019) and how companies can manipulate messaging to create a favourable, yet often false, impression of their sustainability efforts (Davis, 1995; Entman, 1993). Furthermore, the visual elements in green advertising increasingly influence consumer perceptions (Lim et al., 2020; Parguel, Benoit-Moreau, & Russell, 2015). This growing demand for corporate transparency (de Freitas Netto et al., 2020) underscores the critical need for authentic action over empty promises.

Effective communication about sustainability—defined as the exchange of information, interpretations, and opinions on sustainability issues (Newig et al., 2013)—is complex. While communication about sustainability strives to foster awareness and open discourse across various platforms (Newig et al., 2013), an overload of information can lead to "green fatigue" among consumers (Strother & Fazal, 2011). This highlights a crucial shift towards "communication for sustainability", which prioritizes measurable actions that drive social transformation, moving beyond mere awareness campaigns (Adomßent and Godemann, 2011; Newig et al., 2013). However, even with genuine communication for sustainability efforts, the instantaneous and pervasive nature of social media significantly compounds the challenges of managing corporate reputation.

In this challenging environment, social media storms pose an immediate and severe threat to corporate standing. Traditional post-crisis corporate social responsibility (CSR) initiatives often fall short, primarily because widespread user scepticism leads them to be perceived as disingenuous "greenwashing." This research argues for a "strike first-strike hard" proactive crisis management approach. Key findings reveal: (1) the ineffectiveness of conventional post-crisis CSR initiatives due to deep-seated user scepticism; (2) the imperative for a proactive, aggressive crisis management strategy; and (3) the critical need to consistently demonstrate empathy, responsiveness, preparedness, transparency, and open discourse, while strategically disengaging from social media trolls. This proactive approach mandates direct and comprehensive engagement with individuals generating negative commentary, offering personalized information, and clearly communicating ongoing mitigation efforts. Ultimately, the absence of such a robust, proactive strategy signals either organizational defensiveness or a damaging lack of preparedness, inevitably eroding public trust and further harming the organization's image.

Conceptual Background

The landscape of crisis communication has long been guided by established theoretical frameworks, with Situational Crisis Communication Theory (SCCT) being dominant. SCCT, primarily developed by Coombs (2007), provides an evidence-based framework for understanding how organizations can maximize reputational protection through post-crisis communication. It posits that effective crisis response strategies should align with the perceived responsibility stakeholders attribute to the organization for the crisis.

SCCT categorizes crisis response strategies into three main groups based on perceived acceptance of responsibility: denial, diminishing, and rebuilding (Coombs, 2006; Coombs, 2007). While traditionally focused on the sender's message, the dynamic nature of social media environments necessitates a broadened perspective that also considers the perceptions of receivers (Cheng, 2018).

A crucial evolution within SCCT, particularly relevant to the digital age, is the concept of a paracrisis. Coombs and Holladay (2012) introduced paracrises as early reputational threats that, if unmanaged, can escalate into full-blown crises. These situations, often surfacing on social media, are characterized by three conceptual components: power (stakeholder ability to damage reputation), legitimacy (other consumers perceiving the issue as problematic), and urgency (stakeholders' willingness to act). The 2017 Pepsi campaign serves as a notable example, where consumer petitions rapidly gained legitimacy and urgency on social media, demonstrating a paracrisis that could have severely escalated without early intervention (Nicholson, 2017). This highlights how crisis prevention, through proactive communication, begins long before a full-blown crisis erupts.

Social media platforms have fundamentally altered the dynamics of crisis communication, creating an environment where a minor incident can rapidly transform into a full-scale social media storm (SMS). The inherent characteristics of these platforms—namely virality, speed of information dissemination, disintermediation, and user-generated content (UGC)—significantly escalate crises and challenge traditional response models (Liu, Austin, & Jin, 2017). Information, whether accurate or not, can spread instantly and globally, often without traditional journalistic gatekeepers, leading to what some refer to as a "contagion effect" where negative reactions gain rapid momentum and result in detrimental reputation spillover (Laufer and Wang, 2018; Zimand-Sheiner et al., 2021).

Unlike traditional media, social media fosters a sense of social connectedness among users (Gage-Bouchard et al., 2016), who often prioritize information shared by peers over corporate messaging (Vernuccio et al., 2015). This environment allows even inaccurate information to propagate unfiltered, potentially influencing public opinion (Lee, 2020). Moreover, crises on social media can be triggered not only by genuine corporate misdeeds but also by consumer petitions based on misguided product use or biased interpretations of corporate behaviours. This underscores the critical importance of early detection and response to consumer petitions, regardless of their initial perceived legitimacy, to prevent crisis escalation (Veil, Buehner, & Palenchar, 2011).

Organizational reputation and trust are invaluable, intangible assets (Fombrun & van Riel, 2004). However, crises inherently threaten these assets, leading to potential shifts in stakeholder interaction (Barton, 2001). The ethical imperative in crisis communication dictates that the priority is to protect stakeholders from harm, both physical and psychological, before focusing on reputational repair (Coombs, 2007). This involves providing instructing information, adapting information to help cope with psychological stress, and expressing concern for victims (Sellnow et al., 1998). Only after addressing these foundational concerns can organizations ethically turn to rebuilding trust.

Trust is built through consistent, credible interactions (Dirks & Ferrin, 2002). In a crisis, the process of trust repair is critical and heavily influenced by the organization's communication. Research consistently shows that consumers perceive a company's engagement with complaints positively, which can significantly mitigate the negative impact of an event on consumer satisfaction (Kim & Lim, 2020). Responsiveness, empathy, and transparency are paramount in alleviating consumer anxiety and frustration, reducing the likelihood of negative electronic word-of-mouth (eWOM), and fostering a sense of perceived organizational awareness and management of the issue (Vafeiadis, 2023). An empathetic, prepared, and transparent approach can mitigate long-term reputational damage and even foster renewed trust, demonstrating that effective crisis handling directly impacts an organization's future public confidence and consumer behaviour.

The field of crisis management has historically operated on a reactive paradigm, often attempting to repair reputations after damage has occurred (Coombs, 2015). However, the rise of social media has rendered purely reactive models largely insufficient. The "strike first-strike hard" approach advocated by this research represents a critical shift towards a proactive crisis management model, asserting that a robust offense is the best defence in the volatile social media landscape. This model emphasizes early detection and swift, decisive action before a paracrisis escalates into a full-blown social media storm.

Proactive models contrast sharply with traditional reactive ones by focusing on anticipating potential risks, developing pre-emptive communication strategies, and equipping communication teams with the necessary tools and training (Schwarz, 2012). The ability to quickly and effectively respond to negative user-generated content, providing personalized information and transparently highlighting mitigation efforts, is central to this proactive stance. Ignoring user engagement or failing to respond decisively can exacerbate anxiety and frustration, reinforcing the power of negative information dissemination through social networks (Einwiller & Steilen, 2015). Figure 1 below depicts a conceptual model outlining the dynamic interplay of key themes in proactive social media crisis management within the context of an oil and gas company facing a social media storm (SMS). The model illustrates how various factors influence an organization's response and ultimately shape public trust and future intentions.

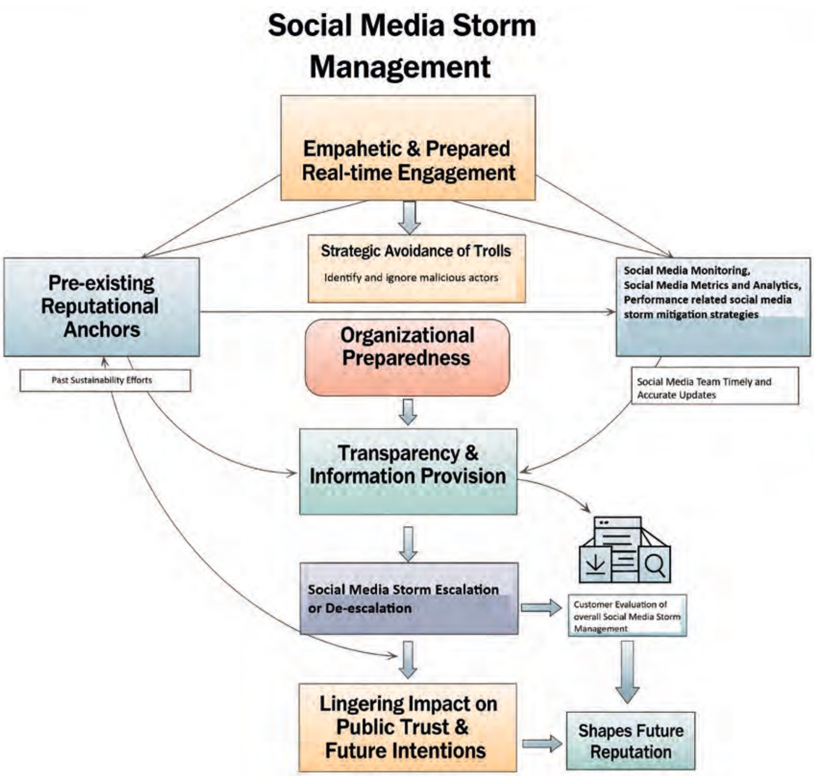


Figure 1. Conceptual Model

The diagram's central element is the Urgency of Empathetic & Prepared Real-time Engagement (Theme 2), emphasizing the critical need for swift, compassionate, and well-planned responses during a crisis. This engagement is directly influenced by: Pre-existing Reputational Anchors (Theme 1): An organization's established reputation forms a crucial baseline, impacting initial public sentiment and the willingness of stakeholders to accept explanations. Strategic Avoidance of Trolls (Theme 4): The discerning decision to disengage from purely disruptive online actors to maintain focus on constructive dialogue. Organizational Preparedness (Theme 6): This foundational theme encompasses the readiness (plans, resources, training) that enables effective real-time engagement and transparent communication. Effective engagement and organizational preparedness collectively lead to Transparency & Information Provision (Theme 3), highlighting the importance of open communication and the dissemination of accurate, timely information to de-escalate the crisis and control the narrative. Ultimately, all these interconnected elements contribute to the Lingering Impact on Public Trust & Future Intentions (Theme 5), which represents the long-term ramifications of crisis handling on public confidence and future consumer behaviour. A crucial feedback loop demonstrates that this lingering impact actively "Shapes Future Reputation," reinforcing the cyclical nature of crisis management and its continuous influence on the organization's pre-existing reputational anchors. The model underscores the strategic imperative of a "strike first-strike hard" approach in navigating social media crises.

Methodology and Sample Description

This study utilized an experiential, multi-stage methodology, integrating vignette simulation with a role-playing game (Greenberg & Eskew, 1993). This approach, favoured over netnography (Kozinets, 2015, 2023; An & Alarcon, 2021) for controlled exposure, investigated real-time value co-creation during a social media storm (SMS). The design addressed managerial practicality, required progressive exploration mirroring evolving SMS events (cf. Rydén et al., 2022), and aligned with a plausible business context.

A detailed conceptual model for social media crisis management in the oil and gas sector was developed from existing literature. This model formed a base model, subsequently converted into the role-playing game. Game objects and scheduling meticulously represented the base model's elements. To enhance realism, the role-playing game was parameterized with real-world data (Cowlrick et al., 2011; Rungtusanatham et al., 2011), ensuring players exhibited realistic behaviours. Participant selection prioritized realism. Stakeholder composition was matched to reality using a clustering technique on empirical datasets (Utomo et al., 2020), increasing the likelihood of participants encountering familiar situations. A design of experiments approach mitigated potential biases (e.g., group processes, observer-expectancy), pre-planning structure, data collection, and analysis.

The vignette methodology (Barter & Renold, 2000; Jenkins et al., 2010; Sampson & Johannessen, 2020) was central to eliciting realistic participant responses. A developmental vignette unfolded in stages (e.g., Hughes, 1998; Hughes & Huby, 2004; Jenkins et al., 2010), enabling participants' meaningful contribution through real-life simulation (Jenkins et al., 2010) and collaborative role-playing (e.g., Chasek, 2005; Chen & Martin, 2015). A significant role-playing component enhanced engagement (Rao & Stupans, 2012), fostering active learning and deeper engagement via "learning by doing" and continuous reflection across the vignette-based role-playing experience (e.g., Greenberg & Eskew, 1993; Paschall & Wustenhagen, 2012). The study exhibited moderately high involvement over the three-week SMS duration (Greenberg & Eskew, 1993). Participants were 52 executive education students (average age: 35; 63.4% women; diverse ethnic backgrounds) holding relevant business positions, selected for alignment with the research objective (Ashraf & Merunka, 2017; Espinosa & Ortinau, 2016).

Participants, divided into small groups (oil and gas company, concerned citizens), engaged in the role-playing game on a Facebook-like platform. The SMS simulation unfolded in three stages: warm-up, fully fired-up, and cooling down. The scenario, depicting an oil and gas company facing scrutiny, was structured for realism and plausibility (Barter & Renold, 2000; Hughes & Huby, 2004; Jenkins et al., 2010). Methodology included specific rules and debriefing to enhance engagement (Chasek, 2005; Smith & Boyer, 1996), with reflective reports submitted post-completion.

Data Analysis

This study's qualitative data, comprising 52 participant reflective reports and 142 posts from two simulated social media storms, underwent qualitative content analysis (Krippendorff, 2004; Schreier, 2014). The analysis adhered to established qualitative research guidelines (Schreier, 2012; Strauss & Corbin, 1998). Categories were inductively developed from the data (Schreier, 2012), with all materials systematically coded using this emergent framework. The process was cyclical, involving iterative refinement between the qualitative material and the evolving thematic structure (Daymon & Holloway, 2010; Schreier, 2012).

To ensure coding reliability, two independent coders performed blind coding. They achieved an inter-coder agreement of 86.4% and a Cohen's kappa coefficient of 82.1%, surpassing the 80% threshold (Krippendorff, 2004; Neuendorf, 2002), indicating satisfactory reliability. Disagreements were resolved through discussion.

The validity of the coding frame was ensured through its inductive development, accurately capturing constructs (Schreier, 2012). Face validity was further secured by an initial pilot coding phase, low frequencies in residual categories, the absence of unusually high frequencies in any single subcategory, and maintaining a medium level of abstraction during data reduction (Schreier, 2012).

Results

The qualitative content analysis of social media crisis communication, particularly within the context of a "social media storm" (SMS), revealed critical themes underpinning the effectiveness of a proactive, "strike first-strike hard" approach. These themes highlight the dynamic interplay between organizational response and public perception, ultimately shaping the trajectory of reputational damage or recovery within the specific context of an oil and gas company. The findings, derived from the analysis of social media interactions captured via Facebook screenshots and subsequent reflective reports from both social media users and oil and gas communication executives, are presented below:

Theme 1: Pre-existing Reputational Anchors and Initial Public Sentiment

The initial public sentiment upon the outbreak of a social media storm was significantly influenced by the pre-existing sentiment for the oil and gas company. This theme, reflected primarily in the early Facebook screenshots and corroborated by the reflective reports of social media users, captured how prior public perception, informed by past experiences, reviews, and general word-of-mouth concerning the sector, formed a critical baseline. A strong, positive reputation, as noted by some communication executives, could serve as a buffer, fostering a greater willingness among social media users to consider the organization's explanations. Conversely, a weak or negative pre-existing reputation, often articulated by social media users expressing anxiety, amplified scepticism and exacerbated the speed and intensity of public backlash. This theme underscored the long-term investment in positive brand equity as a crucial element of crisis preparedness, as highlighted in both user and executive reflections.

Theme 2: The Significance of Empathetic and Prepared Real-time Engagement

This theme underscored the critical need for the oil and gas company to exhibit empathy, responsiveness, and preparedness from the very outset of a social media storm. Social media users' initial posts often conveyed heightened anxiety and fear, fuelled by early negative information. The communication executives' capacity to quickly and effectively address these negative sentiments, demonstrating genuine concern and a readiness to provide clear, accurate information, was paramount. Failure to do so, as indicated by user reports, quickly escalated the crisis, leading to a breakdown in communication and fostering a perception of organizational incompetence or indifference. This theme directly aligns with the "strike first-strike hard" imperative to exhaust negative commentary with personalized, empathetic responses, a strategy frequently discussed by communication executives in their reports.

Theme 3: Transparency and Information Provision as Crisis De-escalation Tools

Effective crisis management hinged on the oil and gas company's commitment to transparency and comprehensive information provision in real-time.

This theme, evident in the rapid exchange of information within Facebook screenshots, captured the social media users' inherent need for clarification and understanding during a crisis. Communication executives who proactively disseminated personalized information, addressed specific queries, and highlighted their mitigation efforts without exaggeration or perceived "greenwashing," could significantly de-escalate the situation. The continuous flow of accurate and relevant information, as observed by both user and executive participants, helped to counter misinformation and allowed the organization to control the narrative, thereby aligning with the "strike first-strike hard" strategy's emphasis on overwhelming negative commentary with facts and proactive communication.

Theme 4: Strategic Avoidance of Trolls and Toxic Engagement

While transparent and empathetic engagement was crucial, this theme highlighted the importance of strategic disengagement from social media trolls and overtly toxic commentators. Both social media users and communication executives noted that not all engagement was productive. Attempts to address every hostile comment, as reflected in executive reports, could be a drain on resources and inadvertently amplify negative voices. The "strike first-strike hard" approach, while advocating for exhaustive engagement with legitimate concerns, implicitly acknowledged the need to identify and avoid interactions that were designed solely to inflame and undermine, rather than seek resolution. This discerning approach, practiced by communication executives, safeguarded organizational resources and maintained focus on constructive dialogue.

Theme 5: The Lingering Impact of Crisis Handling on Public Trust and Future Intentions

This theme encompassed the long-term ramifications of the oil and gas company's crisis handling on public trust and future consumer behaviour. The way the organization navigated the social media storm, as articulated in the reflective reports from both social media users and communication executives two weeks post-crisis, had profound implications for its ability to regain or maintain public confidence and, crucially, influence future intentions (e.g., willingness to visit). An efficiently managed crisis, characterized by the demonstration of empathy, preparedness, and transparency, could mitigate long-term reputational damage and even foster renewed trust among social media users. Conversely, an ineffective response, as described by disillusioned users, led to enduring negative word-of-mouth and a sustained decline in public trust, reinforcing the necessity of the "strike first-strike hard" approach to secure positive future outcomes.

Theme 6: Organizational Preparedness as a Foundation for Effective Crisis Response

Underpinning all aspects of effective social media crisis management was the theme of organizational preparedness. This included not only the readiness of communication executives to respond to negative social media posts with accuracy and robust information but also the broader organizational capacity of the oil and gas company to handle crises efficiently. The ability to anticipate potential risks, develop proactive communication strategies, and equip communication teams with the necessary tools and training was fundamental. The absence of such preparedness, as perceived by some social media users in their frustration, could create an impression of organizational disarray or even culpability, reinforcing the "strike first-strike hard" strategy's core tenet that a well-organized and proactive defence is the best offense in the volatile landscape of social media storms.

Discussion

The explosion of social media platforms has undeniably transformed the landscape of corporate communication, introducing a dynamic environment where reputational crises, or "social media storms," can escalate with unprecedented speed and reach. The initial, ineffective management of such a storm can precipitate widespread and enduring reputational damage, often proving exceptionally difficult for an organization to redress. In the most optimistic scenarios, embattled companies may merely hope for the public's diminished attention or eventual forgetfulness, given the considerable challenge of altering deeply entrenched public sentiment during periods of widespread condemnation. Furthermore, in such fraught circumstances, key stakeholders and opinion leaders — despite possessing significant social capital and potential willingness to support the affected entity — frequently abstain from intervention, safeguarding their own reputations and public images from association with the controversy.

The Ineffectiveness of Post-Crisis CSR and the "Strike First-Strike Hard" Imperative

Empirical evidence further suggests that post-outburst CSR initiatives, regardless of their intrinsic merit or altruistic intent, often yield weak communicative effects. This diminished impact stems largely from the pervasive scepticism among social media users, who tend to interpret such efforts as "greenwashing" – a cynical attempt to project an image of responsibility and reliability, even as the prevailing user-generated content actively champions a contrary narrative.

In response to these challenges, the present research advocates for a "strike first-strike hard" approach to social media crisis management. This proactive strategy necessitates that organizations facing a storm engage directly and exhaustively with users generating negative commentary. This engagement should be characterized by the provision of personalized information, inquiries regarding satisfaction with current responses, and the dissemination of supplementary data as needed. Concurrently, companies should initiate publicity events and campaigns that transparently highlight their ongoing efforts to mitigate the risks that precipitated the social media storm. Crucially, these communications must avoid exaggeration of corporate motives or overemphasis on CSR initiatives, which, as noted, are often viewed with suspicion.

The cornerstone of this proactive approach lies in the consistent demonstration of empathy, responsiveness, preparedness, transparency, and a genuine willingness to engage in open discourse on all pertinent issues. An essential caveat to this principle, however, is the imperative to abstain from engaging with social media trolls and individuals disseminating overtly toxic commentary, as such interactions typically prove counterproductive. The absence of a robust, proactive strategy conveys an impression of organizational defensiveness or, worse, a lack of preparedness, implying either the concealment of information or systemic inefficiencies in crisis management. Both interpretations inevitably cast the organization in a negative light.

Limitations

It is important to acknowledge three principal limitations of the current research. Firstly, the developed scenario centered on an oil and gas company, a sector inherently susceptible to pervasive challenges concerning its environmental record and public reputation, which may influence the generalizability of the findings. Secondly, the participants comprised communication executives, whose responses in social media correspondence were likely influenced by the dictates of social desirability, potentially limiting the authenticity of their interactions. Finally, participants, offered commentary from a position of calm and detachment. This contrasts sharply with real-world social media storms, where the crucible of fatigue, anger, fear, and internal corporate politics can fundamentally alter the context of participation and, consequently, the nature of stakeholder engagement.

References

Adomßent, M., & Godemann, J. (2011). Sustainability communication: An integrative approach. In *Sustainability communication: Interdisciplinary perspectives and theoretical foundation* (pp. 27-37). Springer Netherlands.

An, W., & Alarcón, S. (2021). From netnography to segmentation for the description of the rural tourism market based on tourist experiences in Spain. *Journal of Destination Marketing & Management*, *19*, 100549.

Ashraf, R., & Merunka, D. (2017). The use and misuse of student samples: An empirical investigation of European marketing research. *Journal of Consumer Behaviour*, *16*(4), 295-308.

Barter, C., & Renold, E. (2000). I wanna tell you a story: Exploring the application of vignettes in qualitative research with children and young people. *International Journal of Social Research Methodology*, *3*(4), 307-323.

Barton, L. (2001). Crisis in organizations II, college division's south-western. *South-Western College Pub: OH, USA*.

Carlson, L., Grove, S. J., & Kangun, N. (1993). A content analysis of environmental advertising claims: A matrix method approach. *Journal of advertising*, *22*(3), 27-39.

Chasek, P. S. (2005). Power politics, diplomacy and role playing: Simulating the UN Security Council's response to terrorism. *International Studies Perspectives*, *6*(1), 1-19.

Chen, F., & Holladay, S. J. (2023). Identifying and responding to social media risks: towards an organizational paracrisis communication framework. *Corporate Communications: An International Journal*, *28*(1), 103-117.

Chen, J. C., & Martin, A. R. (2015). Role-play simulations as a transformative methodology in environmental education. *Journal of Transformative Education*, *13*(1), 85-102.

Cheng, Y. (2018). How social media is changing crisis communication strategies: Evidence from the updated literature. *Journal of contingencies and crisis management*, *26*(1), 58-68.

Coombs, W. T. (2006). The protective powers of crisis response strategies: Managing reputational assets during a crisis. *Journal of promotion management*, *12*(3-4), 241-260.

Coombs, W. T. (2007). Protecting organization reputations during a crisis: The development and application of situational crisis communication theory. *Corporate reputation review*, *10*(3), 163-176.

Coombs, W. T. (2015). The value of communication during a crisis: Insights from strategic communication research. *Business horizons*, *58*(2), 141-148.

Coombs, W. T., & Holladay, S. J. (1996). Communication and attributions in a crisis: An experimental study in crisis communication. *Journal of public relations research*, *8*(4), 279-295.

Coombs, W. T., & Holladay, S. J. (2012). Fringe public relations: How activism moves critical PR toward the mainstream. *Public Relations Review*, *38*(5), 880-887.

Cowlrick, I., Hedner, T., Wolf, R., Olausson, M., & Klofsten, M. (2011). Decision-making in the pharmaceutical industry: Analysis of entrepreneurial risk and attitude using uncertain information. *R&D Management*, *41*(4), 321–336.

Daymon, C., & Holloway, I. (2010). *Qualitative research methods in public relations and marketing communications*. Routledge.

Davis, J. J. (1995). The effects of message framing on response to environmental communications. *Journalism & Mass Communication Quarterly*, *72*(2), 285-299.

de Freitas Netto, S. V., Sobral, M. F. F., Ribeiro, A. R. B., & Soares, G. R. D. L. (2020). Concepts and forms of greenwashing: A systematic review. *Environmental Sciences Europe*, *32*(1), 19.

Dirks, K. T., & Ferrin, D. L. (2002). Trust in leadership: meta-analytic findings and implications for research and practice. *Journal of applied psychology*, *87*(4), 611.

Einwiller, S. A., & Steilen, S. (2015). Handling complaints on social network sites–An analysis of complaints and complaint responses on Facebook and Twitter pages of large US companies. *Public relations review*, *41*(2), 195-204.

Entman, R. M. (1993). Framing: Towards clarification of a fractured paradigm. *Journal of Communication, 43*, 51–58

Espinosa, J. A., & Ortinau, D. J. (2016). Debunking legendary beliefs about student samples in marketing research. *Journal of Business Research*, *69*(8), 3149-3158.

Fombrun, C. J., & Van Riel, C. B. (2004). *Fame & fortune: How successful companies build winning reputations*. FT press.

Gage-Bouchard, E. A., LaValley, S., Mollica, M., & Beaupin, L. K. (2017). Communication and exchange of specialized health-related support among people with experiential similarity on Facebook. *Health communication*, *32*(10), 1233-1240.

Greenberg, J., & Eskew, D. E. (1993). The role of role playing in organizational research. *Journal of Management*, *19*(2), 221-241.

Guix, M., Ollé, C., & Font, X. (2022). Trustworthy or misleading communication of voluntary carbon offsets in the aviation industry. *Tourism Management*, *88*, 104430.

Hadani, M. (2024). The impact of trustworthiness on the association of corporate social responsibility and irresponsibility on legitimacy. *Journal of Management Studies*, *61*(4), 1266-1294.

Heasman, B., & Gillespie, A. (2019). Participants over-estimate how helpful they are in a two-player game scenario toward an artificial confederate that discloses a diagnosis of autism. *Frontiers in Psychology*, *10*, 1349.

Hughes, R. (1998). Considering the vignette technique and its application to a study of drug injecting and HIV risk and safer behaviour. *Sociology of Health & Illness*, *20*(3), 381-400.

Hughes, R., & Huby, M. (2002). The construction and interpretation of vignettes in social research. *Social Work and Social Sciences Review*, *11*(1), 36-51.

Jain, T., & Zaman, R. (2020). When boards matter: The case of corporate social irresponsibility. *British Journal of Management*, *31*(2), 365-386.

Jenkins, N., Bloor, M., Fischer, J., Berney, L., & Neale, J. (2010). Putting it in context: the use of vignettes in qualitative interviewing. *Qualitative Research*, *10*(2), 175-198.

Kao, T. F., & Du, Y. Z. (2020). A study on the influence of green advertising design and environmental emotion on advertising effect. *Journal of cleaner production*, *242*, 118294.

Kim, Y., & Lim, H. (2020). Activating constructive employee behavioural responses in a crisis: Examining the effects of pre-crisis reputation and crisis communication strategies on employee voice behaviours. *Journal of Contingencies and Crisis Management*, *28*(2), 141-157.

Kim, K. H., & Rim, H. (2023). Employees' voice behavior in response to corporate social irresponsibility (CSI): The role of organizational identification, issue perceptions, and power distance culture. *Public Relations Review*, *49*(4), 102366.

Kozinets, R. V. (2015). *Netnography: Redefined.* Sage.

Kozinets, R. V. (2023). Immersive netnography: a novel method for service experience research in virtual reality, augmented reality and metaverse contexts. *Journal of Service Management, 34*(1), 100-125.

Krippendorff, K. (2004). *Content analysis: An introduction to its methodology*. Sage Publications.

Laufer, D., & Wang, Y. (2018). Guilty by association: The risk of crisis contagion. *Business Horizons*, *61*(2), 173-179.

Lee, S. Y. (2020). Stealing thunder as a crisis communication strategy in the digital age. *Business Horizons*, *63*(6), 801-810.

Lim, D., Baek, T. H., Yoon, S., & Kim, Y. (2020). Colour effects in green advertising. *International Journal of Consumer Studies*, *44*(6), 552-562.

Liu, B. F., Austin, L., & Jin, Y. (2011). How publics respond to crisis communication strategies: The interplay of information form and source. *Public relations review*, *37*(4), 345-353.

Lyon, T. P., & Montgomery, A. W. (2015). The means and end of greenwash. *Organization & environment*, *28*(2), 223-249.

Matthes, J. (2019). Uncharted territory in research on environmental advertising: Toward an organizing framework. *Journal of Advertising*, *48*(1), 91-101.

Nardella, G., Brammer, S., & Surdu, I. (2023). The social regulation of corporate social irresponsibility: Reviewing the contribution of corporate reputation. *International Journal of Management Reviews*, *25*(1), 200-229.

Neuendorf, K. A. (2002). *The content analysis guidebook*. Sage Publications.

Newig, J., Schulz, D., Fischer, D., Hetze, K., Laws, N., Lüdecke, G., & Rieckmann, M. (2013). Communication regarding sustainability: Conceptual perspectives and exploration of societal subsystems. *Sustainability*, *5*(7), 2976-2990.

Nicholson, R. 2017. From Coke's flower power to Kendall Jenner's Pepsi ad – how ads co-opt protest. *The Guardian*. https://www.theguardian.com/business/2017/apr/05/from-cokes-flower-power-to-kendall-jenners-pepsi-ad-how-ads-co-opt-protest. Accessed July 18, 2025.

Parguel, B., Benoit-Moreau, F., & Russell, C. A. (2015). Can evoking nature in advertising mislead consumers? The power of 'executional greenwashing'. *International Journal of Advertising*, *34*(1), 107-134.

Paschall, M., & Wüstenhagen, R. (2012). More than a game: Learning about climate change through role-play. *Journal of Management Education*, *36*(4), 510-543.

Rao, D., & Stupans, I. (2012). Exploring the potential of role play in higher education: Development of a typology and teacher guidelines. *Innovations in Education and Teaching International*, *49*(4), 427-436.

Rungtusanatham, M., Wallin, C., & Eckerd, S. (2011). The vignette in a scenario-based role-playing experiment. *Journal of Supply Chain Management*, *47*(3), 9–16.

Rydén, P., Hossain, M. I., Kottika, E., & Škare, V. (2022). *Social media storms: empowering leadership beyond crisis management*. Routledge.

Rydén, P., Kottika, E., Hossain, M. I., Škare, V., & Morrison, A. M. (2020). Threat or treat for tourism organizations? The Copenhagen Zoo social media storm. *International Journal of Tourism Research*, *22*(1), 108-119.

Sampson, H., & Johannessen, I. A. (2020). Turning on the tap: The benefits of using 'real-life' vignettes in qualitative research interviews. *Qualitative Research*, *20*(1), 56-72.

Schwarz, N. (2012). Feelings-as-information theory. *Handbook of theories of social psychology*, *1*, 289-308.

Sellnow, T. L., Ulmer, R. R., & Snider, M. (1998). The compatibility of corrective action in organizational crisis communication. *Communication Quarterly*, *46*(1), 60-74.

Smith, E. T., & Boyer, M. A. (1996). Designing In-class simulations. *PS: Political Science & Politics*, *29*(4), 690-694.

Schreier, M. (2012). *Qualitative content analysis in practice*. Sage Publications.

Schreier, M. (2014). Qualitative content analysis. In: U. Flick (Ed.), *The SAGE handbook of qualitative data analysis* (pp. 170-183). Sage Publications.

Strauss, A., & Corbin, J. (1998). *Basics of qualitative research: Techniques and procedures for developing grounded theory*. Sage Publications.

Strother, J. B., & Fazal, Z. (2011, October). Can green fatigue hamper sustainability communication efforts?. In *2011 IEEE International professional communication conference* (pp. 1-6). IEEE.

TerraChoice. 2010. The sins of greenwashing: Home and family edition. TerraChoice. https://www.twosides.info/wp-content/uploads/2018/05/Terrachoice_The_Sins_of_Greenwashing_-_Home_and_Family_Edition_2010.pdf. Accessed July 18, 2025.

Utomo, D. S., Onggo, B. S. S., Eldridge, S., Daud, A. R., & Tejaningsih, S. (2020). Eliciting agents' behaviour using scenario-based questionnaire in agent-based dairy supply chain simulation. *Journal of Simulation*, 1–15.

Vafeiadis, M. (2023). Message interactivity and source credibility in online dental practice reviews: responding to reviews triggers positive consumer reactions regardless of review valence. *Health Communication*, *38*(1), 80-90.

Veil, S. R., Buehner, T., & Palenchar, M. J. (2011). A work-in-process literature review: Incorporating social media in risk and crisis communication. *Journal of contingencies and crisis management*, *19*(2), 110-122.

Vernuccio, M., Pagani, M., Barbarossa, C., & Pastore, A. (2015). Antecedents of brand love in online network-based communities. A social identity perspective. *Journal of Product & Brand Management*, *24*(7), 706-719.

Zimand-Sheiner, D., Levy, S., & Eckhaus, E. (2021). Exploring negative spillover effects on stakeholders: A case study on social media talk about crisis in the food industry using data mining. *Sustainability*, *13*(19), 10845.

DETERMINANTS OF INTERMEDIARY COUNTRY SELECTION IN TRADE REROUTING TO EVADE EU ANTIDUMPING DUTIES

Victoria Pistikou
Department of Economics, Democritus University of Thrace, Greece.
vpistiko@econ.duth.gr

Anastasios Ketsetsidis
Department of Economics, Democritus University of Thrace, Greece.
ketsetsidis@yahoo.gr

ABSTRACT

Anti-dumping duties are vital for protecting domestic industries from unfair competition by countering foreign firms selling below market value. However, these measures often lead to evasion strategies like trade re-routing through intermediary countries to bypass duties, particularly in the European Union (EU). This thesis examines the determinants of intermediary country selection in re-routing practices, focusing on economic, legal, and policy factors. Using econometric analysis, including descriptive statistics, correlation analysis, and binary logistic regression, the study analyzes bilateral trade flows between the EU, targeted countries, and intermediaries to identify re-routing patterns and assess anti-dumping measure effectiveness. Findings indicate that geographic proximity and cultural affinity significantly influence intermediary selection, while robust trade relations unexpectedly reduce the likelihood of a country being used as an intermediary. Corruption levels showed no significant effect, challenging assumptions about their role in evasion. The research highlights limitations *in current regulatory frameworks, suggesting enhanced international cooperation, improved trade monitoring, and stricter enforcement to counter re-routing. By addressing gaps in anti-dumping circumvention literature, this study offers policy recommendations to strengthen trade regulations and enforcement. It contributes to understanding global trade strategies and the challenges of anti-dumping enforcement, providing insights for policymakers and regulators.*

Keywords: *Anti-dumping, Trade Re-routing, Duty Evasion, Protectionism*

1. Introduction

This study examines a complex dimension of Anti-dumping enforcement: the strategic selection of intermediary countries in trade Re-routing. While Anti-dumping duties are central instruments of trade protection, firms frequently employ sophisticated tactics to circumvent them, undermining their effectiveness. Among these, Re-routing goods through third countries has emerged as a particularly effective and challenging strategy to detect.

Anchored in the realist theoretical framework, this research views Anti-dumping measures not as neutral economic tools but as strategic instruments of power and protectionism. Firms' decisions to reroute trade reflect rational calculations shaped by geopolitical positioning, institutional vulnerabilities, and competitive pressures in the international system. Despite extensive literature on Anti-dumping practices, limited empirical research has investigated why specific intermediary countries are chosen to facilitate circumvention.

To address this gap, the study develops a binary logistic regression model assessing four determinants: geographic proximity, cultural affinity, trade intensity, and the level of corruption. Using a dataset of definitive EU Anti-dumping measures and bilateral trade flows, the analysis reveals that proximity and cultural ties significantly increase the likelihood of a country being used as a Re-routing hub. Conversely, strong trade relationships with the EU have a negative effect, suggesting exporters deliberately avoid high-visibility jurisdictions to reduce enforcement risks. Notably, corruption levels were not found to have a statistically significant impact, challenging common assumptions about the role of institutional weakness.

By systematically identifying these factors, the research contributes to both policy and academic debates on trade distortion and regulatory evasion. The findings provide actionable insights for policymakers seeking to design targeted monitoring and anti-circumvention measures. Ultimately, this study advances understanding of how firms adapt to protectionist barriers and how enforcement can evolve to address these challenges more effectively.

The paper is structured to ensure a coherent and comprehensive presentation of the research. The Literature Review examines the evolution of Anti-dumping measures, their association with protectionism, and existing perspectives on circumvention strategies such as trade Re-routing, gradually narrowing the focus to the determinants of intermediary country selection. The Methodology section outlines the development of the analytical framework, describes the data sources and statistical techniques, and explains the binary logistic regression model used to test the proposed hypotheses. The Results section presents the empirical findings, highlighting the significance and direction of the relationships between key explanatory factors and the likelihood of a country being used as a Re-routing hub. Finally, the Discussion and Conclusion critically interpret these results in the context of existing research and assess their implications for trade policy and enforcement.

2. Literature Review

Anti-dumping measures have emerged as a central instrument of trade policy, evolving from mechanisms intended to counteract unfair competition into tools increasingly associated with protectionism. Early scholarship, including Blonigen and Prusa (2001), argued that Anti-dumping regulations provide an "open door" for industries to secure trade relief, often substituting for more transparent forms of protection such as tariffs. Nelson (2006) further contends that Anti-dumping laws, with their complex and sometimes ambiguous definitions of dumping, have been routinely exploited to shield domestic producers rather than to ensure fair competition. Davis (2009a) reinforces this perspective, highlighting that many Anti-dumping cases appear motivated by political considerations and domestic lobbying rather than clear evidence of predatory pricing.

Several studies have examined the strategic use of Anti-dumping measures within broader trade negotiations. Bekker (2006) and Wruuck (2015) argue that governments deploy these duties not only to protect industries but also as bargaining tools to secure concessions in international forums. This political dimension is evident in the work of Iliescu (2017), who documents how domestic lobbying increases the likelihood of Anti-dumping petitions succeeding, with organized industries exerting significant pressure on policymakers to impose trade remedies.

A notable development over recent decades has been the expansion of Anti-dumping measures beyond traditional users such as the United States and the European Union to include emerging economies. Bown (2011) and de Azevedo Couto Firme and Vasconcelos (2015) identify this shift as one of the most significant post-WTO trends. Countries like India, China, and Brazil increasingly rely on Anti-dumping duties both defensively in order to protect nascent industries and offensively, as instruments of retaliation against trading partners. This "retaliation and contagion" effect, as described by Vandenbussche and Zanardi (2008), helps explain the global proliferation of Anti-dumping cases even as multilateral trade agreements have aimed to liberalize markets.

Parallel to the spread of Anti-dumping practices, scholars have explored their macroeconomic determinants. Feinberg (1989) and Knetter and Prusa (2003) found that economic downturns and rising unemployment significantly increase the likelihood of Anti-dumping petitions. These measures are often framed as necessary interventions to protect domestic employment and production during recessions. Similarly, Bown (2009) emphasizes that declining industrial output and heightened import penetration can trigger protectionist demands. Choi and Kim (2014) further demonstrate that distressed industries facing profit erosion are more inclined to seek Anti-dumping protection as a defensive strategy.

Beyond macroeconomic drivers, trade Re-routing has emerged as a sophisticated strategy to circumvent Anti-dumping duties. Liu and Shi (2019) document how exporters repackage goods in intermediary countries to obscure origin and avoid tariffs. Hayakawa and Sudsawasd (2024) analyze similar patterns during the US-China trade conflict, showing how firms deliberately adapted supply chains to exploit gaps in enforcement. Cheng et al. (2001) highlight that this form of regulatory arbitrage involves complex logistical and legal planning, often blending Re-routing with false declarations or misclassification of products. Such practices not only undermine the intended protective effect of Anti-dumping duties but also distort global trade flows and challenge the credibility of enforcement regimes.

Recent research has also examined the broader consequences of Anti-dumping enforcement and evasion. Prusa (1997) and Lasagni (2000) identify trade destruction as a common effect, with imports from targeted countries often falling sharply after duties are imposed. However, trade diversion and deflection are equally significant: imports shift to alternative suppliers, and targeted exporters redirect their goods to third markets (Bown and Crowley, 2006). These dynamics often leave the total volume of trade unchanged while reconfiguring supply chains, sometimes increasing costs for consumers and undermining the competitiveness of domestic industries in the long term.

Finally, ethical and strategic considerations permeate the discourse. Sykes (2007) questions whether the widespread use of Anti-dumping measures remains consistent with the principles of free trade, especially when combined with Re-routing tactics that exploit legal loopholes. Pistikou and Ketsetsidis (2023) emphasize that increasingly sophisticated evasion practices highlight the need for better international coordination, improved data sharing, and more proactive monitoring mechanisms.

Collectively, the literature underscores the complex and often contradictory role of Anti-dumping measures: while intended to level the playing field, they frequently function as tools of protectionism, political leverage, and strategic maneuvering. The combination of economic pressures, political incentives, and adaptive circumvention strategies has created a dynamic in which Anti-dumping enforcement remains both essential and persistently contested in global trade relations.

3. Analytical Framework and Methodology

Trade re-routing through intermediary countries is a well-documented strategy to evade anti-dumping duties, yet the factors influencing the selection of these intermediaries remain underexplored. This study investigates the economic, legal, and policy determinants driving firms to choose specific third countries for re-routing trade flows to bypass anti-dumping measures, particularly in the European Union (EU). By analyzing bilateral trade data, the research examines how anti-dumping duties alter trade patterns and identifies key factors shaping intermediary country selection, offering insights for policymakers to strengthen enforcement.

The study first confirms the effects of anti-dumping duties on trade patterns: trade destruction (H1), reducing direct trade between the imposing and targeted countries; trade diversion (H2), substituting imports from targeted countries with those from non-targeted countries; and trade deflection (H3), redirecting exports to third-country markets. Hypothesis H4 specifically tests whether anti-dumping duties increase indirect trade through intermediaries, facilitating re-routing. The analysis then explores determinants of intermediary selection: geographic proximity (H5), cultural affinity (H6), established trade relations (H7), and weak regulatory enforcement or corruption (H8).

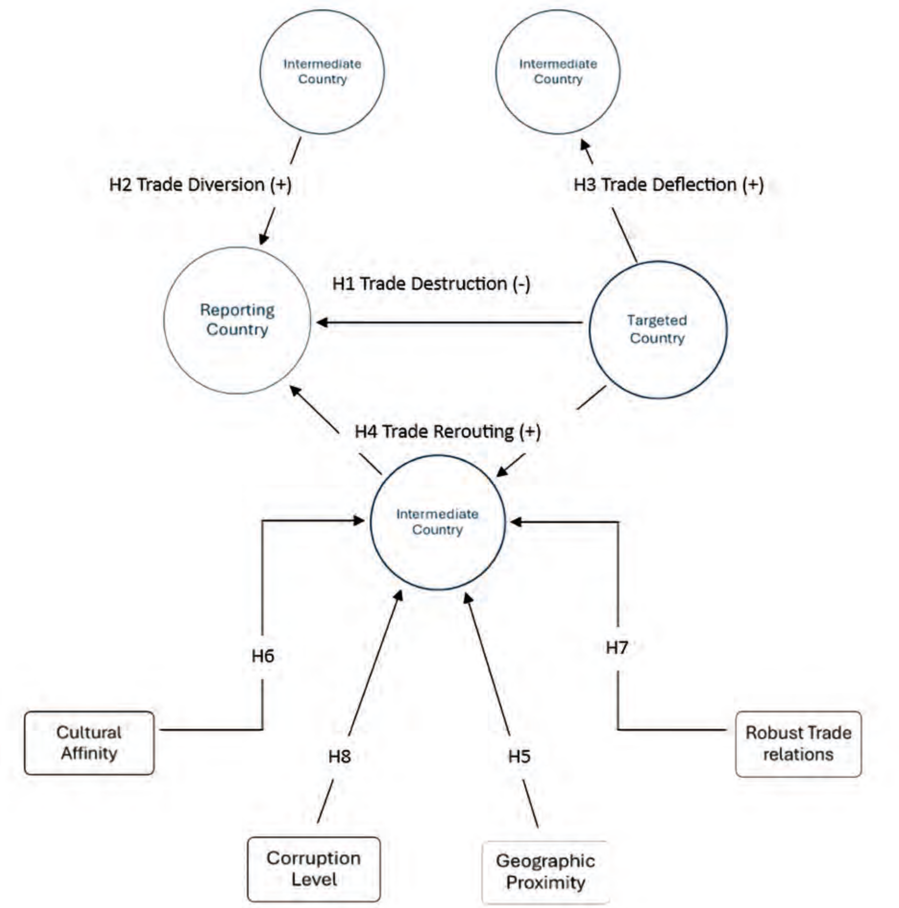
Table 1. Summary of Research Hypotheses.

Hypothesis 1 (H1)	*The imposition of Anti-dumping duties leads to a reduction in direct trade between the imposing country and the targeted country (trade destruction).*
Hypothesis 2 (H2)	The imposition of Anti-dumping duties leads to a substitution of imports from targeted countries with imports from non-targeted countries (trade diversion).
Hypothesis 3 (H3)	The imposition of Anti-dumping duties leads targeted exporters to redirect their exports to third-country markets instead of the imposing country (trade deflection).
Hypothesis 4 (H4)	The imposition of Anti-dumping duties leads to an increase in indirect trade through third countries, which act as intermediaries in trade Re-routing.
Hypothesis 5 (H5)	Geographic proximity between the targeted country and the intermediary country increases the likelihood of its selection as a Re-routing hub.
Hypothesis 6 (H6)	The existence of cultural affinity between the intermediary country and the targeted country increases the likelihood of its selection as a Re-routing hub.
Hypothesis 7 (H7)	Strong trade relations between the targeted country and the intermediary country increase the likelihood of its selection for Re-routing.
Hypothesis 8 (H8)	Intermediary countries where customs or regulatory enforcement can be more easily circumvented through corrupt practices increase the likelihood of their selection for Re-routing.

Source: Compiled by the author.

The conceptual framework illustrates the sequential impact of anti-dumping duties: trade destruction (H1), followed by diversion (H2), deflection (H3), and re-routing through intermediaries (H4). Arrows indicate positive (+) or negative (–) effects on trade flows. Determinants of intermediary selection—geographic proximity (H5), cultural affinity (H6), trade relations (H7), and regulatory enforcement (H8)—are mapped to clarify their influence on re-routing decisions. This framework guides the empirical strategy, using econometric analysis (descriptive statistics, correlation, and logistic regression) to operationalize variables and test causal linkages.

The findings enhance understanding of trade re-routing dynamics, revealing how firms exploit trade networks to minimize anti-dumping costs. By identifying key indicators of re-routing behavior, the study supports the development of targeted detection and prevention strategies. It highlights the need for improved trade monitoring, international cooperation, and stricter enforcement to address circumvention. This research contributes to the literature on anti-dumping circumvention and provides actionable policy recommendations to strengthen global trade regulations.



Graph 1. Conceptual Framework of the Research Hypotheses

Source: Compiled by the author

The dataset comprises 120 definitive Anti-dumping measures imposed by the European Union over approximately 35 years. These cases target exports primarily from China, Russia, India, South Korea, and Indonesia, among others, across 375 six-digit HS codes. Trade flows are measured in annual values (USD) and cover a time horizon extending from three years before to up to seven years after the imposition of duties. The three-year pre-duty period was selected to minimize distortions caused by short-term fluctuations.

Trade data were extracted from the EU Access2Markets and UN Comtrade databases. These sources provide harmonized, product-level trade statistics with high temporal and sectoral granularity. Data on Anti-dumping investigations and legal measures were collected from the WTO database to ensure consistency in case identification and classification.

To analyze the determinants of intermediary country selection, the study combines trade data with additional variables:

- Geographic proximity is defined using UN Geospatial Information and CIA World Factbook records, considering both land borders and maritime access.
- Cultural affinity is assessed through shared language, religion, or colonial ties, using Ethnologue, the World Religion Database, and the Harvard Colonial History Database.
- Established trade relations are classified based on whether a country consistently ranked among the top 10 trade partners of the targeted country.
- Corruption levels are measured by the Transparency International Corruption Perceptions Index (CPI), categorizing countries as high- or low-corruption environments.

This comprehensive data selection ensures that the analysis reflects the structural, institutional, and relational drivers of trade Re-routing behavior.

The empirical strategy proceeds in four main stages, beginning with Trade Destruction Analysis. To confirm H1, time-series analysis calculates the annual percentage change in import volumes from targeted countries before and after Ant-dumping duties imposition. The formula:

$$\Delta Xt = \frac{Xt - Xt - 1}{Xt - 1} X\ 100$$

quantifies year-on-year shifts, while cumulative changes track sustained effects over multiple years.

In the next stage of our analysis we focus on Trade Diversion and Deflection Tests. For H2 and H3, the analysis isolates HS codes exhibiting significant trade destruction. Trade diversion is identified by positive, statistically significant increases in imports of identical products from non-targeted countries. Trade deflection is measured by increases in exports from the targeted country to those same third countries, indicating a strategic reallocation of sales.

Trade Re-routing Identification follows as the next important stage of our analysis. To test H4, the research assesses whether exports from the targeted country to an intermediary correlate strongly with the intermediary's re-exports to the EU. A Pearson correlation coefficient above 0.5 signals a high likelihood of Re-routing, distinguishing this practice from ordinary trade diversion or deflection.

In the final stage we test H5 - H8 using binary logistic regression in SPSS in order to justify the Intermediary Country Selection. The dependent variable is whether a country functions as a Re-routing hub (1) or not (0). Independent variables are coded as binary indicators:

- Geographic proximity (1=proximate; 0=not)
- Cultural affinity (1=present; 0=absent)
- Established trade relations (1=top 10 partner; 0=other)
- Corruption level (1=high corruption; 0=low corruption)

This model estimates the likelihood that each factor increases the probability of Re-routing, providing statistical evidence of their relative importance.

This study acknowledges several limitations that shaped its methodological choices and the interpretation of findings. A primary constraint is the use of annual trade data, which may obscure the immediate effects of Anti-dumping duties depending on the timing of their imposition. Although monthly data would offer greater precision, limited accessibility led to a focus on cumulative effects over time. Additionally, to maintain analytical clarity, the analysis of trade diversion was limited to three countries per case. This decision reflects the tendency for rerouting intensity to diminish after the first few intermediary countries, with subsequent trade shifts often being marginal in volume. Regarding the determinants of intermediary country selection, only variables supported by internationally recognized rankings were included to ensure objectivity and replicability, excluding potentially relevant but unquantifiable or subjective factors. A further limitation lies in the study's inability to fully account for the influence of dynamic geopolitical relations. Structural variables like geographic proximity and cultural affinity fail to fully capture the evolving nature of political conflict and diplomacy, as demonstrated in cases such as Russia–Ukraine and Iran–Saudi Arabia.

By sequentially establishing the effects of Anti-dumping duties on trade flows and modeling the determinants of intermediary country selection, this methodology offers a rigorous, data-driven framework. The approach connects theory and empirical evidence, yielding insights for both policy-makers and researchers seeking to understand and counteract the strategic circumvention of trade protection measures.

4. Comparative Analysis

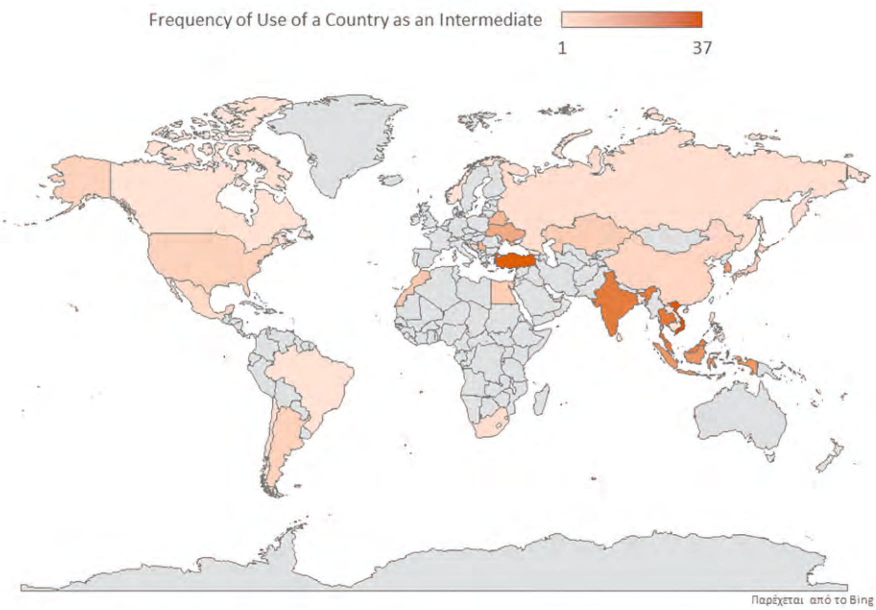
Our analysis focuses on 375 HS codes over multiple years reveals that nearly 80% experienced substantial reductions in import volumes after Anti-dumping measures were imposed. In the first year, 73% of codes were affected, with a median import decline of –56.83%. This impact deepened over time, with the median reduction reaching –78.34% by the latest year observed, suggesting both immediate and delayed trade suppression. Sectoral analysis showed pronounced concentration of Anti-dumping actions in base metals (e.g., steel, aluminum), where over 83% of codes were affected, underscoring this sector's vulnerability due to frequent dumping allegations. In contrast, technologically advanced sectors like machinery had significantly lower exposure, with only 23% of codes impacted. Geographically, China emerged as the primary target, accounting for nearly 50% of all affected HS codes. Russia and Turkey followed at considerable distances. Several countries with fewer codes under investigation, such as Egypt, Malaysia, and the USA, exhibited 100% impact rates, though small sample sizes limit interpretation.

The three main findings stand out from the descriptive statistics are as follow: first, the widespread and enduring trade destruction effect across most targeted products; second, the sectoral concentration in base metals, which may influence patterns of trade Re-routing; and third, China's central role as the predominant focus of EU Anti-dumping enforcement. This verified trade destruction provides the foundation for subsequent analysis of trade diversion, deflection, and Re-routing. While Re-routing can theoretically occur without observable trade declines, especially in fast-growing sectors, such cases remain rare and were excluded from this study. The next stage examines how disrupted trade flows are redirected via intermediary countries, ultimately identifying concrete evidence of Re-routing practices.

Following the study focuses on the identification of trade Re-routing practices aimed at circumventing EU Anti-dumping duties. To classify a case as Re-routing, three criteria had to be met: firstly, clear evidence of trade destruction, i.e., significant import decline from the targeted exporter; secondly, a sustained rise in imports from an intermediary country (trade diversion); and finally, a strong positive correlation ($r > 0.5$) between the decline in imports from the targeted country and the increase from the intermediary country (trade deflection).

Analysis of 299 HS codes resulted in 726 country-code combinations examined for potential Re-routing. Findings reveal that 193 HS codes (64.55%) show evidence of Re-routing, while 106 (35.45%) do not. Among the identified cases, Re-routing most often involves a single intermediary country (59%), though more complex routes involving two or three countries account for 28% and 13% of cases, respectively. This highlights the prevalence and sophistication of circumvention strategies.

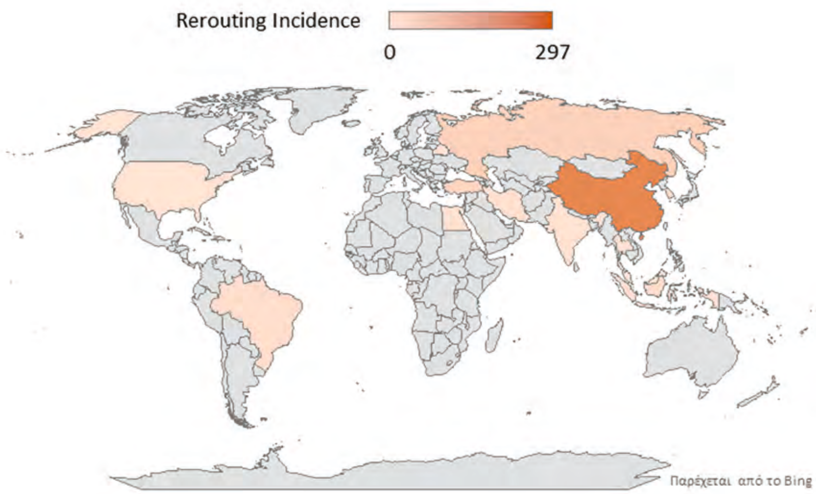
The study further distinguishes between two dimensions: the frequency with which specific countries serve as intermediaries and the frequency with which targeted exporters rely on Re-routing. Vietnam ($f = 37$), Turkey ($f = 35$), Thailand ($f = 28$) , India ($f = 26$) and Malaysia ($f = 25$) emerged as the top intermediary hubs, frequently facilitating re-export flows. In contrast, many countries appeared only sporadically in this role. Graph 2 provides a visual illustration of the geographical distribution of countries acting as intermediaries in trade Re-routing cases. The intensity of shading corresponds to the frequency of use, highlighting key transit hubs and offering a spatial perspective on the patterns discussed above.



Graph 2. Frequency of Use of a Country as an Intermediate in Trade Re-routing.

Source: Compiled by the author.

On the other hand, China stands out as the most active exporter in Re-routing practices, with evidence of circumvention in 183 out of 299 HS code cases. Russia and Turkey also showed notable engagement (35 and 25 respectively), while several countries had little or no involvement. Graph 3 offers a geographical representation of the Re-routing incidence among Anti-dumping-targeted countries. The shading intensity reflects the number of cases in which each country has been found to engage in circumvention practices, visually reinforcing the variation in Re-routing behavior discussed above.



Graph 3. Frequency of Use of a Country as an Intermediate in Trade Re-routing.

Source: Compiled by the author.

These patterns underscore the need for enforcement policies to address both key intermediary hubs and persistently non-compliant exporters. They also reveal how trade Re-routing is embedded in broader networks of global commerce, warranting further research into systemic vulnerabilities and coordinated enforcement.

In the next stage, in order to examine the impact of the four factors under investigation we have to prepare the dataset for statistical analysis, assigning binary values (1 or 0) to each of four explanatory variables for every country. These variables (geographic proximity, cultural affinity, trade relations, and corruption level) were defined in the methodology chapter. Each country thus received a score ranging from 0 to 4, representing the total number of conditions met. This scoring system aimed to capture the degree to which each country aligns with the hypothesized profile of an intermediary country likely to be used in trade Re-routing.

Table 2 presented the comparative distribution of these scores between countries classified as intermediaries (those identified as being involved in Re-routing) and non-intermediaries. Among the 429 non-intermediary country observations, most (40.09%) met only one condition, and 23.08% met two conditions. Only 7.23% fulfilled all four, while 10.02% did not satisfy any. This distribution suggests that non-intermediary countries generally display weaker alignment with the hypothesized factors. In contrast, among the 297 intermediary countries, the majority met more of the conditions. Specifically, 31.65% satisfied all four factors, and 30.30% satisfied three, together representing over 61% of the intermediary group. Only 17.85% met two conditions, 17.17% met one, and a minimal 3.03% met none. This clear divergence in profiles supports the premise that intermediary countries more frequently exhibit multiple characteristics associated with Re-routing suitability.

Table 2. Number of Conditions Met for both Intermediary and Non - Intermediary Countries.

	Non-Intermediary Countries (0)	% Rate	Intermediary Countries (1)	% Rate
4 Variables	31	7,23%	94	31,65%
3 Variables	84	19,58%	90	30,30%
2 Variables	99	23,08%	53	17,85%
1 Variable	172	40,09%	51	17,17%
0 Variables	43	10,02%	9	3,03%
	429		297	

Source: Compiled by the author.

As mentioned in the beginning, the purpose is to test the impact of the four independent variables or else predictors, on the dependent variable. Thus, the method that we will use in order to execute the above test in SPSS, will be binary logistic regression. According to literature, before the implementation of binary logistic regression, there are some important assumptions that should be tested, in order the results of the method to be valid. These assumptions are:

1. Binary Dependent Variable
2. Independence of observations
3. Linearity of Logits
4. No perfect Multicollinearity

When it comes to the first two assumptions, the dependent variable is indeed binary, by construction and the observations for each variable were taken without affecting each other and thus there is no correlation between them, concluding the independence of them. The linearity of logits refers to the linear relationship between the independent variables and the logarithmic odds (Log Odds) of the outcome; since it is a logistic regression that is implemented. However, this assumption regards only continuous variables. Since all of the independent variables are nominal and binary, there is no need to test this assumption. For the multicollinearity assumption, even though the predictors are binary they can still be highly correlated with each other and this can distort results. Thus, we have to make sure that this assumption is met. The Collinearity Diagnostics results are shown in the table below (Table 3).

Table 3: Collinearity Diagnostics for the predictors

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	Cultural Affinity	,893	1,120
	Trade Realations	,954	1,048
	Corruption Level	,886	1,129

a. Dependent Variable: Geographic Proximity

Source: SPSS analysis.

In order to determine on multicollinearity, according to literature there is no multicollinearity when Tolerance > 0.1 or respectively when VIF < 5. We see that all predictors have Tolerance > 0.1 and VIF < 5. Thus there is no multicollinearity and the assumption is met.

All of the above assumptions are met and thus we can proceed in the implementation of binary logistic regression. For the analysis we will assume that the level of significance (a) is 5%.

The output of the test is separated in two blocks. The Block 0 informs us about the results of the binary logistic regression without any of the independent variables in the model, but only the constant. These results alone are not useable as they provide not important information. However, they serve as a good baseline for comparing these results with the results of the model including the independent variables. The results of the Block 0 are presented in Table 4, Table 5 and Table 6.

In Table 4, we see that the overall percentage of correct predictions with only the constant in the model is 59.1%, which is medium and not strong enough.

Table 4: Classification Table for Block 0

Classification Table[a,b]

Observed			Predicted: Intermediary Country: The candidate country is not intermediary country	Predicted: Intermediary Country: The candidate country is intermediary country	Predicted: Percentage Correct
Step 0	Intermediary Country	The candidate country is not intermediary country	429	0	100,0
		The candidate country is intermediary country	297	0	,0
	Overall Percentage				59,1

a. Constant is included in the model.

b. The cut value is ,500

Source: SPSS analysis.

Table 5 shows that the constant should be included in the model, which is intuitively obvious, since there are no other variables and Table 6 shows the independent variables that are not included in the Equation. The null hypothesis that is tested on this table for each one is whether the variable is statistically significant when added alone in the model (Table 5).

Table 5: Variables in the Equation of Block 0

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-,368	,075	23,731	1	,000	,692

Source: SPSS analysis.

It seems that all variables, except the Trade Relations, look important to the model. However, what should be kept in mind is that this table is just a preview and does not reflect the final model, which might differ.

Table 6: Variables not in the Equation of Block 0

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Geographic Proximity	83,425	1	,000
		Cultural Affinity	114,346	1	,000
		Trade Relations	3,724	1	,054
		Corruption Level	25,891	1	,000
	Overall Statistics		156,119	4	,000

Source: SPSS analysis.

In Block 1 of the output, the same tests as in Block 0 are implemented, but this time including all variables in the model. Additionally, we get tests that assess the goodness of fit of the data from the model.

The first test of goodness of fit obtained is the Omnibus Test (Table 7). The null hypothesis that is assessed from this test is that the model with only the constant (see Table 5) fits the data as well as the model with the predictors. The null hypothesis is rejected (Model p-value < 0.05) concluding that the model with the predictors fits the data better and thus significantly improves prediction of the dependent variable.

Table 7: Omnibus Test for goodness of fit

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	165,151	4	,000
	Block	165,151	4	,000
	Model	165,151	4	,000

Source: SPSS analysis.

The second test of goodness of fit obtained is the Hosmer – Lemeshow (Table 8). It assesses the null hypothesis that the model with the predictors fits the data well and there are no significant differences between observed and predicted values. The hypothesis can't be rejected (p – value = 0.830 > 0.05).

Table 8: Hosmer and Lemeshow Test for goodness of fit.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	2,832	6	,830

Source: SPSS analysis.

Indeed, as shown in Table 9, for each category of the dependent variable the observed (left column) are not very different from the expected (right column). Thus, the model fits the data good enough.

Table 9: Contingency Table.

Contingency Table for Hosmer and Lemeshow Test

		Intermediary Country = The candidate country is not intermediary country		Intermediary Country = The candidate country is intermediary country		
		Observed	Expected	Observed	Expected	Total
Step 1	1	65	66,088	10	8,912	75
	2	43	43,084	9	8,916	52
	3	129	132,002	42	38,998	171
	4	51	46,830	19	23,170	70
	5	60	58,587	38	39,413	98
	6	37	34,234	35	37,766	72
	7	34	38,494	100	95,506	134
	8	10	9,680	44	44,320	54

Source: SPSS analysis.

The conclusion above can be enhanced by, but not totally restricted at, the pseudo R^2 of Nagelkere (Table 10). It is different from R^2 of linear regression, but is an approximate indicator of model performance. It is not the variance explained, but an indication of how much better is this model at predicting outcomes compared to chance and provides a sense on how well the model explains the outcome. Hence, we can conclude that we have a moderate explanation of 27.4%.

Table 10: Pseudo R Square of Nagelkerke

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	817,165[a]	,203	,274

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than ,001.

Source: SPSS analysis.

The next classification table (Table 11) provides an indication of how well the model is able to predict the correct category once the predictors are added. We can compare this with the classification table of Block 0 (Table 4). There is an improvement in the prediction. Without the predictors in the model the overall percentage of the correct predictions was 59.1%, but now is increased to 73.7%. The first row of the table represents the specificity of the model, meaning the number of cases that belong in the non – target category and have been predicted correctly to fall in the non – target category. The specificity of the model is 83%, which is strong enough. Hence, 83% of countries that are not intermediary have been predicted correctly. The second row represents the sensitivity of the model, meaning the cases of the target group (country that is an intermediary) that were predicted correctly to fall in the target group. The sensitivity of the model is 60.3%, which is also strong. Thus, 60.3% of countries that are intermediaries were predicted right. In summarize, the model has strong specificity and sensitivity and the overall accuracy rate of model predictions is 73.7%.

Table 11: Classification table when predictors are added in the model.

Classification Table[a]

Observed			Predicted: Intermediary Country: The candidate country is not intermediary country	Predicted: Intermediary Country: The candidate country is intermediary country	Predicted: Percentage Correct
Step 1	Intermediary Country	The candidate country is not intermediary country	356	73	83,0
		The candidate country is intermediary country	118	179	60,3
	Overall Percentage				73,7

a. The cut value is ,500

Source: SPSS analysis.

The last table shows which of the independent variables have significant impact on the dependent variable (Table 12). In other words it indicates which factors affect significantly the decision of choosing the intermediary country. The null hypothesis for each predictor is that it is not needed in the final model. The hypothesis is rejected for Geographic Proximity, Cultural Affinity and Trade Relations implying that they are significant factors and should be included in the final model (p – value < 0.05). It should be noted, that Trade Relations is ultimately a significant predictor in contrast with the results of Table 4. The column B in table 12, shows the regression coefficients of the predictors and are the predicted change in Log Odds (column Exp(B)). For one unit of change in the predictors there is Exp(B) change in the probability of the outcome as shown in the corresponding column. If the Log Odds (Exp B) are greater than 1, this means that the probability of falling in the target group is higher than the probability of falling in the non-target group. If the Log Odds (Exp B) are less than 1, this means that the probability of falling in the target group is lower than the probability of falling in the non-target group

Specifically, if the geographic proximity increases by a unit, there is a 4.096 increase in the probability of a country to be intermediary. If the cultural affinity increases by a unit there is a 3.783 increase in the probability of a country to be intermediary, while an increase in the trade relations will lead to a 0.556 decrease in the probability of a country to be intermediary.

The corruption level shouldn't be included as is it not a significant factor (p – value = 0.110 > 0.05).

Table 12: Variables that impact the dependent variable.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Geographic Proximity	1,410	,224	39,479	1	,000	4,096	2,639	6,360
	Cultural Affinity	1,331	,186	51,242	1	,000	3,783	2,628	5,446
	Trade Relations	-,587	,223	6,937	1	,008	,556	,359	,860
	Corruption Level	,356	,223	2,560	1	,110	1,428	,923	2,208
	Constant	-1,575	,222	50,135	1	,000	,207		

a. Variable(s) entered on step 1: Geographic Proximity, Cultural Affinity, Trade Relations, Corruption Level.

Source: SPSS analysis.

5. Conclusions

This study provides a comprehensive analysis of the trade-distorting effects of EU anti-dumping measures, confirming their significant impact on global trade flows and the strategic responses they elicit. The analysis reveals trade destruction in approximately 80% of the 375 examined HS codes, with a median import decline of –78.34% over time, particularly affecting base metals (83% of codes) and imports from China (50% of cases). This underscores the measures' effectiveness in curbing direct trade from targeted countries but also highlights their vulnerability to circumvention. Trade re-routing, identified in 64.55% of cases, emerges as a prevalent evasion strategy, with Vietnam (f=37), Turkey (f=35), Thailand (f=28), India (f=26), and Malaysia (f=25) serving as primary intermediary hubs. This practice, often involving complex multi-country pathways (41% of cases), reveals the sophistication of firms' efforts to bypass duties.

Binary logistic regression identifies key determinants of intermediary country selection: geographic proximity (odds ratio 4.096) and cultural affinity (3.783) significantly increase the likelihood of a country being chosen as a re-routing hub, facilitating logistical efficiency and trust-based networks. Conversely, strong trade relations with the EU (odds ratio 0.556) reduce this likelihood, likely due to heightened regulatory scrutiny in established trade corridors, challenging assumptions that robust trade ties enable evasion. Surprisingly, corruption levels (p=0.110) showed no significant effect, suggesting firms prioritize operational and relational factors over exploiting institutional weaknesses. The model's 73.7% predictive accuracy, validated by robust goodness-of-fit (Hosmer-Lemeshow p=0.830) and adherence to logistic regression assumptions, ensures the reliability of these findings.

These results extend prior literature, including Prusa (1997), Bown and Crowley (2006), and Liu and Shi (2019), by quantifying intermediary selection thresholds and questioning the role of corruption in circumvention strategies. The findings highlight systemic vulnerabilities in global trade networks, where re-routing distorts trade flows and undermines anti-dumping enforcement. Policy recommendations include adopting risk-based customs enforcement targeting shipments from geographically and culturally proximate intermediaries, enhancing international cooperation for real-time trade monitoring, and integrating granular, operational-level corruption data to improve detection. Additionally, leveraging advanced analytics to track multi-country re-routing patterns could strengthen enforcement.

Future research should explore dynamic geopolitical influences, such as evolving trade alliances or conflicts (e.g., Russia–Ukraine), which may shape intermediary selection. A promising field of inquiry is the role of Harmonized System (HS) code falsification as a strategy to evade anti-dumping duties, where exporters misclassify goods to obscure their origin or nature. Investigating this practice could reveal additional circumvention mechanisms and inform targeted regulatory responses. Incorporating micro-level trade data and longitudinal analyses could further refine predictive models, addressing limitations in annual data granularity. These insights enable policymakers to design adaptive, evidence-based strategies, ensuring anti-dumping measures protect domestic industries while mitigating evasion-driven distortions in global trade.

References

Bekker, D. (2006). The Strategic Use of Anti-dumping in International Trade. *South African Journal of Economics*, 74(3), 501-521. https://doi.org/10.1111/j.1813-6982.2006.00088.x

Blonigen, B. A., & Prusa, T. J. (2001). Antidumping. *NBER Working Paper Series, (8398)*. https://doi.org/10.1002/9780470756461.ch9

Bown, C. P. (2009). The global resort to antidumping, safeguards, and other trade remedies amidst the economic crisis (World Bank Policy Research Working Paper No. 5051). https://doi.org/10.1596/1813-9450-5051

Bown, C. P. (2011). Taking stock of antidumping, safeguards and countervailing duties, 1990–2009. *World Economy*, 34(12), 1955–1998. https://doi.org/10.1111/j.1467-9701.2011.01388.x

Bown, C. P., & Crowley, M. A. (2006). Policy externalities: How U.S. antidumping affects Japanese exports to the EU. *European Journal of Political Economy*, 22(3), 696–714. https://doi.org/10.1016/j.ejpoleco.2005.12.004

Cheng, L., Qiu, L. D., & Wong, K. P. (2001). Anti-dumping measures as a tool of protectionism: A mechanism design approach. *Canadian Journal of Economics*, 34(3), 639–660. https://doi.org/10.1111/0008-4085.00092

Choi, C. H., & Kim, J. W. (2014). Determinants for macroeconomic factors of antidumping: A comparative analysis of India and China. *International Trade Journal*, 28(3), 229–245.

Davis, L. (2009). Anti-dumping investigation in the EU: How does it work? (Working Paper No. 04/2009). European Centre for International Political Economy. https://ssrn.com/abstract=1395688

European Commission. (n.d.). Access to markets: Statistics. Access2Markets. Retrieved April 22, 2025, from https://trade.ec.europa.eu/access-to-markets/en/statistics

Feinberg, R.M. (1989). Exchange Rates and "Unfair Trade." *Review of Economics and Statistics*, 71(4), 704-707. https://doi.org/10.2307/1928116

Firme, V. de A. C., & Vasconcelos, C. R. F. (2015). Evolution in the use of antidumping mechanism after Uruguay round. *EconomiA*, 16(3), 321–342. https://doi.org/10.1016/j.econ.2015.09.004

Hayakawa, K., & Sudsawasd, S. (2024). Trade effects of the US–China trade war on a third country: Preventing trade rerouting from China (IDE Discussion Paper No. 916). Institute of Developing Economies, Japan External Trade Organization (JETRO). http://hdl.handle.net/2344/0002000839

Iliescu, N. (2017). US lobby activity and antidumping outcomes. https://api.semanticscholar.org/CorpusID:238755848

Knetter, M. M., & Prusa, T. J. (2003). Macroeconomic factors and antidumping filings: Evidence from four countries. *Journal of International Economics*, 61(1), 1–17. https://doi.org/10.1016/S0022-1996(02)00080-6

Lasagni, A. (2000). Does country-targeted anti-dumping policy by the EU create trade diversion? *Journal of World Trade*, 34(4), 137–160. https://doi.org/10.54648/273729

Liu, X., & Shi, H. (2019). Anti-dumping duty circumvention through trade rerouting: Evidence from Chinese exporters. *World Economy*, 42(5), 1427–1466. https://doi.org/10.1111/twec.12747

Nelson, D. (2006). The political economy of antidumping: A survey. *European Journal of Political Economy*, 22(3), 554–590. https://doi.org/10.1016/j.ejpoleco.2005.12.002

Pistikou, V., & Ketsetsidis, A. (2023). Recent evidence on antidumping duties as a tool of protectionism. *In Springer proceedings in business and economics* (pp. 3–33). Springer. https://doi.org/10.1007/978-3-031-34059-8_1

Prusa, T. J. (1997). The effects of U.S. trade protection and promotion policies (NBER Working Paper No. 5440). National Bureau of Economic Research. http://www.nber.org/papers/w5440.pdf

Sykes, A. O. (2007). International trade: Trade remedies. In A. T. Guzman & A. O. Sykes (Eds.), *Research handbook in international economic law* (pp. 62–105). Edward Elgar Publishing. https://doi.org/10.4337/9781847204233.00007

United Nations. (n.d.). UN Comtrade database. Retrieved April 02, 2025, from https://comtradeplus.un.org/

Vandenbussche, H., & Zanardi, M. (2008). What explains the proliferation of antidumping laws? *Economic Policy*, 23(53), 94–138. https://doi.org/10.1111/j.1468-0327.2007.00196.x

World Trade Organization. (n.d.). *World Trade Organization home page*. Retrieved March 20, 2025, from https://www.wto.org/

Wruuck, P. (2015). The political economy of anti-dumping protection: A strategic analysis. In *Contributions to economics* (pp. 79–128). Springer. https://doi.org/10.1007/978-3-319-11224-4

MODERN TRENDS IN RECRUITMENT AND SELECTION OF PERSONNEL (AI, AUTOMATION, LINKEDIN)

Elenica Sofijanova
Faculty of Economics, Goce Delcev University, Stip, North Macedonia,
elenica.sofijanova@ugd.edu.mk

Theodore Koutroukis
Department of Economics, Democritus University of Thrace, Komotini, Greece
tkoutro@econ.duth.gr

Marija Majhosheva
Faculty of Economics, Goce Delcev University, Stip, North Macedonia
marija.30829@student.ugd.edu.mk

Liljana Pushova Stamenkova
Faculty of Economics, Goce Delcev University, Stip, North Macedonia
liljana.30826@student.ugd.edu.mk

ABSTRACT

The rapid, dynamic, and evolutionary technological progress has contributed to significant transformations in the recruitment and selection process. The business sector is undergoing a progressive and ongoing transformation towards the integration and full adaptation of digital tools. The progress of new technologies has precipitated profound changes in the manner in which companies select and choose their employees. Contemporary trends have emphasized the utilization of artificial intelligence (AI) automation and the impact of social networks in the process of attracting and selecting suitable personnel.

In this paper, we analyze how AI improves the process and what contribution it has to improving the quality of selection decisions. The objective of this paper is to methodically analyze and explore the predominant advantages, disadvantages, opportunities, and risks associated with the utilization of contemporary technology and to determine whether the implementation of digital tools will enhance the efficacy of the recruitment and selection process by increasing its transparency.

Through a survey and statistical analysis of data obtained from HR professionals in North Macedonia and analysis of secondary data, the study finds a correlation between trust in AI and its adoption. The findings suggest that although traditional methods remain prevalent, the future of recruitment lies in a hybrid approach combining digital tools and human judgment.

This study highlights the ongoing shift from traditional to technology-enabled recruitment practices. While full automation is not yet prevalent in North Macedonia, the adoption of platforms like LinkedIn and AI-based tools is increasing, especially among IT companies.

To ensure the successful integration of artificial intelligence and digital technologies within human resource management, it is essential to invest in the continuous training of HR professionals. By equipping them with the necessary skills and knowledge, organizations can enhance their capacity to leverage advanced tools effectively. Equally important is the development of comprehensive ethical guidelines that govern the use of AI, with particular attention to promoting fairness, transparency, and the protection of sensitive employee data. Furthermore, organizations are encouraged to adopt hybrid models that balance the efficiency of automation with the irreplaceable value of human expertise and intuition. Such models not only improve decision-making process, but also foster trust and adaptability among employees. To accelerate the broader adoption of these innovations, it is vital to showcase real-world examples of successful implementation. The future of recruitment lies in balancing technological advancement with ethical, inclusive, and human-centric approaches.

Keywords: *artificial intelligence, platforms, recruitment, selection, human resource development*

1. Introduction

Recruiting and retaining suitable personnel is a growing challenge for modern organizations operating in a fast-paced and competitive global environment. The nature of work has changed, with employees now placing greater emphasis on flexibility, well-being, and company values rather than solely on salary and job stability (LinkedIn Talent Solutions, 2023). Simultaneously, businesses face pressure to attract and retain talent capable of navigating these evolving demands (Cappelli, 2019).

To meet these challenges, organizations are integrating digital tools, including artificial intelligence and recruitment platforms, into their talent acquisition strategies. These innovations have shifted the landscape from traditional, manual processes to more automated, data-driven approaches (Upadhyay & Khandelwal, 2018; Van Esch et al., 2019). This paper explores these developments, focusing on the implications of AI, automation, and LinkedIn in modern recruitment.

Traditional recruitment relied heavily on manual processes—newspaper ads, referrals, job fairs, and face-to-face interviews. While these methods ensured human interaction and in-depth evaluation, they were time-consuming and limited in reach (Dineen & Allen, 2016).

In contrast, modern recruitment leverages technologies like:

- AI and automation, which assist in screening resumes, predicting candidate fit, and reducing time-to-hire (Tambe et al., 2019; Meijerink et al., 2020).
- LinkedIn and similar platforms, which facilitate talent sourcing, employer branding, and networking (LinkedIn Talent Solutions, 2023).
- Applicant tracking systems (ATS), which streamline application management (Upadhyay & Khandelwal, 2018).
- Chatbots and VR tools, which improve candidate experience and enable remote recruitment (Van Esch et al., 2019).

Numerous studies highlight the benefits of these tools in terms of cost-effectiveness, efficiency, and candidate satisfaction (Chamorro-Premuzic et al., 2017; Tambe et al., 2019). However, concerns remain regarding data privacy, bias, loss of human judgment, and ethical implications (Leicht-Deobald et al., 2019).

A significant challenge confronting contemporary business enterprises pertains to the identification and retention of personnel who are well-suited for specific roles. Businesses operate in conditions of dynamic and rapid technological change and great global competition. The requirements for employees are becoming more and more specific and dynamic, necessitating expertise, dedication, and knowledge from the workforce. Furthermore, organizations encounter difficulties in identifying suitable personnel. These personnel must possess the ability to attract new employees and also ensure their continuous engagement within the organization. In the contemporary era, employees have become increasingly transient, transitioning between jobs with greater frequency. This phenomenon stands in contrast to the past, when individuals prioritized security and stability in their professional pursuits, and employment was the primary objective. In the contemporary professional landscape, the demands placed upon employees have undergone a significant transformation, becoming increasingly multifaceted in nature. These contemporary demands encompass a wide array of conditions and criteria that were not previously subjects of discourse. The majority of requirements and conditions are established by the job candidates themselves. This shift represents a departure from historical practices, in which employers wielded a predominant influence in shaping the terms of employment.The criteria for employment have evolved beyond the traditional factors such as job position and salary. A new emphasis has emerged, placing significant value on the manner in which companies support and care for their employees. This encompasses aspects such as the allocation of free time, the company's capacity to nurture its workforce, their mental well-being, and the provision of opportunities for additional leisure time.

The evolving perspectives of employees and the mounting, nuanced demands of contemporary organizations have precipitated a paradigm shift in recruitment and selection methodologies. These fundamental functions in the identification of suitable personnel are becoming increasingly integrated with advanced digital tools and platforms. The advent of artificial intelligence, new platforms, and automation has precipitated a paradigm shift in the dynamics of the labor market, thereby facilitating a more expeditious and streamlined approach to acquiring the requisite personnel. The majority of businesses have recognized the advantages of this approach and have concentrated on aligning their applications and corporate identity with the contemporary paradigm.

2. Literature Review

The recruitment and selection of personnel have evolved dramatically in recent decades, shaped by rapid technological advancement, digital transformation, and shifting expectations in the labor market. Traditional recruitment models, characterized by manual screening, print advertisements, and face-to-face interviews, have been increasingly replaced by data-driven, automated, and platform-based approaches. These modern tools—particularly artificial intelligence (AI), automation, and professional networking platforms such as LinkedIn—are fundamentally reshaping how organizations identify, assess, and engage talent.

Historically, recruitment relied on time-intensive processes such as in-person job fairs, newspaper advertisements, and manual screening of resumes (Dineen & Allen, 2016). While these methods allowed for a deep, personalized assessment of candidates, they were often limited in reach and scalability. With the globalization of labor markets and the digitization of business processes, there has been a growing need for faster, more efficient, and wider-reaching recruitment strategies (Cappelli, 2019).

AI and automation have emerged as powerful enablers in modern recruitment. These technologies are now used to screen resumes, conduct preliminary assessments, and even predict a candidate's job performance and cultural fit through machine learning algorithms (Upadhyay & Khandelwal, 2018; Tambe, Cappelli, & Yakubovich, 2019). AI-driven tools can reduce time-to-hire, minimize human biases in candidate evaluation, and enhance the overall efficiency of recruitment processes (Meijerink, Bondarouk, & Lepak, 2020). For example, predictive analytics can analyze past hiring data to identify the traits and qualifications of high-performing employees, thereby improving the precision of candidate selection.

However, the adoption of AI also raises significant concerns. Scholars have noted risks related to algorithmic bias, lack of transparency in decision-making, and over-reliance on technology that may inadvertently perpetuate discriminatory practices (Leicht-Deobald et al., 2019). These challenges highlight the importance of ethical frameworks and human oversight in AI-based recruitment.

LinkedIn and similar digital platforms have become central in the talent acquisition process, offering new pathways for sourcing both active and passive candidates. Unlike traditional job boards, LinkedIn combines job postings with professional profiles, endorsements, and networking capabilities, enabling recruiters to evaluate candidates in a more holistic context (Van Esch, Black, & Ferolie, 2019). The platform also facilitates employer branding, allowing companies to communicate their culture and values to potential applicants (LinkedIn Talent Solutions, 2023).

According to research, companies that actively manage their employer brand on LinkedIn experience higher application rates, better candidate engagement, and stronger retention outcomes (Chamorro-Premuzic, Akhtar, Winsborough, & Sherman, 2017). Moreover, the use of advanced search filters, AI-driven matching algorithms, and real-time analytics on LinkedIn has significantly improved the efficiency of candidate sourcing and outreach.

Applicant Tracking Systems (ATS) have become standard in large organizations, enabling recruiters to organize, filter, and track applications efficiently. ATS platforms often integrate with AI tools to automate resume parsing and shortlist candidates based on predefined criteria (Upadhyay & Khandelwal, 2018). In addition, chatbots and virtual assistants are increasingly being used to engage with candidates in the early stages of recruitment, answer FAQs, schedule interviews, and provide updates throughout the application process (Van Esch et al., 2019). These tools enhance the candidate experience by offering immediate responses and reducing uncertainty.

Despite the benefits of these technological advancements, several scholars stress the importance of addressing the associated risks. Data privacy, informed consent, fairness, and transparency are critical concerns in the use of AI and digital recruitment tools (Leicht-Deobald et al., 2019). Furthermore, excessive reliance on algorithms may undermine the human element in recruitment, leading to a loss of intuition, empathy, and personalized judgment in hiring decisions. Researchers advocate for hybrid models that combine technological efficiency with human expertise to ensure balanced and ethical hiring practices (Meijerink et al., 2020).

The integration of artificial intelligence into recruitment processes has introduced a range of benefits that significantly enhance the efficiency and quality of hiring. AI allows companies to process large volumes of candidate data rapidly, enabling predictive analytics and automated decision-making based on predefined job criteria (Tambe, Cappelli, & Yakubovich, 2019; Upadhyay & Khandelwal, 2018). This facilitates more efficient candidate screening and better alignment between job requirements and candidate qualifications. Notably, AI supports 24/7 availability, improves candidate engagement through tailored interactions, and enhances communication via chatbots and virtual assistants powered by natural language processing (Van Esch, Black, & Ferolie, 2019). These tools contribute to a more personalized and consistent candidate experience, while also reducing recruiters' workload by automating routine tasks (Meijerink, Bondarouk, & Lepak, 2020). Furthermore, studies suggest that AI reduces recruitment costs in the long run and improves hiring quality by up to 52% (Chamorro-Premuzic, Akhtar, Winsborough, & Sherman, 2017).

Despite these advantages, the use of AI in recruitment is not without challenges. One major concern involves data privacy and compliance with personal data protection laws, which vary across countries (Leicht-Deobald et al., 2019). Organizations must ensure ethical and lawful data usage when processing candidate information. Another issue is the lack of human judgment in AI-driven systems; while AI excels at pattern recognition, it may overlook qualified candidates who fail to use specific keywords or who do not conform to algorithmic criteria (Tambe et al., 2019). This can lead to unintended bias and the exclusion of potentially strong candidates. Additionally, the possibility of fraudulent or inaccurate profiles on platforms such as LinkedIn raises further concerns about the reliability of automated decisions (LinkedIn Talent Solutions, 2023). Lastly, AI systems require regular updates and ethical oversight to maintain accuracy and protect user privacy. A balanced approach combining AI's efficiency with human expertise is therefore essential for fair, transparent, and effective recruitment (Meijerink et al., 2020; Leicht-Deobald et al., 2019).

3. Data and Methodology

The foundation of this study is predominantly composed of findings and statistical analysis of data obtained from primary sources, and analysis of data from secondary sources. The statistical analysis is conducted using Excel. A comprehensive review of the relevant professional literature was conducted, encompassing research publications and additional sources found in books and scientific papers. In order to better analyze and understand the existence of artificial intelligence, automation and modern social networks that facilitate networking, it is necessary to use different approaches that will enable their more detailed examination. To be able to see the theory in practice, we continued the research using a structured questionnaire, which we formed in a way that allowed us to see how many of our Macedonian companies rely on modern methods of selection and recruitment of personnel and how much they trust them. Interviews with some of the recruiters were conducted, in order to get a clearer picture of their views on this area. The interviews gave us more personalized answers and details that we would not be able to get in a questionnaire with specific answers.

This paper implements data and analysis for recruiters who are part of different sectors. The data implemented in the research is mostly used by contacting HR managers and professionals in the field of human resources who have long-term experience in recruitment and selection of personnel.

The following set of hypotheses was established:

H0: There is a statistically significant relationship between the use of AI and trust in automated systems.

H1: The frequency of AI tool usage in daily tasks is positively correlated with perceived system transparency.

H2: Employees with higher digital literacy exhibit greater trust in AI-driven systems.

H3: Trust in automated systems mediates the relationship between AI usage and job satisfaction.

4. Results and Discussion

In order to confirm or deny the hypotheses set, we used various qualitative, quantitative and statistical methods. Initially, we used the questionnaire as an opportunity to obtain different answers from the respondents that would give us a picture of their attitude and subjective assessments of digitalization, and additionally we used cross-tabulation. Cross-tabulation helped us discover a certain connection that allowed us to confirm/deny the hypotheses set. It is a quantitative, descriptive statistics that helped us reach the appropriate results.

This survey was conducted among people who are part of the HR sector in various industries and was conducted on the LinkedIn platform. The survey itself shows that most of the respondents come from the IT industry, which proves that this sector, unlike others, is more present on LinkedIn in Macedonia. Of the respondents, 54.9% are users of artificial intelligence, automation and digital platforms, which means that it cannot yet be said that modern methods are accepted in our country. Of the tools listed in the survey, the most used are LinkedIn and Chat GPT, and the use of these tools by 58.7% is assessed as partially positive. Analyzing the fact that a very small percentage of people responded that these tools have a negative impact, it can be concluded that digitalization certainly has a future in our country and in the field of HR and recruitment. In terms of the extent to which these tools are used, there is still no enviable level, but we say again that there is hope that the situation will change, given the fact that only 17.6% of respondents answered that they never use LinkedIn to select a candidate. In terms of trust, recruiters are still a bit skeptical and do not rely entirely on digital tools. According to the interviews with them, we realized that, digital tools only help traditional ones and speed up the process of selecting a candidate. In general, they use LinkedIn to select candidates, and then continue with traditional interviews, testing, etc. The surveyed recruiters use LinkedIn for different things and for different purposes, like finding candidates, reviewing profiles, publishing advertisements, etc. Regarding the question of whether they believe that they receive quality candidates through LinkedIn, the majority of them, i.e. 51%, believe that the fact of whether they will receive a quality or less quality candidate depends mostly on the position they are filling. A general comment and conclusion is that they believe that the highest quality personnel can be found when filling a position in the field of Information Technology because such types of profiles are most present on this network. Half, or 50% of the respondents believe that there may be a risk of discrimination through LinkedIn, and 32.7% believe that it is very small. The majority of the recruiters agreed with the last question, or as many as 80.4% responded that in the future the modern recruitment process and the presence of artificial intelligence will be more present.

In order to more reliably analyze the relationship between trust in modern tools and their use or non-use, we included analysis through cross-tabulation and ANOVA:

Table 1. Cross Tabulation

	Trust AI	Do not trust AI	Don't know	Total
Uses AI	8	8	6	22
Does not use AI	4	13	11	28
Total	12	21	17	50

Source: Authors research

Table 2. Expected Values

	Trust AI	Do not trust AI	Don't know
Uses AI	5.28	9.24	7.48
Does not use AI	6.72	11.76	9.52

Source: Authors research

P- value	0.19

The result obtained from the cross-sectional analysis showed that p-value = 0.1899=> 0.19, this result is greater than the standard significance level of 0.05. From this we cannot come to a final statistical result that there is a significant relationship between AI and trust in automated selection systems, but we can freely say that respondents who have greater trust in AI and automated systems use them more, while those who do not trust them more refrain from using them. Finally, it can be noted that the use of new tools is related to trust, but it also depends on a number of other factors such as: the experience of recruiters, knowledge of the systems, the skepticism of recruiters towards innovations, technological readiness and so on. With these results, we cannot completely rule out the first hypothesis.

Additionally, we used ANOVA where we looked at recruiters who use artificial intelligence in the recruitment process and their level of trust, which was marked by answers Yes (that they trust AI) I don't know, and No (recruiters who do not trust artificial intelligence). To do this analysis, we looked at questions 2 and 6 of the survey and obtained the following results:

With a value of 2 for the second question: Do you use artificial intelligence (AI) or automated tools in the recruitment process? Recruiters who use artificial intelligence in the recruitment process have answered with a value of 1, and those who do not use it with a value of 1. On the 6th question: . Do you trust in automated candidate selection systems? Those who do not trust digitalization answered with a 1, those who are neutral with a 2, and those who trust it with a 3. An ANOVA was conducted for users who use AI and who have different levels of trust in it and the following results were obtained:

Anova: Single factor

SUMMARY

Groups	Count	Sum	Average	Variance
6. Do you trust automated candidate selection systems?	51	94	1.843137	0.654901961
2. Do you use artificial intelligence (AI) or automated tools in your recruitment process?	51	74	1.45098	0.25254902

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	3.921568627	1	3.921569	8.643042351	0.004078	3.936143
Within Groups	45.37254902	100	0.453725			
Total	49.29411765	101				

The F – value is 8.64, which means that we obtained a value greater than the critical value 3.936. This leads to the result that there is a difference between the groups.

The p – value is 0.004<0.05, which means that the difference is statistically significant with 95% confidence.

Additionally, an analysis was conducted for users who do not use artificial intelligence and who have different levels of trust in it and the following results were obtained:

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
6. Do you trust automated candidate selection systems?	48	88	1.833333	0.65248227
2. Do you use artificial intelligence (AI) or automated tools in the recruitment process?	48	68	1.416667	0.24822695

ANOVA

Source of Variation	SS	df	MS	F
Between Groups	4.166666667	1	4.166667	9.251968504
Within Groups	42.33333333	94	0.450355	

The F - value is 9.25 which means that we obtained a value greater than the critical value 3.942. This leads to the result that there is a significant difference between the groups.

The p – value is 0.003 <0.05 which means that the difference is statistically significant.

The findings of this study indicate a moderate, but growing adoption of AI-driven tools among HR professionals, particularly within the IT sector. Despite the increasing global presence of AI in HR analytics, only slightly more than half of the surveyed respondents reported active usage of such technologies in their recruitment processes. LinkedIn and ChatGPT emerged as the most commonly used platforms, primarily due to their accessibility and integration into existing digital ecosystems. However, the overall frequency of usage remains limited, reflecting a cautious and gradual transition rather than widespread acceptance.

One of the central themes emerging from the analysis is the complex relationship between trust and technology adoption. While some respondents expressed confidence in AI's ability to enhance efficiency and streamline candidate selection, others maintained a preference for traditional recruitment practices, highlighting perceived risks related to bias, lack of transparency, and the inability of algorithms to fully capture human qualities. Interestingly, many HR professionals view AI tools not as replacements but rather as supplementary instruments that support—but do not substitute—human judgment. This hybrid approach appears to be the prevailing sentiment, suggesting that technological adoption in recruitment is more evolutionary than revolutionary.

The analysis further revealed significant differences in trust levels across various user groups. The ANOVA results demonstrated that both users and non-users of AI hold diverse and statistically significant views regarding the reliability of automated systems. This variation underscores the importance of individual and contextual factors—such as technological literacy, previous experience, organizational readiness, and industry norms—in shaping perceptions and influencing adoption. Particularly in sectors where digital competence is higher, trust in AI systems tends to be more favorable, reinforcing the role of digital skills as a critical enabler in technology acceptance.

Moreover, concerns regarding the potential for discrimination and ethical misuse of AI tools were evident among participants. Approximately half of the respondents acknowledged a risk of bias in AI-powered recruitment platforms, particularly when algorithms operate without adequate oversight or contextual interpretation. These concerns highlight the need for clear ethical guidelines, algorithmic transparency, and mechanisms to ensure fairness and accountability in AI-supported decision-making.

From a strategic perspective, the findings suggest that while AI adoption in HR is on the rise, it remains in a transitional phase. Organizations are experimenting with digital tools, but a full transformation will likely depend on a combination of structural, cultural, and educational interventions. As the technology evolves, so too must the competencies of HR professionals, who must be equipped not only with technical skills but also with critical thinking and ethical awareness to navigate the complexities of automated recruitment.

In sum, this study contributes to the growing body of literature on AI in human resource management by offering empirical insights into user perceptions and behavioral patterns. The findings suggest that successful integration of AI in recruitment requires more than technical deployment—it demands trust-building, capacity development, and organizational alignment. As such, future research should focus on longitudinal studies that track changes in perceptions over time, incorporate standardized measures of digital readiness, and explore the impact of AI on broader organizational outcomes such as job satisfaction, diversity, and retention.

5. Conclusion and Recommendations – Future Perspectives of AI, Linkedin and Automation in Recruitment

This study explored the integration of artificial intelligence (AI), automation, and digital platforms in recruitment and selection practices, with a specific focus on HR professionals in North Macedonia. The findings suggest a transition toward more technologically enhanced recruitment processes, particularly within sectors such as IT, which exhibit greater digital readiness. Despite the global proliferation of AI in human resource management, the adoption in North Macedonia remains uneven, with many organizations still relying on traditional approaches alongside emerging tools.

A central theme revealed through the analysis is the importance of trust in AI-driven recruitment systems. Statistical results, particularly from the ANOVA tests, demonstrated that trust significantly differs between AI users and non-users, emphasizing its role as a determinant of adoption. These findings align with broader literature suggesting that trust is a critical enabler of technology acceptance (Venkatesh et al., 2003; van Esch et al., 2019). Furthermore, the research indicates a positive feedback loop: increased exposure to AI tools leads to greater trust and, consequently, greater willingness to adopt them.

However, the study also revealed persistent concerns regarding algorithmic transparency, bias, and fairness, especially among those unfamiliar with AI systems. Nearly half of the respondents perceived a potential risk of discrimination through automated platforms, echoing concerns raised in prior studies about the ethical and legal limitations of current AI applications in hiring (Raghavan et al., 2020; Sánchez-Monedero et al., 2020).

In conclusion, while AI and automation are gradually becoming integrated into HR practices, a full transition depends not only on technological availability but also on building trust, enhancing digital competence, and ensuring ethical safeguards. The human element remains essential in final decision-making, reinforcing the need for hybrid models that combine the strengths of both automation and human insight (Chamorro-Premuzic et al., 2019).

The recommendations based on the research are the following:

- Strengthening digital literacy among HR professionals
  Organizations should prioritize continuous digital upskilling for HR staff. Increased digital literacy leads to higher comfort levels with AI tools, reduces skepticism, and improves the quality of decision-making (Meijerink et al., 2021). This is particularly important in emerging markets, where digital divides may hinder full adoption.
- Promoting transparency of AI Systems
  Developers and vendors of AI-powered recruitment platforms should ensure algorithmic transparency and interpretability. When users understand how decisions are made, they are more likely to trust the system and adopt it ethically (Raghavan et al., 2020). Explainable AI frameworks should be embedded in all HR technology solutions.
- Development of ethical and legal frameworks for AI use
  Governments, in collaboration with HR professional bodies, must establish clear legal and ethical guidelines for AI use in recruitment. These should include safeguards against bias, requirements for data privacy compliance, and mechanisms for candidate appeals (Sánchez-Monedero et al., 2020). Alignment with global frameworks such as the EU AI Act and GDPR is critical.
- Encouragement of hybrid recruitment models
  Organizations should adopt hybrid recruitment strategies that combine automated screening with human assessment. While AI can improve efficiency in candidate shortlisting, human interaction is indispensable for evaluating soft skills, cultural fit, and ethical concerns (Chamorro-Premuzic et al., 2019; van Esch et al., 2019).
- Expansion of future research on long-term impacts
  There is a pressing need for longitudinal and cross-national studies on the impact of AI in recruitment. Future research should investigate how AI tools influence not just hiring efficiency, but also job satisfaction, organizational performance, and diversity outcomes (Upadhyay & Khandelwal, 2018).

References

Bhanumathi, P., Basu, S., & Babu, S. (2024). Artificial intelligence and machine learning-powered recruitment for smart hiring. In Global practices on effective talent acquisition and retention (pp. 20–40). IGI Global.

Cappelli, P. (2019). Your approach to hiring is all wrong. Harvard Business Review. https://hbr.org/2019/05/your-approach-to-hiring-is-all-wrong

Chamorro-Premuzic, T., Akhtar, R., Winsborough, D., & Sherman, R. A. (2017). The talent delusion: Why data, not intuition, is the key to unlocking human potential. Piatkus.

Deloitte. (2018). AI, robotics, and intelligent machines. https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2018/ai-robotics-intelligent-machines.html

Dennison, K. (2022, June 27). Are AI recruitment tools ethical and efficient? The pros and cons of ATS. Forbes. https://www.forbes.com/sites/karadennison/2022/06/27/are-ai-recruitment-tools-ethical-and-efficient-the-pros-and-cons-of-ats/

Dineen, B. R., & Allen, D. G. (2016). Internet recruiting 2.0: Shifting paradigms. In The Oxford handbook of recruitment (pp. 382–401). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190209980.013.18

Harvard Business Review. (2019, May). Your approach to hiring is all wrong. https://hbr.org/2019/05/your-approach-to-hiring-is-all-wrong

Korn Ferry. (2024). AI in recruiting: Navigating trends for 2024. https://www.kornferry.com/insights/featured-topics/talent-recruitment/ai-in-recruiting-navigating-trends-for-2024

Leicht-Deobald, U., Busch, T., Schank, C., Weibel, A., Scherer, A., & Schafheitle, S. (2019). The challenges of algorithm-based HR decision-making for personal integrity. Journal of Business Ethics, 160, 377–392.https://doi.org/10.1007/s10551-019-04204-w

LinkedIn Corporation. (2023). About LinkedIn. https://about.linkedin.com/

LinkedIn Newsroom. (n.d.). About us - statistics. https://news.linkedin.com/about-us#Statistics

LinkedIn Talent Solutions. (2023). Global talent trends report 2023. https://business.linkedin.com/talent-solutions/reports/global-talent-trends

Meijerink, J., Bondarouk, T., & Lepak, D. P. (2020). New directions in HRM and technology research: Insights from a review of the past and predictions for the future. Human Resource Management Review, 30(1), 100690. https://doi.org/10.1016/j.hrmr.2019.100690

Mujtaba, D. F., & Mahapatra, N. R. (2024). Fairness in AI-driven recruitment: Challenges, metrics, methods, and future directions. arXiv. https://doi.org/10.48550/arXiv.2405.19699

Omnicore Agency. (2025). 90 LinkedIn statistics you need to know in 2025. https://www.omnicoreagency.com/LinkedIn-statistics/

Open Space - ETF. (n.d.). Difficulties in finding qualified IT women employees are still present in North Macedonia. https://openspace.etf.europa.eu/blog-posts/difficulties-finding-qualified-it-women-employees-are-still-present-north-macedonia

Recruiter.com. (n.d.). Pros and cons of using AI in recruiting. https://www.recruiter.com/recruiting/pros-and-cons-of-using-ai-in-recruiting/

Russell, S. J., & Norvig, P. (2020). Artificial intelligence: A modern approach (4th ed.). Pearson.

Schellmann, H. (2023). The algorithm: How AI can hijack your career and steal your future. HarperCollins.

Seppälä, P., & Małecka, M. (2024). AI and discriminative decisions in recruitment: Challenging the core assumptions. SAGE Open, 14(1), 1–15. https://doi.org/10.1177/21582440241235872

Statista. (2023). LinkedIn - statistics & facts. https://www.statista.com/topics/951/linkedin/

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. California Management Review, 61(4), 15–42. https://doi.org/10.1177/0008125619867910

TechnologyAdvice. (n.d.). AI in recruiting. https://technologyadvice.com/blog/human-resources/ai-recruiting/

Thakur, A., Hinge, P., & Adhegaonkar, V. (2023). Use of artificial intelligence (AI) in recruitment and selection. In Proceedings of the International Conference on Applications of Machine Intelligence and Data Analytics (ICAMIDA 2022) (pp. [missing pages]). Atlantis Press. https://doi.org/10.2991/978-94-6463-136-4_54

Upadhyay, A. K., & Khandelwal, K. (2018). Artificial intelligence-based recruitment and selection: A recent review. International Journal of Advance Research in Computer Science and Management Studies, 6(4), 34–38.https://www.ijarcsms.com/docs/paper/volume6/issue4/V6I4-0010.pdf

Van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. Computers in Human Behavior, 90, 215–222. https://doi.org/10.1016/j.chb.2018.09.009

FINANCIAL MARKET REGULATION AND INVESTORS' BEHAVIOR

Thomas Poufinas
Department of Economics, Democritus University of Thrace
tpoufina@econ.duth.gr

Dimitrios Zygiotis
Graduate Program in Business Mathematics, University of Athens & Athens University of Economics and Business

George Galanos
Department of International and European Studies, University of Piraeus

ABSTRACT

The level of financial market regulation is often the objective of debates with the supporters claiming that it protects all interested parties and the opponents reacting that it is discouraging investors. In recent years, especially in the aftermath of the financial crisis, we see more and more laws aiming at transparency and increased disclosures, as well as appropriate risk profiling, so that each investor is matched to the investments that are appropriate for his or her risk profile. At the same time, a lot of attention is paid to properly informing investors so that the investment decision they make is well informed. On one hand, one can claim that this approach is well intended and that investors can make choices after having received all the necessary information. Consequently, they tend to keep their investment assets or portfolio longer in order to realize better returns. On the other hand, one can observe that such a process is cumbersome and not all investors are willing to go through it. As a result, they may be reluctant *to invest and abstain from doing so. We use data from the Organization for Economic Cooperation and Development (OECD) countries to investigate whether financial market regulation affects customers' behavior and, if yes, in what direction. Our sample size consists of the OECD countries and the focus is primarily on the European Union (EU) countries. The analysis uses linear regression to examine the relationship between the financial market regulation indicators (the independent variables) and the investors' behavior metrics (the dependent variables). The investors' behavior metrics reflect the intention of the investors to remain in a financial market, as is measured indicatively by the market cap, the trading volume, and the market performance. The financial market regulation indicators (are defined by the authors) measure the extent to which a country has implemented its investor agreements and contracts the works that the relevant regulation provision for. The findings can be of use to policymakers, if they wish to further strengthen their case or for financial intermediaries if they need to explain the rationale to candidate investors.*

Keywords: *financial market regulation; investors' behavior; transparency; disclosures; investment returns.*

1. Intuition

Investors' protection has been, is and is expected to be in the spotlight at all times, especially after the burst of a financial crisis. Regulators attempt to enhance investors' protection by voting, adapting and amending the relevant legislation, so as to secure increased transparency, extensive disclosures and comprehensive risk profiling, as well as appropriate intermediation. The intention is that investors are in a position to make well informed – if not prudent – decisions that match their risk appetite and tolerance and help them achieve the desired returns. This is definitely well intended and offers a sense of security.

At the same time though there are voices claiming that we have experienced over-regulation during the last decade; hundreds of thousands of pages of regulation have been produced and the sentiment of a part of interested parties is that it is a problem (Norbert, 2016), that it creates bank brain drain (Parker and Gupta, 2015) and that it risks killing financial innovation at birth (Booth, 2017), among others. Would that be the case, investors would have been unwilling to invest and this would have an impact on financial markets.

The most well-known framework in the European Union is the MiFID, i.e., the Markets in Financial Instruments Directive (2004/39/EC). According to the European Securities and Markets Authority (ESMA, 2018),"MiFID is a cornerstone of the EU's regulation of financial markets seeking to improve their competitiveness by creating a single market for investment services and activities and to ensure a high degree of harmonized protection for investors in financial instruments. It has been applicable across the European Union since November 2007. MiFID sets out:

- conduct of business and organizational requirements for investment firms;
- authorization requirements for regulated markets;
- regulatory reporting to avoid market abuse;
- trade transparency obligation for shares; and
- rules on the admission of financial instruments to trading.

On 20 October 2011, the European Commission adopted a legislative proposal for the revision of MiFID which took the form of a revised Directive and a new Regulation. After more than two years of debate, the Directive on Markets in Financial Instruments repealing Directive 2004/39/EC and the Regulation on Markets in Financial Instruments, commonly referred to as MiFID II and MiFIR (Markets in Financial Instruments Regulation), were adopted by the European Parliament and the Council of the European Union. They were published in the EU Official Journal on 12 June 2014.

MiFID II is anticipated to bring some improvements. MiFID II and MiFIR will ensure fairer, safer and more efficient markets and facilitate greater transparency for all participants. New reporting requirements and tests will increase the amount of information available, and reduce the use of dark pools and OTC (Over-the-Counter Trading). The rules governing high-frequency-trading will impose a strict set of organizational requirements on investment firms and trading venues, and the provisions regulating the non-discriminatory access to central counterparties (CCPs), trading venues and benchmarks are designed to increase competition.

The protection of investors is strengthened through the introduction of new requirements on product governance and independent investment advice, the extension of existing rules to structured deposits, and the improvement of requirements in several areas, including on the responsibility of management bodies, inducements, information and reporting to clients, cross-selling, remuneration of staff, and best execution."

The natural question that rises is whether this protective financial regulation affects investors' behavior. In other words, do investors trust and continue to invest in markets where the regulation is applied or are they appalled and tend to stay away? Our paper will attempt to answer this question by investigating the relation between the implementation of the financial market regulation and the stance of the investors. The former is measured practically by the number of sanctions imposed and the sanctioned amount. However, we produce a few more indicators out of it so as to capture the size of the market. For the latter, we use a series of market metrics that reflect the willingness of the investors to stay in the market. We find evidence in both directions, depending on the metric used. To the best of our knowledge, such an approach has not been exploited in the past and there lies the contribution and novelty of our work

2. Literature Review

The existing literature represents advocates of both views, i.e., supporters, as well as opponents of the need for (more) regulation. In their work, Hanson et al. (2011) offer a detailed vision of how a macroprudential regime might be designed. Their prescriptions follow from a specific theory of how modern financial crises unfold and why both an unregulated financial system, as well as one based on capital rules that only apply to traditional banks, is likely to be fragile. They start by identifying the key market failures at work: why individual financial firms, acting in their own interests, deviate from what a social planner would have them do. Next, they discuss a number of concrete steps to remedy these market failures. They conclude by comparing their proposals to regulatory reforms that emerged in the second half of 2010. Their focus is primarily on the recommendations made by the Basel Committee on Banking Supervision in September 2010 as part of the so-called

"Basel III" process. They raise a final question about how such regulation might be implemented.

Gillan and Starks (2003) examine the relation between corporate governance and ownership structure, focusing on the role of institutional investors. In many countries, institutional investors have become dominant players in the financial markets. They discuss the theoretical basis for, history of, and empirical evidence on institutional investors' involvement in shareholder monitoring. They examine cross-country differences in ownership structures and the implications of these differences for institutional investor involvement in corporate governance. Although there may be some convergence in governance practices across countries over time, the endogenous nature of the interrelation among governance factors suggests that variation in governance structures will persist.

Shiller's (2003) analysis refers to the collaboration between finance and other social sciences that has become known as behavioral finance and has led to a profound deepening of the knowledge of financial markets. In judging the impact of behavioral finance to date, it is important to apply the right standards. He argues that we should not expect market efficiency to be so egregiously wrong that immediate profits should be continually available. But market efficiency can be egregiously wrong in other senses. He says that since there is no fundamental psychological principle that people tend always to overreact or always to underreact, it is no surprise that research on financial anomalies does not reveal such a principle either.

While theoretical models of efficient markets have their place as illustrations or characterizations of an ideal world, one cannot maintain them in their pure form as accurate descriptors of actual markets. He concludes that we have to distance ourselves from the presumption that financial markets always work well and that price changes always reflect genuine information. Evidence from behavioral finance helps us to understand, for example, that the recent worldwide stock market boom, and then crash after 2000, had its origins in human foibles and arbitrary feedback relations and must have generated a real and substantial misallocation of resources. The challenge for economists is to make this reality a better part of their models.

Baker and Wurgler (2007) take the origin of investor sentiment as exogenous and instead focus on its empirical effects. They document that it is quite possible to measure investor sentiment, and that waves of sentiment have clearly discernible, important, and regular effects on individual firms and on the stock market as a whole. Looking forward, the investor sentiment approach faces a number of challenges: characterizing and measuring uninformed demand or investor sentiment; understanding the foundations and variation in investor sentiment over time; and determining which particular stocks attract speculators or have limited arbitrage potential. Much remains to be done in terms of spelling out this framework, but the potential payoffs of an improved understanding of investor sentiment are substantial. Furthermore, they have seen that sentiment affects the cost of capital. Therefore it may have real consequences for the allocation of corporate investment capital between safer and more speculative firms.

Using newly assembled data on regulation in several sectors of many OECD countries, Alesina et al. (2003) provide substantial and robust evidence that various measures of regulation in the product market, concerning in particular entry barriers, are negatively related to investments. The implications of their analysis are clear: regulatory reforms, especially those that liberalize entry, are very likely to spur investment. They argue that tight regulation of the product markets has had a large negative effect on investment. The data for sectors that have experienced significant changes in the regulatory environment suggest that deregulation leads to greater investment in the long-run. The component of reforms that plays the most important role is entry liberalization, while industry-level measures of privatization do not seem to affect investment significantly. This is consistent with what one would expect a priori. A reduction in entry barriers leads to a reduction of the markup and, hence of the penalty of expanding production, in terms of lost monopoly profits. This leads to greater investment. However, when it comes to public ownership, there are contrasting forces at work. While a reduction in public ownership can be seen as a reduction in the shadow cost of entry, agency problems affecting the behavior of public managers may lead to over-accumulation of capital. These results are robust to several sensitivity checks and extensions. They also find that the marginal effect of deregulation depends on how deep the change is: more decisive regulatory reforms have a greater marginal impact. Moreover, the marginal effect is greater when one starts from lower levels of regulation. Finally, as was mentioned, the implication of their analysis is that regulatory reforms that substantially lower entry barriers spur investment.

Crotty (2009) analyzes the structural flaws in the financial system that helped bring on the current crisis and discusses prospects for financial reforms. His main thesis is that, although problems in the US subprime mortgage market triggered the current financial crisis, its deep cause on the financial side is to be found in the flawed institutions and practices of the current financial regime, often referred to as the New Financial Architecture. He supports that several decades of deregulation and innovation grossly inflated the size of financial markets relative to the real economy. It is not possible for the value of financial assets to remain so large relative to the real economy because the real economy cannot consistently generate the cash flows required to sustain such inflated financial claims. Governments thus face a daunting challenge: they have to stop the financial collapse in the short run to prevent a global depression, while orchestrating a major overhaul and contraction of financial markets over the longer run. The US economy is especially vulnerable because growth over the past few decades has been driven largely by rising household spending on consumption and residential investment. The saving rate is rising rapidly as households repay debt and attempt to rebuild wealth to create a cushion against job and income loss. Meanwhile, wealth is evaporating. Nevertheless, in the longer run the financial system must shrink by a substantial amount. He insists on the fact that in order to force financial markets to play a more limited but more productive and less dangerous role in the economy, a combination of aggressive financial regulation coordinated across national markets as well as nationalization of financial institutions where appropriate is needed. Efficient financial theory must be replaced as the guide to policy making by the more realistic theories associated with Keynes and Minsky, and domination of financial policy making by the Lords of Finance must end. The design and implementation of the changes needed in financial markets is a political as much as an economic challenge. He concludes his paper supporting the view that until the US administration adopts a radical change in its financial market policies, US and global financial markets are likely to remain fatally structurally flawed.

Zingales (2004) revisits the controversy on regulation and applies its insights to the debate on corporate governance and mutual funds. He says that when it comes to regulation, and especially regulation of financial markets, academics are divided into two opposite camps. On the one hand, there are the extreme libertarians (e,g., Smith, 2003) who oppose any type of regulation. On the other hand, there are the interventionists (e.g., Stiglitz, 1989) who see pervasive market failures and advocate massive intervention. The general result of this exercise is that a strong case can be made in favor of more mandatory disclosure. He advocates a skeptical middle ground. Identifying an externality is not a sufficient call for regulation. Apparent externalities might be due to existing regulation and even when they are not, they can be effectively dealt with by the market system unless transaction costs are very large. When these costs are indeed large (as are enforcement costs for dispersed shareholders) there is scope for welfare enhancing regulation. That such a scope exists, it does not necessarily imply that welfare enhancing legislation can be designed and even less so that it can be approved via the legislative process. Even when the benefits of an ideal form regulation are large, the costs of its practical incarnation might be far in excess. Furthermore, it is difficult to see how this ideal regulation could emerge from the political process, which tends to be dominated by incumbent firms, especially in concentrated sectors. Any piece of regulation will be biased in their favor. He proposes a mechanism to reduce this bias.

Brunnermeier's et al. (2009) report applies macroeconomic analysis and insight to the design of financial regulation. Their intention is to develop a program of practical initiatives that could better attack the key features of externalities and systemic failure in financial markets. They set their sights on moderating the recurring cycle of financial crises, cycles that in their view are not wedded to particular instruments, institutions, individuals or information. They indicate the importance of preventing a banking crisis in comparison to other industries and the endogeneity of a certain risk that may occur. They distinguish between micro and macroprudential regulation. Microprudential regulation concerns itself with factors that affect the stability of individual institutions, while macroprudential regulation concerns with factors that affect the stability of the financial system as a whole. They illustrate that the nature of the regulation applied to an individual financial institution depends crucially on how "systemic" its activities are. They support that the structure of regulation should reflect the purposes and powers of the regulatory authorities. Macro and microprudential, instruments are both needed, but differ in focus and in their needed professionalism. On the top of their key recommendations on macroprudential measures and mark-to-funding, they make proposals on a whole series of minor issues, such as the role of stress tests, the adoption of maximum loan-to-value ratios in mortgage markets, etc.

3. Data, Variables and Methodology

Data and Variables

Our dataset consists of thirty-one countries – the twenty-eight countries of the European Union and three more. These are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden and the United Kingdom. The analysis spans the period 2012-2017, as this is the period for which the relevant European legislation has been applied. Data come from ESMA (European Securities and Markets Authority, 2018) and The World Bank (2018).

The variables that are used as the financial market regulation indicators (the independent variables) are the number of sanctions, the (total) amount of sanctions, the number of sanctions/entity, the amount/sanction, the (total) amount of sanctions/market cap and the (total) amount of sanctions/trading volume; all these are per country.

The variables that are used as the investor behavior metrics (the dependent variables) are the market cap as a percent of GDP, the market cap amount, the trading volume as a percent of GDP, the trading volume amount, the stocks traded turnover, the market performance, the number of listed firms, the market cap per listed firm, the trading volume amount per listed firm, the market cap/ active population, the market cap/ total population, the trading volume amount/ active population and the trading volume amount/ total population; all these are per country.

The descriptive statistics of the variables, as shown in Table 1, indicate that the number of sanctions, as well as the (total) amount of sanctions can vary significantly by country; this affects the volatility of the (four) derived financial market regulation indicators, which seem to be even more volatile. The market related metrics, i.e., the dependent variables, which are used as replicas of the investor behavior, also receive a wide range of values; however, they appear to be less volatile.

Table 1: Descriptive Statistics

Statistic	Mean	Standard Deviation	Max	Mean
Dependent Variables				
Market cap % of GDP	45,18	29,90	107,03	4,91
Market cap amount	3,99E+11	6,31E+11	2,20E+12	2692934305
Trading volume % of GDP	19,28	23,66	77,30	0,14
Trading volume amount	3,27E+11	5,90E+11	2,17E+12	73503354,05
Stocks traded turnover	44,86	49,87	212,51	0,16
Market performance	6,83	7,97	18,07	-24,02
No of listed firms	399,62	758,67	3335,33	15
Market cap/ listed firm	1684544868	1990093085	7675887676	30543678,32
Trading volume amount/ listed firm	818013926,3	1258001863	4302140597	1260299
Market cap/ active population	41812,28	54789,60	236089,49	0
Market cap/ total population	21511,60	27241,92	114980,12	867,88
Trading volume amount/ active population	15841,31	20387,02	65183,92	50,52
Trading volume amount/ total population	7797,77	10195,20	33415,41	25,47
Independent Variables				
No of sanctions	42,21	83,46	403	1
Amount of sanctions	3126625,22	5546102,70	17314240	0
No of sanctions/ entity	0,38	1,01	4,69	1,84E-04
Amount/ sanction	123502,13	184428,43	592521	0
Amount of sanctions/ market cap	1,24E-04	4,15E-04	1,62E-03	0
Amount of sanctions/ trading volume	2,76E-03	9,51E-03	0,04	2,73E-07

Source: Created by the authors using data from the World Bank (2018) and ESMA (2018).

Methodology

We use a regression modelling approach in order to investigate the relationship between the financial market regulation indicators (the independent variables) and the investor behavior metrics (the dependent variables). The general form of the regression equation is:

$$\boldsymbol{B} = \beta_0 + \beta_1 \cdot FMR + u \quad (1)$$

where *IB* is any of the aforementioned investors' behavior metrics and *FMR* is any of the above financial market regulation indicators.

We use White's test to detect potential heteroskedasticity and we use Robust Standard Errors to tackle it when present.

4. Empirical analysis

We regressed each of the independent variables with each of the dependent variables as shown in Table 2.

Table 2: Individual Regressions Summary

Variables/ Regressions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variables												
Market cap % of GDP	X	X	X	X	X	X						
Market cap amount							X	X	X	X	X	X
Independent Variables												
No of sanctions	-.2275771 (-0.94)						1.71e+09 (0.37)					
Amount of sanctions		1.53e-06 (1.21)						69352.01*** (4.35)				
No of sanctions/ entity			-57.12995 (-1.54)						-6.24e+11 (-0.85)			
Amount/ sanction				.0001008** (2.55)						2963079*** (7.93)		
Amount of sanctions/ market cap					-22782.04 (-1.13)						-2.49e+14 (-0.64)	
Amount of sanctions/ trading volume						-905.694 (-1.05)						-1.17e+13 (-0.71)
Constant	51.94611*** (4.79)	38.48918*** (3.92)	52.35349*** (5.79)	31.96607*** (3.69)	48.11109*** (5.68)	47.6207*** (5.20)	3.08e+11 (1.48)	5.04e+10 (0.41)	4.35e+11** (2.44)	-3.37e+10 (0.687)	3.89e+11** (2.39)	4.05e+11** (2.31)
Observations	15	15	15	15	15	14	15	15	15	15	15	14
Adjusted R-squared	-0.0085	0.0314	0.0894	0.2816	0.0193	0.0077	-0.0658	0.5619	-0.0197	0.8155	-0.0439	-0.0397

Variables/ Regressions	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**	**(22)**	**(23)**	**(24)**
Dependent Variables												
Trading volume % of GDP	X	X	X	X	X	X						
Trading volume amount							X	X	X	X	X	X
Independent Variables												
No of sanctions	-.0400815 (-0.61)						-6.50e+08 (-0.42)					
Amount of sanctions		2.69e-06*** (3.40)						52940.72** (2.51)				
No of sanctions/ entity			-6.390923 (-1.24)						-1.12e+11 (-0.89)			
Amount/ sanction				.0001001*** (5.26)						2510719*** (6.01)		
Amount of sanctions/ market cap					-13253.4 (-0.91)						-1.74e+14 (-0.61)	
Amount of sanctions/ trading volume						-663.4474 (-0.96)						-1.13e+13 (-0.68)
Constant	22.24919*** (3.31)	11.01127* (1.97)	23.17414 (3.76)	6.650399 (1.43)	21.52902*** (3.51)	22.94911*** (3.46)	3.53e+11** (2.20)	1.36e+11 (0.91)	3.72e+11** (2.50)	-2.90e+10 (-0.28)	2.82e+11** (2.35)	3.83e+11 (2.39)
Observations	19	18	19	18	15	17	19	18	19	18	15	17
Adjusted R-squared	-0.0358	0.3825	0.0284	0.6104	-0.0130	-0.0044	-0.0481	0.2379	-0.0113	0.6735	-0.0471	-0.0347

Variables/ Regressions	**(25)**	**(26)**	**(27)**	**(28)**	**(29)**	**(30)**	**(31)**	**(32)**	**(33)**	**(34)**	**(35)**	**(36)**
Dependent Variables												
Stocks traded turnover	X	X	X	X	X	X						
Market performance							X	X	X	X	X	X
Independent Variables												
No of sanctions	.9422186** (2.85)						.000297 (0.01)					
Amount of sanctions		6.03e-06*** (3.97)						-3.53e-08 (-0.10)				
No of sanctions/ entity			-.5992669 (-0.01)						.1593429 (0.09)			
Amount/ sanction				.0000869 (1.11)						2.80e-06 (0.26)		
Amount of sanctions/ market cap					-27801.2 (-0.80)						-19651.6*** (-5.49)	
Amount of sanctions/ trading volume						-1360.774 (-0.92)						-800.79*** (-5.49)
Constant	18.76325 (1.27)	19.60569 (1.67)	46.41299*** (2.80)	34.85776* (2.04)	49.78674*** (3.41)	51.02078*** (3.26)	6.355068*** (2.99)	6.422914*** (2.79)	6.303075*** (3.13)	5.92816** (0.024)	7.926898*** (5.11)	7.37721*** (5.15)
Observations	15	15	15	15	15	15	22	21	22	21	14	16
Adjusted R-squared	0.3366	0.5139	-0.0769	0.0169	-0.0264	-0.0114	-0.0500	-0.0521	-0.0496	-0.0488	0.6914	0.6600

Variables/ Regressions	(37)	(38)	(39)	(40)	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)
Dependent Variables												
No of listed firms	X	X	X	X	X	X						
Market cap/ listed firm							X	X	X	X	X	X
Independent Variables												
No of sanctions	-.6442509 (-0.30)						-9472478 (-0.58)					
Amount of sanctions		.0000616* (1.98)						105.6423 (1.25)				
No of sanctions/ entity			-94.18002 (-0.53)						-3.08e+09 (-1.21)			
Amount/ sanction				.0020829** (2.28)						7938.038*** (3.36)		
Amount of sanctions/ market cap					-210290.3 (-0.37)						-1.18e+12 (-0.86)	
Amount of sanctions/ trading volume						-12523.9 (-0.53)						-5.28e+10 (-0.91)
Constant	467.8352** (2.09)	219.2651 (1.00)	478.7439** (2.27)	150.2704 (0.67)	420.8578* (1.79)	505.7279** (2.24)	1.97e+09** (2.68)	1.23e+09* (1.89)	2.08e+09 (3.35)	6.48e+08 (1.25)	1.84e+09*** (3.21)	1.89e+09*** (3.06)
Observations	19	18	19	18	15	17	15	15	15	15	15	14
Adjusted R-squared	-0.0534	0.1462	-0.0415	0.1975	-0.0654	-0.0467	-0.0502	0.0390	0.0324	0.4242	-0.0191	-0.0139

Variables/ Regressions	**(49)**	**(50)**	**(51)**	**(52)**	**(53)**	**(54)**	**(55)**	**(56)**	**(57)**	**(58)**	**(59)**	**(60)**
Dependent Variables												
Trading volume amount/ listed firm	X	X	X	X	X	X						
Market cap/ active population							X	X	X	X	X	X
Independent Variables												
No of sanctions	-1031823 (-0.30)						-534.3716 (-1.17)					
Amount of sanctions		138.1497*** (3.23)						-.0000184 (-0.01)				
No of sanctions/ entity			-2.65e+08 (-0.96)						-91745.31 (-1.26)			
Amount/ sanction				3578.592** (2.55)						.0550765 (0.60)		
Amount of sanctions/ market cap					-6.10e+11 (-0.64)						-3.02e+07 (-0.76)	
Amount of sanctions/ trading volume						-2.82e+10 (-0.77)						-1119051 (-0.67)
Constant	8.73e+08** (2.45)	3.37e+08 (1.12)	9.44e+08*** (2.87)	3.42e+08 (1.00)	9.76e+08** (2.43)	9.58e+08** (2.71)	62301.58*** (3.05)	46744.1** (2.35)	58012.54*** (3.26)	39384.39* (1.96)	50411.81*** (3.03)	47424 (2.67)
Observations	19	18	19	18	15	17	15	15	15	15	15	14
Adjusted R-squared	-0.0533	0.3576	-0.0044	0.2446	-0.0444	-0.0263	0.0256	-0.0769	0.0396	-0.0479	-0.0309	-0.0445

Variables/ Regressions	(61)	(62)	(63)	(64)	(65)	(66)	(67)	(68)	(69)	(70)	(71)	(72)
Dependent Variables												
Market cap/ total population	X	X	X	X	X	X						
Trading volume amount/ active population							X	X	X	X	X	X
Independent Variables												
No of sanctions	-276.2346 (-1.23)						-40.39733 (-0.72)					
Amount of sanctions		-.0000774 (-0.06)						.0020084*** (2.71)				
No of sanctions/ entity			-45949.66 (-1.28)						-5570.279 (-1.25)			
Amount/ sanction				.0259071 (0.57)						.084557*** (4.98)		
Amount of sanctions/ market cap					-1.49e+07 (-0.76)						-1.10e+07 (-0.87)	
Amount of sanctions/ trading volume						-543221.2 (-0.66)						-508284.6 (-0.88)
Constant	31062.73*** (3.09)	23321.55** (2.38)	28662.9*** (3.26)	19554.85* (1.97)	24821.04*** (3.02)	23088.73** (2.65)	18416.16*** (3.19)	9584.166* (1.83)	18944.89*** (3.58)	4903.479 (1.18)	17558.22*** (3.31)	17396.92*** (3.13)
Observations	15	15	15	15	15	14	19	18	19	18	15	17
Adjusted R-squared	0.0355	-0.0766	0.0430	-0.0505	-0.0313	-0.0453	-0.0273	0.2719	0.0306	0.5832	-0.0172	-0.0143

Variables/ Regressions	(73)	(74)	(75)	(76)	(77)	(78)
Dependent Variables						
Trading volume amount/ total population	X	X	X	X	X	X
Independent Variables						
No of sanctions	-22.27311 (-0.80)					
Amount of sanctions		.0008911** (2.30)				
No of sanctions/ entity			-2766.107 (-1.24)			
Amount/ sanction				.0420143*** (4.91)		
Amount of sanctions/ market cap					-5406822 (-0.87)	
Amount of sanctions/ trading volume						-247527.4 (-0.86)
Constant	9192.091 (3.20)	5097.094* (1.86)	9342.28*** (3.53)	2362.672 (1.13)	8556.708*** (3.29)	8475.227*** (3.07)
Observations	19	18	19	18	15	17
Adjusted R-squared	-0.0204	0.2011	0.0296	0.5760	-0.0175	-0.0161

Notes: t-values in parenthesis; ***statistically significant at the 1% level; **statistically significant at the 5% level; *statistically significant at the 10% level.
Source: Results of regressions run by the authors using data from the World Bank (2018) and ESMA (2018).

From the individual regressions of market cap as a percent of GDP we find that it is positively correlated at the 5% significance level with the amount/ sanction. The remaining of the variables show no statistical significance. However, the market cap as a percent of GDP is negatively correlated with the number of sanctions, the number of sanctions/entity, the amount of sanctions/market cap and the amount of sanctions/trading volume. It is positively correlated with the amount of sanctions. The regressions of the market cap amount yield that it is positively correlated at all levels with the amount of sanctions and the amount/sanction, whereas the remaining variables exhibit no statistical significance. The market cap amount though is negatively correlated with the number of sanctions/entity, the amount of sanctions/market cap and the amount of sanctions/trading volume. It is positively correlated with the number of sanctions.

From the regressions of trading volume as a percent of GDP we infer that it is positively correlated at all levels with the amount of sanctions and the amount/sanction. The rest of the variables have no statistical significance. We note though that the trading volume as a percent of GDP is negatively correlated with all of them. From the regressions of trading volume amount we get that it is positively correlated at the 5% significance level with the amount of sanctions and at all levels with the amount/ sanction. The rest of the variables have no statistical significance. We observe that the trading volume amount is negatively correlated with all of them. The stocks traded turnover is positively correlated with the number of sanctions and the amount of sanctions at all levels. The other variables are not statistically significant. We see though that the stocks traded turnover is negatively correlated with the number of sanctions/entity, the amount of sanctions/ market cap and the amount of sanctions/trading volume. It is positively correlated with the amount/sanction.

The regressions of market performance yield that it is negatively correlated with the amount of sanctions/market cap and the amount of sanctions/trading volume at all levels. The remaining variables show no statistical significance. However, we realize that it is positively correlated with the number of sanctions, the number of sanctions/entity and the amount/sanction. It is negatively correlated with the amount of sanctions. The number of listed firms is positively correlated with the amount of sanctions at 10% and the amount/ sanction at 5%. The other variables show no statistical significance; we see that it is negatively correlated with them. The market cap per listed firm is positively correlated at the 1% significance level with the amount/sanction. The remaining of the variables shows no statistical significance. However, the market cap per listed firm is negatively correlated with the number of sanctions, the number of sanctions/entity, the amount of sanctions/market cap and the amount of sanctions/trading volume. It is positively correlated with the amount of sanctions.

The traded volume amount per listed firm is positively correlated at all levels with the amount of sanctions and the amount/ sanction, whereas the remaining variables exhibit no statistical significance. We realize that it is negatively correlated with all of them. The regressions of the market cap/ active population show that none of the independent variables is statistically significant. We observe that it is negatively correlated to all of them except for the amount/ sanction, with which it is positively correlated. The regressions of the market cap/total population exhibit the same exact results with the corresponding regressions of the market cap/active population.

The trading volume amount/active population is positively correlated at all levels with the amount of sanctions and the amount/ sanction. The rest of the variables have no statistical significance. We note though that the trading volume/active population is negatively correlated with all of them.

The trading volume amount/ total population is positively correlated at the 5% significance level with the amount of sanctions and at all levels with the amount/sanction. The rest of the variables have no statistical significance. We observe that the trading volume amount/total population is negatively correlated with all of them.

We ran a series of joint regressions in order to examine the validity of our findings. The results are depicted in Table 3.

Table 3: Joint Regressions Summary

Variables/ Regressions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Dependent Variables													
Market cap % of GDP	X												
Market cap amount		X											
Trading volume % of GDP			X										
Trading volume amount				X									
Stocks traded turnover					X								
Market performance						X							
No of listed firms							X						
Market cap/ listed firm								X					

Variables/ Regressions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Trading volume amount/ listed firm									X				
Market cap/ active population										X			
Market cap/ total population											X		
Trading volume amount/ active population												X	
Trading volume amount/ total population													X
Independent Variables													
No of sanctions	.2340779 (0.24)	-9.1e+09 (-1.05)	.0747027 (0.19)	1.65e+09 (0.43)	1.890657** (2.87)	.0835053 (0.44)	-51.78635* (-2.05)	9.90e+07** (2.37)	8.33e+07* (2.23)	643.8045 (0.26)	318.9627 (0.26)	405.9989 (1.35)	171.305 (0,99)

Variables/ Regressions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Amount of sanctions	-2.57e-06 (-0.48)	60094 (1.27)	2.47e-06 (1.15)	57609.39** (2.75)	8.44e-07 (0.23)	-1.40e-06 (-1.60)	.0003556** (2.58)	-689.304*** (-3.03)	-329.9755 (-1.62)	-.0060411 (-0.44)	-.0030988 (-0.47)	-.0002403 (-0.15)	-.0001782 (-0.19)
No of sanctions/ entity	-54.30692 (-0.44)	1.17e+12 (1.07)	-14.71444 (-0.30)	-2.67e+11 (-0.55)	-237.025** (-2.86)	-24.86137 (-1.20)	5967.616* (1.88)	-1.33e+10** (-2.54)	-1.05e+10* (-2.23)	-148247 (-0.47)	-73631.76 (-0.48)	-53149.67 (-1.41)	-22693.96 (-1.05)
Amount/ sanction	.0001619 (1.40)	1886722* (1.85)	.0000116 (0.25)	74017.64 (0.16)	-.0000533 (-0.69)	.0000282 (1.46)	-.005784* (-1.95)	21317.87*** (4.36)	9416.954* (2.15)	.1791255 (0.61)	.0909168 (0.64)	.0631063 (1.79)	.0340096 (1.68)
Amount of sanctions/ market cap	-92755.62 (-0.40)	-8e+14 (-0.39)	49323.82 (0.53)	-2.37e+14 (-0.26)	234451.8 (1.51)	402318.5 (1.83)	171060.3 (0.03)	8.32e+12 (0.84)	3.87e+12 (0.44)	4642787 (0.01)	9316556 (0.03)	3.32e+07 (0.47)	1.69e+07 (0.41)
Amount of sanctions/ trading volume	2903.617 (0.30)	2.38e+13 (0.28)	-2544.708 (-0.67)	2.75e+12 (0.07)	-10904.77 (-1.71)	-17363.81* (-1.92)	-11629.97 (-0.05)	-3.98e+11 (-0.98)	-1.90e+11 (-0.53)	-1388386 (-0.06)	-964967 (-0.08)	-1776073 (-0.61)	-889734.3 (-0.53)
Constant	36.51969 (2.54)	-2.9e+10 (-0.23)	7.638832 (1.33)	-6.93e+09 (-0.12)	27.18578 (2.83)	8.837527 (3.69)	384.3516 (1.04)	8.53e+08 (1.40)	5.18e+07 (0.10)	50507.9 (1.39)	24855.5 (1.40)	2577.943 (0.59)	1355.773 (0.54)
Observations	14	14	14	14	14	13	14	14	14	14	14	14	14
Adjusted R-squared	0.1574	0.8123	0.7389	0.9314	0.8686	0.7956	0.2274	0.6630	0.4365	-0.5037	-0.4919	0.7724	0.6765

Notes: t-values in parenthesis; ***statistically significant at the 1% level; **statistically significant at the 5% level; *statistically significant at the 10% level.

Source: Results of regressions run by the authors using data from the World Bank (2018) and ESMA (2018).

The joint regression of market cap as a percent of GDP with all the independent variables posted that none of them has any statistical significance. The regression of the market cap amount with all the market regulation indicators showed that it is positively correlated only with the amount/ sanction at the 10% level, whereas the remaining of the variables have no statistical significance. The regression of the trading volume as a percent of GDP with all the independent variables yielded that none of them has any statistical significance. The regression of the trading volume amount with all the market regulation indicators showed that it is positively correlated only with the amount of sanctions at the 5% significance level. By regressing the stocks traded turnover with all the independent variables we see that it is positively correlated at the 5% level with the number of sanctions and negatively correlated at the 5% level with the number of sanctions/entity, whereas the remaining of the variables have no statistical significance. When we regressed the market performance with all the market regulation indicators we realized that it is negatively correlated with the amount of sanctions/ trading volume; the rest of the variables have no statistical significance.

The number of listed firms is positively correlated with the amount of sanctions at the 5% significance level and with the number of sanctions per entity at the 10% level. It is negatively correlated with the number of sanctions and the amount/ sanction at the 10% significance level. The other variables have no statistical significance. The market cap per listed firm is positively correlated with the amount/ sanction at all significance levels and the number of sanctions at the 5% level. It is negatively correlated with the amount of sanctions at all levels and the number of sanctions per entity at the 5% level. The rest of the variables have no statistical significance. The traded volume amount per listed firm is positively correlated at the 10% level with the number of sanctions and the amount/ sanction and it is negatively correlated at the 10% significance level with the number of sanctions/ entity. The other variables post no statistical significance. The market cap/ active population, the market cap/total population, the trading volume/total population and the trading volume/total population are not correlated with any of the market regulation indicators.

5. Result Interpretation

The regressions ran indicate globally a positive correlation of the investor behavior metrics and the financial market regulation indicators, wherever there is statistical significance and in particular the amount of sanctions and the amount/ sanction. This is probably explained by the fact that countries with bigger equity markets also experience higher total amount of sanctions and consequently amount per sanction. Alternatively, it could mean that investors continue to invest in markets with increased regulation enforcement and this leads to an increase of these markets.

The only evidence that violation of market regulation can have some negative effects is the negative correlation of the market performance with the amount of sanctions/market cap and the amount of sanctions/trading volume. This implies that high amounts of sanctions relevant to the size of the market may influence investors from staying in the market. As a matter of fact, even without statistical significance, all investors' behavior metrics are negatively correlated with these two financial market regulation indicators. In addition, in all but one case the same holds true for the number of sanctions/ entity and in all but three cases for the number of sanctions. The joint regressions reaffirm the aforementioned findings in the cases that the financial market regulation indicators are statistically significant. There are some cases though in which some of the independent variables become statistically significant, whereas in the individual regressions they were not.

We thus observe that the stocks traded turnover, the market cap per listed firm and the traded volume turnover per listed firm is negatively correlated to the number of sanctions per entity. This is an indication that investors may abstain from certain stocks when they realize that the number of sanctions per entity increase. The market cap per listed firm and the traded volume amount per listed firm are positively correlated with the number of sanctions, which is similar to our individual regression findings. The market cap per listed firm is negatively correlated with the amount of sanctions. These results are probably interpreted by the fact that countries with bigger equity markets experience also a higher number of sanctions. The number of listed firms is negatively correlated with the number of sanctions and the amount/ sanction, which could mean that new entrants are discouraged from increased market regulation.

The aforementioned findings provide some evidence that policymakers need to carefully implement the financial market regulation so as to increase the feeling of security of the investors and not discourage them from investing in these markets.

6. Further Research

At this first attempt on tackling the topic we used the entire set of sanctions (number and amounts), without distinguishing the year it was imposed, for the entire period for which data is available. This is since 2012 and until 2017 (in some cases the first months of 2018 are included). The year 2012 is the year at which the relevant legislation was applied. As a consequence, we used the total number of sanctions and total amount of sanctions per country, whereas for the country figures we used the averages of these years. As part of our future research, we intend to separate the data per year and apply a more detailed econometric analysis (panel data). In addition, we will try to separate the different legal frameworks and distinguish further the violations that led to the sanction being imposed. Our findings may be of use to policymakers so that they reinforce the financial market regulation in such a way that they increase the feeling of security of the investors and entrepreneurs so that they do remain or even join the markets of the relevant countries.

7. Conclusion

This paper managed to find some evidence that the investor behavior is connected with the financial market regulation implemented in a country. The findings seem to go both ways, but if we try to combine them we conclude that on one hand, countries with bigger equity markets experience most likely higher total amount of sanctions and consequently amount per sanction, but investors continue to invest in such markets – possibly as a sign of trust due to the increased regulation enforcement, which sustains the increase of these markets. On the other hand, high amounts of sanctions relevant to the size of the market may influence investors from staying in the market. These results are not necessarily conflicting and further research will shed morelight.

References

Alesina, A., Ardagna, S. Nicoletti, G.and Schiantarelli, F. (2003), Regulation and investment, National Bureau of Economic Research, Working Paper 9560,http://www.nber.org/papers/w9560, Accessed 24.01.2019.

Baker M. and Wurgler J. (2007), Investor Sentiment in the Stock Market, Journal of Economic Perspectives, 21 (2), 129–151.

Booth, P. (2017), Over-regulation risks killing financial innovation at birth, Institute of Economic Affairs, https://iea.org.uk/over-regulation-risks-killing-financial-innovation-at-birth/, Accessed: September 10, 2018.

Brunnermeier M., Crocket A., Goodhart Ch., Hellwig M., Persaud A.V., and Shin H. (2009), The Fundamental Principles of Financial Regulation, International Center for Monetary Studies, Geneva Report on the World Economy 11, https://cepr.org/sites/default/files/geneva_reports/GenevaP197.pdf

Crotty J. (2009), Structural causes of the global financial crisis: a critical assessment of the 'new financial architecture', Cambridge Journal of Economics, 33, 563–580

ESMA (2018), MIFID II, www.esma.europa.eu/policy-rules/mifid-ii-and-mifir, Accessed: September 10, 2018.

ESMA (2018), Registers, https://registers.esma.europa.eu/publication/searchRegister? core=esma_registers_upreg, Accessed: September 1, 2018.

ESMA (2018), Sanctions, https://registers.esma.europa.eu/publication/searchSanction, Accessed: September 1, 2018.

Norbert, M. (2016), Time to fix the overregulation problem in financial markets, Forbes, https://www.forbes.com/sites/norbertmichel/2016/05/03/time-to-fix-the-overregulation-problem-in-financial-markets/#72f2451a3db8, Accessed: September 10, 2018.

Parker E. and Gupta M. (2015), Too much regulation creates bank brain drain, Financial Times, https://www.ft.com/content/4dfc4190-719f-11e5-9b9e-690fdae72044, Accessed: September 10, 2018.

Shiller, R. J. (2003), From Efficient Markets Theory to Behavioral Finance, Journal of Economic Perspectives, 17 (1), 83–104.

Hanson, S. G., Kashyap, A. K. and Stein, J. C. (2011), A Macroprudential Approach to Financial Regulation, Journal of Economic Perspectives 25 (1), 3–28.

Gillan, S. L. and Starks, L. T. (2003) Corporate Governance, Corporate Ownership and the Role of Institutional Investors: A Global Perspective, Wenberg Center for Corporate Governance, University of Delaware, WP 2003 – 01,, Accessed: 24.1.2019.

The World Bank (2018), World Development Indicators, https://data.worldbank.org/products/wdi, Accessed: September 1, 2018.

Zingales L. (2004), The Costs and Benefits of Financial Market Regulation, University of Chicago, NBER, CEPR and ECGI, Law Working Paper N°. 21/2004, http://ecgi.global/sites/default/files/working_papers/documents/ssrn-id536682.pdf, Accessed: 24.1.2019.

SECTION 2

AUTHORS' BIOGRAPHIES

AUTHORS' BIOGRAPHIES

Dionysios Chionis (Professor)

Dionysios Chionis is currently Professor of Economics in Democritus University of Thrace. He holds a PhD in Economics from the University of Strathclyde and a MSc from the University of Glasgow. In recent years, Professor Chionis has held high positions in the public and private sectors while his scientific articles have been published in important journals (International Journal of Finance and Economics, Journal of European Research Studies, Journal of Financial Stability). He has also participated (as coordinator) to numerous research projects funded by national and international public authorities, as well as private organizations. Finally, his research interests focus on macroeconomics, international economics, financial markets and monetary policy.

Dimitrios Dimitriou (Professor)

Dimitrios Dimitriou is Professor in management of infrastructure, specialized in transportation and supply chain and the Head of the Department of Economics, Democritus University of Thrace. He is the Director of the Research Laboratory MaGBISE (governance, management, business intelligence, business ethics) and he established an UNESCO regional unit in Business ethics. His specialization deals with investment appraisal, large projects financing, project management, transport and supply chain economics, management performance, decision making, project development, strategic management, sustainable development, strategic planning and management. He is member of international expert and management committees in international associations and professional bodies and he is a regular member of the Special Synodical Committee of the Church of Greece. He was awarded of his Valuable Contribution by the Chamber of Evros and the

Professional Achievement Award in Greece from the British Council for the British Universities graduates.

Ioannis Dokas (Associate Professor)

Ioannis Dokas is an Associate Professor at the Department of Economics of the Democritus University of Thrace, in the field of accounting. He was born in 1977 and holds a degree in Economics from the Department of Economics of the National and Kapodistrian University of Athens (2000) and a PhD in Financial Accounting from the Department of Public Administration of Panteion University (2007). His doctoral thesis was completed under the Heraclitus Scholarship Program, earning him honors. He has a long teaching experience in undergraduate and postgraduate programs at leading universities in the country such as the National and Kapodistrian University of Athens (Department of Economics) and the National Technical University of Athens (National Technical University of Athens). He also has extensive teaching experience in distance education, having been a member of the Hellenic Open University's teaching staff since 2012, and currently teaching at the Open University of Cyprus. Previously, he worked as a specialist at the National Statistical Service and the General Secretariat for Lifelong Learning. He has been a lecturer at the National School of Local Government. He has co-authored four scientific books (in Greek) and his work has been published in prestigious international journals and peer-reviewed volumes, such as the *Journal of the Operational Research Society*, *Research in International Business and Finance, North American Journal of Economics and Finance, Euromed Journal of Business, Applied Economics, Operational Research: An international Journal, International Journal of Financial Research, International Journal of Business Administration, Economic Analysis and Policy, Journal of Corporate Accounting and Finance, Journal of Policy Modeling, Journal of Economic Studies* etc.

Evaggelos Drimpetas (Professor)

Evangelos Drimpetas is an economist and professor in the Department of Economics at Democritus University of Thrace. He has served as head of the department and as dean of the School of Social, Political, and Economic Sciences. A graduate of the Economics Department at Aristotle University of Thessaloniki, he completed his postgraduate and doctoral studies at Sorbonne University in Paris. His extensive research includes five books and numerous articles in international scientific journals, focusing on finance, capital and money markets, and corporate governance. Professor Drimpetas has served as an expert for the European Commission and has participated in various committees and boards within the European Commission, as well as in the broader public and private sectors. He is currently a member of the Council of the Cyprus Agency of Quality Assurance and Accreditation in Higher Education (CYQAA).

George Galanos (Associate Professor)

George Galanos is Associate Professor of Economic Policy and Competitiveness at the Department of International and European Studies of the University of Piraeus. He studied Economics (BSc), completed an MBA in Tourism Management, and earned a PhD in International Economics at the same university. His doctoral dissertation focused on the determinants of European and international competitiveness in the tourism industry, with Greece as a case study. His teaching experience covers a wide range of subjects including international economics, monetary theory and policy, European economic integration, competitiveness, and regional development, at both undergraduate and postgraduate levels in several Greek universities. His research work includes a monograph, book chapters published by international academic publishers such as Springer and Palgrave Macmillan, and articles in peer-reviewed journals addressing topics such as competitiveness, fiscal adjustment, the shadow economy, the governance of the Eurozone, and the economic dimensions of tourism. He has also participated in collective volumes and conference proceedings, presenting his research at numerous international conferences in Europe and North America. In addition, he has collaborated in a variety of European and national research projects, often focusing on regional development strategies, tourism policy, and economic governance. Dr. Galanos has served in research and advisory roles within public institutions and local government, contributing to studies on administrative reform, competitiveness, and development planning. His work has received attention in the academic community, with citations in international publications reflecting the relevance of his contributions. Overall, his academic activity combines teaching, research, and applied policy analysis, with an emphasis on issues of economic policy, European integration, and international competitiveness.

George Geronikolaou (Associate Professor)

Dr. George Geronikolaou is an Associate Professor of Industrial Economics at the Department of Economics, Democritus University of Thrace (Greece). He holds a degree in Economics from Aristotle University of Thessaloniki (Greece), a MSc in Mathematical Economics and Econometric Methods from the University of Tilburg (the Netherlands) and a Ph.D. in Economics from Aristotle University of Thessaloniki (Greece). His research has focused on topics such as the financing of innovation through Venture Capital and Private Equity, consumer behavior and choices under uncertainty, gambling behavior and its implications on lottery pricing and gambling operators' profit maximization. His research on the relevant topics has been conducted by both empirical methodologies as well as theoretical-mathematical modelling.

Nikos Giannakis (PhD Candidate)

Nikos Giannakis is a PhD Candidate in the Department of Economics at Democritus University of Thrace, specializing in Artificial Intelligence applied to economics. With an MBA from the University of Aegean, an MSc in AI from Aristotle University of Thessaloniki, and an MSc in Big Data Analytics from Derby University, Nikos has developed expertise at the intersection of technology, data, and business. Before transitioning to academia and the tech industry, served as an Officer in the Hellenic Army for 13 years, after graduating from the Hellenic Military Academy. Currently, works as a Data Analyst and Full Stack Developer at a Valuation Advisory investment bank, applying advanced analytics and full-stack development skills to drive business insights and improve financial strategies. With a focus on AI, data analytics, and their applications in economics, he aims to contribute innovative solutions to both academic and industry challenges.

Periklis Gogas (Professor)

Periklis Gogas is a Professor at Democritus University of Thrace and was previously a Visiting Scholar in Finance at the Ross School of Business, University of Michigan. He received his Ph.D. from the University of Calgary, his Master's degree from the University of Saskatchewan and his B.A. from the University of Macedonia. His research interests include macroeconomics, banking and finance, forecasting, complex networks, artificial intelligence, and machine learning. He presented invited seminars at the ECB, the University of Michigan, Temple University, etc. He is an Associate Editor of the Journal of Economic Asymmetries and Open Economies Review. He published in the Journal of Money Credit and Banking, Journal of Banking and Finance, International Journal of Forecasting, International Review of Economics and Finance, International Finance, Journal of Forecasting, Physica A, Computational Economics, Economic Modelling, Open Economies Review, Energy Economics, etc.

Panagiotis Goumenidis (PhD candidate)

Panagiotis Goumenidis is Deputy Director and Deputy Head of the General Commercial Registry Department (GEMI) at the Evros Chamber of Commerce. In these positions he is responsible for supervising strategic operations, manages the processing of company registrations and ensures compliance with Greek and EU regulations. At the same time he is a PhD candidate in the Department of Economics at the Democritus University of Thrace, where he also completed his MSc, focused on applying quantitative and computational machine learning models to specific economic and business challenges. Prior to the current roles in the public sector he gained valuable experience as a freelance accountant, financial and tax consultant and insurance consultant for nearly two decades.

Konstantinos J. Hazakis (Professor)

Dr Konstantinos J. Hazakis is Professor of economic development and entrepreneurship, at the Department of Economics, in Democritus University of Thrace and a research fellow at the Institute of International Economic Relations in Athens. His research interests include European political economy, economic development, institutional economics, regional integration, and international economic policy coordination. His most recent monograph is the book, "European political economy: Theory and policy", (Lexington, USA, 2018).

Aristi Karagkouni (Assistant Professor)

Aristi Karagkouni is currently an adjusted Lecturer in the Department of Economics (Democritus University of Thrace) in the research field of Supply Chain Corporate Performance. Her educational background includes Doctorate (PhD) in Sustainable Development and Management of Infrastructure from Democritus University of Thrace (Department of Economics), MSc in Environmental Management for Business from Cranfield University (UK) and Diploma (equivalent to 4 years BA and 1-year MSc) in Civil Engineering (Transportation planning). Her scholarly activity is evidenced by more than 100 publications in scientific contributions, including peer-reviewed journal publications, conference papers, book chapters, and presentations at international conferences. Furthermore, she has actively contributed to four funded research projects addressing complex issues related to sustainable infrastructure, economic development, and corporate performance. She is member of the Research Laboratory MaGBISE 'Management, Governance, Business Intelligence, Strategy and Corporate Ethics in Infrastructure Operators, Networks and Supply Chain' at the Department of Economics (DUTh).

Anastasios Ketsetsidis (Doctor)

Anastasios Ketsetsidis is an employee of the Independent Authority for Public Revenue at the Kavala Customs Service, managing the Customs Procedures

Office. He graduated from the University of Macedonia Department of Business Administration in 2001. He has a Master degree in Finance and Financial Information Systems from the University of Greenwich (2002) and a Master in International Business from the University of Macedonia (2018). In 2025, he obtained a PhD in Economics from the Democritus University of Thrace, with the title "Anti-dumping and Anti-subsidy Measures as Trade Defense Instruments in the European Union." He has presented at international conferences and published articles in scientific journals. His professional duties include overseeing imports, exports, and customs regimes, such as those for authorized exporters and consignors. His research focuses on unfair trade practices and trade defense mechanisms, contributing significantly to the field.

Andreas Kontos (PhD Candidate)

Andreas Kontos is a PhD candidate in the Department of Economics at the Democritus University of Thrace. His research is focused on Machine Learning applications in Economics. He holds an MBA and a BSc in Economics from the Democritus University of Thrace, as well as a diploma in Education from the School of Pedagogical And Technological Education. He has experience as a freelance accountant, and he was an IVY Interreg Project Partner for the Region of East Macedonia and Thrace. His research interests are mainly Macroeconomics, Machine Learning, Forecasting and Finance.

Theodoros Koutroukis (Professor)

Theodore Koutroukis (M.A., M.Sc., Ph. D., Post.Doc.) is a Professor at the Democritus University of Thrace and Deputy Head at the Department of Economics. His research interests cover Personnel Economics, Employment Relations, Vocational Training, Negotiations, Labour Market and Human Resource Management. He has taught at several Universities (Aegean University, Athens University of Economics and Business, Hellenic Open University, University of Ioannina, Open University of Cyprus, Frederick University of Cyprus etc). He is an experienced regional and national co-ordinator/expert of EU funded projects (ESF, ADAPT, RETEX, NOW, EQUAL, YOUTHSTART etc.) and evaluator of projects funded by the Greek Ministries of Education and Labour. Also he is an experienced Researcher of many studies and research projects concerning industrial relations, labour market, vocational training 1990-present and an Arbitrator at the Greek Organisation for Mediation and Arbitration 1998-present (Providing Mediation Services in Labour Disputes/ Conflicts between trade unions and management and advised social partners in developing social dialogue procedures). He is a member in the International Labour and Employment Relations Association (1989) and the European Association of Labour Economists (2002) and Member of the Committee of Ethics and Deontology of tha Agricultural University of Athens (2025-).

Christos Leontidis (Post - doctoral researcher/ Adjunct Lecturer)

Christos Leontidis is a post-doctoral researcher in the Department of Economics at Democritus University of Thrace and the Department of Economics at the National and Kapodistrian University of Athens. He also serves as an adjunct lecturer in the Department of Accounting and Finance at Democritus University of Thrace, having taught Auditing, Public Sector Accounting, Management Accounting, and Firm Valuation. He holds a PhD in Accounting from Democritus University of Thrace, where he also completed his Master of Business Administration. In addition, he completed his undergraduate studies in Accounting and Finance at the University of Macedonia in Thessaloniki. His research interests include the quality of financial reporting, financial and management accounting, and IFRS implementation. His research has been published in international journals and presented at international conferences. Beyond academia, he has professional experience in the banking sector (internship) and has worked as both an employed and self-employed accountant and tax consultant since 2013. He also provides consulting services on European funding projects for SMEs and organizations.

Marija Majhosheva (Professional in Financial Sector)

Marija Majhosheva is an experienced banking and finance professional in North Macedonia with a proven record in financial services and client relationship management. She currently serves as an SME Relationship Associate at Sparkasse Bank AD Skopje, managing and expanding client portfolios for small and medium-sized enterprises while providing tailored financial solutions that align with clients' business goals. Previously, Marija worked as a Compliance Officer at Fido Services, ensuring regulatory compliance while strengthening client trust and relationships. She also gained extensive experience in financial reporting and analysis as an Accountant at EMR Express, handling bookkeeping and financial management with precision and a solution-focused approach. Earlier in her career, she worked as a Sales Advisor at Stopanska Banka AD Skopje, where she developed expertise in negotiation and customer relationship management while meeting sales targets consistently. Marija holds a Bachelor's Degree in Financial Banking and Tax Management from the European University of Skopje and two Master's Degrees: one in Monetary Economy, Finance, and Banking from Ss. Cyril and Methodius University of Skopje, and another in Economics from the University of Skopje. She is currently pursuing a PhD in Economics at the University "Goce Delcev" Shtip, focusing her research on human resources management, aligning with her interest in optimizing people management practices within organizations. Her research in HR management has shaped her understanding of the role human capital plays in organizational success, which she applies professionally by building strong client relationships and recognizing people-driven dynamics in business growth. Marija is skilled in business planning, negotiation, Microsoft Office, and public speaking. She is committed to continuous learning and contributing to the development of the banking and financial services sector in North Macedonia while advancing the role of human resources management in economic growth.

Fotios Mitropoulos (postdoctoral research)

Dr. Fotios Mitropoulos is a postdoctoral research fellow in economics at the Democritus University of Thrace. He holds a BSc in Business Administration from the Athens University of Economics and Business (2012), an MSc in International and European Economic Studies from the same institution (2014), and a PhD in Economics from the Democritus University of Thrace (2019). He was a visiting PhD student at Brunel University London in 2017 and an economic advisor to the Economic Chamber of Greece from 2017 to 2022. Dr. Mitropoulos is an economic researcher at Alpha Bank's Economic Research Division and has taught undergraduate economics at the Democritus University of Thrace. His research interests focus on macroeconomics, labor markets, international economics and economic analysis. He has also contributed to numerous research projects funded by national and European sources.

Theophilos Papadimitriou (Professor)

Theophilos Papadimitriou received the Diploma degree in Mathematics from the Aristotle University of Thessaloniki, Greece, the Master degree from the University of Nice-Sophia Antipolis, France, both in 1996 and the PhD degree from the Polytechnic School of the Aristotle University of Thessaloniki in 2000. In 2001, he joined the Department of Economics, Democritus University of Thrace, Komotini, Greece, where he, currently, holds the position of Professor. Dr Papadimitriou co-authored more than 140 journal papers, conference papers and book chapters combined. He served as a reviewer for various publications and as a member to scientific committees for Conferences and Workshops. Theophilos Papadimitriou worked as a member or the project coordinator in various research projects. He gave invited talks at the University of Michigan, Temple University, University of Strasbourg, and the European Central Bank. Theophilos Papadimitriou current research interests include complex networks, machine learning, and data analysis.

Kosmas Papadopoulos (Post Doc Researcher)

Kosmas Papadopoulos is Post Doc Researcher in the Department of Economics at Democritus University of Thrace. His postdoctoral research is entitled: "Control of chaotic dynamics in oligopoly models". His research activity focuses on the field of mathematical economics and mathematical modeling. More specifically, he has dealt with nonlinear dynamics, game theory and oligopoly theory. He was a member of a research team of a co-funded project as a PhD candidate. He is the author of scientific articles that have been published in scientific journals after the crisis and has participated in international scientific conferences with announcements of original works. He is a graduate of the Department of Mathematics of the Aristotle University of Thessaloniki and holds an MBA from the Department of Economics of the Democritus University of Thrace. He has received 2 financial scholarships for excellence as a postgraduate student and as a doctoral candidate.

Victoria Pistikou (Associate Professor)

Victoria Pistikou is an Associate Professor of International Economic Relations in the Department of Economics at the Democritus University of Thrace. She earned a degree in Political Science and History from Panteion University in 2009, followed by a Master's degree in International Relations and Strategic Studies in 2011. In 2016, she completed her PhD in International Political Economy (University of the Peloponnese), with a dissertation titled *"Economic Interdependence and National Security."* Her research appears in international academic journals, focusing on the interaction between international economics and politics. Her work examines how political strategies affect economic relations among states, businesses, and international organizations, as well as how economic structures and trends impact global political and economic governance, particularly regarding international trade and development. Her teaching responsibilities include courses such as International Economic Relations, Economic Diplomacy, and International Economic Development.

Vasilios Plakandaras (Associate Professor)

Vasilios Plakandaras is an Associate Professor at the Department of Economics of the Democritus University of Thrace, Greece. He holds a Bachelor's degree from the same department, where he completed his graduate studies, leading to a PhD in Applied Economics. His research interests focus on studying complex non-linear systems and their application to economic problems, using machine learning and econometric approaches. He has published more than 30 studies in leading peer-reviewed journals as the

International Journal of Finance and Economics, *Economics Letters*, *Economic Modelling*, *Journal of Policy Modelling, Journal of Forecasting, Resources Policy, International Finance, Empirical Economics* and *Applied Economics,* compiling numerous citations. He participated in research programs funded by national and European sources, while teaches Econometrics, Applied Economics and Quantitative methods at the undergraduate and graduate level.

Thomas Poufinas (Associate Professor)

Thomas Poufinas is Associate Professor at the Department of Economics of the Democritus University of Thrace. He holds a PhD in Financial Mathematics from the Ohio State University, USA, and a BSc in Mathematics from the University of Athens. Prior to his employment at the University, he pursued a career in the investment and insurance industry. He has worked in the USA and in Greece for multinational investment and insurance organizations. He has taught for Ohio State University, as Teaching Assistant, Instructor, and Visiting Faculty Member. He has held Visiting Faculty Member positions at the Department of Statistics, Actuarial and Financial Mathematics at the University of the Aegean, and at the Department of Accounting and Finance at the Athens University of Economics and Business. He has taught courses for a series of Graduate Programs, offered by the University of Athens, the Athens University of Economics and Business, the University of the Aegean and the University of Piraeus. He has also taught courses for the Hellenic Open University. He offered a broad spectrum of seminars for several organizations, such as the Athens Stock Exchange. His teaching appointments cover a period of more than three decades, and span from business mathematics, financial mathematics, probability and statistics to financial analysis, investments, actuarial science, portfolio management, risk management, derivatives, banking, insurance, pensions and corporate finance/ company financing. His research interests include finance, investment, risk management, actuarial science, insurance, pension plans, banking, corporate finance, and their applications. He has a wide range of research work in international journals and writing work/ books both in Greek and international publishing houses. He has participated and presented his work in several international conference all over the globe. He leads and has led and participated in several research programs, with both private and public funding.

Konstantinos Rigopoulos (Assistant Professor)

Dr. Konstantinos Rigopoulos, Assistant Professor of Marketing and Market Research at Democritus University of Thrace, embodies a career defined by the rigorous integration of academic excellence and profound practical experience in marketing. His comprehensive educational background comprises a degree in Marketing and Communication from the Athens University of Economics and Business, an M.Sc. in Business Administration obtained from the prestigious Rotterdam School of Management (Erasmus University), and a Ph.D. in Business-to-Business Marketing from the renowned Nyenrode Business Universiteit in the Netherlands, with both postgraduate degrees notably facilitated by a scholarship from the Greek State Scholarship Foundation. Dr. Rigopoulos' expertise lies at the intersection of cutting-edge marketing disciplines: digital B2B marketing, the intricate dynamics of social media storms, and effective present-day sales management. His scholarly contributions are recognized in academic circles, with research appearing in journals like the Journal of Personal Selling & Sales Management and featuring in the proceedings of esteemed conferences such as the American Marketing Association and the European Marketing Academy.

Beyond academia, Konstantinos brings over 12 years of successful frontline managerial experience within multinational companies. This hands-on expertise spans digital marketing, digital communication, social media crisis management, and B2B sales, enriching his teaching and research with invaluable real-world insights. He was also a founding member and on the scientific committee of the LightHub start-up incubator, demonstrating his commitment to fostering innovation.

Currently, he serves as the Secretary General of the Greek Marketing Academy since 2023 and is an active member of the European Marketing Academy (EMAC). He passionately teaches a wide array of courses at both undergraduate and postgraduate levels, covering from market research and digital communication to international export marketing and immersive technologies, shaping the next generation of marketing professionals in Greece and abroad.

George Sarafopoulos (Professor)

George Sarafopoulos is Professor of Mathematics at the Department of Economics, Democritus University of Thrace. He is a graduate of the Mathematical Department of Aristotle University of Thessaloniki (Greece) with a Master's Degree (DEA) in Mathematics from the Fourier Institute, University of Grenoble (France) and a PhD of Mathematics from Claude Bernard University (France). His teaching interests include the teaching of Mathematics, Game Theory and Quantitative Methods at undergraduate and postgraduate levels. His research activity concerns issues of Dynamical Systems and Game Theory, Geometric Analysis and topics pertaining to mathematics education. He is the author of many scientific papers published in international scientific journals and conference proceedings. He is scientific supervisor of research projects, member of scientific committees of international conferences and reviewer in international scientific journals. He was Vice Head of the Department of Economics and Dean of the Faculty of Social, Political and Economic Sciences. Democritus University of Thrace.

Antonios Sarantidis (Adjunct Assistant Professor)

Dr. Antonios Sarantidis is an Adjunct Assistant Professor of Economics in the Department of Management Science and Technology at the University of Peloponnese. He holds a BSc in Economics from Aristotle University of Thessaloniki (2007), an MSc in Economic Analysis from the University of Peloponnese (2012), and a PhD in Financial Econometrics from the Hellenic Open University (2021). Dr. Sarantidis has taught economics at both undergraduate and postgraduate levels at the Hellenic Open University and the University of Peloponnese. His research interests focus on econometrics, macroeconomics, and financial and economic crises. He has also contributed to numerous research projects funded by national and international public authorities, as well as private organizations.

Maria Sartzetaki (Associate Professor)

Maria Sartzetaki is Associate Professor of Management (Business Administration) in Dept. of Economics at Democritus University of Thrace (DUTh), while she is member of the Research Laboratory MaGBISE (Management, Governance, Business Intelligence, Strategy and Corporate Ethics in Infrastructure Operators, Networks and Supply Chain), as well as the UNESCO regional unit in Business ethics. Her specialization profile is focused on strategic management, corporate governance, organizational behaviour and leadership, business intelligence, operational and supply chain management, risk management, project management, and corporate social responsibility. She has participated in many research projects providing papers and presentations in distinguished international events. She actively collaborates with research networks and international organizations, linking academic knowledge with business practice and corporate management. In her professional truck record are included occupation of executive advisory positions in organizations and enterprises, subject matter expertise in fields of business development and corporate management, while in 2019 she received the "Study UK Alumni Award" for Professional Achievement from the British Council.

Elenica Sofijanova (Professor)

Elenica Sofijanova, PhD**,** is a Full Professor at the Faculty of Economics, "Goce Delchev" University in Shtip, with academic expertise in Management. She earned her PhD in Management from the Institute for Sociological, Political and Juridical Research at "Ss. Cyril and Methodius" University in Skopje in 2007, where she also completed her postgraduate studies in Human Resources. Her teaching portfolio includes courses such as Business Communication, Small Business Management, Human Resource Management, Organizational Behavior, Project Management, Change Management, and Agribusiness Management. Her research interests focus on strategic management, market orientation in SMEs, and education in economic sciences. Professor Sofijanova has extensive academic and practical experience, gained through participation in numerous conferences, social initiatives, and collaborations with various organizations. Her professional interests include group dynamics, teamwork, and the development of value-based collaboration within academic and organizational settings.

Eleftherios Spyromitros (Professor)

Eleftherios Spyromitros holds a PhD in Economics from the University of Strasbourg. He currently serves as a professor at Democritus University of Thrace, Department of Economics. His work has been published in refereed journals such as Economic Letters, Macroeconomic Dynamics, Journal of International Financial Markets, Institutions and Money, Manchester School, Scottish Journal of Political Economy, Economic Modelling, Finance Research Letters, Research in International Business and Finance, Journal of Economic Studies, Bulletin of Economic Research, Economic Analysis and Policy, Sustainability, Operational Research, Euromed Journal of Business, and Managerial Finance in the areas of macroeconomics, monetary economics, and finance.

Liljana Pushova Stamenkova (Doctoral Researcher)

Liljana Pushova Stamenkova is a Doctoral Researcher and Teaching Assistant at the Faculty of Economics, MIT University in Skopje, specializing in sustainable and circular economy. She holds a Master's degree in Economics and is currently a PhD student. Her recent research is primarily focused on issues related to sustainability and circular economy, with particular emphasis on improving resource efficiency, analyzing national policy frameworks, and exploring opportunities for the development of green jobs. Within this context, she examines the role of institutional support, business sector readiness, and societal awareness in fostering a transition toward more sustainable production and consumption models. Ms. Pushova Stamenkova actively participates in academic conferences, seminars, and professional workshops, where she presents her work and engages in knowledge exchange with researchers and practitioners. She is also involved in interdisciplinary and cross-sector collaborations aimed at promoting sustainable economic development in North Macedonia, contributing to both academic discourse and the practical implementation of circular and green economy principles.

Despoina Terzopoulou (PhD Candidate)

Despoina Terzopoulou is a PhD Candidate at Department of Economics, Democritus University of Thrace. Her research focuses on nonlinear dynamics and mathematical economics, with an emphasis on the application of advanced mathematical tools to economic modeling. She obtained her BSc in Mathematics from Aristotle University of Thessaloniki and her BSc in International and European Studies from University of Macedonia. She holds a Master's degree in Pure Mathematics and a Master's degree in Economics from Aristotle University of Thessaloniki. Since 2018, she has been working as a mathematician at a secondary school. In recent years, she has attended relevant conferences and published her work on topics related to dynamical systems and economic theory.

Dimitrios Zygiotis

Dimitrios Zygiotis holds an MSc in Business Mathematics from the National and Kapodistrian University of Athens and a BSc in Production and Management Engineering from the Technical University of Crete. His MSc Thesis, "How Transparency Affects Investment Linked Insurance Products" supervised by Professor Thomas Poufinas, was published in International Advances in Economic Research (Springer, 2017), providing valuable insights into how transparency influences the performance and attractiveness of complex financial products. He also presented elements of this research at the 6th National Conference of the Financial Engineering and Banking Society (University of Piraeus, 2015), highlighting his early academic engagement in applied financial analysis. He is a professional in the field of Sports Betting, currently serving as a Pre-Event Team Leader in Basketball & U.S. Sports at Novibet. With over 7 years of experience in the Sports Betting industry, his work involves compiling and trading odds, analyzing market dynamics and customer behavior, overseeing risk management procedures, the development of data-driven tools and streamlining operations. He is also actively involved in mentoring, training and leading specialized teams to ensure the delivery of a robust and comprehensive sports product. Combining a rigorous mathematical background with practical expertise in sportsbook operations, Mr. Zygiotis exemplifies the application of quantitative methods to complex real-world decision making, in both financial and sports trading contexts. His career trajectory demonstrates both scholarly engagement and industry leadership in high-pressure environments, positioning him as a dynamic professional capable of bridging academic knowledge with operational excellence and strategic insight in fast-paced environments. His research interests focus on decision-making, finance, risk management, and their applications, in particular in the sports industry.

SCIENTIFIC COMMITTEE:

ISBN 978-960-02-4584-4

9 789600 245844

www.papazissi.gr