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Faculté de Droit et des Sciences Économiques
Laboratoire d'Analyse et de Prospective Économiques (LAPE) – UR 13335

Thèse
Pour obtenir le grade de
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Présentée et soutenue publiquement par
Mehrafarin SHETABI
Limoges, le 8 janvier 2025

Opacity, Financial Analysts, and Optimized Risk Assessment: Evidence from Banking and FinTech Sectors

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Keywords: Bank Stability, Earnings Management, Financial Analyst, Fintech Market, Market Discipline, Opacity, Risk Optimization

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Summary

General Introduction 1

Chapter 1. Opacity, Financial Analysts and Bank Risk: Evidence from US and European Publicly Traded Banks 4

1.1. Introduction 6

1.2. Related Work and Hypothesis Development 10

1.3. Econometric Specification and Methodology 16

1.4. Measurement and Data 18

1.5. Empirical Findings and Analysis 27

1.6. Summary and Conclusion 53

Appendix I 55

Chapter 2. The Influence of Financial Analyst Characteristics on Forecast Accuracy: A Comparative Analysis Across Global Banking Markets 64

2.1. Introduction 66

2.2. Related Work 69

2.3. Research Design and Methodology 73

2.4. Research Data 80

2.5. Empirical Result 84

2.6. Summary and Conclusion 105

Appendix II 108

Chapter 3. Evolutionary-Based Ensemble Feature Selection Technique for Dynamic Application-Specific Credit Risk Optimization in Fintech Lending 116

3.1. Introduction 118

3.2. Related Work 122

3.3. Proposed EFSGA Model 127

3.4. Empirical Evaluation Of The Proposed Method 136

3.5. Discussion And Conclusion 154

3.6. Future Research Directions 155

Appendix III 157

General Conclusion 166

Bibliography 168

General Introduction

The global financial system operates as a delicate equilibrium, where transparency and market discipline are critical safeguards against instability. Yet, at its core, the banking sector remains uniquely opaque, characterized by complex structures, asymmetric information, and high leverage that obscure risk profiles and challenge regulatory oversight. This inherent opacity not only exacerbates systemic vulnerabilities but also amplifies agency conflicts, moral hazard, and risk-taking behaviors. As intermediaries in this opaque landscape, financial analysts play a pivotal role in mitigating information asymmetries and enhancing market discipline. However, their influence is not unequivocally stabilizing; analysts also have the potential to amplify market volatility and risk-taking, particularly in highly opaque banking environments.

Despite significant advancements in financial research, key areas remain underexplored. Traditional studies rely heavily on backward-looking metrics, which fail to capture the dynamic and predictive risks associated with bank opacity. Additionally, while the structural differences between market-driven systems like the U.S. and bank-driven systems like Europe are acknowledged, their nuanced implications for bank risk-taking and systemic stability remain insufficiently analyzed. Furthermore, the dual role of financial analysts—as both transparency enhancers and potential drivers of volatility—has not been adequately examined, leaving critical gaps in understanding how their behavior interacts with opacity to influence risk.

Moreover, while opacity and information asymmetry have long been recognized as destabilizing forces in banking, their effects are even more profoundly magnified in the rapidly evolving and highly interconnected FinTech markets. Indeed, the rapid digitization of financial services has significantly improved accessibility and efficiency; however, it has also introduced substantial vulnerabilities due to its inherent characteristics, including information asymmetry, lack of transparency, and minimal regulatory oversight, which further exacerbate uncertainty and instability.

This thesis examines these critical issues through three interconnected chapters, each exploring distinct yet complementary dimensions of opacity, information asymmetry, and risk in financial systems. The research is guided by the following questions: How does opacity influence systemic risk and stability in banking, and what roles do financial analysts and dividend policies play in moderating or amplifying these effects? How do the characteristics and motivations of financial analyst's shape forecasting behaviors, and what implications do these behaviors have for market discipline and career trajectories in global banking markets? Finally, how can advanced metaheuristic techniques and machine learning frameworks be leveraged to optimize credit risk management in the highly dynamic and opaque FinTech sector?

The first chapter investigates the destabilizing effects of bank opacity on systemic stability, introducing forward-looking measures—analysts' forecast errors and dispersions—to capture the dynamic risks associated with opacity. By analyzing publicly traded U.S. and European banks from 2000 to 2020, this chapter provides a nuanced perspective on the opacity-risk nexus. It highlights critical gaps in the literature, including the limitations of backward-looking metrics that fail to capture dynamic risks, the underexplored dual role of financial analysts as transparency enhancers and volatility amplifiers, and the lack of comparative analysis of opacity's effects across distinct financial systems. The findings reveal that opacity significantly undermines bank stability, with destabilizing effects most acute under conditions of overvaluation and economic uncertainty, particularly in the U.S. Analyst coverage emerges as a double-edged sword: while it enhances market discipline, it paradoxically amplifies risk in highly opaque U.S. banks—especially smaller institutions—by intensifying reactions to negative earnings signals. Dividend policies further complicate this dynamic, serving as stabilizing signals when moderate but exacerbating opacity-driven risks when excessive. A comparative analysis underscores distinct regional dynamics, with the market-driven U.S. system exhibiting heightened sensitivity to opacity and analyst pressures, while the bank-driven European system demonstrates more tempered responses.

The second chapter shifts the focus to the role of financial analysts, exploring how their characteristics and career motivations shape earnings forecast accuracy across global banking markets. Using data from the I/B/E/S Detail History Database, the study examines 516 publicly traded banks across the U.S., Europe, and Asia from 2000 to 2023. The findings reveal significant regional variations in forecasting precision and strategic behaviors. General and bank-specific experience significantly enhance forecast accuracy, with the strongest effects observed in the U.S. However, portfolio complexity produces contrasting effects: broader coverage improves accuracy in the U.S. and Asia but increases errors in Europe due to geographical diversification challenges. Boldness, often driven by career motivations, exhibits regional nuances. In the U.S., experienced analysts leverage bold forecasts to signal expertise and advance their careers, while less experienced analysts herd to minimize risks. In Asia, boldness consistently supports career progression across all experience levels, while in Europe, early-career analysts use bold forecasts to gain visibility but often trade off accuracy for career advancement.

The third chapter extends the analysis to the FinTech sector, where the destabilizing effects of opacity and information asymmetry are most pronounced. It introduces the Evolutionary-Based Ensemble Feature Selection Technique using Genetic Algorithms (EFSGA), an innovative framework designed to address the limitations of traditional credit risk assessment models in this rapidly evolving sector. Unlike conventional methods, EFSGA hybridizes metaheuristic algorithms with machine learning to provide real-time, dynamic solutions for managing credit risk in high-dimensional, imbalanced datasets. By incorporating heterogeneous ensemble learning and optimizing classification thresholds using genetic algorithms, the model significantly enhances predictive accuracy and interpretability. Tested on FinTech lending datasets, EFSGA demonstrates a 23% improvement in application-specific evaluation metrics, providing a transformative approach to credit risk management in an era of heightened uncertainty and complexity. This dynamic framework is uniquely positioned to address the challenges posed by FinTech markets, ensuring adaptability to evolving borrower behaviors and macroeconomic conditions while meeting stringent regulatory requirements.

Together, these chapters provide a comprehensive examination of the destabilizing effects of opacity and information asymmetry in banking and FinTech markets. By bridging traditional banking challenges with innovative solutions for the FinTech era, this thesis offers actionable insights for policymakers, regulators, and financial institutions, emphasizing the need for dynamic, forward-looking strategies to mitigate systemic risks and enhance financial stability in an increasingly interconnected global economy.

Chapter 1

Opacity, Financial Analysts and Bank Risk: Evidence from US and European Publicly Traded Banks

This chapter is based on the working paper titled *"Opacity, Financial Analysts, and Bank Risk: Evidence from US and European Publicly Traded Banks*." An earlier version of this article was presented at the AAP Region Workshop organized by the University of Bordeaux, December 2–3, 2021, and at the Ph.D. Seminar held at the University of Poitiers on November 24, 2022. These events provided valuable opportunities to refine the research through insightful discussions and feedback from esteemed participants.

Abstract

This study rigorously examines opacity—captured through analyst forecast errors and dispersion—and its destabilizing influence on bank stability across U.S. and European markets. We delve into the intricate role of financial analyst pressure in moderating market discipline within opaque banks and further analyze how dividend payout policies intersect with the Risk-Opacity channel to shape sectoral stability. Leveraging an extensive dataset of publicly traded banks from 2000 to 2020, we present four pivotal findings. First, we uncover that heightened opacity markedly undermines bank stability, with destabilizing effects most acute under conditions of elevated market overvaluation and economic uncertainty, particularly in the U.S. market. Second, analyst coverage emerges as a nuanced force: while it often promotes market discipline, it can paradoxically intensify risk in U.S. opaque banks—especially smaller institutions—by heightening sensitivity to negative earnings signals, with a much weaker effect in the EU. Third, the impact of analyst recommendations and revisions becomes pronounced during heightened uncertainty, with negative signals compounding opacity-induced risk in U.S. banks, while positive signals offer a more constrained stabilizing effect. The interplay between opacity, adverse recommendations, and extensive analyst coverage exerts considerable pressure on U.S. banks, driving asset price volatility that edges institutions closer to default thresholds and underscores the disciplinary role of analyst coverage in aligning valuations with risk. Lastly, we observe that excessive dividend payouts exacerbate opacity's adverse effects on stability, particularly within U.S. banks. This suggests that while dividend policies can signal strength, overly aggressive distributions may erode resilience in opaque banking environments, highlighting the critical balance between transparency and financial prudence in fostering systemic stability. Overall, our findings highlight how opacity, analyst influence, and dividend policies uniquely shape bank risk within market- and bank-driven financial systems, offering key insights for enhancing systemic stability in an interconnected financial landscape.

JEL classification: G01; G14; G21; L11

Keywords: Bank opacity; Bank Risk; Financial Analysts; Market discipline; Dividend Policy.

1.1. Introduction

Bank opacity presents an enduring and fundamental challenge in contemporary financial research, exerting a profound influence on risk management practices, systemic stability, and regulatory frameworks. This inherent opaqueness arises from banks' unique asset and liability compositions—distinguished by illiquid and often non-transparent assets, elevated leverage ratios, and substantial insured liabilities—all of which intensify agency conflicts and moral hazard issues (Morgan, 2002; Flannery et al., 2004; Dang et al., 2017). These complex features elevate the cost of external funding and exacerbate systemic vulnerabilities, situating transparency as a cornerstone in discussions of bank fragility and regulatory efficacy (Jones et al., 2012; Bushman, 2016). Relative to other firms, banks exhibit a heightened opacity that obscures accurate assessments of their intrinsic value and solvency (Morgan, 2002; Blau et al., 2017), complicating efforts by external stakeholders to reliably gauge institutional soundness. Regulatory interventions, such as Basel III, have thus increasingly prioritized transparency and market discipline as mechanisms to reinforce sectoral stability (Basel Committee on Banking Supervision, 2013). The theoretical interface between opacity and market discipline emerges as a central concern, as opacity inherently distorts risk-taking incentives and may ultimately compromise financial stability (Demsetz & Lehn, 1985; Cordella & Yeyati, 1998; Boot & Schmeits, 2000; Nier, 2005). Empirical studies substantiate the intrinsic connection between opacity and heightened insolvency risks, underscoring how opacity amplifies systemic fragilities across the banking landscape (Jones et al., 2012; Dewally & Shao, 2013a; Fosu et al., 2017). Understanding this relationship is pivotal, necessitating an intricate examination of how internal governance choices and external stakeholder perceptions coalesce to shape risk profiles and transparency within the sector. Existing research, however, is constrained by its reliance on backward-looking accounting disclosures, which are fundamentally limited in capturing the dynamic and forward-looking risks associated with bank opacity (Nier, 2005; Nier & Baumann, 2006). This retrospective lens constrains our understanding of market discipline's influence on bank stability, particularly amid today's increasingly complex and interconnected financial ecosystems.

Addressing these limitations, this study introduces a novel approach, leveraging direct and forward-looking metrics of opacity—specifically, analysts' forecast errors and dispersions—to empirically evaluate opacity's impact on bank stability. These measures capture degrees of uncertainty and disagreement among expert analysts, offering a refined and more predictive assessment of banks' future economic trajectories. This approach allows for an investigation into how forecast dispersion and volatility reflect genuine uncertainty regarding banks' prospective stability, particularly in response to negative earnings surprises[1]. A secondary, yet equally critical, objective of this research is to examine the contribution of financial analyst pressure as information intermediaries within the opaque banking sector and their potential to influence market discipline. Specifically, we analyze how informational shocks stemming from analysts' recommendations and earnings forecasts are interpreted by market participants and the extent to which these shocks influence stock market performance. By evaluating the predictive validity of analysts' reports, we examine whether analysts serve as external monitors that enforce discipline or if their coverage inadvertently drives banks toward riskier behaviors to meet market expectations. Although existing studies suggest that analysts mitigate information asymmetry by providing credible insights (Cheng & Subramanyam, 2008; Mansi et al., 2011; Derrien et al., 2016; Kosaiyakanont, 2013), the complex, dualistic role they play in banking remains underexplored. Our research thus delves into both the informational efficiency of analyst insights and the potential pressures their coverage imposes, seeking to clarify whether analysts reinforce market discipline or inadvertently act as catalysts for elevated risk-taking[2]. In addition, this study explores the moderating influence of dividend payout policies on the opacity-risk relationship. Dividend payments are frequently construed as signals of financial strength, capable of conveying private information to the market and enforcing discipline by aligning the interests of internal managers with external stakeholders (Easterbrook, 1984; Jensen, 1986). While dividend distributions may constrain a bank's capital reserves, they can simultaneously enhance market discipline by reducing informational asymmetry (Onali, 2010). Despite their theoretical importance, the implications of dividend policies on market discipline in opaque banking environments remain insufficiently examined. By investigating how dividend payments interact with opacity in influencing risk, we endeavor to shed light on the mechanisms that underpin bank stability.

Furthermore, recognizing the distinct regulatory and market-driven differences between the U.S. and European banking sectors, this study conducts separate analyses for these regions. In

[1] This study equates "analyst forecast error" with "earnings surprise," the difference between reported and expected earnings, often based on analyst forecasts (Defond et al., 2001; Pinto et al., 2010). Negative values indicate optimistic bias, while positive values suggest pessimism. A negative earnings surprise may lead market participants to adjust expectations downward, increasing uncertainty about the firm's value (Hayn, 1995). Research on earnings surprises and stock returns shows positive surprises tend to increase trading volume, whereas negative surprises generally result in stock price declines (Bamber, 1987; Kinney et al., 2002).

[2] Notably, we examine how analysts intensify market reactions to negative earnings surprises for banks. This investigation aims to deepen our understanding of the dual role financial analysts play—both as enhancers of market discipline and as potential drivers of risk within the banking sector.

the U.S., market dynamics and analyst scrutiny are typically more pronounced, while European banks operate under more stringent regulatory oversight. These structural divergences imply that the interplay between opacity, analyst influence, and bank stability may vary substantially across these regions. To assess the robustness of our findings, we examine U.S. and European subsamples, capturing the nuances of these financial ecosystems and their impact on risk-taking behaviors and stability. In sum, this research addresses pressing gaps in the literature by applying forward-looking measures of bank opacity, analyzing the complex role of financial analysts, and assessing the moderating effects of dividend policies on risk across varied regulatory landscapes. Through these multi-faceted inquiries, we aspire to advance our understanding of market discipline, promoting a more resilient and transparent banking sector.

Our empirical analysis, based on a dataset of 341 publicly traded U.S. and European banks spanning 2000 to 2020, uncovers critical insights that illuminate the opacity-risk nexus in banking: First, our analysis shows that a high degree of opacity significantly undermines bank stability[3], with destabilizing effects—manifesting as reduced profitability and heightened earnings volatility, leading to higher default risk—most evident in overvalued banks and under conditions of elevated uncertainty[4]. Regionally, the destabilizing influence of opacity is more severe in the U.S., although it remains present, albeit to a lesser extent, in the EU. This also implies that analysts' earnings forecast dispersion and bias are effective proxies for opacity, yielding substantial insights into future bank risk and earnings volatility, particularly with stronger effects observed in the U.S.

Second, our findings highlight the complex role of analyst coverage in moderating risk-taking, particularly among high-opacity banks. While analyst coverage generally enhances market discipline and curbs excessive risk-taking globally[5], its effect on opaque banks is highly heterogeneous across regions. In the U.S., increased analyst coverage tends to amplify pressure on opaque banks, often pushing them toward riskier behaviors, especially within smaller institutions**.** Thus, heightened analyst coverage amplifies market reactions to negative earnings surprises in highly opaque U.S. banks, intensifying the impact of opacity on risk-taking amid strong market responses. In contrast, the European context reveals a more tempered dynamic:

[3] This destabilizing effect of opacity is robust, persisting across various risk proxies and remaining significant even after accounting for a wide array of both observable and unobservable bank characteristics.

[4] These findings underscore the sensitivity of overvalued banks, as indicated by elevated market-to-book ratios, to negative earnings surprises, likely driven by market expectations that surpass the bank's actual financial strength. This suggests that overvalued growth stocks tend to underperform value stocks following earnings disappointments, highlighting the risks inherent in investor optimism.

[5] In the US market, greater analyst coverage has a pronounced disciplining effect on risk-taking, particularly among banks with moderate perceived valuations, larger size, and higher volatility. The European market however, exhibits a weaker and more inconsistent influence.

analyst coverage moderately curtails risk-taking in smaller banks while marginally intensifying risk for larger opaque institutions. This nuanced finding underscores the limited yet region-specific moderating effect of analyst coverage on opacity-induced risk.

Our analysis highlights the robust predictive power of financial analysts' insights in assessing default risk, particularly in the U.S. and notably during periods of elevated market uncertainty[6]. Negative analyst signals—such as sell recommendations and downgrade revisions—amplify opacity's destabilizing effects on U.S. banks, while positive recommendations and upgrades provide some stabilization, though less significantly, and with minimal impact in Europe. The interplay between opacity, negative-toned recommendations or revisions, and high analyst coverage creates substantial pressure on opaque U.S. banks. The heightened market pressure from analyst forecasts often drives asset price fluctuations that potentially edge banks closer to default risk thresholds, emphasizing how extensive analyst coverage can promote disciplined market behaviors by making bank valuations more responsive to forecast shifts. Ultimately, this dual role of analysts—as both transparency enhancers and volatility influencers—positions them as key players in shaping the opacity-risk relationship within the banking sector.

Beyond the impact of analysts, our findings suggest that while dividend payments generally enhance bank stability, excessive payouts can magnify the adverse effects of opacity, thereby reducing their stabilizing role and potentially contributing to greater instability. This destabilizing effect of high dividend payouts is most pronounced in the U.S. but remains significant, though somewhat less intense, within the EU. These insights emphasize the importance of market dynamics, analyst influence, and regulatory context in shaping the opacity-risk relationship across varied financial systems. The U.S. market-driven environment fosters a heightened reactivity to analyst forecasts, often compelling banks to undertake riskier actions to meet market expectations, particularly following negative earnings surprises[7].

Despite extensive literature examining systemic differences in analyst forecasts, particularly outside the banking sector, and numerous attempts to measure bank risk using public data, the

[6] Our findings indicate that market reactions to analyst recommendations are significantly heightened for banks characterized by elevated opacity and heightened uncertainty.

[7] In these settings, the pressure to meet or exceed analyst expectations can lead to significant adjustments in bank behavior. For instance, when market participants react strongly to earnings surprises—especially negative ones—banks may feel compelled to take on additional risks to meet these elevated targets. This dynamic may not only influence stock prices but also impact broader risk management practices within banks, with the intensity of such reactions varying across different market structures.

intermediary role of financial analysts in bridging market data and the interpretation of banking risk has seen surprisingly limited scrutiny. This study offers several key contributions to address this gap: First, we integrate research on banking opacity, market discipline, and financial analyst influence to deliver a nuanced and comprehensive understanding of banks' risk-taking behaviors. By adopting an interdisciplinary approach, this study addresses a critical gap, offering insights into the complex interactions that shape bank stability in ways previously underexplored. Second, we investigate the moderating role of financial analysts within the opacity-risk nexus, examining whether an optimal level of analyst pressure exists that could mitigate the adverse effects of opacity. This analysis challenges traditional views by introducing a novel perspective on the dual role of analysts, positioning them as both information enhancers and potential risk amplifiers. By exploring this duality, our research expands the boundaries of existing literature on market discipline and information intermediation. Third, we conduct a rigorous assessment of the impact of dividend payout policies on the opacity-risk relationship, contributing meaningfully to ongoing regulatory discussions concerning the prudential role of dividend policies in enhancing bank resilience. Our findings provide nuanced evidence on the potential for dividend payouts to serve as a prudential mechanism counterbalancing opacity-driven risks, offering actionable insights for policymakers in developing robust disclosure and dividend frameworks. Finally, our research illuminates the divergent dynamics of opacity and market discipline across distinct financial environments, specifically contrasting market-driven with bank-driven systems. By revealing how these differing systems uniquely influence the interaction between opacity and risk, we furnish regulators and market participants with critical insights for devising tailored strategies that mitigate bank risk effectively within varied contexts.

The remainder of the paper is structured as follows: Section 1. 2 presents a review of the relevant literature. Section 1. 3 discusses the empirical estimation methods. Section 1. 4 describes the data and variables used in the study. Section 1. 5 presents the empirical results, and Section 1. 6 concludes.

1.2. Related Work and Hypothesis Development

Extensive literature has explored the multifaceted dynamics between transparency, accounting disclosures, stock performance, and risk-taking behaviors in the banking sector. These studies underline the influence of country-level transparency measures on financial stability, while a parallel stream investigates the role of financial analysts in promoting market discipline and the implications of dividend payout policies on bank risk. Drawing from these existing works, this 1. synthesizes key theories and empirical insights to support the development of three key hypotheses relating to (i)bank opacity and risk-taking, (ii)the contribution of financial analyst pressure as a potential moderator on the nexus between bank opacity and bank risk-taking activities, (iii) we also control for the moderating effect of dividend payout policy on the relationship between bank opacity and risk.

1.2.1. Bank Opacity, Risk and Earnings Volatility

Bank assets are typically regarded as opaque, raising significant concerns about the efficacy of market discipline in curbing risk-taking behavior (Morgan, 2002; Flannery et al., 2013). Theoretical frameworks suggest that opacity in the banking sector fuels risk-taking incentives, as the difficulty of assessing a bank's true risk profile leads to higher funding costs, which, in turn, motivate riskier strategies (Fosu et al., 2017). This opacity-driven risk-taking is often exacerbated by external observers' limited visibility into banks' internal monitoring and asset quality, resulting in elevated interest rates on deposits and investments that reflect the perceived level of risk (Cordella & Yeyati, 1998; Boot & Schmeits, 2000). In contrast, greater transparency is seen to enhance market discipline, generally encouraging banks to adopt less risky behaviors. The higher cost of capital associated with opacity creates a financial incentive for banks to take on greater risks to offset these costs, positioning transparency as a benchmark for effective risk management (Nier, 2005).

Prior research extensively documents the inefficiencies that arise from information asymmetry in opaque institutions. These inefficiencies manifest in suboptimal investment and financing decisions (Myers & Majluf, 1984; Diamond, 1991; Derrien & Kecskés, 2013), elevated costs of capital (Kelly & Ljungqvist, 2012), and the erosion of market valuations (Chung & Jo, 1996). Furthermore, opacity can encourage managerial opportunism, reduce financial reporting quality, and lead to capital misallocation (Yu, 2008; Chen et al., 2015; Irani & Oesch, 2013). Banks, especially those with high levels of opacity, may engage in financial statement manipulation to smooth earnings, circumvent capital requirements, or minimize tax liabilities. Such practices not only hinder private governance and regulatory oversight but also pose substantial risks to stability and asset quality (Beatty & Liao, 2011; Bushman & Williams, 2012; Huizinga & Laeven, 2012). Empirical evidence consistently aligns with these theoretical predictions. Fosu et al. (2017) demonstrate that opacity is closely linked to insolvency risks among U.S. banks, and Jones et al. (2012) argue that opacity introduces systemic vulnerabilities by increasing financial instability, price contagion, and amplifying systemic risk. Dewally and

Shao (2013b) further emphasize that excessive opacity weakens market-based discipline, diminishing market participants' ability to effectively constrain bank risk-taking. Recent studies continue to explore these dynamics in various contexts. For example, Iannotta and Kwan (2022) find that unexpected loan loss provisions elevate bank opacity, thereby encouraging risk-taking and diminishing performance. Similarly, Zheng and Wu (2023) demonstrate that during financial crises, opacity leads to significant declines in bank valuation, contributing to systemic instability. In emerging markets, Nguyen and Tran (2022) show that under conditions of heightened uncertainty, opacity adversely affects bank stability and performance. These findings highlight the importance of robust and reliable measures of opacity, which traditional accounting-based indicators—focused on asset composition—often fail to capture fully due to limitations such as vulnerability to managerial manipulation and lack of market-based perspectives (Burks et al., 2017; Bushman et al., 2016; Jiang et al., 2016).

To overcome these limitations, some researchers advocate for the use of analysts' forecasts as more dynamic, market-related indicators of disclosure quality. Analysts' earnings forecasts provide independent assessments of firm opacity and expected earnings volatility, with larger forecast errors and greater forecast dispersion serving as indicators of higher opacity (Flannery et al., 2004). Studies show that greater transparency reduces forecast dispersion, enhances liquidity, and improves market efficiency (Roulstone, 2003). During the financial crisis, Anolli et al. (2014) observed that forecast accuracy was especially crucial as stock price volatility intensified amidst high uncertainty. Additionally, research on earnings surprises and stock returns reveals that the variance between analyst estimates and actual earnings significantly influences market reactions: Positive surprises correlate with increased trading volume, while negative surprises are often associated with declines in stock returns (Bamber, 1987; Kinney et al., 2002). Fosu et al. (2017) also used analysts' forecasts to assess opacity among U.S. bank holding companies, confirming that forecast errors serve as effective proxies for bank opacity. High forecast dispersion often signals elevated uncertainty about future cash flows and reflects a lower quality of disclosures.

Building on this literature, we employ analysts' forecast error and dispersion as proxies for bank opacity to examine their influence on bank risk-taking and stability. This approach allows us to capture market participants' perceptions of opacity as they relate to banks' future performance and volatility. Consequently, we propose the following hypothesis:

Hypothesis 1a: *Opacity increases risk-taking behavior and exacerbates bank instability and performance.*

This hypothesis tests the informational efficiency of analysts' earnings forecasts as forward-looking indicators of opacity in banks. Specifically, it posits that banks with higher forecast dispersion are more likely to engage in riskier behavior, which diminishes stability and performance. Conversely, banks with greater transparency are expected to exhibit stronger profit efficiency and lower volatility in earnings[8].

1.2.2. The Role of Financial Analysts in the Nexus Between Bank Opacity and Risk

Financial analysts play a pivotal role in shaping market discipline through two primary mechanisms: the coverage effect and the informational effect. Together, these mechanisms have the potential to not only influence banks' visibility and market valuation but also modulate risk-taking behaviors in the context of opacity within the banking sector.

(i) **The Coverage Effect:** Analyst coverage heightens a bank’s visibility and subjects it to increased market scrutiny. As more analysts cover a bank, pressure mounts to meet or exceed market expectations, creating dual and sometimes contradictory outcomes. On the one hand, increased coverage can bolster market discipline, encouraging banks to adopt more prudent risk management practices to align with investor expectations. On the other hand, excessive pressure to perform can incentivize banks to undertake riskier strategies, particularly when reacting to earnings surprises that shift market expectations. This duality reflects a delicate balance where analyst coverage, while improving transparency, can also foster short-term pressures that drive riskier behaviors as banks attempt to conform to heightened expectations.

(ii) **The Informational Effect:** Financial analysts significantly enrich the informational environment by providing earnings forecasts and issuing stock recommendations that range from buy/strong buy to sell/strong sell. These outputs mitigate information asymmetry by offering investors insights into a bank’s financial health and growth prospects, which can impact the bank’s cost of capital, market valuation, and overall risk profile. By enhancing transparency, analyst insights help investors form clearer perceptions of risk, which theoretically encourages banks to adopt more transparent practices and align risk strategies accordingly.

[8] Extension: The impact of opacity on risk-taking is moderated by market structures and market uncertainty, with stronger effects in market-based financial systems compared to bank-based systems. This hypothesis posits that market-driven systems, such as those in the U.S., are more sensitive to the effects of opacity, particularly under conditions of market uncertainty. In contrast, bank-based systems, may see more moderated effects due to stronger regulatory oversight.

Prior research underscores the dual benefits of analyst coverage in reducing information asymmetry and promoting shareholder monitoring, often lowering firms' cost of debt (Cheng & Subramanyam, 2008; Mansi et al., 2011; Derrien et al., 2016). For instance, Fang (2007) shows that firms with high analyst coverage are less inclined toward earnings management, especially when covered by leading analysts. Similarly, Guo et al. (2018) demonstrate that analyst coverage can influence firms' investment strategies, while Hassan et al. (2021) highlight that analyst coverage moderates the relationship between career concerns and loan costs. In the banking sector, where the stakes of financial opacity are high, analysts' recommendations and earnings forecasts are crucial in anticipating risk and bankruptcy measures. For example, Parnes et al. (2010) find that changes in analyst reports yield insights into default risk, and Barniv et al. (2020) reveal that alignment between recommendations and forecasts positively affects market reactions. Furthermore, studies show that analyst recommendations are especially valuable for banks facing elevated risk and high information asymmetry (Premti et al., 2016).

Given these dynamics, our second hypothesis explores the moderating influence of financial analysts on market discipline and risk-taking behaviors within the opaque banking sector:

Hypothesis 2a: *Higher analyst pressure enhances insights into default risk and shapes market perceptions.*

Hypothesis 2b: *Higher analyst pressure moderates the marginal effect of opacity on bank risk-taking.*

These hypotheses rest on the premise that greater analyst coverage enhances the availability of information to investors, making it increasingly challenging for banks to engage in opaque practices without market scrutiny. Consequently, the informational pressure exerted by analysts is expected to strengthen the information environment, improve transparency, and thereby reduce risk-taking behaviors associated with opacity. This also underscores the predictive role of analyst reports and their connection to bankruptcy risk measures, supporting the argument that analysts' recommendations are highly informative in evaluating bank stability and influencing market dynamics. Moreover, we posit that stock prices respond to analyst recommendations and revisions, impacting market-based return volatility and risk measures like MZScore and TR. As such, the presence of robust analyst coverage may foster more disciplined market behaviors by heightening the sensitivity of bank valuations to forecast updates.

1.2.3. The Moderating Effect of Bank Dividend Payout Policy on Opacity and Risk

Dividend policies hold significant implications in the banking sector, often serving as critical signals of financial strength, especially in opaque environments. Given the inherent complexities of bank balance sheets, investors and stakeholders frequently look to the frequency and magnitude of dividend payments to infer a bank's financial health. In addition to being indicators of stability, dividend policies are closely tied to capital adequacy and form an essential component of robust risk management practices (Onali, 2010). The literature presents varying perspectives on the role of dividends in promoting bank stability. While dividend payments can serve as a stabilizing force, excessive payouts may also incentivize risk-taking behaviors (Tran, 2021). To understand the influence of dividend policies on bank risk, we consider two primary mechanisms:

(i) **Dividends-Stability Channel:** Dividend payouts can limit a bank's ability to retain capital buffers, potentially increasing dependence on riskier assets and thereby eroding overall stability (Kanas, 2013). When banks distribute a substantial portion of earnings as dividends, they may reduce their capacity to absorb shocks, especially under volatile conditions. This can intensify risk-shifting behaviors, as banks might turn to higher-risk investments to meet profitability targets and shareholder expectations, particularly when deposit insurance premiums mitigate downside risks (Acharya et al., 2009; Onali, 2010). During financial crises, banks prioritizing dividend payouts may amplify systemic risks, as evidenced by institutions that maintained dividends despite increased financial vulnerability (Floyd et al., 2015). However, dividends can also impose a level of external monitoring, potentially curbing excessive managerial risk-taking and imposing discipline on bank management (Onali, 2010).

(ii) **Dividends-Opacity Channel:** Dividend payments can serve as a form of market discipline by reducing the private benefits of control, thereby limiting the scope for earnings management. In opaque banking environments, dividends signal a commitment to transparency and act as a counterbalance to managerial discretion. Banks adhering to stable dividend targets are generally less likely to engage in earnings manipulation, especially when payout restrictions are tied to debt covenants or regulatory thresholds (Tran & Ashraf, 2018). Under this framework, dividends help mitigate conflicts between insiders and external stakeholders, enforcing a form of market-driven discipline that aligns management incentives with shareholder interests (Easterbrook, 1984; Jensen, 1986). The Dividends-Opacity Channel thus posits that dividend payments can serve as a prudential mechanism, reinforcing transparency and curbing opportunistic behaviors.

This study examines the extent to which dividend policies impact bank risk-taking, particularly by moderating the relationship between bank opacity and risk. The analysis focuses on dividends as a potential prudential tool that facilitates external monitoring in opaque banking environments. In this context, we propose two hypotheses:

Hypothesis 3a: *Dividend payments enhance market discipline in banks and are associated with greater stability.*

Hypothesis 3b: *The marginal effect of opacity on bank risk-taking is moderated by the extent of dividend payments.*

These hypotheses reflect the dual roles of dividends as signals of financial strength and as mechanisms for market discipline. Specifically, we posit that regular dividend payments bolster stability by fostering transparency and accountability, which may restrain excessive risk-taking behaviors. Additionally, we hypothesize that the stabilizing influence of dividend payouts diminishes when payout levels become excessive, potentially leading to increased risk as banks deplete capital reserves. By assessing how dividends interact with opacity to influence risk-taking, this study contributes to the broader discourse on the use of dividend policies as prudential tools within regulatory frameworks aimed at promoting bank stability.

1.2.3.1. Furthered Considerations: Bank vs Market-driven Environments

Banking systems in Europe and the U.S. operate within distinct market structures and regulatory frameworks, influencing how opacity—measured here through analyst forecast bias and dispersion—affects risk. European banks may experience different risk dynamics than U.S. banks, where market discipline plays a larger role in moderating risk-taking behavior. Given these structural differences, the relationships between opacity, analyst pressure, and bank stability are likely to vary across regions. To test these additional considerations, this study analyzes how the proposed hypotheses apply in different market contexts, specifically examining whether the impact of opacity, analyst pressure, and dividend policies on risk-taking and bank performance diverges between bank-driven and market-driven environments.

1.3. Econometric Specification and Methodology

In the preceding discussion, we established the relationship between bank risk-taking, stability, and future stock returns with respect to bank-specific factors such as opacity, analyst coverage, dividend payout policy, and bank business models. Drawing on this framework and controlling for other variables, as outlined in Beck et al. (2013), we model bank risk-taking, stability, and future stock returns as functions of bank-level opacity (derived from analysts' forecast errors and dispersion), analyst pressure (including coverage, recommendations, and revisions), and dividend payout policy. The general econometric model is specified as follows:

$$Risk_{\,i,t} = \alpha + ß\,Opacity_{i,t-1} + \sum_{k=1}^{m} \rho_k Analyst\_Pressure_{\,k,i,t-1} + \Upsilon\ DIV\_Policy_{\,i,t-1} + \sum_{n=1}^{p} \varphi_n Controls_{n,i,t} + \varepsilon_{i,t} \tag{1}$$

where Risk represents bank risk, as explained in Section 1. 4.1, while *Opacity* serves as a proxy for bank opacity, derived from analysts' forecast errors and dispersion. *Analyst_Pressure* encompasses proxies such as analyst coverage, recommendations, and revisions, whereas *DIV_Policy* reflects the bank's dividend payout policy. Controls include additional control variables as defined in Section 1. 4. The parameters *β, ρ, and γ* are the coefficients to be estimated. The variable m indicates the number of variables within the *Analyst_Pressure* category, ranging from 1 to 4, and p represents the number of control variables, ranging from 1 to 7. The error term *ε* is assumed to have a mean of zero and a constant variance σ^2.

To account for potential nonlinearities in the effects of opacity, analyst pressure, and dividend payout on bank risk-taking, we reformulate Eq. (1) as follows:

$$Risk_{\,i,t} = \alpha + ßOpacity_{i,t-1} + \sum_{k=1}^{m} \rho_k Analyst\_Pressure_{k,i,t-1} + \Upsilon\ DIV_{Policy\ i,t-1} + \left(\sum_{k=1}^{m} \mu_k Analyst\_Pressure_{k,i,t-1} + \alpha\ DIV_{Policy\ i,t-1} \right) {}^{*}Opacity_{i,t-1} + \sum_{n=1}^{p} \varphi_n Controls_{n,it} + \varepsilon_{i,t} \tag{2}$$

In this formulation, the interaction term captures the non-linear effects of analyst pressure and dividend policy on opacity's impact on bank risk-taking. This approach allows us to comprehensively assess how these variables, both individually and interactively, influence bank risk-taking and stability.

1.4. Measurement and Data

1.4.1. Measuring Bank Risk

To assess bank risk and profitability, we compute several accounting-based indicators. Profitability is measured using the Return on Assets (ROA), defined as the ratio of net income to total assets. For bank risk-taking, we utilize the standard deviation of the return on assets (SDROA), calculated over a rolling window of three years ([t−2, t]). A higher SDROA indicates greater risk-taking. Additionally, we employ the Z-Score as a proxy for bank default risk, computed as proposed by Boyd and Graham (1986):

$$Z - Score_{i,t} = \frac{EQUITY_{i,t} + + MROA_{i,t}}{\sigma_p(ROA)} \tag{3}$$

where MROA represents the three-year rolling average of ROA, EQUITY is the ratio of total equity to total assets, and $\sigma_p(ROA)$ denotes the standard deviation of ROA over the same rolling window. The Z-Score is a well-established measure of bank soundness or solvency, with lower values indicating a higher probability of failure[9]. For further granularity, we decompose the Z-Score into Z1SCORE (leverage risk) and Z2SCORE (asset risk), as detailed by Goyeau and Tarazi (1992) and Lepetit et al. (2008). This decomposition allows us to discern whether changes in the Z-Score are driven by asset risk or leverage risk. We also incorporate the market-based Z-Score (MZScore) into our risk proxies for a more comprehensive analysis[10].

We complement these accounting-based measures with market-based indicators, particularly for listed banks, as accounting variables may not fully reflect sudden shifts in bank profit volatility and overall risk[11]. We estimate systematic and idiosyncratic risks using the market model:

$$R_{i,t} = \alpha + \beta R_{m,t} + \varepsilon_{j,t} \tag{4}$$

[9] e.g., Lepetit and Strobel, (2013); Köhler, (2015); Mollah et al., (2016); Mergaerts and Vennet, (2016).

[10] The Market-based ZScore is calculated using the formula: MZScore = 100 + (Return/std(Return)), where Return and std(Return) are expressed as percentages. Return is the mean of daily bank stock returns over a calendar year. The MZScore standardizes how much a stock's return deviates from its average performance in relation to its volatility.

[11] The literature utilizes various risk measures, including beta and the standard deviation of residuals from a regression of daily stock returns on market portfolio returns (Rozeff, 1982; Li & Zhao, 2008; Hoberg & Prabhala, 2009). Other common risk measures include the standard deviation of stock returns or the residuals from a regression of excess returns on the three Fama and French (1992) factors.

Where $R_{i,t}$ represents the daily return on the stock of bank **i**, and $R_{m,t}$ is the daily return of the Local Market Index (LI). For our sample of U.S. and European banks, we utilize 26 Local Market Indexes, as detailed in Appendix A, sourced from Thomson Reuters DataStream. Following established methodologies (e.g., Pathan, 2009), systematic risk (BETA)[12] is captured by the estimated coefficient β, while total risk (TR_{it}) is represented by the annual standard deviation of the bank's daily stock returns. For robustness, we measure default risk using Merton's distance to default (DD) and default probability (PD), derived from the option pricing model of Black and Scholes (1973) and Merton (1974). The formulas for distance-to-default (DD) and default probability (PD) are as follows:

$$DD_{i,t} = \frac{\ln\left(\frac{VA_{it}}{L_{it}}\right) + \left(r_f - \frac{\sigma^2{}_{A,it}}{2}\right) \times T}{\sigma_{A,it}\sqrt{T}} \tag{5}$$

$$PD = 1 - N(DD) \tag{6}$$

where $VA_{i,t}$ is the market value of the bank's assets, $L_{i,t}$ is the book value of debt, T is its maturity, $\mathbf{r_f}$ is the risk-free interest rate (10-year Government Bond Yields: Main (Including Benchmark) for the Euro Area & US, Percent, Monthly), and σ_A is the volatility of the bank's assets. DD is computed as the number of standard deviations between the expected asset value at maturity T and debt threshold and the PD, defined as the probability of the asset value below denotes the relation with liability threshold at the end of the time horizon T. Details on the computation of Merton's distance to default (DD) are provided in Appendix B. Additionally, we consider Price Volatility (Price_VOL) as a measure of a stock's annual price fluctuation from its mean. For example, a stock with 20% price volatility indicates a historical variation of ±20% from its average annual price.

Fig. B.1 in Appendix B displays the distribution of key bank risk measures, including solvency and profitability (Z-Score, SD ROA, Total Risk) and market and credit risk metrics (Beta, Price Volatility, Distance to Default).

[12] Systematic Risk (Beta, β): Beta measures the relationship between a stock's volatility and the overall market's volatility. This coefficient is calculated using the percentage changes in price over a period of 23 to 35 consecutive month-end data points, compared to a local market index. Beta indicates the extent to which a security's return tends to move in tandem with the overall stock market.

1.4.2. Measuring Opacity using Analyst EPS Forecasts

In this section, we outline the construction of our opacity measures. Our approach builds on the intuition provided by Morgan (2002), Flannery et al. (2004), Anolli et al. (2014), and Fosu et al. (2017), which suggests that increased uncertainty about an institution's future tends to reduce the accuracy of EPS forecasts. Accordingly, we use these proxies as our measures of opacity in this study. Specifically, we measure analysts' forecast error as the absolute value of the difference between the mean analysts' forecasts and the corresponding firm-year's actual earnings per share (EPS), deflated by the share price at the end of the period:

$$FE - EPS_{i,t} = \left| \frac{AEPS_{i,t} - FEPS_{i,t}}{Price_{i,t}} \right| \tag{7}$$

This alternative measure of opacity is calculated as the standard deviation of analyst forecasts of earnings per share (EPS), scaled by the share price at the end of the period. It represents the level of disagreement or dispersion among analysts regarding future EPS estimates, providing insight into the uncertainty and variation in market expectations:

$$Forecast\ Dispersion_{\ i,t} = \frac{\sigma(FEPS_{\ i,t})}{Price_{i,t}} \tag{8}$$

where $FEPS_{i,t}$ represents the average of all earnings forecasts for bank i in fiscal year t; $AEPSi,t$ is the actual earnings per share for bank i in fiscal year t; and $Pricei,t$is the share price of bank i at the end of fiscal year t.

1.4.3. Measuring Analyst Pressure: Coverage Effect

Analyst coverage is primarily quantified by the number of analysts monitoring a bank in the prior year (t−1). Additionally, we use the natural logarithm of analyst coverage to capture potential changes over time. To account for the possibility that analyst coverage is endogenous—where larger banks or those with higher returns on assets (ROA) are more likely to attract analysts (Das et al., 2006; Lee and So, 2017)—we consider several factors influencing analyst coverage. These factors include firm size, past performance, growth, external financing activities, and business volatility, all of which may also influence a bank's profitability and risk (Bhushan, 1989; Dechow & Dichev, 2002; Kasznik, 1999). To address this potential endogeneity, following Yu (2008) and Lee and So (2017), we create an alternative measure called Residual_Coverage. This variable is derived as the residual from a regression of Analyst

Coverage on Bank Size (measured as the natural logarithm of assets) and Past Performance (measured as lagged ROA), controlling for year-fixed effects:

$$Analyst\ Coverage_{i,t} = \alpha + \beta 1 Bank\ Size_{i,t-1} + \beta 2 BPast\ Performance_{i,t-1} + Year\ Dummies + \varepsilon_{i,t} \tag{9}$$

The residuals from this model, labeled as Residual_Coverage, serve as an alternative proxy for analyst coverage[13].

1.4.4. Measuring Analyst Pressure: Informational Effect

To assess the predictive ability and perceived value of analyst reports—especially recommendations—by market participants, we use proxies based on the distribution of consensus recommendation levels and changes. Specifically, we include Recommendation Consensus (REC_Con), with values ranging from 1 for "Strong Buy" to 5 for "Strong Sell," and Recommendation Revisions, capturing the frequency of upgrades (REC_Rev_Up) and downgrades (REC_Rev_Dn). For easier interpretation, we express recommendation distributions as percentages of favorable, non-favorable, and hold recommendations, along with dummy variables for buy and sell recommendations (e.g., REC_BUY, REC_SELL).

1.4.5. Measuring Bank Dividend Payout

We measure Dividend Payout Per Share (%) by dividing Stock Dividends Per Share by Earnings Per Share and multiplying the result by 100. To ensure robustness, we include an additional proxy: Growth in Dividend Yield, calculated by dividing Dividends Per Share by the Market Price at Year-End and multiplying by 100. These metrics provide a comprehensive view of dividend distribution and yield growth for analysis.

1.4.6. Control Variables

Our econometric models incorporate several bank-specific control variables that are expected to impact profitability and risk. We include the natural logarithm of total assets (*SIZE*) and the ratio of equity to total assets (*EQUITY2A*) to account for bank size and capitalization, respectively. Larger banks, benefiting from diversification and economies of scale, may achieve higher profitability through non-interest-generating activities (Hughes et al., 2001). However,

[13] The results remain consistent across all tests, whether using the raw number of analysts, the natural logarithm, or residual coverage as the measure.

their complexity may increase agency costs, potentially reducing profitability (Berger et al., 1987). Regarding risk, large banks can diversify more effectively, potentially lowering the risk (Demsetz & Strahan, 1997), but may also engage in riskier behavior due to too-big-to-fail policies (Galloway et al., 1997). *Credit risk* is measured by the ratio of non-performing loans to gross loans (*NPL*), which includes loans that are non-accrual or overdue by 90 days or more. To capture differences in business models, we use the ratio of net noninterest income to total assets (*NI2A*), following Köhler (2015). Banks with higher noninterest income typically face increased risk and lower risk-adjusted profitability (Stiroh, 2004; Lepetit et al., 2008; Demirguc-Kunt & Huizinga, 2010; Altunbas et al., 2011). Non-interest income can also be more volatile, potentially destabilizing banks (Liikanen, 2012). We also consider the ratio of deposits to total assets (*DEPOSITS*), as banks with higher deposit ratios may take on greater risk, especially when deposits are insured, which reduces depositor incentives to monitor bank activities (Demirguc-Kunt & Detragiache, 2002; Barth et al., 2004). To account for macroeconomic conditions, we include the real GDP growth rate (*GDPgr*) and the inflation rate, as higher GDP growth is generally associated with increased profitability (Molyneux & Thornton, 1992; Albertazzi & Gambacorta, 2009) and reduced risk (Beltratti & Stulz, 2012; Distinguin et al., 2013).

1.4.7. Data Collection and Preprocessing

We collected consolidated balance sheets, income statements, and market data from the Thomson Reuters Datastream database, including daily and monthly stock prices and local market indices. Analyst-related data, such as forecasts, recommendations, and coverage, were retrieved from the Institutional Brokers Estimate System (I/B/E/S), while macroeconomic variables were sourced from Federal Reserve Economic Data (FRED). Our initial sample comprised 987 publicly traded commercial banks from the U.S. and Europe, covering 2000 to 2020. We focused on listed banks due to the availability of detailed market data (e.g., market value of assets, dividends) and comprehensive balance sheet information. To refine the sample, we filtered for "primary quotes only" and applied sector-specific criteria (GICS sectors: Banks; TRBC sectors: Banking services, Banks, and Investment banking and brokerage services), yielding 845 listed commercial banks (591 in the U.S. and 254 in Europe). We then excluded bank-year observations with negative values for interest income, non-interest income, or stock prices to prevent noise or spurious correlations. Banks without analyst coverage were also excluded, and each bank holding company was required to have at least three consecutive years of data to ensure robustness. After merging datasets and removing incomplete observations, our final sample consisted of 341 banks across 25 countries in the U.S. and Europe, spanning the years 2000 to 2020. To mitigate the impact of outliers, we applied winsorization to continuous bank-level variables at the 1% and 99% levels.

1.4.8. Summary Statistics and Correlation Matrix

Table 1. 1 provides an overview of the variables used in this study, along with their summary statistics. The mean ZScore, an inverse measure of risk-taking, is 66.95, indicating that, on average, profits would need to decline approximately 66 times before the average bank faces default. The ZScore exhibits high variability (SD = 67.87), with a range from 3.3 to 326.3, highlighting significant heterogeneity across banks. The average risk-adjusted profit is 6.9, while risk-adjusted capital averages 59.8, indicating that bank stability largely relies on capitalization. Both metrics display substantial variability. For market-based risk measures, the mean values are as follows: total risk (1.89%), systematic risk (0.8), market-based ZScore (55.17), and distance to default (1.26). Most market measures show moderate variability, though the distance to default has greater fluctuations. The two opacity measures, analysts' forecast error (0.24) and forecast dispersion (0.12), reveal high variability, with maximum values of 8.27 and 2.55, respectively. The average analyst recommendation consensus is 2.56, indicating a balance between buy and hold recommendations, with an average of seven analysts covering each bank.

Table 1. 2 presents the correlation matrix for key explanatory variables. Overall, correlation coefficients are low, with some notable relationships between bank size (Log(Assets)), Equity (equity-to-assets ratio), and analyst coverage. To address multicollinearity, we orthogonalized Equity and Analyst coverage concerning Log(Assets). The summary statistics and pairwise correlations suggest our sample does not suffer from significant outliers or limited variability. The correlation between Opacity_F_Er (forecast error) and Coverage is 0.0672, suggesting a weak positive relationship, indicating that opacity may persist despite higher analyst coverage. This could be due to analyst herding, where analysts converge on similar predictions, leading to high forecast error despite greater coverage, especially in opaque environments. The correlation between Opacity_F_Er and Opacity_FD (forecast dispersion) is 0.439, indicating that banks with higher forecast error (i.e., more opacity) also tend to have greater forecast dispersion, reinforcing the notion that opacity increases uncertainty among analysts. The correlation between DIV_Payout and Opacity_F_Er is slightly negative at -0.026, suggesting that banks with higher dividend payouts tend to have marginally lower opacity, aligning with the Dividends-Opacity Channel, where dividend payments impose market discipline. However, the

relationship is very weak, suggesting additional factors may influence opacity. Non-performing loans (NPL) show a weak positive correlation with both Opacity_F_Er (0.1543) and Opacity_FD (0.1111), indicating that banks with higher credit risk are likelier to engage in opaque practices, possibly to obscure underlying issues. Inflation and GDP growth show minimal correlation with opacity (measured by forecast error and dispersion), suggesting that macroeconomic conditions have little impact on the accuracy or consistency of analysts' predictions in this sample.

Additionally, Table B2 in Appendix B provides the correlation matrix for risk and opacity variables, detailing their significance levels and further illustrating the relationship between opacity and bank risk-taking behavior. We also explore the relationship between opacity and risk-taking by plotting detrended measures of opacity, derived from analysts' forecast error and dispersion, against detrended risk-taking, represented by the Z-score. The scatter plots with fitted trend lines in Figures 1 and 2 illustrate a negative correlation between bank opacity and risk-taking.

Table 1.1 Variables Definition and Summary Statistics

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Dependent variables		Obs	Mean	Std. Dev.	Min	Max
SDROA	Three-year rolling-window standard deviation of the return on assets (%)	5,780	0.38	0.53	0.00	3.25
ZScore	ZScore = (MROA + Equity)/SDROA, Equity is the ratio of total equity to total assets, MROA is the three-year rolling window average of ROA	5,780	66.95	67.88	3.37	326.66
Z1Score	Measure of leverage risk. Z1Score = Equity/SDROA	5,780	59.87	60.87	3.33	292.84
Z2Score	Measure of bank asset risk. Z2Score = ROA/SDROA	5,780	6.98	7.41	-0.53	34.70
MZScore	Market based Zscore: 100+ (mean of daily stock return within a calendar year(%) /standard deviation of daily stock returns within a calendar year (%)	5,759	55.18	31.28	0.00	413.14
TR	Market based bank risk defined as the standard deviation of daily stock returns within a calendar year (%)	5,780	1.86	1.37	0.00	8.57
BETA	Systematic risk.Shows the relationship between the volatility of the stock and the volatility of the market.	5,780	0.84	0.57	-1.24	2.92
Price_VOL	A measure of a stock's average annual price movement to a high and low from a mean price for each year.	5,780	23.15	7.26	5.89	47.52
DD_mert	Bank distance to default, calculated using the 'mertonByTimeSeries' method. For further details, refer to Appendix B.	5,780	1.25	10.08	-33.18	80.53
PD_mert	Bank probability of default, calculated using the 'mertonByTimeSeries' method.	5,780	0.52	0.42	0.00	1.00
Variables Of Interest						
Analysts Forecasts and Recommendations						
Forecast Error	Measure of Opacity:1Y_FWD_EPS_Forecast_Error: This is calculated as the absolute value of the difference between the mean analyst forecast of earnings per share (EPS) and the actual EPS, scaled by the share price at the end of the period.	5,780	0.24	1.05	0.00	8.27
Forecast Dispersion	This alternative measure of opacity is calculated as the standard deviation of analyst forecasts of earnings per share (EPS), scaled by the share price at the end of the period.	5,780	0.12	0.36	0.00	2.55
Forecast_Optimism	The dummy variable is equal to one if the difference between Actual earnings and forecasted earnings is negative which indicates overestimation or negative earning surprise.	5,780	1.46	6.72	-9.96	39.12
Coverage	Analyst_Coverage :Number of analysts per bank	5,780	7.18	9.05	0.00	46.00
REC_Con	Recommendation consensus (average), 1 = Strong buy, 5 = Strong sell,	5,780	2.56	0.52	1.00	5.00
REC_Rev_Dn	Recommendations revisions Downgrade :NO. OF RECMND DOWN (revision)	5,780	0.17	0.54	0.00	7.00
REC_Rev_Up	Recommendations revisions: NO. OF RECMND UP(revision)	5,780	0.14	0.46	0.00	5.00
REC_Cons_ BUY %	REC BUY %	5,780	38.52	30.01	0.00	100.00
REC_Cons_ HOLD %	REC HOLD %	5,780	53.55	29.46	0.00	100.00
REC_Cons_ SELL %	REC SELL%	5,780	7.93	14.94	0.00	100.00
REC_BUY	Dummy variable equal to one for buy, moderate buy, and strong buy recommendations; zero otherwise.	5,780	0.73	0.44	0.00	1.00
REC_SELL	Dummy variable equal to one for sell, moderate sell, and strong sell recommendations; zero otherwise.	5,780	0.11	0.31	0.00	1.00
DIV_Payout	Dividend Payout Per Share (%) :Dividends Per Share / Earnings Per Share * 100	5,780	32.07	22.70	0.00	91.50
DIV_Yield	Stock Performance Ratio,Dividend Yield - Close, Dividends Per Share / Market Price-Year End * 100	5,780	2.39	1.82	0.00	9.09
Control Variables						
DEPOSITS	Ratio of customer deposits to total assets (%)	5,780	70.55	15.19	24.79	89.87
EQUITY2A	Ratio of Equity % Total Assets	5,780	10.05	3.50	2.88	23.48
SIZE	Natural logarithm of total assets	5,780	9.90	0.91	7.73	12.53
NI2A	Ratio of net noninterest income to total assets (%)	5,780	1.39	1.38	0.00	29.22
NPL	Non-Performing Loans % Total Loans	5,780	2.46	3.55	0.01	23.63
MTBV	Market to Book Value of equity capital(%) proxy for Franchise Value,The market value of equity capital divided by total book value of equity capital* 100	5,780	132.70	65.08	19.00	378.00
GDPgr	GDP growth (annual %)	5,780	1.62	2.20	-5.79	6.12
Inflation	Inflation, consumer prices (annual %)	5,780	1.94	1.24	-0.69	6.36

Table 1.1 describes the variables used in the analysis, with summary statistics including observations, mean, standard deviation, minimum, and maximum values. Variables are categorized into Dependent Variables, Variables of Interest, and Control Variables.

Table 1.2 Correlation Matrix.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Opacity_F_Er	1													
2	Opacity_FD	0.439	1												
3	Coverage	0.0672	0.0118	1											
4	REC_Consensus	0.0068	0.0406	0.0732	1										
5	REC_Rev_Dn	0.0354	0.0413	0.2604	0.093	1									
6	REC_Rev_Up	0.0654	0.0726	0.3024	0.0229	0.2155	1								
7	DIV_Payout	-0.026	-0.1023	0.0898	0.1385	0.003	0.0044	1							
8	NPL	0.1543	0.1111	0.142	0.0518	0.1309	0.1532	-0.1813	1						
9	SIZEnew	-0.0227	-0.0065	0.0149	-0.1561	0.0063	0.0243	-0.0419	0.0188	1					
10	EQUITY2A	-0.0709	-0.0455	-0.1195	-0.0737	-0.1595	-0.1474	-0.0034	-0.073	-0.0889	1				
11	NI2A	0.1693	0.0442	0.1175	0.0355	0.0354	0.0569	0.0376	0.1177	-0.1341	0.1313	1			
12	DEPOSITS	-0.1244	-0.072	-0.2708	-0.063	-0.2104	-0.2141	-0.0745	-0.0819	-0.0972	0.3333	-0.1267	1		
13	GDPgr	-0.0496	-0.029	0.0015	0.0451	-0.027	-0.0096	-0.0277	-0.1277	-0.1659	0.0614	0.0092	0.0585	1	
14	Inflation	-0.0157	-0.0208	-0.113	0.054	-0.0345	-0.0298	-0.0603	-0.154	-0.214	0.0607	0.0692	0.0147	0.2723	1

Table 2 displays the correlation matrix for key explanatory variables available in Table 1.

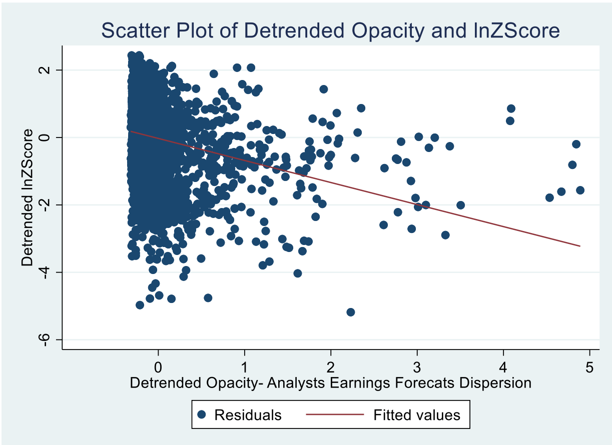

Fig. 1.1: Scatter plot of detrended opacity and risk-taking. This figure shows a scatter plot of detrended opacity, measured by analysts' earnings forecast dispersion, in relation to bank risk-taking.

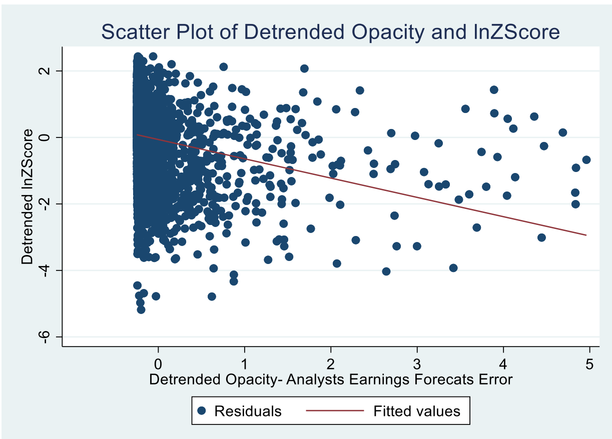

Fig. 1.2: Scatter plot of detrended opacity and risk-taking. This figure shows a scatter plot of detrended opacity, measured by analysts' earnings forecast error, in relation to bank risk-taking.

1.5. Empirical Findings and Analysis

This section presents the core empirical results from estimating Eq. (1), incorporating bank- and year-fixed effects to address unobserved heterogeneity. Subsequent sections provide robustness checks and marginal effect analyses derived from Eq. (2) to validate the stability and reliability of findings.

1.5.1. Opacity, Analyst Influence, and Bank Risk Taking

In this section, we explore the influence of bank opacity, analyst coverage, and dividend policies on risk profiles, with model specifications evolving from opacity-only analysis to the inclusion of analyst pressure and dividend variables. Table 1. 3 presents the empirical results for Eq. (1), where we test the validity of using analyst forecast errors and forecast dispersion as proxies for bank opacity. We also examine the effects of these opacity measures, along with analyst pressure and dividend payout policies, on bank risk profiles. We begin with Models 1 and 7, where bank risk-taking is explained solely by opacity. In both models, the coefficient on opacity is negative and statistically significant at the 1% level, providing strong support for Hypothesis 1: Opacity increases risk-taking behavior and reduces profit efficiency among banks. In Models 2 and 8, we extend the analysis by including traditional determinants of bank risk-taking. We further control for analyst pressure, specifically the coverage effect, in Models 3 and 9. Additionally, we control for analysts' informational effect through their recommendations and revisions in Models 4-5 and 10-11. Finally, we introduce the dividend payout ratio in Models 6 and 12.

Across all model specifications, the coefficient on opacity remains negative and statistically significant at the 1% level. The results suggest that a one-unit increase in opacity leads to at least a 4.9% increase in bank risk-taking. In fully specified models (Models 6 and 12), a one standard deviation increase in opacity corresponds to a 6-15% rise in bank risk-taking. Our results indicate that analysts' earnings forecast dispersion and bias are informative about future bank profitability and risk, supporting the notion of analysts' informational efficiency as a forward-looking proxy for measuring opacity in banks.

The coefficient on the coverage index is positive in Models 3-6 and 9-12, indicating that increased analyst coverage is associated with reduced bank risk-taking. Specifically, in Models 9 and 12, a one standard deviation increase in analyst coverage is associated with a 7.4-8% decrease in risk-taking, with this effect being statistically significant at the 1% level. This supports our second hypothesis: *Higher Analyst Coverage disciplines banks from risk-taking*. Higher analyst coverage is generally associated with lower default risk and less risk-taking, therefore it has a mitigating effect on risk. Models 4-6 and 10-12 reveal a significant, negative relationship between analyst recommendations (*REC_CON*) and default risk. Specifically, sell-oriented recommendations (higher *REC_CON* values) are associated with elevated default risk, as indicated by the negative and significant coefficients in the ZScore models. These findings reinforce the predictive power of analyst recommendations in signaling bankruptcy risk, highlighting that analysts can effectively identify banks with higher risk levels. The association of sell recommendations with increased bank risk indicates that analysts accurately recognize and communicate risks to the market, underscoring their informative role in predicting bank stability and influencing market dynamics. For recommendation revisions, Models 5-6 and 11-12 indicate that downgrade revisions are significantly associated with higher bank risk, particularly when the initial recommendation is "sell" or "strong sell." Conversely, while upgrade revisions are associated with higher bank solvency when the initial recommendation is "buy" or "moderate buy," their effect is not strong or statistically significant. This suggests that downgrade revisions carry greater weight in signaling risk, whereas upgrade revisions offer a weaker and less consistent signal regarding bank stability.

The dividend payout ratio is positively and significantly correlated with bank solvency. A one standard deviation increase in the dividend payout ratio corresponds to a 12.6-12.7% improvement in bank stability, supporting our third hypothesis that dividend payments enhance market discipline and contribute to higher bank stability. This suggests that banks distributing more profits to shareholders through dividends tend to exhibit greater stability and are less likely to engage in aggressive risk-taking, reinforcing dividends as signals of financial health and prudent management. These results align with the broader literature, which often views stable dividend policies as indicators of strong financial discipline.

Among control variables, a higher non-performing loan (NPL) ratio significantly increases risk, indicating a negative effect on stability. Bank size has a positive and significant effect, suggesting that larger banks are generally more stable. Similarly, the equity-to-assets ratio positively impacts stability, as higher equity levels bolster solvency. The net non-interest income to assets variable, however, is not significant, showing no clear association with stability in our sample. The deposits-to-assets ratio has a slight negative effect, indicating that higher deposit levels may marginally increase risk. Additionally, GDP growth positively and significantly impacts stability, suggesting that economic growth supports bank resilience, while inflation shows no significant relationship with stability.

Table 1.3: Opacity and Bank Risk-Taking-Fixed Effect Estimation Results

Dependent Variable: ln(Z-Score)												
	Analyst Forecast Error						Analyst Forecast Dispersion					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Opacity	**-0.206*** **	**-0.148*** **	**-0.149*** **	**-0.145*** **	**-0.160*** **	**-0.149*** **	**-0.0849** **	**-0.0747*** **	**-0.0730** **	**-0.0692** **	**-0.0707** **	**-0.0600** **
	(-5.95)	**(-4.69)**	**(-4.77)**	**(-4.60)**	**(-4.76)**	**(-4.49)**	**(-2.55)**	**(-2.61)**	**(-2.59)**	**(-2.52)**	**(-2.49)**	**(-2.33)**
Coverage			0.0103***	0.0102***	0.0118***	0.0103***		0.00979***	0.00971***	0.0114***	0.00991***	0.00951***
			3.67	3.58	4.39	3.77		3.43	3.35	4.15	3.57	3.24
REC_Con				-0.147***		-0.128***				-0.147***		-0.132***
				(-4.39)		(-3.66)				(-4.33)		(-3.71)
REC_Rev_Dn					-0.0557**	-0.0466**					-0.0491**	-0.0404*
					(-2.58)	(-2.15)					(-2.24)	(-1.83)
REC_Rev_Up					-0.0445	-0.0488*					-0.0440*	-0.0488*
					(-1.65)	(-1.71)					(-1.69)	(-1.76)
DIV_Payout						0.00559***						0.00556***
						5.93						5.82
NPL		-0.0744***	-0.0747***	-0.0730***	-0.0695***	-0.0643***		-0.0773***	-0.0777***	-0.0759***	-0.0728***	-0.0675***
		(-8.20)	(-8.23)	(-8.19)	(-7.67)	(-7.40)		(-8.53)	(-8.54)	(-8.48)	(-8.00)	(-7.72)
SIZEnew		0.488***	0.483***	0.438***	0.589***	0.576***		0.515***	0.510***	0.464***	0.613***	0.596***
		5.07	5.05	4.65	5.93	5.8		5.32	5.29	4.9	6.1	5.93
EQUITY2A		0.0460***	0.0459***	0.0452***	0.0491***	0.0499***		0.0463***	0.0461***	0.0455***	0.0492***	0.0499***
		6.34	6.39	6.51	6.56	6.88		6.27	6.31	6.43	6.43	6.75
NI2A		-0.0418*	-0.0392	-0.0388	-0.0353	-0.0361		-0.0427	-0.0403	-0.0399	-0.0361	-0.037
		(-1.67)	(-1.58)	(-1.58)	(-1.41)	(-1.45)		(-1.63)	(-1.54)	(-1.54)	(-1.31)	(-1.35)
DEPOSITS		-0.00340**	-0.00354**	-0.00395**	-0.00288*	-0.00298*		-0.00332**	-0.00345**	-0.00385**	-0.00277*	-0.00288
		(-1.98)	(-2.12)	(-2.29)	(-1.77)	(-1.66)		(-1.98)	(-2.11)	(-2.28)	(-1.74)	(-1.63)
GDPgr		0.0883***	0.0867***	0.0861***	0.0803***	0.0829***		0.0891***	0.0876***	0.0870***	0.0814***	0.0838***
		14.59	14.24	14.35	13.46	13.6		14.67	14.34	14.45	13.62	13.73
Inflation		-0.00391	0.000575	0.00443	0.0041	0.0114		-0.00249	0.0018	0.00566	0.00539	0.0128
		(-0.30)	0.04	0.34	0.31	0.87		(-0.19)	0.14	0.44	0.42	0.99
_cons	3.768***	3.632***	3.557***	3.958***	3.451***	3.578***	3.731***	3.604***	3.533***	3.933***	3.423***	3.563***
	449.07	25.35	27.09	25.85	26.17	21.51	709.01	25.34	26.93	25.7	25.78	21.43
Observations	5775	5775	5775	5775	5435	5435	5775	5775	5775	5775	5435	5435
Number of banks	340	340	340	340	340	340	340	340	340	340	340	340
R-square	0.0196	0.151	0.154	0.16	0.156	0.171	0.00726	0.147	0.15	0.156	0.149	0.165

This table presents fixed-effects estimation results based on Equation (1), evaluating the impact of opacity on bank risk-taking, proxied by the natural logarithm of the Z-Score (default risk). Opacity is quantified using analysts' forecast error (absolute deviation of mean forecasts from actual EPS, scaled by share price) and forecast dispersion (standard deviation of EPS forecasts, scaled by share price). Analyst coverage is measured as the number of analysts covering a bank in year ttt. Additional proxies include Recommendation Consensus (REC_Con) and Recommendation Revisions (upgrades: REC_Rev_Up, downgrades: REC_Rev_Dn). Dividend payout (DIV_Payout) is calculated as Stock Dividends Per Share divided by Earnings Per Share. Control variables include bank size (log of total assets, SIZE), equity-to-assets ratio (EQUITY2A), non-performing loans ratio (NPL), net non-interest income to assets ratio (NI2A), deposits-to-assets ratio (DEPOSITS), GDP growth (GDPgr), and inflation. Robust standard errors are clustered at the bank level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

1.5.1.1. Alternative Measures for Analyst Coverage

We examine alternative metrics for analyst coverage, including logarithmic transformations and residual-based measures, to assess coverage effects independently of bank size and performance, ensuring robustness against endogeneity. *Ln_Coverage* accounts for potential nonlinear effects over time, while *Residual Coverage* isolates analyst attention independent of bank size and past performance, addressing endogeneity concerns. By regressing analyst coverage on bank size (log of total assets), past performance (lagged ROA), and year-fixed effects, we derive *Residual Coverage* as the unexplained variation. As shown in Appendix C (Tables C1 and C2), these alternative proxies remain positive and statistically significant against default risk measures, reinforcing our main findings. This consistency confirms that greater analyst scrutiny is linked to higher default risk, supporting our hypothesis.

1.5.1.2. Threshold Effects of Dividend Payout and Analyst Coverage on Stability

While moderate dividend payouts have been historically linked to improved bank solvency and enhanced market discipline, a closer examination reveals a more nuanced relationship at higher payout levels. As shown in Table 1.4, when the dividend payout ratio exceeds the 75th percentile, the coefficient shifts to negative territory, indicating a departure from the expected stabilizing effect. This reversal suggests that beyond a certain threshold, excessive dividend distributions may weaken a bank's financial resilience. While attractive to shareholders, large dividend payouts can deplete the capital buffer that banks need to effectively manage risks. As internal resources shrink, banks may resort to riskier investment strategies to sustain profitability and meet shareholder demands. Consequently, rather than reinforcing market discipline, excessive dividends could incentivize risk-taking behaviors that ultimately jeopardize financial stability[14]. The analysis shows that the negative effect of opacity on the Z-Score lessens with higher analyst coverage, with the opacity coefficient dropping from -0.225 below 50% coverage to -0.117 above 50% (Table 1.4, columns 4-5). This suggests that increased analyst scrutiny improves the information environment, reducing opacity's adverse impact on bank risk. Additionally, REC_Con coefficients strengthen in columns 5-7, indicating that negative recommendations ("sell") have a more pronounced impact on bank stability with coverage above 75%, implying that higher coverage amplifies market reactions to negative recommendations, potentially driving riskier behaviors or exacerbating vulnerabilities in banks.

[14] As a robustness check, we used an alternative proxy for dividends, specifically the ***dividend yield***, and the results remain consistent with the main indicator, which is the *dividend payout ratio*.

Table 1.4: Threshold Effects of Dividend Payout and Analyst Coverage on Stability.

Dependent Variable: ln(Z-Score)									
	Dividend Payout Ratio			Analyst Coverage			Dividend_Yield		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	< 50th%	> 50th%	> 75th%	< 50th%	> 50th%	> 75th%	< 50th%	> 50th%	> 75th%
Opacity	-0.129***	-0.114**	-0.0981*	-0.225***	-0.117***	-0.115***	-0.121***	-0.231***	-0.146**
	(-2.79)	(-2.37)	(-1.96)	(-5.15)	(-3.49)	(-2.88)	(-3.06)	(-2.89)	(-2.29)
Dividend_Payout	0.0108***	0.00205	-0.00599**	0.00576***	0.00524***	0.00571***	0.204***	-0.0510***	-0.0830***
	4.33	1.37	(-2.57)	3.57	4.74	3.84	-5.33	(-3.20)	(-3.85)
Coverage	0.0141***	0.00515*	0.00716*	0.0382	0.0123***	0.00908*	0.0105**	0.00665**	0.0101***
	3.21	1.81	1.86	0.95	3.81	1.94	2.31	2.39	2.99
REC_Con	-0.165***	-0.0972*	-0.0563	-0.0966*	-0.198***	-0.221***	-0.150***	-0.102*	-0.0589
	(-3.68)	(-1.78)	(-0.71)	(-1.95)	(-4.12)	(-3.54)	(-3.29)	(-1.97)	(-0.96)
_cons	3.443***	3.211***	3.820***	3.695***	3.763***	3.881***	3.388***	3.547***	3.264***
	22.02	6.97	5.7	15.74	15.31	11.28	-20.34	-8.67	-6.16
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2725	2710	1361	2192	3243	1554	2700	2576	1390
Number of banks	308	319	263	264	281	172	306	315	272
R-square	0.179	0.126	0.102	0.219	0.171	0.163	0.183	0.168	0.178

This table presents the fixed-effect estimation results based on Eq. (1), analyzing the impact of opacity on bank stability, with a focus on the moderating effects of dividend payout ratio, analyst coverage. Bank risk-taking is proxied by the natural logarithm of the Z-Score. Opacity is quantified using analysts' forecast error (absolute deviation of mean forecasts from actual EPS, scaled by share price) and forecast dispersion (standard deviation of EPS forecasts, scaled by share price). The analysis is segmented by different thresholds of dividend payout ratios (<50%, >50%, >75%), analyst coverage (<50%, >50%, >75%), and dividend yield (<50%, >50%, >75%). All estimations include time-fixed effects, and robust standard errors clustered at the bank level are displayed in parentheses. Statistical significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively. Control variables are included but not shown for brevity.

1.5.1.3. Employing Market-Based Risk Metrics for Robustness

To capture rapid risk fluctuations, this analysis incorporates market-based metrics such as total risk and systematic risk alongside traditional accounting measures, offering a more dynamic perspective on opacity's impact. The heightened market pressure stemming from analyst forecasts can induce a more volatile market environment, with frequent fluctuations in asset prices potentially bringing banks closer to their default thresholds. We hypothesize that stock prices respond to analyst recommendations and revisions, impacting market-based return volatility and risk measures like MZScore and TR. Additionally, we decompose ZScore into Z1Score (risk-adjusted capital) and Z2Score (risk-adjusted profit) alongside market-based risk measures introduced in Section 1.4.1. Table 1.5 shows that across models (1-3) and (7-9) for *ZScore*, *Z1Score*, and *Z2Score*, the opacity coefficient is consistently negative and significant at the 1% level, supporting Hypothesis 1 that higher opacity correlates with increased bank risk-taking. Models (4) and (10) with *MZScore* yield similar results, confirming robustness. For total risk (*TR*) and earnings volatility (*SDROA*) in models (5-6) and (11-12), opacity remains positively associated with bank risk. These findings consistently indicate that higher opacity, measured by forecast error or dispersion, aligns with increased profit volatility and overall risk, suggesting that opaque banks, less transparent to investors, often adopt riskier financial strategies, heightening vulnerability to instability.

Analyst coverage shows a positive relationship with default risk proxies (ZScore, Z1Score, MZScore) while negatively associated with risk-taking proxies (SDROA and TR), though not significant for asset risk (Z2Score). This implies that higher analyst coverage generally enhances market monitoring, reducing default risk and curbing risk-taking behaviors. Analyst recommendations (REC_CON) show a negative correlation with default risk proxies and a positive association with risk-taking proxies, meaning sell-oriented recommendations align with higher default risk and risk-taking behaviors. Downgrade revisions (Rec_REV_Dn) negatively correlate with default risk and increase volatility, especially with sell recommendations. In contrast, upgrade revisions (Rec_REV_Up) show no significant link to risk-taking, suggesting stronger market reactions to negative recommendations. These findings indicate that analyst recommendations and revisions significantly influence stock prices, affecting market-based return volatility and risk measures such as MZScore and TR. Finally, Dividend payout ratios positively correlate with default risk proxies while showing a negative relationship with risk-taking proxies. Excessive payouts, however, turn this coefficient negative, suggesting that moderate payouts improve stability, whereas excessive payouts may increase risk.

Our analysis using alternative risk proxies reveals that diversification into non-interest income-generating activities increases risk-taking, as evidenced by SDROA, aligning with findings by DeYoung and Roland (2001) and Stiroh (2004a, b, 2006). Higher non-performing loans are also positively associated with risk, indicating that banks with greater credit risk exhibit lower stability. Moreover, larger banks and those with higher equity ratios are generally less risky, whereas banks with a higher deposits-to-assets ratio are more likely to engage in excessive risk-taking.

Table 1.5: Opacity and Bank Risk – Employing Alternative Risk Metrics for Robustness

	Analyst Forecast Error						Analyst Forecast Dispersion					
Dependent Variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ZScore	Z1Score	Z2Score	MZScore	SDROA	TR	ZScore	Z1Score	Z2Score	MZScore	SDROA	TR
Opacity	-0.149***	-0.140***	-0.394***	-0.0481***	0.0826***	0.189***	-0.0600**	-0.0539**	-0.228***	-0.0327**	0.0192	0.0873*
	(-4.49)	(-4.44)	(-4.70)	(-2.81)	3.71	3.48	(-2.33)	(-2.16)	(-3.32)	(-2.26)	1.29	1.73
Coverage	0.0103***	0.0115***	0.00559	0.00751***	-0.00351**	-0.0140***	0.00991***	0.0111***	0.00423	0.00738***	-0.00335**	-0.0135***
	3.77	4.19	1.09	6.07	(-2.38)	(-3.99)	3.57	4	0.82	5.98	(-2.23)	(-3.77)
REC_Con	-0.128***	-0.112***	-0.261***	-0.0704***	0.0677***	0.154***	-0.132***	-0.116***	-0.264***	-0.0699***	0.0714***	0.158***
	(-3.66)	(-3.28)	(-3.93)	(-4.47)	-3.35	-3.28	(-3.71)	(-3.35)	(-3.88)	(-4.45)	-3.47	-3.37
REC_Rev_Dn	-0.0466**	-0.0505**	-0.00442	-0.00479	0.00976	0.0528	-0.0404*	-0.0448**	0.0149	-0.0022	0.00693	0.0445
	(-2.15)	(-2.34)	(-0.10)	(-0.35)	0.98	1.4	(-1.83)	(-2.03)	0.32	(-0.16)	0.68	1.2
REC_Rev_Up	-0.0488*	-0.0522*	0.0266	0.00602	-0.00471	-0.0113	-0.0488*	-0.0525*	0.0314	0.0077	-0.00361	-0.012
	(-1.71)	(-1.82)	0.38	0.55	(-0.28)	(-0.36)	(-1.76)	(-1.87)	0.46	0.7	(-0.23)	(-0.37)
DIV_Payout	0.00559***	0.00510***	0.0156***	0.00187***	-0.00280***	-0.00490***	0.00556***	0.00509***	0.0153***	0.00183***	-0.00285***	-0.00483***
	5.93	5.49	8.44	3.54	(-5.36)	(-3.28)	5.82	5.4	8.29	3.52	(-5.36)	(-3.25)
NPL	-0.0643***	-0.0571***	-0.173***	-0.0357***	0.0340***	0.0864***	-0.0675***	-0.0601***	-0.181***	-0.0363***	0.0358***	0.0904***
	(-7.40)	(-7.14)	(-8.78)	(-7.14)	-6.87	-6.51	(-7.72)	(-7.44)	(-9.00)	(-7.28)	-7.13	-6.73
SIZEnew	0.576***	0.545***	0.924***	0.492***	-0.254***	-0.614***	0.596***	0.564***	0.977***	0.503***	-0.266***	-0.640***
	5.8	5.56	5.51	8.62	(-4.73)	(-2.90)	5.93	5.69	5.88	8.86	(-4.91)	(-3.04)
EQUITY2A	0.0499***	0.0533***	0.0224*	0.0136***	0.00236	-0.0284***	0.0499***	0.0533***	0.0228**	0.0137***	0.00242	-0.0285***
	6.88	7.07	1.95	4.21	0.55	(-3.19)	6.75	6.96	1.97	4.22	0.55	(-3.16)
NI2A	-0.0361	-0.0404	0.0313	0.0116	0.0374**	-0.0381*	-0.037	-0.0413	0.0304	0.0101	0.0382**	-0.0372
	(-1.45)	(-1.52)	0.82	1.18	2.2	(-1.88)	(-1.35)	(-1.43)	0.82	1.04	2.07	(-1.54)
DEPOSITS	-0.00298*	-0.00238	-0.0102***	0.00328	0.00194**	0.00616	-0.00288	-0.00229	-0.0100***	0.00325	0.00188**	0.00605
	(-1.66)	(-1.15)	(-5.67)	1.13	2.12	0.72	(-1.63)	(-1.13)	(-5.51)	1.13	2.09	0.71
GDPgr	0.0829***	0.0818***	0.0985***	0.0663***	-0.0377***	-0.180***	0.0838***	0.0827***	0.101***	0.0669***	-0.0382***	-0.181***
	13.6	13.61	9.14	22.55	(-9.25)	(-20.04)	13.73	13.75	9.17	22.85	(-9.38)	(-19.97)
Inflation	0.0114	0.00109	0.0940***	-0.0329***	-0.00627	0.0647***	0.0128	0.00253	0.0957***	-0.0325***	-0.00751	0.0632***
	0.87	0.09	3.79	(-5.10)	(-0.85)	4.34	0.99	0.2	3.99	(-5.17)	(-1.03)	4.36
_cons	3.578***	3.370***	1.834***	3.724***	0.083	1.559**	3.563***	3.355***	1.794***	3.720***	0.0916	1.578**
	21.51	18.12	7.6	16.77	0.85	2.37	21.43	18.08	7.43	16.95	0.93	2.41
Observations	5435	5440	5440	4936	5440	5440	5435	5440	5440	4936	5440	5440
Number of banks	340	340	340	340	340	340	340	340	340	340	340	340
R-square	0.171	0.164	0.216	0.239	0.143	0.196	0.165	0.158	0.212	0.24	0.134	0.192

This table presents fixed-effect estimation results based on Eq. (1), examining the impact of opacity, measured through analyst forecast error and forecast dispersion, on various banking risk metrics. Dependent variables include ZScore, Z1Score, Z2Score, MZScore, SDROA, and TR across two models (Analyst Forecast Error and Analyst Forecast Dispersion). Time-fixed effects are included in all estimations, and robust standard errors clustered at the bank level are reported in parentheses. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively.

1.5.1.4. Contextual Drivers of Bank Risk: Impacts of Valuation, Volatility, and Size

This analysis addresses how variables like optimism valuation, indicated by market-to-book value, volatility, and bank size, modulate the opacity-risk relationship, highlighting conditions where opacity exerts a stronger influence on bank risk. The analysis first focuses on the role of a bank's Market-to-Book Value (MTBV) ratio in assessing how perceived valuation affects the relationship between risk and opacity, measured by analyst forecast error. The MTBV ratio serves as a proxy for market optimism or potential overvaluation, revealing discrepancies between perceived and intrinsic value[15]. For banks with MTBV ratios below and above the median, opacity has a statistically significant negative effect on the Z-score, indicating that increased opacity undermines bank stability (Table 1.6, Models 1 and 2). Specifically, for banks

[15] Prior research links the book-to-market (BTM) effect to earnings announcements, showing that investor optimism often leads to the mispricing of growth stocks, which then face larger price reversals after disappointing earnings (La Porta et al., 1997; Skinner & Sloan, 2002; Billings & Morton, 2001).

with above-median MTBV ratios, the impact of opacity on risk-taking is more pronounced, suggesting that the detrimental effect of opacity is amplified for banks perceived as overvalued. This heightened vulnerability likely stems from investor optimism and elevated market expectations exceeding the bank's actual financial resilience. These findings align with valuation models in the accounting literature, which indicate that overvalued growth stocks tend to underperform value stocks following earnings disappointments (Ohlson, 1995; Rees, 1997; Collins et al., 1999). Overall, the results suggest that opacity has a greater negative impact on bank stability when perceived market valuations are higher, likely due to market pressure and heightened expectations exacerbating the risks associated with opaque practices.

To further explore how market uncertainty shapes the opacity-risk dynamic, we examine the effects of opacity under different levels of stock price volatility, dividing the sample into low- and high-volatility groups[16]. Results from Model 4 in Table 1. 6 show that opacity has a consistently positive and statistically significant effect on risk-taking at the 1% level in high-volatility environments. This implies that in uncertain conditions, opacity drives banks toward riskier behavior, with a one-standard deviation increase in opacity linked to a 12.2% rise in risk-taking. In more stable, low-volatility contexts, however, the relationship between opacity and risk weakens, suggesting that the destabilizing impact of opacity intensifies as market uncertainty increases.

Finally, we investigate the influence of bank size on the opacity-risk relationship by categorizing banks into small and large groups based on the median of total assets[17]. In Models 5 and 6, opacity exhibits a significantly negative association with bank stability, particularly among smaller banks. This suggests that smaller institutions are more susceptible to the adverse effects of opacity, underscoring the heightened vulnerability of smaller banks to opacity-driven risk. Beyond opacity, the data reveal that the disciplining impact of Analyst coverage on bank risk-taking is stronger for larger banks. Moreover, the favorable analyst recommendations (BUY/Strong Buy) correlate positively with bank stability in high-uncertainty periods, highlighting the critical role of market perceptions shaped by analysts when uncertainty is heightened. Additionally, dividend payouts demonstrate a consistently positive association with

[16] Price volatility, calculated as the annual deviation from mean stock price, serves as a proxy for market uncertainty.
[17] Bank size is measured by the natural logarithm of total assets, with a mean of 9.96, a standard deviation of 0.97, and a median of 9.735. The sample is split into small banks (below the median) and large banks (above the median) to evaluate how the opacity-risk relationship differs across bank sizes.

bank solvency across all models, especially when volatility is high, underscoring dividends as a stabilizing force even as other risk factors fluctuate.

Table 1. 6: Contextual Drivers of Bank Risk: Impacts of Valuation, Volatility, and Size

Dependent Variable:: ln(Zscore)						
Analyst Forecast Error						
	(1)	(2)	(3)	(4)	(5)	(6)
	Market to Book Value (MTBV)		Price _ Volatility		SIZE	
	<Median	>Median	<Median	>Median	<Median	>Median
Opacity	-0.116***	-0.250***	-0.185**	-0.117***	-0.233***	-0.0934**
	(-3.62)	(-4.22)	(-2.39)	(-3.58)	(-5.29)	(-2.55)
Coverage	0.00844***	0.00899**	0.0103**	0.00998***	0.00492	0.00819***
	2.9	2.17	2.45	3.33	-0.63	-3.17
REC_BUY	0.189***	0.0922**	-0.026	0.356***	0.132**	0.0989**
	3.36	1.99	(-0.58)	5.71	2.23	2.01
DIV_Payout	0.00352***	0.00394***	0.00219	0.00404***	0.00720***	0.00479***
	-3.35	-2.94	-1.63	-3.59	4.51	4.4
_cons	2.794***	2.729***	3.889***	2.372***	3.088***	2.135***
	22.32	7.26	9.48	14.42	7.8	7.43
Control Variables	yes	yes	yes	yes	yes	yes
Observations	2815	2620	2680	2755	2673	2762
Number of banks	322	335	315	292	209	237
R-square	0.178	0.212	0.0802	0.229	0.216	0.15

This table presents fixed-effect estimation results based on Eq. (1), exploring how bank opacity (measured through analyst forecast error) influences bank risk, as represented by the ZScore, across different contextual drivers: Market-to-Book Value (MTBV), Price Volatility, and Size. Each contextual variable is split at the median, showing effects in lower (<Median) and higher (≥Median) segments. Key variables include Opacity, Coverage, REC_BUY, and Dividend Payout. Time-fixed effects are included in all estimations, and robust standard errors clustered at the bank level are shown in parentheses. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively. Control variables are included but not shown for brevity.

1.5.1.5. Interactions between Analyst Coverage, Dividend Policies, and Bank Risk

We explore the non-linear dynamics between opacity and risk, focusing on how the interplay between analyst pressure and dividend policies affects risk profiles under varying conditions. Table 1. 7 presents the results from Eq. (2), which captures this non-linearity. To validate our findings, we conduct several robustness checks: Models 1 and 7 exclude control variables to assess their impact, while Models 2-6 gradually introduce bank-specific control variables. Subsequently, Models 3-4 and 9-10 incorporate Dividend Payout and Analyst Recommendation variables, along with their interactions with opacity. Models 5, 6, 11, and 12 include all variables for a comprehensive analysis. Additionally, we provide results using both coverage proxies (Coverage and Ln_Coverage) to ensure robustness.

The main focus is the interaction between opacity—measured through analyst forecast error and dispersion—and analyst pressure (Coverage), as well as Dividend Payout adjustments. The coefficient for opacity remains negative and statistically significant at the 1% level across models. The interaction between opacity and Coverage is positive and statistically significant at the 10% level. However, the marginal effect of opacity, derived from analysts' forecast dispersion, does not reach statistical significance, indicating a weak moderating effect of analyst coverage on the opacity-risk relationship. Conversely, a reduction in analyst coverage may amplify the risk-taking incentives associated with opacity, providing limited support for Hypothesis 2b, which posits that higher analyst pressure (through information and coverage) moderates the impact of opacity on risk-taking. Although a moderating effect of analyst pressure is observed, its economic significance remains modest.

To further illustrate these results, Table 1. 8 presents the marginal effects calculated using Eq. (2) based on Models 5, 6, 11, and 12 from Table 1. 7. Panel 1 of Table 1. 8 shows that the marginal effect of opacity, as derived from analysts' forecast error, is –0.1835 at the 25th percentile of the Coverage proxy. This effect decreases by 67% to –0.1095 at the 90th percentile of the Coverage index, translating into a 7.2 percentage point reduction in opacity-induced risk-taking. These results indicate that bank opacity is more likely to escalate the risk profile when analyst coverage is low. The moderating role of dividend payout adjustments in the opacity-risk-taking relationship suggests that excessive dividend payout ratios have a modest accentuating effect. In Table 1. 7, the interaction between opacity (based on analysts' forecast dispersion) and dividend payout adjustments is negative and statistically significant at the 5% level in Models 11 and 12. The joint significance of opacity and dividend payout adjustments, as highlighted in Panel 2 of Table 1. 8, suggests that the adverse impact of opacity is slightly intensified by increased dividend payout adjustments. These results challenge Hypothesis 3b, which proposed that the marginal effect of opacity on bank risk-taking would be moderated by the extent of dividend payments. Specifically, opaque banks paying excessive dividends tend to engage in greater risk-taking, highlighting the need for stronger market discipline. Thus, excessive dividend payouts amplify the detrimental effects of opacity on banking stability, particularly when opacity is measured using analysts' forecast dispersion, underscoring the economic significance of this evidence.

Finally, we assess whether analyst recommendation tone (e.g., buy) moderates the opacity-risk relationship by interacting opacity with the buy recommendation variable. Although the coefficient is positive, it does not reach statistical significance. Expanding the analysis, we explored the effects of recommendation tone (positive vs. negative) and recommendation revisions (upgrades and downgrades) on the opacity-risk relationship. As shown in Table C3 in Appendix 3, the results reveal no significant coefficients across models, with a minor exception: upgrade recommendations exhibit a weak moderating effect at the 10% significance level in models 5 and 10.

Table 1.7 Interactions between Analyst Coverage, Dividend Policies, and Bank Risk

	Analyst Forecast Error						Analyst Forecast Dispersion					
Dependent Variable:: ln(Zscore)						Ln_Coverage						Ln_Coverage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Opacity	-0.232***	-0.168***	-0.139***	-0.170***	-0.178***	-0.215***	-0.103**	-0.0797**	-0.0494***	-0.0890**	-0.0699**	-0.0728**
	(-6.03)	(-5.36)	(-4.31)	(-4.73)	(-4.48)	(-5.11)	(-2.30)	(-2.55)	(-2.66)	(-2.36)	(-2.30)	(-2.07)
Coverage	0.00984***	0.0100***	0.0111***	0.0110***	0.0100***	0.0413	0.00984***	0.0102***	0.0104***	0.0105***	0.0103***	0.0448*
	-3.33	-3.16	-3.76	-3.73	-3.16	-1.55	-3.43	-3.31	-3.49	-3.53	-3.35	-1.7
Opacity X Coverage	0.00247*	0.00214*			0.00202*	0.0315***	0.0019	0.0016			0.0000809	0.00181
	-1.76	-1.79			-1.79	-2.65	-0.96	-1.06			-0.05	-0.1
DIV_Payout		0.00480***	0.00491***	0.00483***	0.00491***	0.00500***		0.00475***	0.00533***	0.00475***	0.00531***	0.00540***
		-5.24	-5.17	-5.26	-5.17	-5.25		-5.16	-5.72	-5.15	-5.71	-5.81
REC_Buy		0.131***	0.131***	0.122***	0.124***	0.123***		0.132***	0.131***	0.126***	0.126***	0.124***
		-3.32	-3.31	-3.06	-3.1	-3.04		-3.31	-3.29	-3.16	-3.17	-3.1
Opacity X DIV_Payout			-0.000283		-0.000272	-0.000375			-0.00401**		-0.00388**	-0.00394**
			(-0.51)		(-0.52)	(-0.73)			(-2.48)		(-2.40)	(-2.40)
Opacity X Rec_BUY				0.0387	0.0296	0.0291				0.0396	0.0297	0.0294
				-1.53	-1.28	-1.26				-1.61	-0.93	-0.85
_cons	3.695***	3.365***	3.351***	3.357***	3.365***	3.389***	3.658***	3.335***	3.314***	3.333***	3.318***	3.335***
	-154.32	-21.31	-21.12	-21.1	-21.3	-21.14	-160.19	-20.99	-20.49	-20.93	-20.47	-20.19
Control Variables	no	yes	yes	yes	yes	yes	no	yes	yes	yes	yes	yes
Observations	5775	5775	5775	5775	5775	5775	5775	5775	5775	5775	5775	5775
Number of banks	340	340	340	340	340	340	340	340	340	340	340	340
R-square	0.0242	0.126	0.126	0.126	0.127	0.125	0.011	0.12	0.123	0.121	0.123	0.121

This table presents the fixed-effect estimation results, based on Eq. (2), examining the impact of opacity on bank risk-taking, with a focus on interaction effects between opacity, analyst pressure, and dividend payout policies. The dependent variable is ln(ZScore), and the analysis includes time-fixed effects in all estimations. Robust standard errors clustered at the bank level are shown in parentheses. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively. Notes: The Wald χ^2 test indicates the significance of interaction terms as follows: for Opacity × Coverage, Model 5: 3.19 (P=0.0742), Model 6: 7.02 (P=0.008); for Opacity × DIV_Payout, Model 5: 0.27 (P=0.6052), Model 11: 5.74 (P=0.0166). The interaction term of Opacity × REC_BUY is not significant; additional tests are provided in Appendix C, Table C.3.

Table 1. 8: Marginal Effects of Opacity, Analyst Pressure and Dividend Payout Policy

Dependent Variable: ln(Z-Score)						
	All					
	25th%	50th%	75th%	90th%	Change (25th-90%)	Based on
Panel 1						
Coverage (ln) index at:	0.693	1.386	2.197	3.04		
Forecast Error	-0.1835***	-0.1617***	-0.1361***	-0.1095***	-0.0741***	Table 7, Column 6
	-6.07	-5.88	-4.99	-3.59		
Forecast Dispersion	-0.1765***	-0.1752***	-0.1737***	-0.1722***	-0.0043	Table 7, Column 12
	-3.37	-3.51	-3.39	-3.04		
Panel 1-a						
Coverage index at:	2	4	9	21		
Forecast Error	-0.1608***	-0.1568***	-0.1466***	-0.1223***	-0.0385*	Table 7, Column 5
	-5.34	-5.33	-5.18	-4.04		
Forecast Dispersion	-0.1727***	-0.1725***	-0.1721***	-0.1711***	-0.0015371	Table 7, Column 10
	-3.37	-3.41	-3.46	-3.19		
Panel 2						
Dividend Payout index at:	15	32	46	60		
Forecast Error	-0.1519***	-0.1582***	-0.1634***	-0.1690***	0.0170565	Table 7, Column 6
	-5.55	-5.8	-5.61	-5.16		
Forecast Dispersion	-0.1093***	-0.1752***	-0.2299***	-0.2886***	0.1793**	Table 7, Column 12
	-4.22	-3.51	-3.2	-3.01		

Table 8 presents the marginal effect analysis based on results from Table 8, examining how variations in analyst coverage and dividend payout impact the relationship between opacity and bank risk, measured by Forecast Error and Dispersion. Marginal effects are calculated at the 25th, 50th, 75th, and 90th percentiles of each interacted variable, while other interacted variables are held at their median values. Panel 1 shows the marginal effects of Coverage (ln) on opacity, Panel 1-a details coverage index levels, and Panel 2 focuses on Dividend Payout index levels. Standard errors are shown in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

1.5.2. Comparative Analysis: Opacity-Risk Dynamics Across Bank vs. Market-Driven Financial Systems

This section compares the opacity-risk relationship in bank-driven European and market-driven U.S. financial systems, examining how these distinct environments shape the effects of analyst influence and opacity. Our analysis evaluates whether opacity, driven by analyst forecast errors and dispersion, impacts bank stability differently in these environments. Specifically, we test if analyst pressure and opacity have distinct effects on risk-taking and bank performance in the bank-driven European context versus the market-driven U.S. environment. European banks may exhibit different risk dynamics compared to U.S. banks, where market-based mechanisms like analyst coverage and shareholder activism play a more prominent role in influencing risk behaviors.

1.5.2.1. Differences in Analyst Properties and Risk Profiles

We provide a comprehensive comparative analysis of U.S. and European banks, highlighting how differences in opacity, analyst coverage, and risk factors align with varying regulatory and market structures. This analysis leverages separate regressions on analysts' forecast errors and forecast dispersion as proxies for bank opacity in each region, quantifying how opacity impacts risk and profitability differently under distinct regulatory environments and market forces. Key findings, summarized in Table D1 (Appendix D), reveal the following distinctions:

Analyst Properties: U.S. banks display lower average opacity levels, with analyst forecast error and forecast dispersion averaging 0.09 and 0.08, respectively, in contrast to European banks, which show higher averages of 0.6 and 0.2. The greater standard deviation in Europe (1.8 to 0.5) compared to the U.S. (0.3 to 0.8) further underscores the higher variability in opacity measures across European banks. Additionally, an optimism index highlights this regional disparity, with U.S. banks averaging 0.6 versus 3.47 for European banks, indicating greater optimism and forecast volatility in Europe. European banks also attract more analyst coverage, averaging 11.92 analysts per bank compared to 5.26 for U.S. banks, and face more frequent recommendation revisions, including a higher proportion of negative ratings, such as "Sell" and "Moderate Sell," relative to their U.S. counterparts.

Risk Profiles: U.S. banks exhibit greater financial stability, with an average Z-Score of 75.37 compared to 46.15 for European banks, likely due to stronger profitability, more robust equity buffers, and a more resilient post-crisis recovery. European banks, however, demonstrate higher price volatility (25.60 versus 22.16 in the U.S.) and a greater systematic risk, with a BETA of 1.01 compared to 0.77 for U.S. banks, indicating greater sensitivity to market fluctuations. Additionally, the distance to default (DD_mert) averages 1.88 in the U.S., significantly higher than -0.16 in Europe, reflecting a lower default risk profile among U.S. banks.

Bank level Variables: Regarding control variables, U.S. banks display a greater reliance on deposits (76.3% vs. 56.35% in Europe) and maintain stronger equity-to-assets ratios (10.84% vs. 8.10%), suggesting enhanced capitalization and liquidity. In contrast, European banks report higher net non-interest income relative to assets (1.89% vs. 1.18%) and face elevated credit risk, as evidenced by higher average non-performing loans (4.52% vs. 1.62%). U.S. banks also show a higher market-to-book value (136.05% vs. 124.43%), indicating a stronger perceived investor optimism. In terms of dividend payouts, European banks report higher and more variable ratios (33.59% vs. 31.45% for U.S. banks), reflective of economic volatility and regulatory differences across regions. In contrast, U.S. banks exhibit more stable dividend distributions, underscoring a steady approach to maintaining shareholder value.

Fig. D1 in Appendix D illustrates the annual trends in Analyst Forecast Error, Forecast Dispersion, Analyst Dynamics, and Dividend Payout Adjustments for European and U.S. banks over the period 2004–2020, providing a comparative view of these variables across the two regions. Correspondingly, Table D2 presents the correlation matrix for risk and opacity variables, including significance levels for U.S. and European subsamples, further clarifying the relationships between these variables across different banking environments.

1.5.2.2. Information, Analyst, Dividend Distribution and Risk-taking – U.S. vs. Europe

This section explores how opacity, analyst influence, and dividend policies distinctly affect bank risk within the U.S. and European banking environments, each marked by unique regional risk dynamics. Table 1. 9 presents a comparative analysis using key proxies, such as opacity (measured by analyst forecast error and forecast dispersion), analyst coverage, and dividend policies, and examines their impact on various indicators of risk, profitability, and earnings volatility (e.g., ZScore, Z1Score). This analysis highlights the differential effects of these factors across U.S. and European markets, providing insights into how regional characteristics shape the risk profiles of banks in these financial systems.

The results for both subsamples align with the global trend in Section 1.5.1, showing that higher bank opacity correlates with increased instability and return volatility in both the US and EU. Across models (1-4 & 7-10), opacity consistently shows a negative and significant relationship with Z-Score, indicating elevated risk. In models (5-6 and 11-12), opacity is also positively associated with risk-taking and earnings volatility. The effect is more pronounced in the US, where opacity has a larger negative coefficient and higher significance (e.g., -0.307 in column 1 for Z-Score), suggesting that opacity drives greater instability in US banks compared to EU banks (e.g., -0.0924 in column 1). However, opacity measured by analyst forecast dispersion appears to be a less effective indicator of earnings volatility in the European market (models 11 & 12). Overall, these findings demonstrate that higher opacity not only increases bank instability in both regions but also encourages riskier financial strategies due to reduced transparency, which obscures true risk levels from investors and the market.

The findings for analyst coverage mirror the global trend, with a slightly stronger effect in the US. Higher coverage generally correlates with lower insolvency risk and reduced risk-taking in both US and EU banks, as increased analyst attention enables better market monitoring of risk profiles. While stabilizing in both regions, analyst coverage has a more pronounced impact on bank stability in the US, highlighting regional differences in market response to analyst information. Analyst recommendation consensus aligns with the overall trend, where more sell-oriented recommendations (higher REC_Con values) are associated with higher default risk in both US and European banks, indicated by negative coefficients in the ZScore models. However, REC_Con has a weaker and less consistent effect on stability and earnings volatility in the EU. This implies that sell recommendations effectively highlight banks with higher default risk while also being positively associated with risk-taking, suggesting that banks receiving sell recommendations may adopt riskier strategies, possibly to counter negative market sentiment. Analyst recommendation revisions show similar effects in both US and European banks, consistent with the full sample. Downgrades are associated with higher risk, particularly in the US, while upgrades do not show a significant link to risk. For both US and European banks, higher dividend payouts correlate with lower default risk and reduced risk-taking, reflecting improved stability.

In the US, dividend payouts are more strongly associated with ZScore (e.g., 0.00697 in column 1), suggesting greater stability, while EU coefficients are lower (e.g., 0.00354), indicating a milder effect. This difference may be due to varying regulatory and market dynamics, with European banks generally paying more volatile dividends than US banks.

The regional differences in the impact of control variables on risk and volatility indicators reveal that consistent with the global trend, larger banks and those with higher equity ratios tend to be less risky, while higher non-performing loans are positively associated with risk, indicating that banks with greater credit risk are less stable. In the US, a higher deposits-to-assets ratio is linked to lower stability (ZScore) in line with the global sample but is also associated with reduced total risk and a higher market-based ZScore. Conversely, in Europe, a higher deposits-to-assets ratio does not correlate with stability (ZScore) but is linked to higher total risk. Consistent with global results, regional analysis shows that banks with greater reliance on non-interest income exhibit higher risk-taking, with the effect being more pronounced for US banks. These findings align with Stiroh (2004) for US banks and Lepetit et al. (2008) for European banks.

Table 1.9: Opacity, Analyst Pressure, and Bank Risk – U.S. vs. Europe

	Analyst Forecast Error						Analyst Forecast Dispersion					
Dependent Variable:												
Panel A: US	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ZScore	Z1Score	Z2Score	MZScore	SDROA	TR	ZScore	Z1Score	Z2Score	MZScore	SDROA	TR
Opacity	-0.307***	-0.277***	-0.913***	-0.102***	0.212***	0.382***	-0.325***	-0.290**	-0.826***	-0.0998***	0.146**	0.284***
	(-4.75)	(-4.54)	(-6.73)	(-4.73)	-3.92	-5.12	(-2.66)	(-2.55)	(-3.59)	(-3.12)	-2.01	-3.08
Coverage	0.0292***	0.0299***	0.0449**	0.0258***	-0.00693	-0.0460***	0.0290***	0.0297***	0.0451**	0.0259***	-0.00725	-0.0465***
	2.88	2.97	2.49	6.44	(-1.27)	(-3.49)	2.82	2.92	2.37	6.37	(-1.30)	(-3.46)
REC_Con	-0.119***	-0.106**	-0.210**	-0.0732***	0.0913***	0.190***	-0.116***	-0.103**	-0.207**	-0.0728***	0.0924***	0.191***
	(-2.71)	(-2.55)	(-2.53)	(-3.81)	3.85	3.55	(-2.73)	(-2.55)	(-2.52)	(-3.81)	3.94	3.57
REC_Rev_Dn	-0.0739*	-0.0756**	-0.107	-0.0393*	0.00411	0.149**	-0.0733*	-0.0752**	-0.104	-0.0389*	0.00304	0.147**
	(-1.91)	(-2.02)	(-1.46)	(-1.78)	-0.19	-2.38	(-1.90)	(-2.01)	(-1.36)	(-1.74)	-0.13	-2.31
REC_Rev_Up	-0.0585	-0.0584	-0.0585	-0.00349	0.0156	0.0195	-0.067	-0.066	-0.0836	-0.00624	0.0214	0.03
	(-1.33)	(-1.34)	(-0.66)	(-0.18)	-0.58	-0.35	(-1.50)	(-1.49)	(-0.92)	(-0.32)	-0.78	-0.53
DIV_Payout	0.00697***	0.00645***	0.0178***	0.00122*	-0.00350***	-0.00629***	0.00683***	0.00633***	0.0177***	0.00121*	-0.00362***	-0.00645***
	5.5	5.23	6.82	1.72	(-4.50)	(-3.03)	5.34	5.12	6.74	1.69	(-4.60)	(-3.09)
NPL	-0.140***	-0.128***	-0.334***	-0.0733***	0.0674***	0.161***	-0.143***	-0.131***	-0.347***	-0.0746***	0.0713***	0.167***
	(-7.91)	(-8.04)	(-7.98)	(-6.63)	-6.42	-5.92	(-8.22)	(-8.32)	(-8.41)	(-6.76)	-6.93	-6.2
SIZEnew	0.514***	0.513***	0.808***	0.471***	-0.155***	-0.402**	0.531***	0.529***	0.875***	0.476***	-0.177***	-0.437**
	4.73	4.77	4.36	8.43	(-2.90)	(-2.22)	4.76	4.82	4.44	8.43	(-3.20)	(-2.42)
EQUITY2A	0.0457***	0.0485***	0.0075	0.0131***	-0.00046	-0.0312***	0.0457***	0.0485***	0.00814	0.0131***	-0.000774	-0.0317***
	7.62	8.38	0.66	3.21	(-0.13)	(-3.03)	7.62	8.41	0.71	3.16	(-0.21)	(-3.03)
NI2A	-0.0359	-0.0366	0.0314	0.0202	0.0558**	-0.0733*	-0.0363	-0.0369	0.0292	0.0199	0.0568**	-0.0717*
	(-1.20)	(-1.12)	-0.64	-0.93	-2.47	(-1.73)	(-1.24)	(-1.15)	-0.59	-0.91	-2.54	(-1.69)
DEPOSITS	-0.00869**	-0.00708*	-0.0210***	0.0114***	0.00222	-0.0319***	-0.00790**	-0.00638	-0.0190***	0.0116***	0.00187	-0.0326***
	(-2.23)	(-1.79)	(-3.33)	-5.22	-1.13	(-6.17)	(-2.04)	(-1.63)	(-2.98)	-5.26	-0.95	(-6.21)
GDPgr	0.108***	0.108***	0.121***	0.0827***	-0.0441***	-0.225***	0.110***	0.109***	0.126***	0.0833***	-0.0451***	-0.226***
	-13.13	-13.48	-8.37	-27.64	(-8.27)	(-20.74)	-13.2	-13.51	-8.49	-27.61	(-8.18)	(-20.85)
Inflation	0.00418	-0.00198	0.0621***	-0.0262***	0.000951	0.0436**	0.00443	-0.0018	0.0650***	-0.0258***	-0.000551	0.0413**
	-0.32	(-0.15)	-2.82	(-3.44)	-0.14	-2.59	-0.34	(-0.14)	-3.03	(-3.44)	(-0.08)	-2.51
_cons	4.067***	3.788***	2.706***	2.996***	-0.012	4.719***	4.005***	3.733***	2.531***	2.976***	0.0256	4.788***
	12.56	11.4	5.04	15.12	(-0.07)	10.09	12.52	11.35	4.64	14.85	0.15	10.12
Observations	3869	3872	3872	3547	3872	3872	3869	3872	3872	3547	3872	3872
Number of banks	242	242	242	242	242	242	242	242	242	242	242	242
R-square	0.261	0.255	0.307	0.347	0.22	0.283	0.259	0.253	0.293	0.345	0.203	0.276

	Analyst Forecast Error						Analyst Forecast Dispersion					
Dependent Variable:												
Panel B: EU	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ZScore	Z1Score	Z2Score	MZScore	SDROA	TR	ZScore	Z1Score	Z2Score	MZScore	SDROA	TR
Opacity	-0.0924***	-0.0904***	-0.205***	-0.0323**	0.0364**	0.131**	-0.0357***	-0.0320**	-0.171***	-0.0275**	0.00701	0.0737
	(-3.01)	(-3.02)	(-2.85)	(-2.17)	-2.05	-2.33	(-3.12)	(-2.62)	(-4.33)	(-2.56)	-0.88	-1.6
Coverage	0.00793***	0.00913***	-0.000462	0.00485***	-0.00272*	-0.00878***	0.00763***	0.00885***	-0.00149	0.00474***	-0.00263*	-0.00826**
	2.91	3.38	(-0.10)	4.34	(-1.89)	(-2.67)	2.78	3.24	(-0.31)	4.28	(-1.81)	(-2.47)
REC_Con	-0.111*	-0.087	-0.292**	-0.0133	0.0224	-0.024	-0.116*	-0.0926	-0.281**	-0.0108	0.026	-0.0223
	(-1.84)	(-1.40)	(-2.60)	(-0.55)	-0.59	(-0.29)	(-1.89)	(-1.47)	(-2.47)	(-0.45)	-0.67	(-0.28)
REC_Rev_Dn	-0.0473**	-0.0518**	0.00593	0.0076	0.0187*	0.0133	-0.0425*	-0.0473*	0.0235	0.0105	0.0173*	0.00467
	(-2.03)	(-2.18)	-0.11	-0.52	-1.91	-0.33	(-1.78)	(-1.94)	-0.43	-0.73	-1.74	-0.12
REC_Rev_Up	-0.044	-0.0487	0.0554	0.00978	-0.0108	-0.0175	-0.0432	-0.0483	0.067	0.0124	-0.0103	-0.0211
	(-1.39)	(-1.50)	-0.68	-0.82	(-0.60)	(-0.48)	(-1.36)	(-1.48)	-0.82	-1.01	(-0.58)	(-0.53)
DIV_Payout	0.00354***	0.00320**	0.0103***	0.00353***	-0.00178***	-0.00695***	0.00333**	0.00301**	0.00932***	0.00341***	-0.00174***	-0.00654***
	2.65	2.36	4.18	5.55	(-3.23)	(-3.59)	2.44	2.17	3.99	5.61	(-3.09)	(-3.50)
NPL	-0.0356***	-0.0294***	-0.104***	-0.0189***	0.0203***	0.0482***	-0.0376***	-0.0313***	-0.109***	-0.0192***	0.0210***	0.0511***
	(-3.57)	(-3.31)	(-4.39)	(-4.07)	-3.32	-3.55	(-3.71)	(-3.45)	(-4.46)	(-4.11)	-3.38	-3.69
SIZEnew	0.404*	0.326	0.402	0.204	-0.209	-0.00933	0.414*	0.334	0.451	0.229*	-0.21	-0.0297
	-1.74	-1.39	-0.98	-1.61	(-1.62)	(-0.02)	-1.74	-1.39	-1.11	-1.85	(-1.62)	(-0.07)
EQUITY2A	0.0496***	0.0538***	0.0284	0.0113**	0.017	-0.0260**	0.0491***	0.0532***	0.0303	0.0125**	0.0174*	-0.0260*
	-2.91	-3.03	-1.17	-2.08	-1.64	(-2.02)	-2.83	-2.95	-1.27	-2.32	-1.66	(-1.96)
NI2A	-0.03	-0.0387	0.0252	0.0159	0.0114	-0.0387	-0.0299	-0.0387	0.0274	0.0149	0.0115	-0.0394
	(-0.93)	(-1.17)	-0.54	-1.35	-0.52	(-1.40)	(-0.86)	(-1.09)	-0.63	-1.27	-0.5	(-1.26)
DEPOSITS	-0.00358	-0.00339	-0.0129***	-0.000619	0.00129	0.0157***	-0.00351	-0.00332	-0.0129***	-0.000692	0.00125	0.0156***
	(-1.49)	(-1.23)	(-4.77)	(-0.37)	-1.21	-3.29	(-1.47)	(-1.21)	(-4.82)	(-0.43)	-1.17	-3.31
GDPgr	0.0408***	0.0379***	0.0566***	0.0303***	-0.0242***	-0.0921***	0.0424***	0.0394***	0.0598***	0.0311***	-0.0249***	-0.0942***
	-4.83	-4.53	-3.83	-8.44	(-3.61)	(-8.49)	-5.04	-4.75	-3.82	-8.68	(-3.74)	(-8.39)
Inflation	-0.0344	-0.0476	0.0524	-0.0481***	0.00314	0.0935***	-0.0342	-0.0472	0.0476	-0.0480***	0.00267	0.0945***
	(-1.16)	(-1.63)	-0.89	(-4.71)	-0.17	-3.13	(-1.16)	(-1.63)	-0.85	(-5.00)	-0.14	-3.31
_cons	3.475***	3.247***	2.103***	3.902***	0.155	1.328***	3.460***	3.234***	2.050***	3.885***	0.158	1.354***
	14.53	12.52	5.31	34.32	1.01	3.54	14.36	12.39	5.17	34.83	1.03	3.61
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1566	1568	1568	1389	1568	1568	1566	1568	1568	1389	1568	1568
Number of banks	98	98	98	98	98	98	98	98	98	98	98	98
R-square	0.106	0.0983	0.19	0.176	0.112	0.21	0.0999	0.0921	0.204	0.183	0.108	0.208

This table presents fixed-effect estimation results, based on Eq. (1), examining the impact of opacity on bank risk-taking for publicly listed banks in the U.S. (Panel A) and Europe (Panel B). The analysis considers the influence of analyst pressure and dividend policies, capturing regional variations in the opacity-risk relationship. Each model incorporates time-fixed effects to account for temporal dynamics. Robust standard errors, clustered at the bank level, are reported in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

1.5.2.3. Threshold Effects of Dividend Policies and Analyst Pressure

Expanding on global findings, this section evaluates if excessive dividend payouts and extensive analyst coverage contribute similarly to risk dynamics in both regions. As detailed in Table 1. 10, both regions mirror the global trend from Section 1. 5.1.2: Moderate dividend payouts support stability, while excessive payouts (columns 3 and 9) reduce resilience. Unlike the global sample, subsample analysis reveals that the negative effect of opacity on Z-Score intensifies with greater analyst coverage, particularly in the US (Table 1. 10, columns 4 and 5). Consistent with the global trend, higher analyst coverage amplifies the impact of recommendations (columns 4, 5, and 6). This suggests that increased coverage may intensify market reactions to negative recommendations, driving riskier behaviors or amplifying vulnerabilities in banks—though this effect is not significant in the European market. Additionally, positive recommendations, when accompanied by higher coverage, are linked to reduced risk.

Table 1. 10: Threshold Effects of Dividend Payouts and Analyst Coverage

Dependent Variable: ln(Z-Score)												
	US Banks						European Banks					
	Dividend Payout Ratio			Analyst Coverage			Dividend Payout Ratio			Analyst Coverage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	< 50th%	> 50th%	> 75th%	< 50th%	> 50th%	> 75th%	< 50th%	> 50th%	> 75th%	< 50th%	> 50th%	> 75th%
Opacity	-0.203***	-1.111***	-1.279***	-0.212***	-0.367**	-0.377*	-0.0683	-0.0577*	-0.117**	-0.0701	-0.0869**	-0.0486
	(-4.05)	(-6.32)	(-3.80)	(-5.17)	(-2.26)	(-1.89)	(-1.19)	(-1.70)	(-2.19)	(-1.32)	(-2.52)	(-1.03)
Dividend_Payout	0.0133***	0.0000911	-0.00458*	0.00441**	0.00894***	0.00977***	-0.000374	0.00274	-0.0105*	0.00591***	0.00244	0.00225
	4.2	0.06	(-1.75)	2.06	6.22	4.59	(-0.10)	1.03	(-1.92)	2.88	1.53	1.02
Coverage	0.0425***	0.00366	0.00433	0.105*	0.0284***	0.0418***	0.00651	0.00600**	0.0118**	-0.0103	0.00213	-0.00308
	2.8	0.28	0.23	1.76	2.61	3.23	1.63	2.1	2.42	(-0.61)	0.46	(-0.31)
REC_Con	-0.136**	-0.0585	-0.0249	-0.0291	-0.244***	-0.370***	-0.163**	-0.163	-0.189	-0.216***	-0.0694	-0.0251
	(-2.31)	(-1.04)	(-0.31)	(-0.54)	(-4.05)	(-3.90)	(-2.20)	(-1.39)	(-1.21)	(-2.66)	(-0.91)	(-0.23)
_cons	4.233***	3.545***	4.615***	3.915***	4.206***	3.156***	3.358***	3.141***	4.833***	3.695***	3.782***	4.127***
	10.48	7.71	7.21	8.02	11.06	5.29	13.26	4.86	5.34	10.36	11.28	7.69
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1934	1935	972	1504	2365	1047	730	764	367	760	806	394
Number of banks	215	225	188	160	210	111	92	92	77	98	98	93
R-square	0.263	0.253	0.233	0.247	0.299	0.347	0.126	0.0865	0.101	0.114	0.104	0.198

This table presents the fixed-effect estimation results based on Eq. (1), analyzing the impact of opacity on bank stability, with a focus on the moderating effects of dividend payout ratio, analyst coverage for publicly listed banks in the U.S. (Columns 1-6) and Europe (Columns 7- 12). The analysis is segmented by different thresholds of dividend payout ratios (<50%, >50%, >75%), analyst coverage (<50%, >50%, >75%), and dividend yield (<50%, >50%, >75%). All estimations include time-fixed effects, and robust standard errors clustered at the bank level are displayed in parentheses. Statistical significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively. Control variables are included but not shown for brevity.

1.5.2.4. Contextual Influences of Volatility, Valuation, and Size on Opacity-Risk in the U.S. and Europe

This part delves into how valuation, volatility, and size create regional disparities in the opacity-risk relationship, underscoring contextual differences in bank risk responses. The results in Table 1. 11 indicate that, consistent with global findings, opacity significantly increases risk-taking in the US sample under high-volatility and optimism overvaluation conditions, with banks being particularly sensitive to valuation pressures and market uncertainties (columns 1-2 and 5-6). In contrast, European banks exhibit a weaker response to opacity under similar elevated market-to-book value and high-volatility conditions (columns 3-4 and 7-8). Across both regions, consistent with the global trend, the impact of opacity is more pronounced in smaller banks, where opacity exacerbates risk-taking to a greater extent than in larger banks (columns 9-12). US smaller banks, in particular, demonstrate the highest risk sensitivity. In contrast, for European banks, the effect of opacity on risk does not vary significantly with bank size, suggesting a more moderated impact across different size segments[18].

Table 1. 11: Contextual Influences of Volatility, Valuation, and Size on Opacity-Risk – U.S. vs. Europe

Dependent Variable:: ln(Zscore)												
Analyst Forecast Error												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Market to Book Value (MTBV)				Price _ Volatility				SIZE			
	US		EU		US		EU		US		EU	
	<Median	>Median	<Median	>Median	<Median	>Median	<Median	>Median	<Median	>Median	<Median	>Median
Opacity	**-0.191*** **	**-0.858*** **	**-0.0667***	**-0.184*** **	**-0.363***	**-0.241*** **	**-0.145*** **	**-0.0357**	**-0.265*** **	**-0.319** **	**-0.109** **	**-0.0850*** **
	(-4.12)	(-4.31)	(-1.85)	(-4.26)	(-1.87)	(-4.33)	(-2.74)	(-0.86)	(-4.81)	(-2.10)	(-2.14)	(-2.76)
Coverage	0.0622***	0.0152	0.00275	0.00908**	0.0204	0.0386**	0.00749**	0.00584*	-0.0166	0.0378***	0.00264	0.00537*
	4.25	0.98	0.88	2.11	1.29	2.57	2.24	1.86	(-0.54)	3.57	0.67	1.99
REC_BUY	0.0706	0.0763	0.296***	-0.0323	-0.0178	0.294***	-0.0152	0.321**	0.132*	0.0791	0.061	0.105
	1.11	1.44	2.96	(-0.35)	(-0.36)	3.98	(-0.15)	2.55	1.95	1.33	0.51	1.21
DIV_Payout	0.00403***	0.00592***	0.00253	0.00204	0.00285*	0.00614***	0.00121	0.00262*	0.00604***	0.00861***	0.00552**	0.00271**
	2.61	4.03	1.66	0.95	1.74	3.83	0.58	1.91	3.01	5.29	2.09	2.1
_cons	3.114***	4.095***	2.453***	3.534***	4.356***	2.839***	2.718***	2.366***	4.258***	3.108***	2.776***	1.628***
	8.13	8.79	14.45	8.23	10.43	7.8	4.62	12.72	9.02	9.2	9.8	5.13
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2003	1866	821	745	1910	1959	768	798	1888	1981	764	802
Number of banks	229	242	91	96	227	213	94	87	164	179	60	61
R-square	0.245	0.295	0.149	0.139	0.114	0.332	0.0862	0.129	0.267	0.253	0.0937	0.229

This table presents fixed-effect estimation results based on Eq. (1), analyzing how opacity (measured through analyst forecast error) impacts bank risk (ZScore) under varying contexts: Market-to-Book Value (MTBV), Price Volatility, and Size. Each contextual factor is divided at the median, comparing effects in lower (<Median) and higher (≥Median) segments across U.S. and European banks. The primary variables include Opacity, Coverage, REC_BUY, and Dividend Payout. Time-fixed effects are applied in all models, with robust standard errors clustered at the bank level shown in parentheses. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively. Control variables are included but omitted from the table for brevity.

[18] In line with the global trend, analyst coverage in the US exerts a stronger disciplining effect on risk-taking among larger banks with higher volatility and lower MTBV ratios, whereas the European market displays a weaker and inconsistent impact. Favorable analyst recommendations (BUY/Strong Buy) are positively correlated with bank stability during high-uncertainty periods in both regions; in the US, this effect is more pronounced for smaller banks, while in Europe, it is stronger for banks with lower MTBV ratios.

1.5.2.5. Interactions and Extensions: Analyst Coverage, Dividend Policies, and Opacity-Risk _ U.S. vs. Europe

Building on prior analysis (Section 1. 5.1.5), this section assesses the nuanced role of analyst coverage and dividend policies as moderators in the opacity-risk nexus across regional systems[19]. Tables 1.12 and 1.13 present the marginal effects of analyst coverage on the risk-taking behavior of opaque banks in the US and Europe, segmented by bank size. Table 1. 14 further details the statistical significance of these effects at varying levels of analyst coverage. For US banks, the results indicate that higher analyst coverage amplifies risk-taking among opaque banks, particularly in those with greater forecast dispersion (Table 1. 12, models 5 and 7; Table 1. 13, model 4). This effect is most pronounced in smaller banks, as shown in Table 1. 13 (models 2 and 5) and confirmed by marginal analysis in Table 1. 14 (Panel 1, columns 2, 4, and 5). In contrast, the effect for European banks is weaker and varies by bank size. Higher analyst coverage increases risk-taking among larger opaque banks (Table 1. 13, models 9 and 12), while for smaller European banks, analyst coverage exerts a modest moderating influence on risk-taking (Table 1. 13, models 8 and 11). Panel 3 (EU) in Table 1. 14 further confirms the relatively weak amplifying role of analyst coverage on risk for larger EU banks.

These findings challenge Hypothesis 2b, which suggests a moderating role for analyst coverage in the opacity-risk relationship across different market structures and bank sizes. While analyst coverage typically enhances banks' visibility and subjects them to greater market scrutiny—potentially promoting market discipline and encouraging prudent risk management—this effect is not consistent for high-opacity banks across regions. In the global sample, analyst coverage exerts only a weak moderating impact on the opacity-risk nexus. However, when examining subsamples based on distinct financial market structures, we find that higher analyst coverage increases pressure on opaque banks, especially in the US. This pressure appears to drive riskier behaviors, as banks may take on additional risk to meet analyst expectations, particularly in markets with strong reactions to earnings surprises. This effect is most pronounced in smaller US banks, where analyst pressure significantly heightens risk-taking. In contrast, the European market shows a less consistent impact: analyst coverage exerts a weak moderating influence on risk-taking in smaller banks but amplifies risk for larger opaque banks. Regarding dividend policy, the results suggest that excessive dividend payouts slightly accentuate risk-taking in both regions, consistent with the global trend. In Europe, however,

[19] In our global sample, we observed a weak moderating role of analyst coverage and an accentuating role of dividend payout adjustments on the opacity and risk-taking relationship; here, we assess whether this effect varies across different financial markets.

this effect is significant when opacity is measured by analyst forecast dispersion (Table 1. 13, columns 1, 4, 7, and 8). Panel 2 and 4 of Table 1. 14 show that increased dividend payouts modestly intensify the adverse impact of opacity, particularly when measured by forecast dispersion, highlighting the economic significance of this relationship for bank stability. Lastly, we examine the moderating effect of positive analyst recommendations (REC_BUY) on the relationship between opacity and bank risk. In the U.S. sample, this interaction is significant, especially under conditions of high forecast dispersion and among smaller banks (see Table 1. 12, columns 5 and 7; Table 1. 13, columns 4 and 5).

To further explore the influence of recommendation tones (positive/negative) and revisions (upgrades/downgrades) on the opacity-risk relationship for both U.S. and European banks, we refined our analysis (refer to Table F1 in Appendix F). The findings indicate that negative recommendations (e.g., "Sell") and downgrade revisions significantly exacerbate the adverse effects of opacity on bank stability, particularly in forecast dispersion models (columns 4, 7, and 8). Conversely, positive recommendations and upgrade revisions exhibit a favorable moderating impact (columns 5, 6, and 10). No significant results were found for European banks in this regard. We extended our analysis by assessing the interaction between opacity and different recommendation tones, focusing on the role of increased analyst coverage. Results from the U.S. sample (Panel A, Table F2) reveal that higher analyst coverage significantly amplifies the effects of negative recommendations and downgrade revisions on bank risk, as evidenced by significant coefficients in models using forecast dispersion (columns 6 and 7). These findings suggest that heightened analyst coverage under high-opacity conditions exacerbates risk-taking behaviors and increases vulnerabilities in U.S. banks. In contrast, for European banks, upgrade recommendation revisions accompanied by higher analyst coverage only weakly moderate the risk of opaque banks (Panel B, Table F2, columns 4 and 8).

Table 1. 12: Interactions: Analyst Coverage, Dividend Policies, and Opacity-Risk – U.S. vs. Europe

	Analyst Forecast Error				Analyst Forecast Dispersion			
Dependent Variable:: ln(Zscore)			Ln_Coverage				Ln_Coverage	
	US	EU	US	EU	US	EU	US	EU
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity	-0.0984	-0.113***	-0.019	-0.144***	-0.0239	-0.0316**	-0.0831	-0.0223
	(-0.90)	(-2.72)	(-0.18)	(-2.75)	(-0.24)	(-2.09)	(-0.96)	(-0.82)
Opacity X Coverage	-0.00889	0.00126	-0.114	0.0207	-0.133***	-0.000613	-0.408**	-0.01
	(-0.51)	-1.22	(-1.14)	-1.6	(-4.10)	(-0.40)	(-2.44)	(-0.65)
Opacity X DIV_Payout	-0.0115***	-0.000105	-0.0117***	-0.000154	-0.0238***	-0.00214**	-0.0262***	-0.00220**
	(-2.88)	(-0.27)	(-3.10)	(-0.40)	(-4.03)	(-2.38)	(-4.69)	(-2.39)
Opacity X REC_BUY	-0.0335	0.0114	-0.0721	0.0111	0.395***	0.0109	0.386***	0.017
	(-0.29)	0.44	(-0.67)	0.44	3.05	0.52	3.03	0.83
Coverage	0.0232**	0.00792**	0.025	0.0599*	0.0278***	0.00828***	0.0453	0.0658**
	2.34	2.47	0.51	1.91	2.95	2.66	0.92	2.12
DIV_Payout	0.00532***	0.00427***	0.00538***	0.00437***	0.00507***	0.00451***	0.00548***	0.00461***
	4.35	2.95	4.42	3.01	4	3.33	4.32	3.38
REC_BUY	0.127***	0.0988	0.144***	0.0963	0.0855**	0.0991	0.103**	0.0953
	2.79	1.31	3.17	1.28	2.01	1.33	2.4	1.28
_cons	3.852***	3.253***	3.903***	3.231***	3.713***	3.206***	3.738***	3.174***
	11.74	17.04	11.7	17.27	11.39	16.54	11.26	16.52
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes
Observations	4111	1664	4111	1664	4111	1664	4111	1664
Number of banks	242	98	242	98	242	98	242	98
R-square	0.206	0.0951	0.205	0.0938	0.222	0.0917	0.215	0.0896

This table presents fixed-effect estimation results based on Eq. (2), assessing how opacity influences bank risk-taking, focusing on the interaction effects of opacity with analyst coverage, dividend payout policies, and REC_BUY. The dependent variable is ln(ZScore), analyzed separately for U.S. and European banks across both Analyst Forecast Error and Analyst Forecast Dispersion models. Time-fixed effects are included in all estimations, with robust standard errors clustered at the bank level in parentheses. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively. Control variables are included but not displayed for brevity.

Table 1. 13: Analyst Coverage, Dividend Policies, and Opacity-Risk —Segmentation by Bank Size

	Analyst Forecast Error			Analyst Forecast Dispersion			Analyst Forecast Error			Analyst Forecast Dispersion		
Dependent Variable:: ln(Zscore)		Size_US			Size_US			Size_EU			Size_EU	
	All	<Median	>Median	All	<Median	>Median	All	<Median	>Median	All	<Median	>Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Opacity	-0.019	-0.00422	0.0334	-0.0831	-0.141	0.815	-0.144***	-0.167*	-0.0692*	-0.0223	-0.111***	0.0314
	(-0.18)	(-0.03)	0.09	(-0.96)	(-1.07)	1.28	(-2.75)	(-1.68)	(-1.92)	(-0.82)	(-4.15)	1.14
Opacity X Ln_Coverage	-0.114	-0.471***	0.0456	-0.408**	-0.563***	-0.659*	0.0207	0.0355	-0.0219***	-0.01	0.0356	-0.0300*
	(-1.14)	(-5.53)	0.25	(-2.44)	(-4.83)	(-1.76)	1.6	1.47	(-2.76)	(-0.65)	1.12	(-1.80)
Opacity X DIV_Payout	-0.0117***	-0.0116***	-0.0247***	-0.0262***	-0.0171***	-0.0387***	-0.000154	-0.000489	0.000980*	-0.00220**	-0.0017	-0.00372
	(-3.10)	(-2.84)	(-3.86)	(-4.69)	(-2.77)	(-4.97)	(-0.40)	(-0.69)	-1.77	(-2.39)	(-1.34)	(-1.25)
Opacity X REC_BUY	-0.0721	0.116	-0.425	0.386***	0.418*	-0.0176	0.0111	0.0135	0.0153	0.017	-0.0189	0.0213
	(-0.67)	0.88	(-1.59)	3.03	1.9	(-0.08)	0.44	0.29	0.54	0.83	(-0.27)	1.22
Ln_Coverage	0.025	0.0188	0.0389	0.0453	0.0206	0.0663	0.0599*	-0.00258	0.0694**	0.0658**	-0.00588	0.0696**
	0.51	0.27	0.51	0.92	0.3	0.86	1.91	(-0.07)	2.21	2.12	(-0.15)	2.35
DIV_Payout	0.00538***	0.00407**	0.00780***	0.00548***	0.00361*	0.00787***	0.00437***	0.00545*	0.00350**	0.00461***	0.00534*	0.00414***
	4.42	2.08	4.99	4.32	1.76	4.98	3.01	-1.87	-2.54	3.38	-1.87	-3.1
REC_BUY	0.144***	0.143**	0.143**	0.103**	0.110*	0.117**	0.0963	0.103	0.1	0.0953	0.0887	0.114
	3.17	2.17	2.49	2.4	1.76	2.06	1.28	-0.82	-1.1	1.28	-0.7	-1.24
_cons	3.903***	4.156***	3.383***	3.738***	4.082***	3.214***	3.231***	2.964***	1.616***	3.174***	2.945***	1.553***
	11.7	8.68	9.4	11.26	8.77	8.86	17.27	-10.42	-4.97	16.52	-10.44	-4.53
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	4111	2050	2061	4111	2050	2061	1664	825	839	1664	825	839
Number of banks	242	169	179	242	169	179	98	64	61	98	64	61
R-square	0.206	0.223	0.201	0.222	0.225	0.219	0.0951	0.0929	0.197	0.0917	0.0913	0.19
Wald χ^2	1.31	30.59	0.06	5.96	23.36	3.11	2.55	2.17	7.62	0.42	1.25	3.24
P- Value	0.235	0.000	0.805	0.0146	0.0000	0.0778	0.1104	0.1407	0.0058	0.5187	0.2643	0.0717

This table provides fixed-effect estimation results based on Eq. (2), examining how opacity affects bank risk-taking with a focus on interaction effects involving analyst coverage, dividend payout policies, and REC_BUY. The dependent variable is ln(ZScore), analyzed for U.S. and European banks, segmented by bank size (below and above the median). Both Analyst Forecast Error and Analyst Forecast Dispersion models are presented. Time-fixed effects are applied in all estimations, and robust standard errors clustered at the bank level are shown in parentheses. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively. Control variables are included but omitted from the display for conciseness.

Table 1. 14: Marginal Effects: Analyst Coverage and Dividend Policies on Opacity-Risk Nexus —by Bank Size

Dependent Variable: ln(Z-Score)		US				Change	
		25th%	50th%	75th%	90th%	25%-90%	Based on
Panel 1	SIZE						
Coverage (ln) index at:		1.38	1.94	2.39	3.04		
Forecast Error		-0.518***	-0.565***	-0.661***	-0.74***	0.221	Table 13, Column 1
		-5.36	-4.85	-3.65	-3.05		
	<Median	-0.248***	-0.574***	-0.765***	-0.901***	0.65***	Table 13, Column 2
		-2.68	-6.01	-6.79	-6.97		
	>Median	-1.065***	-1.04***	-1.019***	-0.99***	-0.08	Table 13, Column 3
		-5.26	-7.09	-6.99	-4.65		
Forecast Dispersion		-0.908***	-1.074***	-1.419***	-1.702***	0.794**	Table 13, Column 4
		-5.29	-5.63	-5	-4.45		
	<Median	-0.319***	-0.709***	-0.937***	-1.099***	0.781***	Table 13, Column 5
		-2.21	-4.56	-5.23	-5.46		
	>Median	-1.447***	-1.816***	-2.114***	-2.54***	1.093*	Table 13, Column 6
		-6.34	-6.41	-5.17	-4.07		
Panel 2							
Dividend Payout index at:		17	31	44	57		
Forecast Error		-0.419***	-0.582***	-0.73***	-0.882***	0.463***	Table 13, Column 1
		-4.26	-4.61	-4.48	-4.3		
Forecast Dispersion		-0.77***	-1.136***	-1.469***	-1.809***	1.04***	Table 13, Column 4
		-4.37	-5.58	-5.93	-5.95		

Dependent Variable: ln(Z-Score)		EU				Change	
		25th%	50th%	75th%	90th%	25%-90%	Based on
Panel 3	SIZE						
Coverage (ln) index at:		1.79	2.48	3.14	3.34		
Forecast Error		-0.112***	-0.096***	-0.08***	-0.072***	-0.04	Table 13, Column 7
		-3.7	-3.69	-3.18	-2.74		
	<Median	-0.126***	-0.106***	-0.082*	-0.064	-0.062	Table 13, Column 8
		-2.62	-2.37	-1.77	-1.26		
	>Median	-0.066***	-0.081***	-0.095***	-0.099***	0.033***	Table 13, Column 9
		-3.78	-4.51	-4.79	-4.82		
Forecast Dispersion		-0.098***	-0.106***	-0.114***	-0.118***	0.02	Table 13, Column 10
		-3.23	-3.54	-3.33	-3.13		
	<Median	-0.135***	-0.115**	-0.091*	-0.073	-0.062	Table 13, Column 11
		-2.61	-2.58	-1.9	-1.18		
	>Median	-0.127***	-0.145***	-0.164***	-0.171***	0.044*	Table 13, Column 12
		-1.29	-1.51	-1.69	-1.75		
Panel 4							
Dividend Payout index at:		5	34	50	72		
Forecast Error		-0.092***	-0.098***	-0.1***	-0.104***	0.011	Table 13, Column 7
		-2.97	-3.73	-3.84	-3.67		
Forecast Dispersion		-0.032***	-0.107***	-0.143***	-0.191***	0.159**	Table 13, Column 10
		-4.35	-3.51	-3.16	-2.93		

This table provides a marginal effect analysis based on results from Table 13, examining how variations in analyst coverage and dividend payout impact the relationship between opacity and bank risk, measured by Forecast Error and Dispersion, in the U.S. and Europe segmented by bank size. Panels 1 and 3 show the effect of varying levels of Coverage on the Opacity-Risk nexus for U.S. and European banks, respectively. Panels 2 and 4 focus on Dividend Payout. Marginal effects are evaluated at the 25th, 50th, 75th, and 90th percentiles for each interacted variable, with other variables held at median values. Standard errors are in parentheses. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

1.5.3. Extended Robustness Analyses

Further robustness tests explore alternative models and variables to reinforce the empirical findings.

1.5.3.1. Opacity and High Default Probability: Evidence from Merton's Model

In this section, we apply Merton's option-based model to examine how bank opacity, defined by analysts' forecast error and forecast dispersion, contributes to heightened default risk and reduced credit stability. This analysis quantifies the Probability of Default (PD) and Distance to Default (DD) across varying levels of opacity, shedding light on the implications of limited transparency in the banking sector. Bank opacity, characterized by limited information transparency, theoretically links to increased default risk via mechanisms like information asymmetry, adverse selection, and reduced market discipline. The Merton model, a widely used option-based framework, calculates PD and DD to evaluate a company's ability to fulfill its financial obligations, offering insights into the credit risk associated with opacity. For banks, analyzing opacity through PD_Mert and DD_Mert measures provides a clear view of how transparency influences default risk and financial instability. Fig. 3 illustrates the relationship between detrended opacity (using forecast error) and two key risk indicators, PD_Mert and DD_Mert, for Global, U.S., and European banks. This visual segmentation allows a comparative analysis of opacity's impact across different regulatory and market settings, revealing that opacity is generally associated with increased default risk and lower financial stability, with the effects being particularly pronounced in the U.S. compared to Europe.

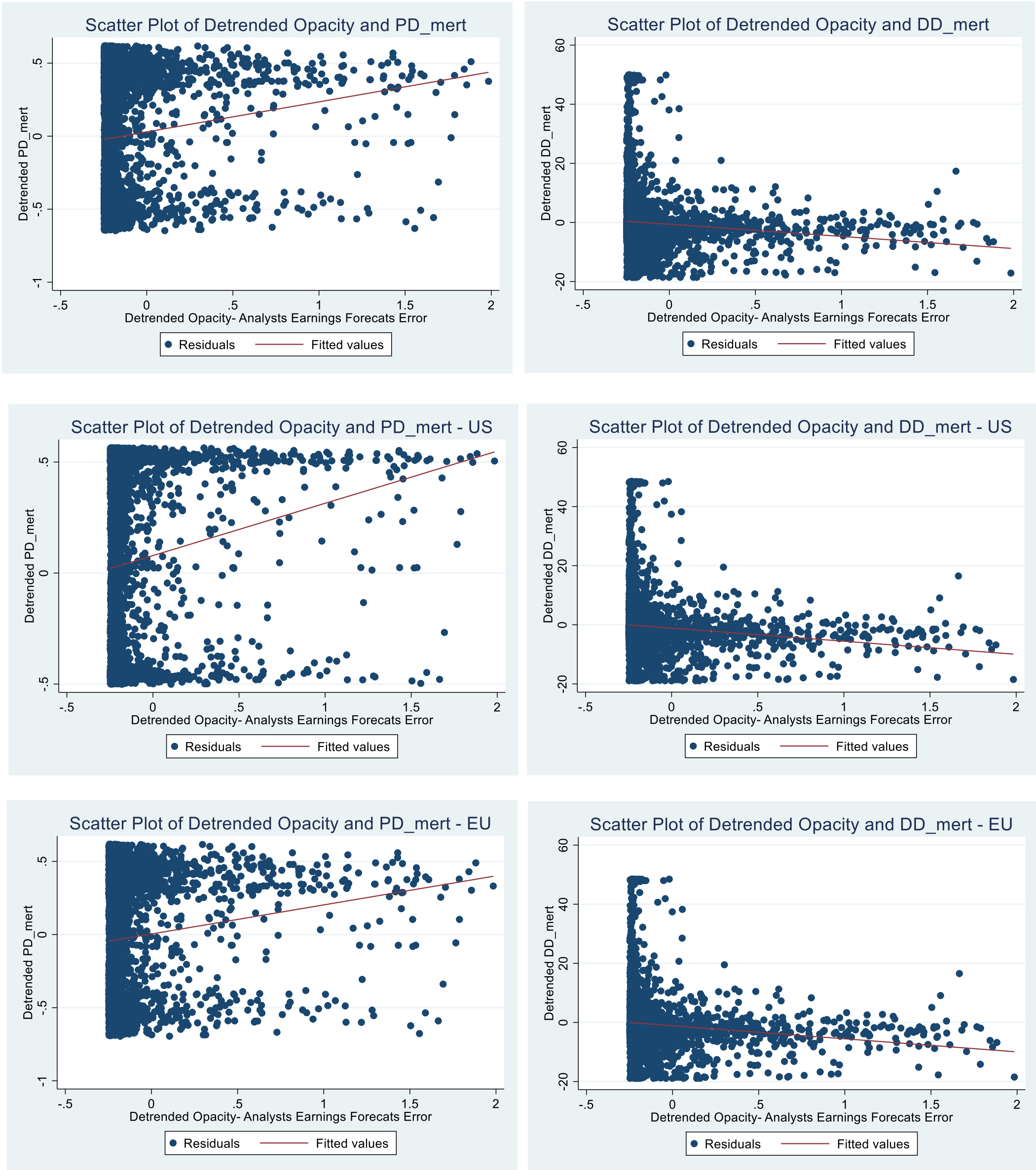

Fig. 1.3: Scatter Plots of Detrended Opacity (Analysts' Forecast Error) and Risk Indicators (PD_Mert and DD_Mert) for Global, U.S., and European Subsamples.

In this analysis, we employ a probit model to investigate how high opacity impacts default probability (PD_Mert) and reduces financial stability (DD_Mert) across U.S. and European banks. To capture extreme risk scenarios, we define two binary indicators: (1) a high-probability default dummy (PD_Mert > 75th percentile) and (2) a low distance-to-default dummy (DD_Mert < 75th percentile), which flag banks at significant instability risk. The probit equation used is as follows:

$$Probability\left[High\_PD\_Mert_{i,t} = 1\right] = Probit\ (\alpha + ß\ Opacity_{i,t-1} + \sum_{k=1}^{m} \rho_k Analyst\_Pressure_{\,k,i,t-1} + Υ\ DIV\_Policy_{\,i,t-1} + \sum_{n=1}^{p} \varphi_n Controls_{n,i,t} + \varepsilon_{i,t} \tag{10}$$

Table 1. 15 provides the probit regression results, assessing the impact of opacity—measured through analyst forecast error and forecast dispersion—on the likelihood of falling into high-risk categories (either elevated default probability, High_PD_Mert, or reduced financial stability, Low_DD_Mert). Results are segmented for global, U.S., and European samples to highlight regional differences in the opacity-risk relationship. The results are segmented for the global, U.S., and European samples, highlighting regional variations in opacity-risk dynamics. For the global sample (Models 1 and 5), opacity shows a statistically significant positive effect on default probability at the 1% level, consistent across both measures of opacity. This suggests that opacity elevates default risk. Moreover, opacity is significantly linked with a lower distance to default (Low_DD_Mert) across global and regional samples (Models 2-4 and 6-8), indicating that higher opacity is associated with reduced financial stability and greater vulnerability to economic shocks though the result is weaker in Europe[20]. The effect is most pronounced in high-PD scenarios, particularly when opacity is measured by forecast dispersion (Model 5), underscoring the role of opacity in exacerbating default risk in the banking sector[21].

Table 1. 15: Opacity and High Default Probability: Evidence from Merton's Model

	Analyst Forecast Error				Analyst Forecast Dispersion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	High_PD_mert	Low_DD_mert			High_PD_mert	Low_DD_mert		
	All	All	US	EU	All	All	US	EU
Opacity	0.0545***	0.0544***	0.219***	0.0347*	0.228***	0.227***	0.470***	0.128***
	3.23	3.22	3.07	1.8	4.98	4.97	4.56	4.13
Coverage	-0.00459	-0.00426	-0.0241***	-0.00278	-0.00375	-0.00342	-0.0233***	-0.00208
	(-1.62)	(-1.51)	(-5.56)	(-0.66)	(-1.33)	(-1.21)	(-5.41)	(-0.49)
REC_Con	0.0257	0.0268	-0.199***	0.299***	0.00941	0.0106	-0.208***	0.278***
	0.69	0.72	(-4.21)	4.77	0.25	0.28	(-4.40)	4.42
DIV_Payout	-0.0124***	-0.0124***	-0.0138***	-0.0125***	-0.0117***	-0.0117***	-0.0131***	-0.0117***
	(-13.32)	(-13.36)	(-11.10)	(-7.97)	(-12.54)	(-12.59)	(-10.55)	(-7.50)
_cons	-0.318**	-0.321**	0.682**	-1.213***	-0.345**	-0.348**	0.681**	-1.217***
	(-1.98)	(-2.00)	2.3	(-5.76)	(-2.15)	(-2.17)	2.29	(-5.77)
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5440	5440	3872	1568	5440	5440	3872	1568

Table 15 presents the probit regression results analyzing the effect of opacity, derived from analyst forecast error and dispersion, on the likelihood y of a bank experiencing a high level of default risk for a global, US and European banks. The dependent variables analyzed include Distance to Default (DD_met) and probability of Default (PD_met); We use a high PD_mert dummy (PD_mert > 75th percentile) to capture banks with elevated default risk. The low DD_mert dummy (DD_mert < 75th percentile) identifies banks with reduced financial stability. The main explanatory variable is opacity, with analyst coverage and other control variables included in the model. Time-fixed effects are incorporated in all estimations, and robust standard errors, clustered at the bank level, are reported in parentheses. ***, **, and * denote significance levels at the 1%, 5%, and 10% levels, respectively.

[20] Opacity, when measured by analyst forecast error, appears to have a weaker relationship with the Merton probability of default proxy in the European subsample, indicating that this measure may not fully capture the risk dynamics in the European banking context.

[21] Other variables reveal that while analyst coverage generally does not significantly alter high PD or low DD probabilities, recommendation consensus shows a modest positive association with risk, suggesting that greater analyst pessimism may correspond to higher risk categories, though the effects are not consistently significant. Dividend payouts exhibit a significant negative relationship across most specifications, suggesting that higher payouts lower the likelihood of high default risk or low stability, thereby playing a stabilizing role.

1.5.3.2. Market Systematic Risk and Price Volatility Analysis

Additional robustness tests assess the effect of opacity on market-based risk measures, specifically evaluating its influence on systematic risk (Beta) and price volatility across global, U.S., and European bank samples. Specifically, we re-estimated our baseline model using Market Systematic Risk (BETA) and Price Volatility (Price VOL). Table 1. 16 presents the fixed-effect estimation results for the global sample as well as US and European subsamples. Across the BETA models (columns 1-3 and 7-9), greater opacity—particularly when measured by analyst forecast dispersion—is positively associated with increased systematic risk, both globally and regionally. For Price Volatility (columns 4-6 and 10-12), higher opacity under both proxies' correlates with increased volatility, indicating that opaque banks are more susceptible to financial distress and market instability. The US subsample shows more pronounced effects for price volatility, suggesting that opacity amplifies risk-taking behavior in the more market-driven US financial environment. In contrast, while the European subsample also demonstrates increased risk linked to opacity, the effect on price volatility is weaker, possibly reflecting the stabilizing influence of stronger regulatory oversight in Europe. Analyst coverage shows a positive association with systematic risk (BETA) globally and regionally, suggesting that increased analyst coverage might elevate perceived systematic risk, but it does not significantly affect price volatility. Dividend payout consistently exhibits a negative relationship with both beta and price volatility, indicating that higher payouts are associated with lower risk and volatility. This finding suggests that dividend policies serve as stabilizing signals of financial strength, mitigating perceived risk and promoting market stability. Overall, these findings underscore that opacity significantly heightens systematic risk and market volatility, particularly in the US, while dividend payouts act as important stabilizing mechanisms.

Table 1. 16: Market Systematic Risk and Price Volatility Analysis

	Analyst Forecast Error						Analyst Forecast Dispersion					
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	BETA			Price_VOL			BETA			Price_VOL		
	All	US	EU	All	US	EU	All	US	EU	All	US	EU
Opacity	-0.00178	0.0217	-0.00684	0.795***	1.624***	0.49	0.0347***	0.0455	0.0349***	0.805***	2.579***	0.659***
	(-0.08)	-0.54	(-0.26)	-2.9	-4.98	-1.41	-3.13	-0.74	-3.29	-3.82	-4.36	-4.68
Coverage	0.00788***	0.0325***	0.00462***	-0.00703	-0.0289	-0.00234	0.0625***	0.0849***	0.0460***	0.0618	0.0702	0.0795
	-6.15	-6.54	-3.76	(-0.48)	(-0.51)	(-0.16)	-5.58	-3.51	-3.98	-0.43	-0.26	-0.55
REC_Con	-0.0363**	0.00384	-0.0624**	-0.239	-0.272	-0.0369	-0.0399**	-0.0076	-0.0713**	-0.271	-0.308	-0.12
	(-2.07)	-0.17	(-2.21)	(-1.11)	(-1.20)	(-0.08)	(-2.25)	(-0.33)	(-2.52)	(-1.27)	(-1.38)	(-0.27)
DIV_Payout	-0.00353***	-0.00347***	-0.00258***	-0.0642***	-0.0708***	-0.0438***	-0.00338***	-0.00331***	-0.00240***	-0.0624***	-0.0679***	-0.0406***
	(-7.15)	(-5.03)	(-3.82)	(-10.33)	(-8.94)	(-4.32)	(-6.98)	(-4.90)	(-3.88)	(-10.29)	(-8.82)	(-4.30)
_cons	1.124***	0.106	1.430***	25.90***	21.85***	25.71***	1.098***	0.177	1.401***	25.88***	22.03***	25.76***
	-8.6	-0.49	-13.52	-29.17	-10.24	-15.69	-8.21	-0.78	-13.27	-28.93	-10.29	-15.79
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5440	3872	1568	5440	3872	1568	5440	3872	1568	5440	3872	1568
Number of banks	340	242	98	340	242	98	340	242	98	340	242	98
R-square	0.133	0.185	0.135	0.227	0.276	0.205	0.137	0.17	0.151	0.24	0.291	0.233

This table presents fixed-effect estimation results examining the impact of opacity on bank risk-taking, focusing on interactions between opacity, analyst forecast error, and forecast dispersion in relation to systematic risk (BETA) and price volatility (Price_VOL). Columns 1–6 analyze the relationship with Analyst Forecast Error, while Columns 7–12 focus on Analyst Forecast Dispersion. The dependent variables are systematic risk (BETA) and price volatility (Price_VOL), with separate estimations provided for U.S., European, and global samples. All models include control variables and time-fixed effects. Robust standard errors clustered at the bank level are shown in parentheses. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively.

1.6. Summary and Conclusion

This study provides an in-depth analysis of bank opacity and its impact on risk within the U.S. and European banking sectors, leveraging forward-looking metrics such as analyst forecast error and forecast dispersion to capture nuances in market discipline and stability. The findings underscore opacity's destabilizing role in the banking industry, with higher opacity associated with increased risk-taking and diminished stability. Notably, this effect is amplified under conditions of market overvaluation and economic uncertainty, particularly within the U.S., where market-driven dynamics and heightened analyst scrutiny create an environment more sensitive to opaque practices. These insights contribute to the growing literature on bank transparency by demonstrating that opacity impairs the ability of market participants to assess bank risk accurately, thereby increasing systemic vulnerabilities.

The role of financial analysts proves to be multifaceted. While analyst coverage generally improves transparency and mitigates risk, it can also place added pressure on opaque banks, potentially encouraging riskier behaviors. This effect is most notable in the U.S., especially among smaller banks that are highly sensitive to analyst coverage. In contrast, European banks experience a moderated impact from analyst scrutiny, particularly among larger institutions, reflecting the influence of regional differences in market structure and regulatory priorities.

Additionally, negative analyst signals—such as sell recommendations and downgrades—intensify opacity-related risks, especially in high-opacity U.S. banks, where market reactions to negative forecasts amplify instability. Positive recommendations provide a stabilizing effect, although less pronounced, underscoring the more significant influence of negative sentiment on market behavior. Dividend policy also interacts with opacity in complex ways. While moderate dividend payouts typically signal stability and enforce market discipline, excessive dividends can exacerbate opacity's negative effects, reducing resilience. This destabilizing effect is most prominent in the U.S., where aggressive dividend distributions may weaken capital buffers and push banks toward riskier strategies to satisfy shareholder expectations. Thus, while dividends can serve a stabilizing function, they may also undermine stability if misaligned with a bank's financial health.

The comparative analysis across the U.S. and European banking sectors reveals that while the negative effects of opacity are present in both regions, the intensity and mechanisms of impact differ. U.S. banks, which operate within a more market-driven framework, exhibit a higher sensitivity to opacity and analyst-induced pressures, often resulting in pronounced risk-taking behaviors. European banks, however, display a moderated response to opacity and analyst coverage, albeit with similar directional effects. In conclusion, this research extends the understanding of how opacity, financial analyst influence, and dividend policies interact to shape bank risk profiles across distinct financial environments.

These findings have critical implications for regulators, policymakers, and market participants. They indicate that nuanced regulatory approaches—accounting for the dual role of analysts and the signaling impact of dividend policies—are crucial for fostering resilience in the banking sector. Tailored oversight, especially in market-driven contexts, can mitigate opacity's destabilizing effects by balancing the informational benefits of analyst coverage with the risks of excessive market pressure. This study contributes meaningfully to our understanding of market discipline mechanisms, highlighting how transparency, regulatory context, and market dynamics together shape banking sector stability in profound and intricate ways.

Appendix I

Appendix A: Details On Dataset

Table A1. Local market index data

Local Market Index	#
S&P 500 COMPOSITE - PRICE INDEX	275
SWISS MARKET (SMI) - PRICE INDEX	15
FTSE ALL SHARE - PRICE INDEX	13
FTSE ITALIA ALL SHARE - PRICE INDEX	11
WARSAW GENERAL INDEX 20 - PRICE INDEX	10
DAX PERFORMANCE - PRICE INDEX	8
OMX COPENHAGEN BMARK (OMXCB) - PRICE INDEX	7
IBEX 35 - PRICE INDEX	6
OMX AFFARSVARLDENS GENERAL - PRICE INDEX	6
SBF 120 - PRICE INDEX	5
WIENER BOERSE INDEX (WBI) - PRICE INDEX	4
ATHEX COMPOSITE - PRICE INDEX	4
MOEX RUSSIA INDEX - PRICE INDEX	3
AEX INDEX (AEX) - PRICE INDEX	3
UKRAINE PFTS - PRICE INDEX	2
ROMANIA BET(L) - PRICE INDEX	2
PRAGUE SE PX - PRICE INDEX	2
BEL 20 - PRICE INDEX	1
BULGARIA SE SOFIX - PRICE INDEX	1
BELGRADE BELEX 15 - PRICE INDEX	1
BUDAPEST (BUX) - PRICE INDEX	1
OMX HELSINKI (OMXH) - PRICE INDEX	1
CROATIA CROBEX - PRICE INDEX	1
PORTUGAL PSI-20 - PRICE INDEX	1
LITHUANIA LITIN 'DEAD' - PRICE INDEX	1
SLOVAKIA SAX 16 - PRICE INDEX	1

Appendix B: Details on Risk Proxies

- *Distance to Default Calculation and Risk Measure Visualizations*

Distance to Default Calculation: [PD,DD] = mertonByTimeSeries(Equity,Liability,Rate)[22]

- Equity: The market value of the firm's equity, calculated as the product of the number of shares and the market price.
- Liability: The liability threshold of the firm, often referred to as the default point, specified as a positive value.
- Rate: The annualized risk-free interest rate, typically represented by the yield on 5-year government bonds.
- Maturity: The time to maturity of the liability threshold, specified as a comma-separated pair ('Maturity,' positive value).
- Drift: The annualized drift rate, representing the expected rate of return on the firm’s assets, specified as a comma-separated pair ('Drift,' numeric value).

Outputs: PD (Probability of Default): The probability that the firm will default by the time the liabilities reach maturity, returned as a numeric value. DD (Distance-to-Default): The number of standard deviations between the mean of the asset distribution at maturity and the liability threshold (default point), returned as a numeric value.

- *Risk distributions:*

Fig. B.1 in Appendix B displays the distribution of key bank risk measures, including solvency and profitability (Z-Score, SD ROA, Total Risk) and market and credit risk metrics (Beta, Price Volatility, Distance to Default). These boxplots reveal the variability across risk profiles, offering context for bank stability and market risk perceptions in our sample.

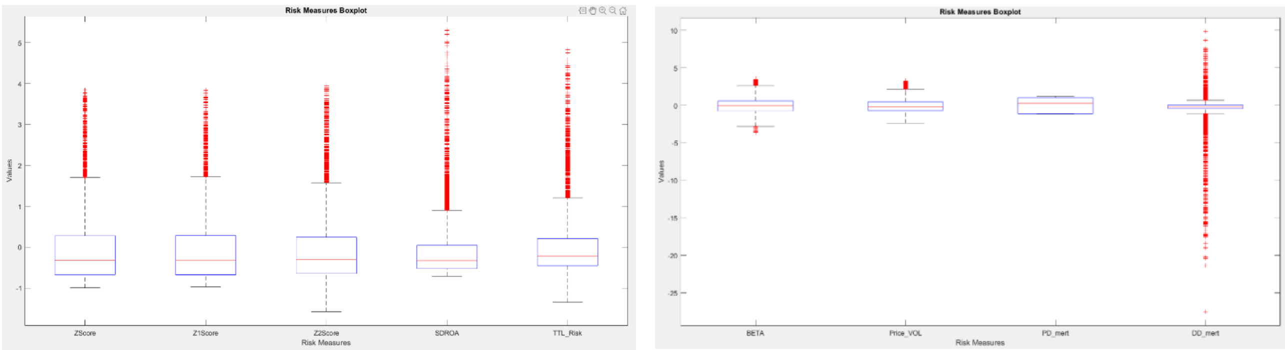

Fig. B.1: Boxplots of Bank Solvency, Profitability, Market, and Default Risk Measures

[22] The function mertonByTimeSeries estimates the default probability using the time-series version of the Merton model in MATLAB, as provided by MathWorks Nordic (https://se.mathworks.com/help/risk/mertonbytimeseries.html).

- *Risk – Opacity Correlations:*

Table B2 Correlation Matrix Risk and Opacity Variables

	1	2	3	4	5	6	7	8	9	10	11	12
Forcast Error	1											
Forecast Dispersion	0.4383 0.0000	1										
lnZScore	-0.1724 0.0000	-0.1391 0.0000	1									
lnZ1Score	-0.1728 0.0000	-0.1347 0.0000	0.9957 0.0000	1								
lnZ2Score	-0.158 0.0000	-0.1801 0.0000	0.789 0.0000	0.7517 0.0000	1							
lnMZScore	-0.0867 0.0000	-0.1113 0.0000	0.4315 0.0000	0.4196 0.0000	0.4471 0.0000	1						
SDROA	0.1283 0.0000	0.097 0.0000	-0.7308 0.0000	-0.7106 0.0000	-0.7177 0.0000	-0.3931 0.0000	1					
TTL Risk	0.0972 0.0000	0.1097 0.0000	-0.3663 0.0000	-0.3558 0.0000	-0.3987 0.0000	-0.9507 0.0000	0.3506 0.0000	1				
PD high Merton	0.0689 0.0000	0.1152 0.0000	-0.1231 0.0000	-0.1189 0.0000	-0.1419 0.0000	-0.0707 0.0000	0.0974 0.0000	-0.0513 0.0001	1			
DD low Merton	0.0691 0.0000	0.1153 0.0000	-0.1247 0.0000	-0.1207 0.0000	-0.1427 0.0000	-0.0715 0.0000	0.1001 0.0000	-0.0509 0.0001	0.9986 0.0000	1		
BETA	0.0808 0.0000	0.1069 0.0000	-0.2304 0.0000	-0.224 0.0000	-0.2106 0.0000	-0.1843 0.0000	0.1348 0.0000	0.1871 0.0000	0.0009 0.9480	0.002 0.8770	1	
Price VOL	0.1837 0.0000	0.2177 0.0000	-0.5272 0.0000	-0.5185 0.0000	-0.5069 0.0000	-0.5492 0.0000	0.4003 0.0000	0.4567 0.0000	0.1764 0.0000	0.1782 0.0000	0.5107 0.0000	1

Table B2 provides the correlation matrix for risk and opacity variables, detailing their significance levels and further illustrating the relationship between opacity and bank risk-taking behavior.

Appendix C: Further Investigations

- Alternative Measures for Analyst Coverage

To enhance robustness, we examine additional proxies for analyst coverage: Residual_Coverage and Ln-Coverage. Ln-Coverage, the natural logarithm of the primary coverage measure, better captures variations in coverage levels, while Residual_Coverage is computed from the residuals of Equation (9).

Table C1: Opacity and bank risk-taking- Using alternative coverage measures: Ln_Coverage

Dependent Variable: ln(Z-Score)												
	Analyst Forecast Error						Analyst Forecast Dispersion					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Opacity	**-0.206*****	**-0.148*****	**-0.150*****	**-0.146*****	**-0.161*****	**-0.150*****	**-0.0849****	**-0.0747*****	**-0.0735*****	**-0.0697****	**-0.0710****	**-0.0603****
	(-5.95)	**(-4.69)**	**(-4.79)**	**(-4.62)**	**(-4.83)**	**(-4.54)**	**(-2.55)**	**(-2.61)**	**(-2.61)**	**(-2.54)**	**(-2.51)**	**(-2.34)**
Ln_Coverage			0.0611**	0.0597**	0.0806***	0.0676***			0.0544**	0.0533**	0.0737***	0.0614**
			-2.51	-2.44	-3.43	-2.85			-2.2	-2.14	-3.06	-2.53
REC_Con				-0.147***		-0.128***				-0.147***		-0.132***
				(-4.38)		(-3.64)				(-4.31)		(-3.70)
REC_Rev_Dn					-0.0571***	-0.0478**					-0.0504**	-0.0415*
					(-2.63)	(-2.19)					(-2.28)	(-1.86)
REC_Rev_Up					-0.0395	-0.0442					-0.0389	-0.0441
					(-1.46)	(-1.55)					(-1.48)	(-1.59)
DIV_Payout						0.00564***						0.00562***
						-5.97						-5.86
_cons	3.768***	3.632***	3.555***	3.956***	3.432***	3.562***	3.731***	3.604***	3.534***	3.935***	3.409***	3.552***
	-449.07	-25.35	-26.57	-25.54	-25.56	-21.22	-709.01	-25.34	-26.45	-25.43	-25.22	-21.17
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5775	5775	5775	5775	5435	5435	5775	5775	5775	5775	5435	5435
Number of banks	340	340	340	340	340	340	340	340	340	340	340	340
R-square	0.0196	0.151	0.153	0.159	0.154	0.17	0.00726	0.147	0.148	0.154	0.148	0.163

This table presents fixed-effect estimation results examining the impact of opacity, as derived from analysts' forecasts, on bank risk-taking, using Ln_ Coverage as an alternative measure for analyst coverage. All estimations include time-fixed effects. Robust standard errors, clustered at the bank level, are shown in parentheses. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

Table C2: Opacity and bank risk-taking- Using alternative coverage measures: Residual _Coverage

Dependent Variable: ln(Z-Score)												
	Analyst Forecast Error						Analyst Forecast Dispersion					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Opacity	**-0.206*****	**-0.148*****	**-0.159*****	**-0.154*****	**-0.159*****	**-0.145*****	**-0.0849****	**-0.0747*****	**-0.0665*****	**-0.0633****	**-0.0648****	**-0.0542****
	(-5.95)	**(-4.69)**	**(-4.70)**	**(-4.54)**	**(-4.61)**	**(-4.29)**	**(-2.55)**	**(-2.61)**	**(-2.60)**	**(-2.55)**	**(-2.46)**	**(-2.32)**
Residual_Coverage			0.0327***	0.0301***	0.0346***	0.0323***			0.0327***	0.0301***	0.0346***	0.0322***
			-4.01	-3.67	-4.29	-4.01			-3.96	-3.62	-4.23	-3.96
REC_Con				-0.127***		-0.132***				-0.131***		-0.137***
				(-3.38)		(-3.54)				(-3.43)		(-3.61)
REC_Rev_Dn					-0.0664***	-0.0582***					-0.0611***	-0.0532**
					(-3.21)	(-2.81)					(-2.91)	(-2.53)
REC_Rev_Up					-0.0501*	-0.0544**					-0.0505**	-0.0553**
					(-1.89)	(-1.98)					(-1.99)	(-2.08)
DIV_Payout						0.00594***						0.00598***
						-6.25						-6.23
_cons	3.768***	3.632***	3.333***	3.690***	3.351***	3.473***	3.731***	3.604***	3.306***	3.675***	3.323***	3.458***
	-449.07	-25.35	-26.07	-22.4	-26.92	-20.65	-709.01	-25.34	-25.62	-22.07	-26.38	-20.47
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5775	5775	5095	5095	5095	5095	5775	5775	5095	5095	5095	5095
Number of banks	340	340	340	340	340	340	340	340	340	340	340	340
R-square	0.0196	0.151	0.16	0.164	0.161	0.179	0.00726	0.147	0.153	0.158	0.155	0.172

This table presents fixed-effect estimation results examining the impact of opacity, as derived from analysts' forecasts, on bank risk-taking, using Residual Coverage as an alternative measure for analyst coverage. All estimations include time-fixed effects. Robust standard errors, clustered at the bank level, are shown in parentheses. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

Table C3: Interactions between Analyst Recommendations, revisions, and Bank Risk

	Analyst Forecast Error					Analyst Forecast Dispersion				
Dependent Variable:: ln(Zscore)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Opacity	-0.215***	-0.202***	-0.184***	-0.212***	-0.217***	-0.0728**	-0.0762*	-0.0603	-0.0674*	-0.0890*
	(-5.11)	(-5.65)	(-3.31)	(-5.51)	(-5.61)	(-2.07)	(-1.95)	(-0.67)	(-1.68)	(-1.89)
Opacity X REC_Buy	0.0291					0.0294				
	1.26					0.85				
Opacity X REC_Sell		0.0248					0.00898			
		0.87					0.41			
Opacity X REC_Con			-0.00431					-0.00269		
			(-0.20)					(-0.11)		
Opacity X REC_Rev_Dn				0.000621					0.0287	
				0.05					1.45	
Opacity X REC_Rev_Up					0.0284*					0.0233*
					1.77					1.81
Opacity X Coverage	0.0315***	0.0324**	0.0326***	0.0317**	0.0281**	0.00181	0.0121	0.0104	-0.0042	0.00834
	2.65	2.57	2.63	2.33	2.06	0.1	0.78	0.7	(-0.26)	0.48
Opacity X DIV_Payout	-0.000375	-0.000523	-0.000451	-0.000365	-0.000293	-0.00394**	-0.00397**	-0.00380**	-0.00434**	-0.00421**
	(-0.73)	(-1.03)	(-0.88)	(-0.62)	(-0.50)	(-2.40)	(-2.44)	(-2.40)	(-1.99)	(-1.99)
_cons	3.389***	3.484***	3.893***	3.292***	3.278***	3.335***	3.435***	3.835***	3.235***	3.230***
	21.14	22.13	22.23	20.22	19.85	20.19	21.23	21.72	19	18.65
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5775	5775	5775	5435	5435	5775	5775	5775	5435	5435
Number of banks	340	340	340	340	340	340	340	340	340	340
R-square	0.125	0.123	0.128	0.127	0.127	0.121	0.119	0.124	0.123	0.123

This table presents the fixed-effect estimation results, based on Eq. (2), examining the influence of opacity on bank risk-taking, specifically through interactions with analyst recommendations (e.g., Buy, Sell, and revisions) and coverage. The dependent variable is ln(ZScore), representing bank stability. Time-fixed effects are included in all estimations, and robust standard errors clustered at the bank level are shown in parentheses. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

Appendix D: Subsamples of US and European Banks

- Variable definitions

Table D1. Variables definition and summary statistics for US and European banks

Variable	US banks					EU banks					
Dependent variables	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	T-Stat.
SDROA	4,114	0.36	0.50	0.00	3.25	1,666	0.44	0.61	0.00	3.90	5.4617***
ZScore	4,114	75.37	70.85	3.76	385.35	1,666	46.15	54.60	0.02	328.13	-15.1161***
Z1Score	4,114	67.63	63.44	3.33	294.43	1,666	40.71	49.01	3.33	213.59	-15.5450***
Z2Score	4,114	7.63	7.80	-0.53	34.70	1,666	5.37	6.06	-0.53	34.70	-10.6003***
MZScore	4,103	55.05	28.15	0.00	183.79	1,656	55.50	37.93	0.00	413.14	0.4919*
TR	4,114	1.87	1.37	0.00	8.57	1,666	1.82	1.37	0.00	8.57	-1.2749*
BETA	4,114	0.77	0.55	-1.24	2.92	1,666	1.01	0.60	-1.24	2.92	14.5257***
Price_VOL	4,114	22.16	6.43	7.96	47.52	1,666	25.60	8.51	5.89	47.52	16.7220***
DD_mert	4,114	1.88	9.30	-27.51	80.53	1,666	-0.16	11.77	-33.18	80.53	-8.788***
PD_mert	4,114	0.46	0.42	0.00	1.00	1,666	0.65	0.38	0.00	1.00	16.2289***
Variables Of Interest											
Analysts Forecasts and Recommendations											
Forecast Error	4,114	0.095	0.36	0.00	8.27	1,666	0.60	1.82	0.00	8.27	17.026***
Forecast Dispersion	4,114	0.08	0.23	0.00	2.55	1,666	0.22	0.54	0.00	2.55	13.6718***
Forecast_Optimism	4,114	0.65	3.33	-9.96	39.12	1,666	3.47	11.11	-9.96	39.12	14.6861***
Coverage	4,114	5.26	6.94	0.00	38.00	1,666	11.92	11.55	0.00	46.00	26.8801***
REC_Con	4,114	2.53	0.50	1.00	5.00	1,666	2.64	0.57	1.00	5.00	19.0044***
REC_Rev_Dn	4,114	0.09	0.35	0.00	4.00	1,666	0.38	0.80	0.00	7.00	21.8289***
REC_Rev_Up	4,114	0.06	0.27	0.00	3.00	1,666	0.34	0.70	0.00	5.00	7.4635***
REC_Cons_ BUY %	4,114	37.70	31.03	0.00	100.00	1,666	40.56	27.24	0.00	100.00	3.2781***
REC_Cons_ HOLD %	4,114	57.71	30.15	0.00	100.00	1,666	43.27	24.86	0.00	100.00	-17.3162***
REC_Cons_ SELL %	4,114	4.59	10.71	0.00	100.00	1,666	16.18	19.88	0.00	100.00	28.5385***
REC_BUY	4,114	0.73	0.44	0.00	1.00	1,666	0.73	0.44	0.00	1.00	-0.0219*
REC_SELL	4,114	0.08	0.27	0.00	1.00	1,666	0.18	0.38	0.00	1.00	10.8115***
DIV_Payout	4,114	31.45	20.87	0.00	91.50	1,666	33.59	26.64	0.00	91.50	3.2506***
DIV_Yield	4,114	2.21	1.53	0.00	9.09	1,666	2.83	2.33	0.00	9.09	11.8483***
Control Variables											
DEPOSITS	4,114	76.30	9.13	24.79	89.87	1,666	56.35	17.65	24.79	89.87	-17.96377***
EQUITY2A	4,114	10.84	2.90	2.88	23.48	1,666	8.10	4.06	2.88	23.48	-22.4679***
SIZE	4,114	9.59	0.71	8.19	12.53	1,666	10.65	0.90	7.73	12.40	55.3501***
NI2A	4,114	1.18	1.11	0.00	15.72	1,666	1.89	1.81	0.01	29.22	18.1537***
NPL	4,114	1.62	1.95	0.01	23.63	1,666	4.52	5.34	0.01	23.63	30.1969***
MTBV	4,114	136.05	60.90	19	378	1,666	124.43	73.77	19.00	378	-6.1684***
GDPgr	4,114	1.69	1.95	-3.64	3.80	1,666	1.45	2.71	-5.79	6.12	-3.8251***
Inflation	4,114	2.03	1.09	-0.36	3.84	1,666	1.71	1.51	-0.69	6.36	-9.0661***

This table shows summary statistics and t-tests comparing U.S. and EU banks across dependent, interest, and control variables. Significant differences between regions are denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Table D2: Correlation Matrix Risk and Opacity Variables

US Sub-sample

	1	2	3	4	5	6	7	8	9	10	11
Forcast Error	1										
Forecast Dispersion	0.612	1									
	0.000										
lnZScore	-0.274	-0.266	1								
	0.000	0.000									
lnZ1Score	-0.270	-0.259	0.997	1							
	0.000	0.000	0.000								
lnZ2Score	-0.339	-0.300	0.823	0.796	1						
	0.000	0.000	0.000	0.000							
lnMZScore	-0.226	-0.178	0.429	0.424	0.440	1					
	0.000	0.000	0.000	0.000	0.000						
SDROA	0.293	0.244	-0.767	-0.752	-0.769	-0.397	1				
	0.000	0.000	0.000	0.000	0.000	0.000					
TTL_Risk	0.206	0.154	-0.365	-0.359	-0.395	-0.958	0.365	1			
	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
DD_low_Merton	0.108	0.126	-0.085	-0.080	-0.105	-0.026	0.079	-0.075	1		
	0.000	0.000	0.000	0.000	0.000	0.110	0.000	0.000			
BETA	0.012	0.044	-0.162	-0.149	-0.179	-0.113	0.146	0.151	-0.021	1	
	0.439	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.181		
Price_VOL	0.297	0.341	-0.511	-0.505	-0.504	-0.508	0.427	0.425	0.143	0.401	1
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

EU Sub-sample

	1	2	3	4	5	6	7	8	9	10	11
Forcast Error	1										
Forecast Dispersion	0.411	1									
	0.000										
lnZScore	-0.110	-0.108	1								
	0.000	0.000									
lnZ1Score	-0.105	-0.098	0.993	1							
	0.000	0.000	0.000								
lnZ2Score	-0.106	-0.198	0.725	0.668	1						
	0.000	0.000	0.000	0.000							
lnMZScore	-0.062	-0.133	0.491	0.468	0.473	1					
	0.019	0.000	0.000	0.000	0.000						
SDROA	0.076	0.064	-0.685	-0.659	-0.617	-0.391	1				
	0.002	0.009	0.000	0.000	0.000	0.000					
TTL_Risk	0.097	0.150	-0.423	-0.406	-0.420	-0.937	0.332	1			
	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
DD_low_Merton	0.028	0.132	-0.123	-0.113	-0.190	-0.166	0.115	0.006	1		
	0.254	0.000	0.000	0.000	0.000	0.000	0.000	0.821			
BETA	0.073	0.144	-0.268	-0.265	-0.240	-0.352	0.083	0.292	-0.028	1	
	0.003	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.262		
Price_VOL	0.122	0.209	-0.495	-0.475	-0.507	-0.675	0.347	0.570	0.176	0.65	1
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00	

- Comparative Analysis of financial stability, analyst dynamics, and dividend policy for European and US Banks (2004-2020).

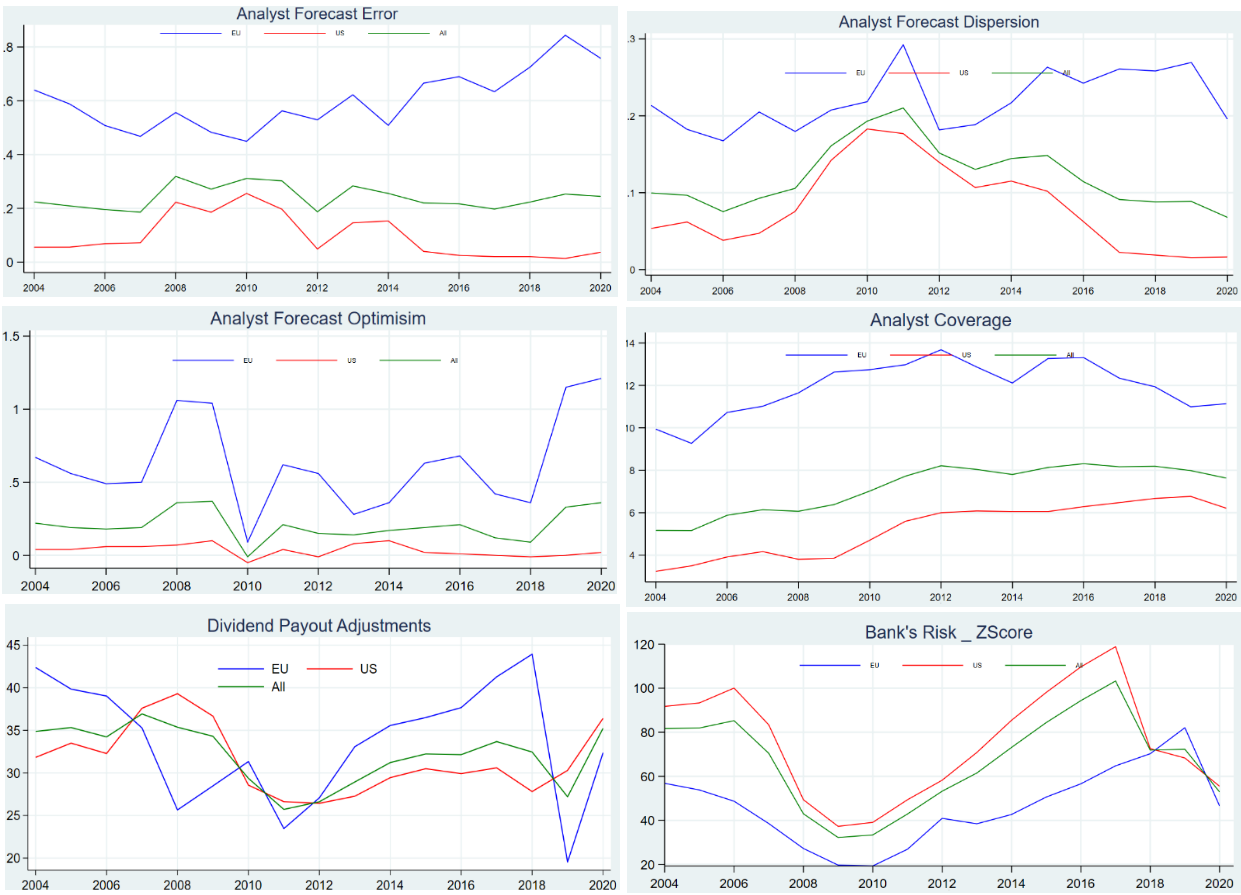

Fig. D.1. This set of charts provides a visual representation of key indicators influencing bank risk and profitability across European and US banks from 2004 to 2020. The indicators include Analyst Forecast Error, Analyst Forecast Dispersion, Analyst Forecast Optimism, Analyst Coverage, Dividend Payout Adjustments, and the ZScore as a measure of bank risk. The data reveals significant regional differences in forecast accuracy, analyst activity, dividend practices, and overall financial stability, highlighting the unique challenges faced by banks in each region.

Appendix F: Additional analysis

Table F1: Interactions and Extensions: Analyst Recommendations, Revisions and Opacity-Risk

	Analyst Forecast Error					Analyst Forecast Dispersion				
Dependent Variable:: ln(Zscore)										
US Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Opacity	-0.019	0.00388	0.43	-0.0885	0.00195	-0.0831	-0.00533	1.083**	0.0427	0.0597
	(-0.18)	-0.04	-1.33	(-0.98)	-0.03	(-0.96)	(-0.05)	-2.11	-0.39	-0.53
Opacity X REC_Buy	-0.0721					0.386***				
	(-0.67)					-3.03				
Opacity X REC_Sell		0.588					-1.240***			
		1.61					(-3.95)			
Opacity X REC_Con			-0.206					-0.388**		
			(-1.50)					(-2.19)		
Opacity X REC_Rev_Dn				-0.494**					-0.349	
				(-2.18)					(-1.50)	
Opacity X REC_Rev_Up					0.876***					0.472***
					2.93					3.34
Opacity X Coverage	-0.114	-0.247**	-0.05	-0.08	-0.347***	-0.408**	-0.297*	-0.340**	-0.370**	-0.434**
	(-1.14)	(-2.19)	(-0.44)	(-0.80)	(-3.52)	(-2.44)	(-1.74)	(-2.04)	(-2.04)	(-2.57)
Opacity X DIV_Payout	-0.0117***	-0.0137***	-0.0107**	-0.0116***	-0.0131***	-0.0262***	-0.0182***	-0.0227***	-0.0205***	-0.0209***
	(-3.10)	(-3.35)	(-2.41)	(-2.78)	(-4.02)	(-4.69)	(-3.25)	(-3.56)	(-2.87)	(-3.01)
_cons	3.903***	3.957***	4.352***	3.822***	3.757***	3.738***	3.833***	4.096***	3.662***	3.627***
	11.7	11.96	12.52	11.11	10.82	11.26	11.69	11.95	10.58	10.46
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	4111	4111	4111	3869	3869	4111	4111	4111	3869	3869
Number of banks	242	242	242	242	242	242	242	242	242	242
R-square	0.205	0.208	0.211	0.211	0.217	0.215	0.217	0.217	0.213	0.214

This table presents fixed-effect estimation results based on Eq. (2), examining how opacity influences bank risk-taking with a focus on the interaction effects of opacity with analyst recommendation tones (positive/negative) and revisions (upgrades/downgrades) in U.S. banks. The dependent variable is ln(ZScore), analyzed across both Analyst Forecast Error and Analyst Forecast Dispersion models. Time-fixed effects are included in all estimations, and robust standard errors clustered at the bank level are shown in parentheses. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively. Control variables are included but not displayed for brevity.

Table F2: Interactions and Extensions: Analyst Recommendations, Revisions, Coverage and Opacity-Risk

	Analyst Forecast Error				Analyst Forecast Dispersion			
Dependent Variable:: ln(Zscore)								
Panel A: US	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity	-0.212***	-0.298***	-0.310***	-0.342***	-0.252***	-0.293***	-0.308***	-0.312***
	(-4.74)	(-4.68)	(-5.02)	(-4.92)	(-2.69)	(-3.03)	(-2.73)	(-2.81)
Opacity X REC_Buy X Coverage	-0.340***				-0.225			
	(-3.20)				(-1.18)			
Opacity X REC_Sell X Coverage		-0.00676				-0.883***		
		(-0.15)				(-2.76)		
Opacity X REC_Rev_Dn X Coverage			-0.227***				-0.501***	
			(-2.84)				(-3.62)	
Opacity X REC_Rev_Up X Coverage				0.0418				-0.0288
				1.52				(-0.17)
_cons	3.869***	3.996***	3.826***	3.779***	3.833***	3.911***	3.767***	3.730***
	11.48	11.96	10.96	10.78	11.33	12	10.8	10.66
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes
Observations	4111	4111	3869	3869	4111	4111	3869	3869
Number of banks	242	242	242	242	242	242	242	242
R-square	0.205	0.197	0.204	0.201	0.198	0.205	0.2	0.196

	Analyst Forecast Error				Analyst Forecast Dispersion			
Dependent Variable:: ln(Zscore)								
Panel B: EU	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opacity	-0.116***	-0.0978***	-0.105***	-0.110***	-0.0461**	-0.0363***	-0.0504**	-0.0614***
	(-3.51)	(-3.47)	(-3.65)	(-3.88)	(-2.50)	(-3.14)	(-2.54)	(-2.84)
Opacity X REC_Buy X Coverage	0.0131				0.00458			
	1.42				0.8			
Opacity X REC_Sell X Coverage		0.00402				-0.00924		
		0.37				(-0.86)		
Opacity X REC_Rev_Dn X Coverage			0.00227				0.00489	
			0.63				1.11	
Opacity X REC_Rev_Up X Coverage				0.00780*				0.0108*
				1.7				1.73
_cons	3.227***	3.296***	3.151***	3.135***	3.192***	3.276***	3.133***	3.120***
	17.08	18.66	17.36	17.29	16.49	18.18	16.82	16.82
Control Variables	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1664	1664	1566	1566	1664	1664	1566	1566
Number of banks	98	98	98	98	98	98	98	98
R-square	0.0934	0.091	0.0879	0.0875	0.0868	0.0855	0.0809	0.0807

This table presents fixed-effect estimation results examining how opacity influences bank risk-taking, with a focus on interactions between opacity and analyst recommendations (Buy/Sell), revisions (Up/Dn), and coverage. Panel A shows results for U.S. banks, while Panel B presents results for European banks. The dependent variable is ln(ZScore), analyzed separately for both Analyst Forecast Error and Analyst Forecast Dispersion models. All estimations include time-fixed effects, and robust standard errors clustered at the bank level are displayed in parentheses. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively. Control variables are included in the analysis but not shown for brevity.

Chapter 2

The Influence of Financial Analyst Characteristics on Forecast Accuracy: A Comparative Analysis Across Global Banking Markets

This chapter is based on the working paper titled *"The Influence of Financial Analyst Characteristics on Forecast Accuracy: A Comparative Analysis Across Global Banking Markets*." An earlier version of this work was presented at the Sixth Edition of the Journées Internationales du Risque, hosted by the IRIAF (Institute of Industrial, Insurance, and Financial Risks) in Niort, France, on June 27–28, 2024.

Abstract

This study explores how financial analyst characteristics and career motivations shape disparities in earnings forecast accuracy and boldness across global banking markets. Using the I/B/E/S Detail History Database, we examine forecasts for 516 publicly traded banks across the U.S., Europe, and Asia from 2000 to 2023, uncovering notable regional disparities in the factors influencing forecast accuracy. While general and bank-specific experience significantly enhances precision—most notably in the U.S.—the benefits of affiliation with top-tier brokerage houses vary, with a smaller impact in Europe, where smaller, specialized firms often hold informational advantages. Portfolio complexity shows contrasting effects: broader bank coverage improves accuracy in the U.S. and Asia but increases errors in Europe due to geographical diversification challenges. Boldness, tied to career trajectories, exhibits nuanced regional patterns. In the U.S., experienced analysts issue bold, accurate forecasts that enhance career mobility, while less experienced analysts herd to avoid the risks of inaccuracy. In Asia, boldness consistently facilitates career advancement, supported by focused portfolios and institutional backing. In Europe, early-career analysts use bold forecasts and geographically diverse portfolios to gain visibility, albeit with a trade-off in accuracy. These findings underscore the interplay of technical expertise, market dynamics, and career incentives in shaping forecasting behavior. The study highlights the need for greater transparency and regulatory oversight to improve forecast reliability and strengthen market discipline in the opaque banking sector.

JEL classification: G11, G12, G14, G24

Keywords: Financial Analysts, Earnings Forecasts, Forecast Boldness, Banking Sector, Career Concerns.

2.1. Introduction

Financial analysts are pivotal in shaping market expectations and guiding investment decisions, particularly in interpreting complex financial data. Their forecasts and recommendations play a critical role in improving the information environment, reinforcing market discipline, and contributing to economic stability (Cheng & Subramanyam, 2008; Mansi et al., 2011; Derrien et al., 2016; Kosaiyakanont, 2013). In the banking sector, characterized by intricate and opaque asset structures, the true risk profiles of banks often remain obscured, raising concerns about the effectiveness of market discipline in curbing banks' risk-taking behavior. This opacity complicates regulatory oversight and diminishes stakeholders’ ability to monitor and influence banking practices (Morgan, 2002; Flannery et al., 2013; Dewally & Shao, 2013a).

The literature reveals systematic differences in analysts' forecast accuracy, largely shaped by market conditions, though such variations remain underexplored in the banking sector. Discrepancies in earnings forecasts often stem from entrenched information asymmetries and low disclosure quality—issues that are particularly acute in banking. These challenges compromise the reliability of earnings per share (EPS) forecasts, a critical metric for assessing firm performance and investor confidence (Anolli et al., 2014; Lang & Lundholm, 1996; Fosu et al., 2017). Factors such as analysts’ experience, portfolio complexity, and access to institutional resources further influence forecast accuracy[23]. Additionally, economic incentives drive patterns of optimism, boldness, and herding behavior, often undermining objectivity. Analysts frequently issue optimistic, bold forecasts influenced by career incentives and conflicts of interest, prioritizing commissions and client relationships over forecast reliability (Bradford et al., 2012; Lehmer et al., 2022; Ljungqvist et al., 2007; Michaely & Womack, 1999; Guo et al., 2023). Addressing these systemic challenges is critical for improving forecast reliability in the opaque banking sector. Despite the banking sector's pivotal role in the global economy, existing research has largely overlooked its unique complexities, with limited exploration of variations across global markets. This study is the first to investigate how analysts’ characteristics and economic incentives shape forecast accuracy, optimism, and boldness within the global banking industry. By addressing these gaps, it provides theoretical and practical insights for enhancing transparency and stability in this critical sector.

This research explores three core themes, beginning with an analysis of how analyst characteristics—such as experience, brokerage affiliation, and industry specialization—

[23] See, e.g., Brown et al. (2015), Bradley, Gokkaya, and Liu (2017); Clement (1999), Lim (2001), Bolliger (2004), Kim, Lobo, and Song (2011), Alves (2017), and Hong et al., (2000), Kecskés et al., (2017), Kothari et al., (2009).

contribute to systematic differences in forecast accuracy within the banking sector across regions. By comparing findings to broader cross-sectoral studies, it uncovers distinctions unique to banking. Prior studies suggest that affiliations with prestigious brokerage houses and specialized expertise enhance accuracy, particularly in the U.S., where labor market dynamics and institutional incentives bolster performance[24]. Conversely, Europe's varied regulatory and labor market structures introduce complexities that temper these effects[25]. Second, the study investigates the incentive-driven dynamics of forecasting behavior, focusing on the relationship between boldness, ability, and career concerns. It examines whether bold forecasts reflect genuine expertise—leveraging private information—or heightened risk-taking. Literature reveals conflicting evidence on whether boldness bolsters credibility or introduces reputational risks, particularly for less experienced analysts[26]. The study also explores how labor market incentives influence forecasting strategies and career trajectories. By exploring these dynamics, the research provides critical insights into the drivers of analysts' behavior and the reliability of earnings forecasts in the banking sector, highlighting global variations in these relationships.

Examining 516 banks across 29 countries, it highlights significant regional disparities in forecast accuracy, shaped by the characteristics of 5,647 analysts from 901 brokerages. General and bank-specific analyst experience emerges as a key determinant of forecast precision, with the strongest effects observed in the US. Affiliation with top-tier brokerage houses enhances accuracy globally, though the impact is weaker in Europe, where smaller, specialized firms often hold informational advantages. Portfolio complexity exhibits contrasting regional effects: while covering more banks improves accuracy in the US[27] and Asia, it increases errors in Europe due to challenges from geographical diversification[28]. This contrast—European analysts managing geographically dispersed portfolios versus Asian analysts focusing on concentrated banks—highlights nuanced regional dynamics in managing larger portfolios. Globally, frequent updates

[24] See, e.g., Top Analyst: Brown et al. (2015); Guan, Wong, and Zhang (2015); Bradley, Gokkaya, and Liu (2017); Clement (1999); Brown (1999); Jacob, Lys, and Neale (2000); Lim (2001). Industry Expertise: Jegadeesh and Kim (2010); Brown and Das (1997). Experience: Mikhail, Walther, and Willis (1997); Clement (1999); Lim (2001); Brown (1999); Jacob, Lys, and Neale (2000).

[25] Grandin (1995) and Bolliger (2004) suggest that in Europe, top brokerage affiliation and general experience may reduce forecast accuracy, likely due to the European labor market's unique structure, including local disadvantages, limited "learning-by-doing," and a lack of incentives.

[26] Career concerns and herding models highlight that forecast accuracy and boldness signal private information quality, influencing analysts' career outcomes (Schipper, 1991; Michaely & Womack, 1999; Ljungqvist et al., 2017). While experienced analysts often issue more accurate bold forecasts, less experienced analysts face greater risks when using boldness to gain visibility (Clement, 2005; Hong et al., 2000).

[27] Our findings contrast prior studies linking broader coverage to reduced accuracy in the US (Clement, 1999; Lim, 2001).

[28] The findings may reflect insufficient centralization in European brokerage research and analysts' limited familiarity with diverse institutional contexts (Bolliger, 2004).

and recent forecasts consistently improve accuracy, while initial forecasts suffer from limited early information. These findings underscore the importance of specialization, institutional support, and regional strategies in optimizing forecast precision, particularly in the opaque and complex banking sector. The analysis reveals significant regional variations in how experience, past performance, and financial analysts' forecast boldness interact. While boldness is often perceived as an indicator of expertise, its impact on reputation varies by regional context and analyst experience. In the United States and Asia, boldness aligns with expertise, as experienced analysts leverage their reputations to issue audacious forecasts. Analysts from top brokerage firms and those with strong past performance also demonstrate higher boldness, supported by institutional resources and confidence in their abilities[29]. Conversely, in Europe, boldness is more tied to career concerns, with younger analysts, those with weaker past performance, and those from smaller brokerage houses more likely to issue bold forecasts. These analysts often cover a broader range of banks and countries, using diverse portfolios and regional knowledge to stand out early in their careers.

This study highlights stark regional variations in how boldness, experience, and past performance influence analysts' career outcomes. In the U.S., poor performance sharply elevates downgrade risks for less experienced analysts, while strong performance alone fails to secure promotion; in Europe, high performance drives upward mobility, with no significant trend for downgrading; and in Asia, high performance drives upward mobility for analysts with strong bank-specific expertise, while lower past performance does not notably increase downgrading risks. Boldness further exerts a nuanced influence on career trajectories across regions, shaped by market structures and professional dynamics. In the U.S., bold forecasts are a double-edged sword: they hinder less experienced analysts, amplifying career risks, yet serve as a strategic asset for seasoned professionals with strong bank-specific expertise, unlocking pathways to top-tier firms. Asia demonstrates a broader acceptance of boldness, where it consistently accelerates career progression and stabilizes prospects across experience levels, underpinned by concentrated portfolios and institutional support. In Europe, boldness plays a pivotal role for early-career analysts, enabling advancement and visibility in competitive markets. Early-career European analysts strategically leverage bold forecasts, geographically diverse portfolios, and active market engagement to progress professionally. However, this strategy entails a trade-off,

[29] Our findings confirm prior US studies linking boldness to ability, reputation, and experience, while extending this by highlighting the roles of bank-specific expertise, accuracy, brokerage size, and portfolio complexity. We also uncover distinct boldness patterns and outcomes in Europe and Asia. See, e.g., Hong and Kubik (2003), Stickel (1992), Jegadeesh and Kim (2010), Harford and Schon (2019), and Clement (2005).

as the ambition to achieve career growth through bold, high-visibility forecasts often compromises forecast accuracy, highlighting the inherent tension between career-driven forecast behavior and forecast reliability.

The findings of this study reveal the complex interplay between technical expertise and incentive-driven behaviors in shaping analysts' forecast accuracy. Forecast precision, while grounded in factors such as experience, industry specialization, and institutional resources, is also influenced by strategic behaviors tailored to market pressures and career incentives. Analysts balance technical expertise with incentive-driven behaviors, employing strategies like portfolio expansion and bold predictions to accelerate career growth. However, these approaches often involve trade-offs, as boldness and optimism may compromise forecast precision, particularly in markets where commission-driven incentives amplify these behaviors. By uncovering these dynamics, this study offers critical insights for investors, financial institutions, and policymakers. It emphasizes the importance of regulatory oversight and transparency in mitigating incentive-driven biases, fostering reliable financial analysis, and enhancing market discipline within the opaque banking sector.

The paper is structured as follows: Section 2. 2 presents the literature review. Section 2. 3 describes the proposed research's empirical methodology. Section 2. 4 assembles our dataset. Section 2. 5 presents our empirical results, and Section 2. 6 concludes.

2.2. Related Work

2.2.1. The Determinants of Financial Analysts' Forecast Accuracy

Financial analysts' forecast accuracy is influenced by a range of factors, including individual characteristics, firm-level dynamics, and regional differences. Extensive research has grouped these determinants to better understand their impact on forecast precision. Analysts' experience and specialization play a critical role in shaping forecast accuracy. Stickel (1992) and Jegadeesh and Kim (2010) highlight the superior performance of U.S. star analysts, whose forecasts are not only more accurate but also exhibit minimal bias, resulting in significant market reactions and higher returns. This finding is consistent with Sinha, Brown, and Das (1997), who show that superior analysts maintain their edge over time, amplifying their influence on the market. *Specialization* in a single industry further enhances forecast accuracy. Desai et al. (2000) and Brown et al. (2015) highlight how industry focus and reliance on sector-specific data enable analysts to better interpret trends and improve predictions. Extending this, Guan et al. (2015)

reveal that supply chain coverage increases accuracy in concentrated industries. Additionally, Bradley, Gokkaya, and Liu (2017) show that prior industry experience boosts forecasting precision by providing nuanced insights into sector-specific dynamics. *Experience* plays a pivotal role in forecast accuracy. Mikhail et al. (1997) and Jacob et al. (2000) argue that more experienced analysts deliver better forecasts due to refined methodologies and reduced errors over time. However, Clement (1999) and Bolliger (2004) suggest diminishing returns with greater experience, citing competing responsibilities and reduced incentives in certain markets, such as Europe, where career motivations differ from the U.S. Lim (2001) suggests that analysts with more excellent experience have greater access to management. Therefore, if the labor market provides sufficient incentives for financial analysts to produce good forecasts, they should produce more accurate forecasts as they age.

The frequency of forecast revisions also plays a role. Gleason and Lee (2003) demonstrate that analysts who revise their forecasts frequently tend to achieve higher accuracy, as their updates reflect new and relevant information. Similarly, Kim, Lobo, and Song (2011) find that experienced analysts from larger firms delay their forecasts strategically, leveraging additional information closer to earnings announcements to enhance precision. Clement (1999) and Brown (1999) also find that longer forecast horizons are associated with lower forecast accuracy.

Institutional and Brokerage-Level Factors: Analysts affiliated with larger brokerage houses generally provide more accurate forecasts, especially those who follow fewer industries, benefiting from better resources and industry specialization (Clement, 1999; Jacob et al., 2000). However, Lim (2001) adds a nuanced perspective, proposing that analysts may issue optimistic forecasts strategically to maintain relationships with management and access better information. This optimism, while initially biased, can lead to better forecasts in subsequent periods. Conversely, regional disparities in Europe, noted by Bolliger (2004), suggest that smaller, specialized firms may occasionally outperform larger institutions in specific niches. According to their findings, the European labor market of financial analysis may not provide sufficient incentives for financial analysts to produce increasingly accurate forecasts as they age.

Regional Differences and Market Structures: Grandin (1995) finds no evidence of superior forecast accuracy in the French market among brokerage houses providing forecasts to the "Associés en Finance" database. Similarly, Bolliger (2004) finds that forecast accuracy in 14 European stock markets improves with firm-specific experience but declines with increased country coverage and older forecasts, while general experience and brokerage size show no significant impact. These findings suggest that specialized knowledge and the ability to navigate regional complexities are crucial for success in European markets.

2.2.2. Forecast Accuracy, Boldness, and Career Outcome

Research consistently demonstrates that forecast accuracy plays a pivotal role in enhancing analysts' career prospects. Analysts with a proven track record of accurate forecasts are more likely to secure promotions and less likely to face job separation. Stickel (1992) and Trueman (1994) emphasize the importance of accuracy for career advancement in the U.S., noting that accurate forecasters are often viewed as competent and reliable, leading to superior career outcomes. Jegadeesh and Kim (2010) further corroborate this, showing that accurate forecasters gain industry recognition and improved career trajectories in the U.S. Hong and Kubik (2003) highlight how the U.S. labor market incentivizes accurate forecasting by increasing the likelihood of analysts with strong track records being hired by high-status brokerage houses. These opportunities, often linked to analyst experience, are crucial for career growth, as they improve compensation and establish analysts as key players in the industry (Phillips & Zuckermann, 2001). Bolliger (2004) identifies similar trends in the European market, noting that analysts achieving high forecast accuracy are more likely to secure promotions to top-tier brokerage houses. However, those managing geographically diverse portfolios or issuing older forecasts face greater accuracy challenges, increasing their risk of termination. This underscores the importance of specialized expertise and the ability to navigate complex, multi-regional markets for sustaining employment and achieving career progression in Europe.

Bold forecasts also play a pivotal yet nuanced role in shaping analysts' career trajectories. Hong et al. (2000) demonstrate that in the United States, inexperienced analysts tend to avoid bold forecasts due to the career risks associated with inaccuracy, whereas experienced analysts leverage their reputations to make bold predictions with lower personal risk. While accurate bold forecasts can enhance an analyst's reputation and accelerate career advancement, their inherent risk can also harm career prospects if proven inaccurate. Harford and Schon (2019) highlight the delicate balance between boldness and career risk, noting that bold forecasts can yield substantial rewards but also carry significant professional stakes. Scharfstein and Stein (1990) and Prendergast and Stole (1996) explore this balance further, suggesting that the interplay between accuracy and boldness creates a complex dynamic in career outcomes. Analysts who combine precise forecasts with occasional bold predictions are often perceived as both skilled and innovative, leading to the most favorable career advancements. Jegadeesh and Kim (2010) reinforce this view, showing that maintaining a balance between boldness and accuracy is key to achieving recognition and career growth in the U.S. market. Overall, career concerns significantly influence herding behavior, particularly among less experienced analysts, as highlighted by studies in the United States, including Hong et al. (2000). Fear of adverse career outcomes from deviating from the consensus often drives these analysts to align with the majority. In contrast, experienced analysts with a proven track record face less career risk, enabling them to issue independent and bold forecasts. Welch (2000) and Clement and Tse (2005) reinforce this dynamic, showing that career concerns are a critical factor shaping the tendency of U.S. analysts to herd, with varying effects based on their level of expertise.

2.2.2.1. Economic Incentives and Analyst Behavior

Research consistently demonstrates that Analysts' compensation is deeply linked to trading volume and broker votes[30]. Cowen et al. (2006) note that firms without investment banking divisions primarily base analyst pay on the trading volume their research generates. Brown et al. (2015) found that success in generating underwriting business or trading commissions was critical to compensation, with 44% of analysts emphasizing this factor. Economic incentives often drive forecast bias. Michaely and Womack (1999) observed significant optimism in forecasts by analysts affiliated with investment banks, aligning with client expectations, while Chan et al. (2003) highlighted strategic adjustments to avoid earnings disappointments during the 1990s bull market. Ljungqvist et al. (2007) confirmed that conflicts of interest in sell-side research result in overly optimistic forecasts, compromising forecast accuracy. Regulatory reforms (Hovakimian & Saenyasiri, 2010) have improved accuracy but not eliminated biases tied to trading incentives. Guo et al. (2023) found that maintaining relationships with management and generating commissions drive optimism, while Lehmer et al. (2022) linked forecast optimism to higher trading volumes and lower demotion risks. Analysts who generate substantial trading activity avoid penalties, reinforcing the critical role of trading volume in career advancement. These findings illustrate how economic pressures push analysts toward optimism, benefiting career progression but often compromising forecast objectivity.

Our motivation stems from a significant research gap in understanding financial analysts' behavior within the banking sector, particularly across global markets. While extensive studies have examined analysts' characteristics, career concerns, and forecast precision, most focus predominantly on the U.S. market and lack the industry-specific insights necessary for capturing the complexities of the banking sector. This omission is critical given the sector's global

[30] Groysberg, Healy, and Maber (2011) found that II all-star analysts earn 61% more than their unrated peers, highlighting strong financial incentives to secure these rankings (Bradley, Gokkaya, and Liu, 2017). This higher pay is partly due to their role in attracting investment banking deals (Clarke et al., 2007). However, the 2003 Global Research Settlement restricted linking analyst pay directly to investment banking. See Appendix A for a review of analyst compensation packages.

economic importance and inherent opacity. Analysts' optimism, boldness, and forecasting reliability are often shaped by economic incentives and potential conflicts of interest, particularly in markets where trading commissions dominate revenue streams. Addressing these dynamics is essential for improving forecast accuracy, safeguarding the credibility of financial analysis, and fostering transparency in the banking industry—a sector where reliable analysis is pivotal for market stability and investor confidence.

2.3. Research Design and Methodology

2.3.1. Measurement of the Proportional Mean Forecast Accuracy

The performance measure employed is the proportional mean absolute forecast error (PMAFE), which evaluates an analyst's forecast accuracy relative to the average forecast accuracy of other analysts following the same stock in a given period. This measure, as utilized by Clement (1999), Brown (1999), Jacob et al. (2000), and Bolliger (2004), is defined as follows:

$$PMAFE_{i,j,t} = \frac{DAFE_{i,j,t}}{mean(\, AFE_{j,t})} \tag{1}$$

where $DAFE_{i,j,t}$ represents the difference between analyst i's absolute forecast error and the mean absolute forecast error for firm j in year t[31].

$$DAFE_{i,j,t} = AFE_{i,j,t} - mean(\, AFE_{j,t} \,) \tag{2}$$

The absolute forecast error ($AFE_{i,j,t}$) is calculated as the absolute difference between an analyst's forecasted earnings per share (EPS) and the actual EPS for the firm in that year, deflated by the actual EPS at the end of the period:

$$AFE_{i,j,t} = \left| \frac{FEPS_{i,j,t} - AEPS_{j,t}}{AEPS_{j,t}} \right| \tag{3}$$

where $FEPS_{i,j,t}$ is the analyst i EPS forecasts for bank j in fiscal year t, and $AEPS_{i,t}$ is the actual EPS for firm j in the same period. PMAFE represents an analyst's forecast error as a fraction of all analysts' average absolute forecast errors for firm j in year t. A negative PMAFE

[31] Clement (1998, 1999) shows that large EPS firms exhibit greater variability in DAFE than small EPS firms and that deflating DAFE by mean(AFE) mitigates heteroscedasticity.

indicates above-average performance, while a positive PMAFE indicates below-average performance. Unlike traditional measures like absolute or relative forecast error, PMAFE enables a consistent comparison of forecast accuracy across firms and time periods unaffected by variations in forecasting difficulty. Factors such as economic conditions (Jacob, 1997) and temporal shifts in available information (Dutta & Nelson, 1996) can influence the ease or challenge of forecasting, yet this measure effectively controls for these variations (Clement, 1998; Bolliger et al., 2004). We applied Clement's (1998) methodology, which highlights that accounting for firm-year effects improves the detection of systematic differences in analysts' forecast accuracy compared to using solely firm-fixed and year-fixed effects. Firm-year effects may arise from events like management disclosures, mergers, or strikes, which can impact the predictability of a firm's earnings for specific years. The PMAFE method addresses these firm-year effects by adjusting an analyst's absolute forecast error with the firm-year average, incorporating analyst *i*'s own forecast error in calculating $AFE_{j,t}$ as they too are influenced by the firm-year effect. We follow Bolliger et al. (2004), including each analyst's last forecast made between the end of the prior fiscal year and the end of the current fiscal year *t* to ensure an adequate sample size[32].

2.3.2. Measures of Analyst General Characteristics

2.3.2.1. Measurement of Experience

To assess the impact of analyst experience on forecast accuracy and market influence, we developed specific metrics to capture both general and specialized expertise, along with two new proxies for cross-regional analysis within the banking sector. These experience metrics provide insights into how analysts' tenure and specialization contribute to forecasting accuracy and market perceptions:

- $GEXP_{i,t}$ (*General Experience*) = Cumulative years through t in which analyst i has issued forecasts, indicating broad expertise and consistency in the forecasting field.
- $BEXP_{i,t}$ (*Bank-Specific Experience*) = Cumulative years through t that analyst i has forecasted for a specific bank, reflecting deeper familiarity with that institution.
- $CEXP_{i,t}$ / $REXP_{i,t}$ (*Country and Region-Specific Experience*): Cumulative years through t that analyst i has issued forecasts for a particular country or region, reflecting in-depth

[32] This restriction applies only to the computation of PMAFE; for other metrics, depending on their definitions, we include all forecasts and revisions made by each analyst within the same period.

expertise in local and regional economic environments and market dynamics supporting robust cross-regional comparisons.

These experience metrics enable an analysis of analysts' effectiveness in the banking sector, from broad market knowledge to institution-specific familiarity, with each analyst's level of expertise assessed relative to peers based on cumulative forecasting activity from 1982 to 2023.

2.3.2.2. Measurement of Portfolio Complexity

To assess the diversity and complexity of an analyst's portfolio, we count the unique IBES ticker codes associated with their forecasts each year. We also evaluate the geographic scope of their coverage by examining the countries and regions of the banks they follow:

- $NBAN_{i,t}$ *(Number of Banks)* = The number of unique banks for which analyst i provided forecasts in year t. A higher NBAN reflects greater portfolio complexity, requiring the analyst to manage and synthesize information from multiple institutions.
- $NCOU_{i,t}$ *(Number of Countries)* = The count of distinct two-digit I/B/E/S country codes associated with the banks covered by analyst i in year t. A higher NCOU suggests a broader specialization across various national markets.
- $NREG_{i,t}$ *(Number of Regions)* = The number of regions covered by analyst iii in year t, indicating geographic diversification. A higher NREG demonstrates the analyst's capacity to navigate different economic and market environments.

2.3.2.3. Analyst Engagement Metrics

This section explores how analyst activity levels relate to forecast accuracy and market impact:

- $NFB_{i,t}$ *(Number of Forecasts/Revisions per Bank)* = The count of forecasts or revisions provided by analyst i for each bank in year t. Higher bank-level activity may reflect greater expertise and deeper focus in specific institutions, potentially enhancing forecast accuracy.
- $NFCOU_{i,t}$ *(Number of Forecasts/Revisions per Country)* = Tracks the number of forecasts or revisions by analyst i at the country level during year t. Frequent country-level forecasting could indicate macroeconomic insight, improving country-specific forecast precision.
- $NFREG_{i,t}$ *(Number of Forecasts/Revisions per Region)* = Counts forecasts or revisions by analyst i at the regional level in year t. Analysts active at the regional level may have

valuable insights into economic conditions and market trends specific to different regions.

- $NFALLL_{i,t}$ *(Total Forecasts/Revisions)* = The total forecasts or revisions provided by analyst i in year t.

2.3.2.4. Measuring Brokerage House Size

To assess how brokerage size impacts forecast accuracy, we classify analysts based on their affiliated brokerage firm's size, following Stickel (1995) and Clement (1999). This approach targets analysts working within larger firms, which generally have better resources, such as superior access to information, advanced analytical tools, and extensive research support, all of which can enhance forecast precision. We define brokerage size and identify the top 5% of brokerage firms as follows:

- $BrokerSize_{i,t}$ *(Brokerage Size)* = Defined by the number of analysts at analyst i's brokerage in year t, with larger firms assumed to provide better resources, supporting forecast accuracy.
- $BIG5_{i,t}$ *(Top 5% Brokerage Firms)* = A dummy variable set to one if analyst i is employed by a top 5% brokerage (by active analyst count) in year t; zero otherwise. Top brokerages often correlate with higher forecast accuracy and better market performance due to superior resources and institutional reputation.

This classification of brokerage size is specifically tailored to analysts active in the banking sector rather than the overall market. By focusing on the banking industry, we aim to align the measure with sector-specific resources and expertise, capturing how brokerage resources support forecast accuracy within a sector characterized by unique regulatory and economic dynamics. However, this approach may not fully reflect brokerages that are widely reputable across the market, potentially diverging from prior studies that consider analyst counts across all industries. To support our methodology of selecting brokerage houses specifically active in the banking industry, we reference Hong and Kubik (2003), which highlights a notable trend in brokerage house specialization in certain industries as opposed to the traditional full-service brokerage houses. By including only brokerage houses active in banking industry, our sample achieves a broker size distribution similar to studies that do not filter by industry. This aligns with Hong and Kubik's (2003) findings on the industry shift since 2003 toward smaller, specialized firms, with a decrease in average brokerage size—from around 21 analysts per firm in 1983 to just over 11 by 2000—reflecting the increasing prevalence of industry-focused brokerage firms. Our reliance on brokerage size data and modeling of analyst movements, such as promotions or demotions (section 2. 5.3), therefore aligns with these industry dynamics, as our mean brokerage house size shows a similar trend, with an average of 11.5 analysts per brokerage, supporting the industry dynamics (Hong and Kubik, 2003 and Hong et al., 2000).

2.3.2.5. Control Variables

Prior research suggests that firm-specific, year-specific effects and forecast age (though context-dependent) should be controlled when evaluating analysts' forecasting performance. The PMAFE method addresses these by adjusting absolute forecast errors to their firm-year means, thus accounting for firm-year effects. We mean-adjust the model's independent variables to firm-year values to control for these effects, as outlined by Greene (1991). The model is specified as follows:

$$Y_{i,j,t} - mean(Y_{j,t}) = (X_{i,j,t} - mean(X_{j,t}))ß \tag{4}$$

Two proxies for Forecast Timeliness are used: $\mathrm{FAGE}_{\mathrm{i,j,t}}$ (Forecast Age), measuring days from fiscal year-end to forecast date for company j in year t, and $\mathrm{FORD}_{\mathrm{i,j,t}}$(Forecast Order), capturing the sequence of forecasts and revisions. Initial forecasts use earlier data, while later revisions may improve accuracy with updated information.

2.3.3. Measures of Analyst Forecast Boldness and Past Performance

2.3.3.1. Forecast Boldness Measurement

We assess an analyst's yearly forecast boldness following a method similar to that of Hong et al. (2000). Boldness is measured by the absolute deviation between an analyst's forecast, F_(i,j,t), and the consensus forecast, $mean(F_{-i,j,t})$:

$$Deviation\ from\ consensus_{i,j,t} = \left|F_{i,j,t} - mean(F_{-i,j,t})\right| \tag{5}$$

where $-i$ represents all analysts except analyst i who provide earnings estimates for firm j in year t, and n is the number of such analysts. The consensus forecast, $mean(F_{-i,j,t})$, is the average of the recent estimates made by other analysts covering firm j in year t. Each year, we rank analysts by their deviation from consensus, with the analyst showing the highest deviation (i.e., boldest) receiving the highest rank. We then calculate a boldness score for each stock in an analyst's coverage portfolio, scaling the analyst's rank by the number of analysts covering the firm. The least bold analyst receives a score of zero, while the boldest analyst receives a top score on a scale from 0 to 100:

$$Score_{i,j,t} = \left| \frac{rank_{i,j,t} - 1}{number\ of\ analysts_{j,t}} \right| * 100 \tag{6}$$

where number of analysts$j,\ t$ is the total count of analysts covering firm j. Each analyst's overall forecast boldness score, BOLDNESS$i,\ j,\ t$, is their boldness score for bank j over the current year t, with higher values indicating bolder forecasts. Additionally, we created a dummy variable (BOLDNESS _Top 20%) for scores in the top 20% of boldness. For job separation models, we used a cumulative boldness score, averaging the analyst's boldness scores over the current year t and the prior three years.

2.3.3.2. Analyst Past Performance Measurement

We now focus on constructing indicators of an analyst's past performance to understand how it affects their probability of job separation. The goal is to rank and score all analysts based on their previous performance. We modified the method of Hong et al. (2000) for this purpose. As mentioned in constructing the proportional mean absolute forecast error (PMAFE), we measure analysts' absolute forecast error ($AFE_{i,j,t}$) as the absolute value of the difference between analysts' forecasts and the corresponding firm-year's actual earnings per share (EPS), deflated by the actual earnings per share at the end of the period. Since an analyst typically covers multiple firms in a year, we aggregate their forecasting accuracy across all the firms they cover. We calculate the forecast errors for each analyst's forecasts for different firms within a year. We then rank and score all analysts based on their previous performance. The average rank of an analyst across all the firms they follow measures their overall accuracy for that year.

To reflect both recent and past forecast accuracy, we compute an overall score as a weighted average of the analyst's scores in year t and all previous years of their active participation. Recent performance is given higher weights, which gradually reduces back to their first forecast performance. This approach overcomes the limitations of prior studies that used a simple average of scores over the current and two previous years (Hong, 2000), which did not account for progress over time and posed challenges for analysts covering firms with low coverage[33].

[33] First, certain types of analysts are likely to have extreme average scores (both good and bad) regardless of their performance. For instance, analysts who cover few firms over the three-year period are more likely to be in the extremes. One very good or poor performance on a firm will greatly affect their average score. Also, analysts who cover thinly followed firms are more likely to be in the extremes. For a given firm, it is easier for an analyst to earn a score near 100 or 0 if there are few other analysts covering the firm in a year.

We then sort all analysts based on their aggregate weighted forecast performance for the year, assigning rankings accordingly: the best analyst receives the first rank, the second-best receives the second rank, and so on until the worst analyst receives the highest rank. This ranking is captured by the metric Past_Per_SCORE, which reflects analyst scores based on their Aggregate Weighted Forecast Performance. For simplicity in analysis, we assign five discrete ranks to analysts (5 for the best analysts and 1 for the worst analysts). Top analysts, defined as those in the top 20th percentile, are indicated by the Top_Performance_index, while the worst analyst is marked by the Poor_Performance_index.

Table B.1 in Appendix B provides a detailed definition of each variable, revealing their respective roles in the analysis.

2.3.4. Estimation Methodology

In this analysis, we use a fixed effects regression model to estimate the impact of various factors on the forecast error metric (PMAFE). We adopt the methodology of Clement (1998), who demonstrated that accounting for firm-year effects enhances the detection of systematic differences in analysts' forecast accuracy compared to models using firm-fixed and year-fixed effects. Additionally, we employ the estimation method introduced by Correia (2017), which estimates linear regressions with multiple levels of fixed effects, thus supporting individual fixed effects with group-level outcomes[34]. Specifically, we specify the model as follows:

$$\begin{aligned} PMAFE_{i,j,t} = & \sum_{k=1}^{4} \alpha_k \,.\, DExperience_{k,i,j,t} + \sum_{m=1}^{4} ß_m \,.\, DPortfolio\_Complexity_{m,i,j,t} \\ & + \sum_{n=1}^{4} \rho_n \,.\, DEngagement_{n,i,j,t} + \ \gamma.DBIG5_{i,j,t} + \ \sigma.DFAGE_{i,j,t} + Bank \\ & - Year\ Fixed\ Effects + \ \varepsilon_{i,j,t} \end{aligned} \tag{7}$$

PMAFE represents an analyst's forecast error as a fraction of all analysts' average absolute forecast errors for firm j in year t. A negative PMAFE indicates above-average performance,

[34] We use the reghdfe command in Stata to implement this model, which is efficient for high-dimensional fixed effects and allows for robust clustering. The syntax used is: *"reghdfe pmfae X, absorb(bank-year) cluster (bank analyst) nocons"*. The absorb(bank-year) option *absorbs* the bank-year fixed effects, which control for any time-invariant characteristics specific to each bank-year observation. The *cluster (bank analyst)* option clusters the standard errors at the bank and analyst levels, accounting for serial correlation within banks and analysts over time. The *nocons* option specifies that we omit the constant term, as it is not needed due to the inclusion of bank-year fixed effects. This model specification allows us to isolate the effect of the independent variables on forecast error while controlling for unobserved heterogeneity at the bank-year level and clustering standard errors to account for potential within-group correlations.

while a positive PMAFE indicates below-average performance. DExperience represents analyst General, regional, country, and bank-specific experience. Portfolio_Complexity represents the number of banks and countries analysts follow. DEngagement shows the number of forecasts and revisions analysts create manually. BIG5 is a proxy for top brokerage firms. Bank-Year Fixed Effects control for unobserved characteristics at the bank-year level that could affect forecast accuracy across analysts and time. Clustered Standard Errors are calculated at both the bank and analyst levels to account for potential correlation within these groups. All variables are adjusted for firm-year means (D indicates differenced). We do not include a constant term, as the means have been subtracted from each variable. A positive (negative) value for the differenced variable indicates that the analyst *i*'s forecast error or characteristic for stock j was above (below) average in year t.

2.4. Research Data

2.4.1. Data Collection

This study utilizes one-year-ahead annual earnings per share (EPS) forecasts (FY1) and actual EPS figures sourced from the Institutional Broker Estimate System (I/B/E/S) US and International Detail History File[35]. To construct a comprehensive sample focused on the banking sector, we carefully integrated data from multiple I/B/E/S files. Each entry in the I/B/E/S Detail Estimate File (DETFILAT) represents an individual forecast or revision, capturing critical details such as the I/B/E/S ticker, broker identifier, analyst identifier, earnings estimate, and forecast date. The unique Analyst Codes and Broker Codes within I/B/E/S ensure consistent identification, even when analysts transition between brokerage firms. However, these codes do not have direct mappings to identifiers in other platforms like Eikon, as I/B/E/S operates as a standalone system without an integrated mapping file. To specifically target bank data, we performed the following steps:

- Bank Identification via TRBC: Using the TRBC (Thomson Reuters Business Classification) file located in the SUPPLEMENTAL_LICENSE folder, we retrieved all tickers classified

[35] *Note on Data Handling:* The IBES FTP system is structured primarily for bulk data retrieval, expecting users to download entire datasets and then apply specific filters independently. This setup presents challenges, requiring row-by-row data extraction for each I/B/E/S ticker, which is then processed through tools like Notepad++ to manage large file sizes efficiently before transfer to Excel or other analytical tools.

under the banking industry. The TRBCDESC file provided the necessary descriptions and industry codes, with “Banks” at level 4 identified by codes 55101010 and 55102010.

- Matching and Cross-Referencing: We mapped I/B/E/S tickers to TRBC PermIDs to identify companies operating within the banking industry, yielding a refined list of 1,733 I/B/E/S tickers across 100 countries from an initial pool of over 44,000 tickers across various sectors.
- Final Bank-Specific Dataset: Using the list of bank tickers, we downloaded and filtered the I/B/E/S estimates file to retain only the data associated with banks. Additionally, from Refinitiv I/B/E/S, we derived a list of publicly traded banks, selecting “primary quotes only” and limiting our scope to specific sectors, including GICS Banks and TRBC Banking Services. Finally, we matched the I/B/E/S and Eikon tickers to confirm a comprehensive selection.

The initial dataset includes forecasts from December 1982 to March 2023, comprising over 509,868 annual earnings forecasts by more than 1,271 brokers and 7,796 analysts, covering 570 publicly traded commercial banks across 40 countries. This sample spans four global regions—U.S., Europe, Asia, and Canada —and captures data from 1981 to 2023. For data consistency, we applied several restrictions: forecasts were required to be issued between the fiscal year-end of the previous year and the end of the current fiscal year; realized earnings per share (EPS) had to be available in the I/B/E/S Actual File; banks needed to be followed by at least three analysts; and selected countries had to have substantial analyst coverage and a sufficient number of forecasts. Additionally, Canadian banks were excluded from the analysis due to statistical discrepancies with U.S. data. These criteria produced a final sample of 398,175 forecasts from 5,647 analysts employed by 901 brokerages, focusing on 516 publicly traded banks across 29 countries. Tables A1 and A2 in the Appendix summarize the I/B/E/S dataset statistics and provide a geographical breakdown of the sample.

2.4.2. Descriptive Statistics of Raw Variables

This section presents the descriptive statistics for the raw (undifferenced) variables, as computed according to the methodology outlined in Section 2. 3. Table 2. 1 offers a comprehensive overview of financial analysts' characteristics across different regions, encompassing forecast bias, experience, portfolio size, complexity, engagement, activity, brokerage house dynamics, and forecast timing preferences. The dataset analysis reveals that financial analysts, on average, possess a tenure of slightly over seven years. However, a notable discrepancy emerges when comparing regional averages: US financial analysts boast an average tenure of approximately nine years, while their European counterparts exhibit an average tenure of about 6.5 years. Asian financial analysts demonstrate the lowest average tenure, with an average of 5.8 years. Furthermore, in terms of bank experience (BEXP), US analysts also lead with a mean of 4.91 years, while European analysts average 4.16 years and Asian analysts average 3.73 years. This observation suggests a higher turnover rate within the financial analysis profession in Europe and Asia than in the US, consistent with Bolliger's (2003) findings.

On average, analysts globally track around nine banks annually, with notable regional differences. US analysts handle a more significant workload, covering an average of 12.41 banks annually, compared to 5.85 banks for European analysts and 7.67 banks for Asian analysts. Regarding the number of countries (NCOU) analysts cover, European analysts show a broader geographical scope with an average of 2.41 countries, whereas Asian analysts cover fewer than 1.4 countries. The broader coverage of European analysts indicates a more diversified portfolio than their US and Asian counterparts. A key aspect of analyst behavior is their level of engagement and activity in issuing forecasts and revisions. Globally, analysts issue approximately 4.5 forecasts and revisions per year for each bank. However, regional differences are notable: US and European analysts issue around five forecasts per bank annually, while Asian analysts issue approximately 3.7. This discrepancy highlights a substantial disparity in forecasting intensity. US analysts issue 66 forecasts and revisions per year, compared to 31 by their European counterparts and 29 by Asian analysts. The relatively lower forecasting activity among European and Asian analysts may be attributed, in part, to less stringent corporate disclosure requirements prevalent in many European and Asian countries, often resulting in limited availability of timely financial information. The higher activity levels among US analysts suggest a more dynamic and competitive market environment, necessitating more frequent forecast updates and revisions.

The average size of brokerage houses (BrokerSize) is relatively consistent across regions, with US firms employing about 11.49 analysts on average, European firms employing around 12.02 analysts, and Asian firms employing about 11.45 analysts. The presence of top-tier analysts (BIG5) also shows a similar distribution across regions. These findings align closely with the observations documented by Hong and Kubik (2003) for the US market, indicating a similar scale of financial analysis of labor markets across the three regions.

The boldness of forecasts, represented by the BOLDNESS score, shows European analysts being the boldest with a mean score of 52.62, followed by Asian analysts at 49.08 and US analysts at 48.51. The proportion of top 20% boldness (BOLDNESS_Top 20%) further supports this, with 27.8% of European analysts in the top 20% boldness category, compared to 24.8% of US analysts and 23.9% of Asian analysts. This indicates that European analysts are likelier to deviate from consensus forecasts than their US and Asian peers. Regarding past performance scores (Past_Per_SCORE), US analysts have a higher mean score of 2.543 compared to European analysts at 1.872 and Asian analysts at 2.089. This ranking reflects better overall past performance for US analysts. The proportion of top analysts (D_TOP_Performance) further supports this, indicating that 32% of US analysts are categorized as top performers, compared to 14.7% of European analysts and 20.7% of Asian analysts. This distribution highlights the higher concentration of top performers among US analysts. European financial analysts exhibit a notable optimistic bias, with a mean value of approximately 0.42, while their Asian counterparts display a slightly lower bias, averaging around 0.31. In contrast, analysts from the US demonstrate the lowest level of optimism, with a mean bias of 0.23. The relative forecast accuracy, measured by the proportional mean absolute forecast error (PMAFE), shows US analysts with an average PMAFE of -0.023, European analysts with -0.013, and Asian analysts with -0.016. These values suggest that US analysts have the highest accuracy, followed by Asian and European analysts. These negative values indicate that European and Asian analysts overestimate future performance, while US analysts exhibit a slightly lower tendency to do so.

In summary, US analysts demonstrate lower forecast bias, longer tenure, and higher engagement levels compared to their European and Asian counterparts. They also cover more banks and issue significantly more forecasts annually, indicative of a more dynamic and competitive market environment. European analysts, while slightly more experienced than their Asian counterparts, exhibit higher forecast bias, specifically higher levels of optimism in their forecasts, and cover fewer banks, but their coverage spans a broader geographical area. In contrast, Asian analysts tend to cover more banks concentrated within a single country, reflecting distinct regional market dynamics. These findings underscore the importance of considering regional differences when evaluating financial analysts' performance and the factors influencing their forecast accuracy.

Table 2. 1 Descriptive Statistics for the Raw Variables

		All Sample			US Analysts			European Analysts			Asian Analysts		
Category	Obs	Mean	Std Dev.	Median	Mean	Std Dev.	Median	Mean	Std Dev.	Median	Mean	Std Dev.	Median
Experience													
GEXP	398,175	7.10	5.05	6.00	8.94	5.65	8.00	6.54	4.75	5.00	5.83	4.09	5.00
CEXP	398,175	6.51	4.94	5.00	8.86	5.62	8.00	5.25	4.28	4.00	5.31	3.84	4.00
REXP	398,175	7.02	5.01	6.00	8.86	5.62	8.00	6.46	4.72	5.00	5.76	4.05	5.00
BEXP	398,175	4.31	3.59	3.00	4.91	3.86	4.00	4.16	3.50	3.00	3.73	3.21	3.00
Portfolio Size & Complexity													
NBAN	398,175	8.68	5.68	7.00	12.41	6.48	12.00	5.85	3.39	5.00	7.67	4.60	7.00
NCOU	398,175	1.55	1.12	1.00	1.04	0.23	1.00	2.41	1.53	2.00	1.35	0.80	1.00
NREG	398,175	1.05	0.21	1.00	1.03	0.17	1.00	1.03	0.18	1.00	1.07	0.26	1.00
Analysts Engagement & Activity													
NFB	398,175	4.51	3.04	4.00	4.92	2.82	5.00	5.03	3.31	5.00	3.55	2.77	3.00
NFCOU	398,175	36.83	35.80	25.00	65.50	43.10	59.00	17.98	17.81	13.00	25.13	19.90	21.00
NFREG	398,175	41.78	35.23	32.00	65.51	43.09	59.00	30.55	23.77	26.00	28.81	21.94	24.00
NFAll	398,175	42.46	35.46	33.00	66.01	43.36	60.00	31.29	23.83	27.00	29.34	22.24	25.00
Forecast Timing													
FORD	398,175	3.24	2.24	3.00	3.40	2.20	3.00	3.57	2.45	3.00	2.77	2.00	2.00
FAGE	398,175	201	104	195	201	102	186	197	106	198	206	104	204
Boldness													
BOLD	398,175	1.89	5.08	0.13	0.28	0.86	0.08	1.60	4.16	0.25	3.89	7.32	0.19
BOLDNESS	398,175	50.02	33.28	51.35	48.51	34.17	50.00	52.62	32.65	55.38	49.08	32.89	50.00
BOLDNESS_Top 20%	398,175	0.254	0.44	0.000	0.248	0.43	0.000	0.278	0.45	0.000	0.239	0.43	0.000
Brokerage House													
BrokerSize	398,175	11.49	10.47	7.00	11.49	9.80	7.00	12.02	10.74	8.00	11.45	10.81	7.00
BIG5	398,175	0.364	0.48	0.000	0.358	0.48	0.000	0.361	0.48	0.000	0.387	0.49	0.000
Analyst Performance													
Past_Per	398,175	0.43	0.69	0.18	0.380	0.59	0.17	0.560	0.85	0.25	0.393	0.61	0.17
Past_Per_SCORE	398,175	2.23	1.47	2.00	2.543	1.43	3.00	1.872	1.36	2.00	2.089	1.45	2.00
D_TOP_Performance	398,175	0.25	0.43	0.00	0.320	0.47	0.00	0.147	0.35	0.00	0.207	0.41	0.00
Forecast Error													
AFE	398,175	0.313	0.69	0.087	0.232	0.57	0.056	0.428	0.79	0.150	0.314	0.71	0.090
PMAFE	106,355	-0.017	0.82	-0.162	-0.023	0.88	-0.200	-0.013	0.81	-0.147	-0.016	0.80	-0.144

2.5. Empirical Result

2.5.1. Analyst Characteristics and Relative Forecast Accuracy

The accuracy of financial forecasts is pivotal to decision-making within the banking sector, yet the factors influencing an analyst's forecasting accuracy are far from uniform across regions. This section investigates how specific analyst characteristics, such as experience level, brokerage house affiliation, and sector specialization, contribute to forecast accuracy and optimism within the U.S., European, and Asian banking markets. By dissecting these regional variations, we aim to uncover the underlying dynamics that drive forecasting success in the banking sector.

2.5.1.1. Regression variables

Table B.4 in Appendix B presents the correlation matrix for the regression variables used in Eq. (7), highlighting their relationships with forecast accuracy across global and regional samples. The findings reveal a strong positive correlation between forecast accuracy and the four experience measures (DGEXP, DCEXP, DREXP, DBEXP), emphasizing the importance of accumulated expertise in enhancing forecast precision. Globally, forecast accuracy increases with the number of banks covered (DNBAN) but decreases as geographical diversification (DNCOU) rises, reflecting the complexity of managing cross-country institutional contexts—a pattern consistent across regions except Europe. Frequent forecasts (DNFB, DNFALL) improve accuracy due to greater market engagement and responsiveness to new information. Moreover, affiliation with larger brokerage houses (DBIG5) correlates positively with forecast accuracy globally and regionally. Lastly, more recent forecasts (DFAGE) are typically more accurate, whereas earlier forecasts (DFORD) show lower precision due to limited initial information.

2.5.1.2. Regression Result

Table 2 presents the findings from Eq. (7), examining the relationship between forecast accuracy, measured by Proportional Mean Absolute Forecast Error (PMAFE), and various analyst characteristics for the global sample. The analysis incorporates variables such as portfolio complexity and geographical diversification (DNBAN, DNCOU), brokerage house size (DBIG5), analyst experience (DGEXP, DCEXP, DREXP, DBEXP), forecast frequency (DNFALL), and forecast timing (DFAGE) as controls. Due to high multicollinearity among experience variables and between portfolio complexity measures (DNBAN, DNCOU) and forecast activity (DNFALL), these variables are used separately in the regressions.

The results reveal that analysts affiliated with larger brokerage houses (DBIG5) tend to produce more accurate forecasts, as evidenced by negative and significant coefficients across all models. Similarly, all experience variables (DGEXP, DCEXP, DREXP, DBEXP) exhibit negative and significant coefficients, with bank-specific experience (DBEXP) having the most pronounced effect on improving forecast accuracy. Furthermore, portfolio complexity demonstrates a nuanced impact: while the number of banks covered (DNBAN) is negatively associated with forecast errors, geographical diversification (DNCOU) is positively and significantly linked to errors, particularly in columns 4-6. This divergence from prior research underscores the unique challenges of covering diverse institutional contexts in the banking sector. Additionally, the analysis shows that frequent updates, as measured by forecast activity (DNFB, DNFALL), improve forecast accuracy, as indicated by negative and significant coefficients, emphasizing the benefits of timely revisions. Regarding forecast timing, more recent forecasts (DFAGE) are consistently associated with higher accuracy, whereas initial forecasts (DFORD) are less precise due to limited early-period information. These findings provide critical insights into the interplay of institutional affiliation, analyst experience, portfolio complexity, and forecast timing in shaping forecast precision.

These findings challenge earlier studies (e.g., Clement, 1999; Lim, 2001; Bolliger, 2004; Hong et al., 2000), which found that analysts with smaller portfolios produce more accurate forecasts. Unlike prior research that included multiple industries, this study focuses exclusively on the banking sector, revealing industry-specific dynamics that influence forecast precision. This highlights the unique challenges analysts face when balancing portfolio complexity and maintaining accuracy in the opaque banking industry.

Table 2. 2: Relative Forecast Error and Individual Analysts' Characteristics

Dependent Variable	Relative Forecast Error _ PMAFE					
Global Regression Results						
	(1)	(2)	(3)	(4)	(5)	(6)
DGEXP	-0.00608***					
	(-5.45)					
DCEXP		-0.00650***				
		(-5.49)				
DREXP			-0.00634***			
			(-5.69)			
DBEXP				-0.00683***	-0.00647***	-0.00615***
				(-4.85)	(-4.82)	(-4.48)
DNBAN	-0.00360***	-0.00397***	-0.00357***			
	(-2.66)	(-3.01)	(-2.64)			
DNCOU				0.00927*	0.0175***	0.00962*
				1.8	3.15	1.87
DBIG5	-0.0406***	-0.0442***	-0.0411***	-0.0451***	-0.0433***	-0.0420***
	(-4.12)	(-4.47)	(-4.18)	(-4.51)	(-4.31)	(-4.19)
DNFB	-0.00537***	-0.00490***	-0.00529***	-0.00565***		
	(-3.17)	(-2.91)	(-3.13)	(-3.27)		
DFORD					-0.00110***	
					(-5.21)	
DNFAll						-0.0234***
						(-5.83)
DFAGE	0.270***	0.270***	0.271***	0.269***	0.269***	0.259***
	25.48	25.46	25.48	25.49	25.51	25.2
Observations	106124	106124	106124	106124	106124	106124
Number of banks	516	516	516	516	516	516
R-square	0.136	0.136	0.136	0.135	0.135	0.135

Table 2. 2 shows the regression results (Eq. 7) analyzing the effect of various analyst characteristics on relative forecast error (PMAFE), defined as the difference between the absolute forecast error for analyst i for bank j at time t and the mean absolute forecast error for that bank at the same time. Key independent variables include portfolio complexity and geographical diversification (DNBAN for number of banks covered and DNCOU for number of countries covered), brokerage house size (DBIG5, indicating if the analyst is affiliated with a top-tier brokerage), analyst experience (DGEXP for general experience, DREXP for regional experience, DCEXP for country-specific experience, and DBEXP for bank-specific experience), forecast frequency (DNFB for forecasts issued per bank and DNFALL for total forecasts issued by the analyst), forecast order (DFORD), and forecast timing (DFAGE) as a control for forecast timing relative to the fiscal period. Statistical significance is marked by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

2.5.1.3. Determinants of Forecast Accuracy Across Regions

Table 2.3 presents the results of regional-based regressions, examining how individual analyst characteristics affect relative forecast error (PMAFE) across the US, Europe, and Asia. The analysis highlights the critical role of financial analysts' experience in shaping forecast accuracy across these regions. General experience (DGEXP) consistently demonstrates a negative and statistically significant relationship with forecast error, indicating that increased experience enhances forecast precision. This trend is most pronounced in the US, where forecast errors see the largest reduction, while bank-specific experience (DBEXP) also significantly reduces errors across all regions, with the US showing the strongest effect[36]. A one-standard-deviation increase in analyst experience is associated with a 2.5–3.1% reduction in relative forecast error (PMAFE), with the effect exceeding 7.2% in the US market. This underscores the critical value of accumulated expertise in enhancing forecasting precision, particularly in the complex banking sector.

Portfolio size and complexity reveal divergent effects across regions. In the US, DNBAN (number of banks covered) improves forecast accuracy, while in Europe, higher bank coverage correlates with increased forecast errors due to the complexity introduced by geographical diversification. This phenomenon is further explored in Section 2. 5.1.4, which investigates the reasons behind reduced accuracy for European analysts covering more banks. Similar to global trends, higher bank coverage in Asia reduces forecast errors. Conversely, DNCOU (number of countries covered) consistently increases forecast errors across all regions, particularly in Europe. A plausible explanation, as suggested by Bolliger (2003), is that European analysts covering companies across diverse countries may lack the institutional familiarity required for accurate forecasting in such varied contexts. Economic interpretation also shows that covering more banks is linked to a 3.4% reduction in PMAFE globally, with the effect rising to 5.3% in the U.S. In contrast, European analysts experience a 2.1% increase in PMAFE, indicating that the added complexity of managing diverse portfolios may hinder accuracy in this region. Geographical complexity presents another challenge, with a one standard deviation increase in cross-country coverage driving a 1.4–2.7% rise in PMAFE. This reflects the difficulty of navigating diverse institutional and market conditions, highlighting the trade-offs between broader coverage and forecast precision. Brokerage house size (DBIG5) is negatively and significantly correlated with forecast error across all regions, indicating that analysts affiliated

[36] These findings align with prior research, such as Clement (1999), but contrast with studies by Hong et al. (2000), Jacob et al. (2000), and Bolliger (2003), which found no "learning-by-doing" effect among European analysts.

with larger brokerage firms benefit from enhanced resources and institutional support, leading to more precise forecasts. The impact is strongest in the US and Asia; in Europe, the effect is weaker but still statistically significant[37]. Affiliation with top-tier brokerage houses contributes to an approximate 1.6% decrease in PMAFE globally, reaching a pronounced 3.1% reduction in the U.S. market. This demonstrates the pivotal role of institutional support and resources in improving forecast accuracy.

These findings underscore the importance of analyst experience, portfolio management, forecasting activity, and institutional resources in determining forecast accuracy across regions. They also highlight the need for further investigation into the regional disparities, particularly in Europe, where institutional and market-specific factors significantly influence forecasting precision.

Table 2. 3: Relative Forecast Error and Individual Analysts' Characteristics

Dependent Variable	Relative Forecast Error _ PMAFE							
Regional Regression Results								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US	US	EU	EU	EU	ASIA	ASIA	ASIA
DGEXP	-0.0128***		-0.00504**			-0.00609***		-0.00609***
	(-5.72)		(-2.10)			(-3.36)		(-3.36)
DBEXP		-0.0120***		-0.00528***	-0.00416**		-0.00416**	
		(-6.82)		(-2.74)	(-2.14)		(-2.14)	
DNBAN	-0.00516***	-0.00824***	0.00540*	0.00626**		-0.00392**		-0.00392**
	(-3.19)	(-4.71)	1.8	2.05		(-2.12)		(-2.12)
DNCOU					0.0137**		0.0137**	
					2.18		2.18	
DBIG5	-0.0511**	-0.0648***	-0.0459**	-0.0423**	-0.0409**	-0.0459***	-0.0409**	-0.0459***
	(-2.54)	(-3.34)	(-2.41)	(-2.23)	(-2.12)	(-3.48)	(-2.12)	(-3.48)
DNFB		0.000549			-0.00584**		-0.00584**	
		-0.15			(-2.38)		(-2.38)	
DFAGE	0.447***	0.450***	0.206***	0.206***	0.204***	0.234***	0.204***	0.234***
	26.77	27.16	14.05	14.07	13.93	19.33	13.93	19.33
Observations	29775	29775	28559	28559	28559	44809	28559	44809
Number of banks	230	230	90	90	90	186	90	186
R-square	0.206	0.208	0.113	0.113	0.113	0.129	0.113	0.129

Table 3 presents the regression results (Eq. 7) for regional-based regressions, analyzing the impact of individual analyst characteristics on relative forecast error (PMAFE) across the US, Europe, and Asia. PMAFE, the dependent variable, represents the difference between the absolute forecast error for analyst iii for bank j at time t and the mean absolute forecast error for that bank at the same time. Key independent variables include portfolio complexity and geographical diversification (DNBAN for number of banks covered and DNCOU for number of countries covered), brokerage house size (DBIG5 for top-tier brokerage affiliation), analyst experience (DGEXP for general experience and DBEXP for bank-specific experience), forecast frequency (DNFB for total forecasts issued by the analyst for each bank), and forecast timing (DFAGE). Statistical significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

[37] Bolliger (2004) posits that insufficient centralization of research operations within large European brokerage houses may reduce their effectiveness, whereas medium and small local brokerage firms specializing in specific countries or sectors may hold informational advantages over their larger counterparts.

2.5.1.4. Portfolio Complexity and Regional Disparities

This section further investigates how portfolio complexity affects forecast accuracy, focusing on European analysts. In Section 2. 5.1.2, we observed that while covering more banks (DNBAN) improves forecast accuracy globally, it increases forecast errors in Europe, likely due to the complexities of a diversified portfolio. Cross-country coverage (DNCOU) also consistently raises forecast errors across all regions, suggesting challenges in adapting to diverse institutional contexts (Bolliger, 2003). Table 2. 4 presents regression results on how portfolio complexity (DNBAN, DNCOU), top brokerage affiliation (DBIG5), and their interactions impact relative forecast error (PMAFE) across the EU, US, and AS regions. For Europe, Column (2) shows a positive and significant interaction between DNBAN and DNCOU, indicating that geographical diversification amplifies the negative effect of covering more banks on forecast accuracy. This suggests that managing banks across multiple countries adds complexity, reducing accuracy. A similar trend is observed in Asia (Column 4), where greater portfolio complexity is linked to higher forecast errors, highlighting the forecasting challenges in diverse settings. European analysts generally handle a wider geographic range—covering an average of 2.41 countries but fewer banks (5.85) than their Asian counterparts, who cover 7.67 banks within fewer countries (~1.4). This contrast in approach—European analysts with broader geographic scope versus Asian analysts with more banks in concentrated regions—helps explain regional disparities in forecast accuracy seen in Tables 2.2 and 2.3. Regarding affiliation with a top broker, as all models show, DBIG5 is associated with reduced forecast errors, with stronger effects in the U.S. and Asia but weaker impacts in Europe. However, the interaction terms suggest that top brokerage affiliation marginally appears to alleviate the decrease in forecast accuracy related to managing a larger, diversified portfolio (column 3).

Our findings suggest that industry-specialized financial analysts with large portfolio sizes and limited geographical coverage produce more accurate forecasts; we can also conclude that more skilled analysts are assigned a more significant number of banks. However, this result is challenging for brokerage houses covering Europe that seek to find an optimal structure for their research operation. Indeed, an industry-organized research department increases forecast accuracy through the industry specialization effect but also increases the number of countries to be covered, which, to some extent, challenges the accuracy of earnings forecasts.

Table 2. 4: Relative Forecast Error and Portfolio Complexity

Dependent Variable	Relative Forecast Error _ PMAFE				
	(1)	(2)	(3)	(4)	(5)
	US	EU	EU	ASIA	ASIA
DNBAN* DNCOU		0.00348**		0.00365**	
		2.28		2.14	
DNBAN	-0.00327*	0.00318	0.00585**	-0.00238	-0.00204
	(-1.83)	0.8	2.12	(-1.06)	(-1.05)
DNCOU		0.00113		0.0177*	
		0.13		1.8	
DNBAN* DBIG5	-0.0018		-0.00935*		0.00562**
	(-0.56)		(-1.75)		2.01
DBIG5	-0.0652***	-0.0364*	-0.0369*	-0.0422***	-0.0387***
	(-3.36)	(-1.97)	(-1.97)	(-3.22)	(-2.92)
DGEXP	-0.0120***	-0.00420**	-0.00417**	-0.00327**	-0.00341**
	(-6.82)	(-2.19)	(-2.11)	(-2.00)	(-2.10)
DNFB	0.000584	-0.00521**	-0.00638**	-0.00961***	-0.0108***
	0.16	(-2.18)	(-2.58)	(-3.71)	(-4.18)
DFAGE	0.450***	0.203***	0.204***	0.232***	0.232***
	27.16	13.9	13.98	19.42	19.36
Observations	29775	28559	28559	44809	44809
Number of banks	230	90	90	186	186
R-square	0.208	0.114	0.114	0.13	0.129

Table 4 presents the regression results based on Eq. (7), examining how portfolio complexity influences relative forecast error (PMAFE) across different regions (EU, US, and AS). Key interaction terms include DNBAN (number of banks covered) combined with DNCOU (number of countries covered) and DBIG5 (affiliation with a top brokerage). The dependent variable, PMAFE, represents the difference between the absolute forecast error for analyst iii for bank j at time t and the mean absolute forecast error for that bank at the same time. Other variables include analyst general experience (DGEXP), forecast frequency (DNFB), and forecast timing (DFAGE). Statistical significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

2.5.2. Boldness, Forecasting Accuracy, and Career Concerns

Economic incentives drive patterns of optimism, boldness, and herding behavior, often undermining objectivity. Analysts frequently issue optimistic. Issuing bold forecasts can be a strategic career move for analysts, influenced by both ambition and reputation-building. Herding theories (e.g., Hong et al., 2000) suggest that future career outcomes may be shaped not only by an analyst's past performance but also by bold or unconventional forecasts that deviate significantly from the consensus. The section investigates the incentive-driven dynamics of forecasting behavior, focusing on the relationship between boldness, ability, and career concerns, investigating whether bold forecasts are perceived as indicators of expertise or risk-taking. We assess whether seasoned analysts approach boldness differently from their less experienced counterparts and examine regional differences in these behaviors.

2.5.2.1. Boldness and Relative Forecast Error

In this section, we begin by examining whether analysts who issue bold forecasts demonstrate higher accuracy than their peers across various regions. Our analysis extends to examine how experience level, brokerage size, and portfolio complexity interact with boldness to influence forecast accuracy. To conduct this, we extend our baseline model (Eq. 7) by integrating a forecast boldness proxy, as introduced in Section 2. 3.3.1: DBOLDNESS $_{i,\ j,\ t}$, representing analyst i's boldness score for bank j at time t. Our enhanced model (Eq. 8) is formulated as follows:

$$
\begin{aligned}
PMAFE_{i,j,t} = {} & \alpha \boldsymbol{DBOLDNESS}_{i,j,t} + \sum_{k=1}^{4} \alpha_k \, . DExperience_{k,i,j,t} \\
& + \sum_{m=1}^{4} ß_m \, . DPortfolio\_Complexity_{m,i,j,t} + \sum_{n=1}^{4} \rho_n \, . DEngagement_{n,i,j,t} \\
& + \gamma . DBIG5_{i,j,t} + \sigma . DFAGE_{i,j,t} + \varepsilon_{i,j,t}
\end{aligned}
\tag{8}
$$

In Table 2. 5, we present regression results on the relative forecast error (PMAFE) with a particular focus on boldness (DBOLDNESS) alongside experience (e.g., DGEXP), bank coverage (DNBAN), and affiliation with a major brokerage (DBIG5) as well as other control variables. The results reveal a general trend of higher forecast errors associated with boldness in the full sample, implying that bolder forecasts tend to exhibit less accuracy. However, regional differences emerge: in the U.S., bolder analysts achieve higher accuracy in forecasts, a finding that contrasts with Europe and Asia, where boldness correlates with increased forecast errors. This nuanced relationship is consistent with the broader trend yet points to potential regional dynamics affecting forecasting efficacy. Notably, our findings in the U.S. align with prior research, suggesting that bold forecasts may enhance accuracy in certain contexts, whereas Europe and Asia warrant further investigation into the specific factors driving forecast errors associated with boldness in these markets.

Table 2. 5: Boldness and Relative Forecast Error

Dependent Variable	Relative Forecast Error _ PMAFE			
	(1)	(2)	(3)	(4)
	All	US	EU	ASIA
DBOLDNESS	**0.00232*** **	**-0.00136*** **	**0.00332*** **	**0.00328*** **
	6.29	(-3.04)	5.54	5.68
DGEXP	-0.00611***	-0.0120***	-0.00421**	-0.00353**
	(-5.59)	(-6.82)	(-2.31)	(-2.25)
DNBAN	-0.000781	-0.00319*	0.00576**	0.000348
	(-0.58)	(-1.80)	2	0.17
DBIG5	-0.0404***	-0.0651***	-0.0366**	-0.0375***
	(-4.19)	(-3.36)	(-2.03)	(-2.92)
DNFB	-0.00512***	0.000666	-0.00626**	-0.0113***
	(-3.06)	0.18	(-2.59)	(-4.57)
DFAGE	0.282***	0.452***	0.216***	0.245***
	27.11	28.05	15.04	20.55
Observations	106124	29775	28559	44809
Number of banks	516	230	90	186
R-square	0.148	0.208	0.135	0.151

Table 4 presents regression results based on Eq. (8), analyzing the relationship between forecast boldness and relative forecast error (PMAFE) across regions: global (All), United States (US), Europe (EU), and Asia (ASIA). The dependent variable, PMAFE, captures the difference between the absolute forecast error for analyst i forecasting for bank j at time t and the mean absolute forecast error for that bank during the same period. Key independent variables include DBOLDNESS i,j,t, representing the analyst i's boldness score for bank j at time t, alongside other controls: analyst general experience (DGEXP), portfolio size (DNBAN, the number of banks covered), top brokerage affiliation (DBIG5), forecast frequency (DNFB), and forecast timing (DFAGE). Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

- Forecast Boldness: Marginal effects of Experience, Brokerage, and Portfolio Size

This section explores factors moderating forecast errors associated with boldness, particularly in European and Asian markets, focusing on bank-specific experience, top brokerage affiliation, and portfolio complexity. Table 2. 6 analyzes the interaction effects of boldness (DBOLDNESS) with bank-level experience (DBEXP), Big Five affiliation (DBIG5), and the number of banks covered (DNBAN). Bold forecasts are consistently associated with higher errors, as indicated by positive and significant DBOLDNESS coefficients. In Europe, affiliation with a Big Five brokerage (DBIG5) significantly reduces errors, and the negative interaction term (DBOLDNESS*DBIG5) shows that bold forecasts from these firms are more accurate. While DBEXP lowers forecast errors, its interaction with boldness is insignificant, indicating no notable combined effect. Likewise, the DBOLDNESS*DNBAN interaction is insignificant; however, in Europe increased bank coverage slightly raises errors for extreme bold predictions (DBOLDNESS_Top20% * DNBAN), suggesting portfolio complexity may heighten inaccuracies. Similar patterns are evident in Asia, where bold forecasts are more accurate when issued by analysts affiliated with top brokerage houses, experienced professionals, and those managing focused portfolios. Overall, bold forecasts are generally less accurate, but the impact varies across regions and is moderated by factors like institutional affiliation and portfolio scope, highlighting a nuanced relationship between boldness, accuracy, and analyst characteristics.

Table 2.6: Relative Forecast Error and Forecast Boldness with Marginal Effect Analysis

Dependent Variable	Relative Forecast Error _ PMAFE					
	BOLDNESS SCORE				BOLDNESS_Top 20%	
	(1)	(2)	(3)	(4)	(5)	(6)
	US	EU	ASIA	US	EU	ASIA
DBOLDNESS	-0.00135***	0.00327***	0.00326***	0.0132	0.288***	0.293***
	(-3.01)	5.5	5.72	-0.43	-6.69	-5.83
DBOLDNESS*DBIG5	0.000457	-0.00204***	-0.000819*	0.0056	-0.144***	-0.0569
	0.75	(-3.21)	(-1.72)	-0.13	(-3.18)	(-1.58)
DBOLDNESS*DBEXP	-0.0000852	0.0000588	-0.0000332	-0.00622	0.00501	-0.00288
	(-1.19)	0.9	(-0.50)	(-1.06)	-1.02	(-0.51)
DBOLDNESS*DNBAN	-0.0000625	0.000135	0.0000561	-0.00948**	0.0128*	0.00574
	(-1.24)	1.27	0.83	(-2.58)	-1.96	-0.96
DBIG5	-0.0571***	-0.0328*	-0.0383***	-0.0562***	-0.0346**	-0.0390***
	(-3.01)	(-1.97)	(-3.14)	(-2.90)	(-2.05)	(-3.13)
DBEXP	-0.0129***	-0.00369	-0.00337*	-0.0132***	-0.00332	-0.00345*
	(-5.91)	(-1.58)	(-1.94)	(-5.75)	(-1.42)	(-1.93)
DNBAN	-0.00505***	0.00444*	-0.000426	-0.00552***	0.00457*	-0.000205
	(-3.08)	-1.69	(-0.23)	(-3.32)	-1.77	(-0.10)
DFB	0.00333	-0.00638**	-0.0108***	0.00345	-0.00669***	-0.0112***
	0.85	(-2.46)	(-4.31)	-0.89	(-2.71)	(-4.53)
DFAGE	0.450***	0.216***	0.244***	0.451***	0.212***	0.239***
	27.96	14.97	20.54	-27.14	-14.55	-19.88
Observations	29775	28559	44809	29775	28559	44809
Number of banks	230	90	186	230	90	186
R-square	0.206	0.136	0.151	0.205	0.146	0.159

Table 6 extends the analysis of the relationship between forecast boldness and relative forecast error (PMAFE), incorporating marginal effect interactions. The table explores how boldness (DBOLDNESS) interacts with key variables such as portfolio size (DNBAN), bank-specific experience (DBEXP), and top brokerage affiliation (DBIG5) across different regions (EU, Asia, and US). The dependent variable, PMAFE, represents the difference between the absolute forecast error for analyst iii forecasting for bank j at time t and the mean absolute forecast error for that bank during the same period. Key independent variables include DBOLDNESS (i,j,t), representing the boldness score for analyst iii covering bank j at time t, and BOLDNESS_Top 20%, a dummy variable indicating if the boldness score falls in the top 20%. Interacting variables include general experience (DGEXP), portfolio size (DNBAN), and top brokerage affiliation (DBIG5). Other control variables include forecast frequency (DNFB) and forecast timing (DFAGE). Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

2.5.2.2. Forecast Boldness and Analyst Characteristics

In this section, we investigate how career concerns influence financial analysts' tendency to issue bold forecasts. Specifically, we examine the role of experience and past performance, focusing on regional variations to understand how these factors, along with career-related motivations, shape analysts' forecasting behavior. Our empirical approach analyzes how career concerns affect forecast accuracy and the likelihood of deviating from consensus estimates. We link forecast boldness to specific analyst characteristics, particularly the differences between younger and more experienced analysts, as captured by past forecast performance.

Additionally, we account for firm-specific influences by including a brokerage house effect as a proxy. To further explore the relationship between experience and deviation from consensus forecasts, we specify the following regression model, building on prior research (Hong et al., 2000; Clement, 2005) to capture how analyst characteristics beyond experience contribute to forecast boldness. The probit model is structured as follows:

$$\begin{aligned} Deviation\ from\ Consensus_{i,j,t} &= \alpha + ß1 Experience_{i,j,t} + ß2\ Past\ Performence_{i,t} \\ &+\ ß3\ Brokerage\ House_{i,t} +\ + ß4 Portfolio\_Complexity_{i,j,t}\ {}_{+}\varepsilon_{i,j,t} \end{aligned} \tag{9}$$

Where Deviation from Consensus (BOLDNESS_Top 20%) is A binary variable indicating if analyst i's forecast for firm j in year t ranks in the top 20% for boldness. It equals 1 if the forecast's boldness score is above the 80th percentile. Experience: Includes both analyst regional experience (REXP) and bank-specific experience (BEXP). Past Performance (Past_Per_SCORE): A proxy for prior forecasting accuracy, as detailed in section 2.3.3.1. Portfolio Complexity (NBAN): Measured as the number of banks an analyst covers. Brokerage House Affiliation (BIG5): A variable capturing the effect of affiliation with one of the top five brokerage firms.

Table B.5 in Appendix B presents the Spearman rank correlation coefficients for the regression variables across different regions. The results highlight regional variations in the relationship between boldness (measured by BOLDNESS and BOLDNESS_TOP20%) and other analyst characteristics. In the U.S. and Asia, bold forecasts are associated with analysts who have higher bank-specific and regional experience, better past performance, and affiliations with top brokerage firms. However, in Europe, this relationship appears to be inversed, indicating potential regional differences in how experience and brokerage affiliation influence forecast boldness.

Table 2. 7 highlights key trends in the relationship between analyst experience and the likelihood of issuing bold forecasts across regions. First, for the US and Asia, the positive and significant coefficients for BEXP suggest that analysts with greater bank-specific expertise are more inclined to issue bold forecasts. This indicates that experienced analysts, confident in their skills and reputations, are more willing to deviate from the consensus, using their expertise to provide unique perspectives. In particular, older analysts in Asia, *as indicated by higher REXP*, are more likely to exhibit boldness and less herding behavior, consistent with findings from Bhagwat and Liu (2020). In Europe, however, the results show a contrasting pattern. The

negative and significant coefficient for REXP suggests that experienced analysts in this region are more conservative, tending to align their forecasts with the consensus. This behavior may stem from the increased scrutiny and accountability that senior analysts face, particularly as they have survived the industry's rigorous selection processes. Conversely, younger analysts in Europe are more likely to issue bold forecasts driven by career advancement motivations and a lower degree of professional accountability.

Second, regarding past performance (Past_Per_SCORE), the positive and significant coefficient in the US indicates that analysts with stronger track records are more inclined to issue bold forecasts. The high past performance likely enhances analysts' confidence, motivating them to take calculated risks in their predictions to maintain a reputation for accuracy and insight. In contrast, the negative and significant coefficient in Europe suggests that better past performance is associated with more conservative forecasts, as analysts with strong reputations may prioritize safeguarding their established credibility. In Asia, the coefficient is insignificant, implying that past performance does not strongly influence bold forecasting, with other factors likely playing a more substantial role in shaping forecast behavior in the region.

Third, considering the brokerage house effect (BIG5), positive and significant coefficients in the US and Asia suggest that analysts affiliated with top brokerage firms in these regions are more likely to issue bold forecasts. This could reflect the enhanced confidence and support provided by well-resourced firms with strong reputations, enabling analysts to adopt bolder positions. Conversely, in Europe, the negative and significant coefficient indicates that analysts at major brokerage houses are less likely to issue bold forecasts, suggesting a more conservative or risk-averse culture within European brokerage firms. Finally, an analysis of analyst portfolio size (NBAN) reveals that bold analysts in the US and Europe tend to cover a larger number of banks, possibly using portfolio diversity to enhance visibility and influence. However, the trend differs in Asia, where bold analysts are less associated with large portfolio sizes, indicating bold Asian analyst tend to maintain more focused portfolio.

The analysis reveals less experienced European analysts are more likely to issue bold forecasts than their seasoned peers. Early-career analysts often take risks to gain recognition and face less scrutiny, allowing greater freedom to deviate from consensus. In contrast, experienced analysts, shaped by a rigorous selection process, prioritize accuracy and reliability over boldness, resulting in more conservative forecasting behavior.

Table 2. 7: The link between Analysts' experience, past performance, and Boldness

Dependent Variable	Deviation of Analysts' Forecasts from the Consensus_Top 80% Boldness							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	US	EU	AS	All	US	EU	AS
BEXP	0.00399***	0.00327***	-0.000976	0.00684***				
	6.3	3.27	(-0.86)	5.6				
REXP					-0.000643	-0.00346***	-0.00272***	0.00378***
					(-1.35)	(-4.74)	(-3.18)	-3.75
BIG5	-0.00327	0.0352***	-0.0644***	0.0175**	-0.00188	0.0343***	-0.0627***	0.0172**
	(-0.72)	4.48	(-7.83)	2.27	(-0.41)	4.38	(-7.60)	2.23
Past_Per_SCORE	-0.00139	0.0115***	-0.0120***	0.000975	-0.000136	0.0114***	-0.0114***	0.00214
	(-0.89)	-4.28	(-4.14)	0.36	(-0.09)	4.24	(-3.94)	-0.8
NBAN	-0.00170***	0.00158***	0.00405***	-0.00278***	-0.000999**	0.00320***	0.00470***	-0.00293***
	(-4.27)	2.61	3.46	(-3.35)	(-2.38)	5.01	3.95	(-3.42)
_cons	-0.659***	-0.757***	-0.563***	-0.722***	-0.647***	-0.730***	-0.555***	-0.720***
	(-123.70)	(-69.68)	(-56.94)	(-76.78)	(-121.45)	(-66.42)	(-56.05)	(-76.09)
Observations	383926	131962	117212	134752	383926	131962	117212	134752

Table 7 presents the regression results (Eq. 9), examining the relationship between analysts' experience, past performance, and their deviation from the consensus, with a focus on top 20% boldness scores (BOLDNESS-Top20%). The results are reported for all regions combined (All) and separately for the US, EU, and Asia (AS). The dependent variable is a dummy set to one if an analyst's forecast ranks in the top 20% for boldness. Independent variables include regional experience (REXP), bank-specific experience (BEXP) and past performance (Past_per_score). Control variables are portfolio size (NBAN), top brokerage affiliation (BIG5). Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

2.5.3. Labor Market Incentives: Balancing Accuracy and Advancement

The section explores how labor market incentives influence forecasting strategies and career trajectories, with a focus on distinctions between younger and more experienced analysts across diverse financial markets. To examine career progression, we first construct indicators of job separation grounded in career theories that highlight job performance as a key determinant of movement within and between firms. We then analyze the relationship between an analyst's past forecast accuracy and job transitions. Finally, informed by herding theories, we assess the role of bold forecasting as an additional factor influencing job separations. The construction of performance and boldness variables is detailed in Section 2. 3.3.

2.5.3.1. Measures of Job Movements

In this section, we examine job movement measures by tracking each analyst forecast and employment history within the I/B/E/S sample, focusing on those in the banking sector. Studies like Hong et al. (2000) note that analysts often specialize within industries, a trend that Hong and Kubik (2003) further highlighted, showing a shift toward smaller, specialized brokerage firms since 2003. By including only banking-focused brokerage houses, our sample achieves a brokerage size distribution that aligns with this industry shift and supports our methodology.

Our approach also accounts for career dynamics, such as promotions and demotions, reflecting the evolving structure of specialized brokerage firms in banking.

In our global sample, the typical brokerage house employs around 12 analysts, while those in the top 5%—classified as top brokerage firms (BIG5)—average approximately 23 analysts. This number differs by region, with top brokerage firms employing an average of 22 analysts in the U.S., 24 in Europe, and 23 in Asia. Being part of a top brokerage often correlates with higher forecast accuracy and enhanced market performance, attributed to the superior resources and strong institutional reputation these firms hold. Career movements are measured in four ways: (1) the number of analysts who change brokerage houses during a year (determined by changes in the analyst's unique brokerage house code), (2) the number of analysts who upgrade to a higher-status brokerage firm during a year, (3) the number of analysts who move from a low-tier brokerage house to a top-tier house during a year, and (4) the number of analysts who downgrade from a high-status brokerage house to a low-status one during a year.

Table 2. 8 presents summary statistics for various measures of career mobility and forecast performance, providing insights into different dimensions of analyst job movements. The table categorizes the data for the overall sample, as well as for US, European, and Asian analysts. The data reveals that, on average, 14.45% of analysts change their brokerage firms over the sample period. US analysts show the highest rate of change at 18.54%, compared to 14.07% for European analysts and 13.46% for Asian analysts. The annual probability of an analyst changing their brokerage firm is approximately 5.2%, slightly higher for US and Asian analysts at 5.5% and 5.7%, respectively, and significantly lower for European analysts at 3.8%. The probability of analysts upgrading to a higher-status brokerage firm is around 1.9%, with US analysts having a slightly higher upgrade rate (2.17%) compared to European analysts (1.58%) and Asian analysts (1.95%). Approximately 1.26% of analysts move to firms of similar size, with this rate being slightly higher for Asian analysts (1.67%) and lower for European analysts (0.71%). The probability of moving to or from a top-tier brokerage firm is relatively low: the likelihood of upgrading to a top-tier firm is 0.37%, while the probability of downgrading from a top-tier firm is 0.28%. US analysts are more likely to upgrade to a top-tier firm (0.43%) compared to European (0.36%) and Asian analysts (0.29%).

Table 2. 8: Descriptive Statistics of Job Movements Dataset

	All Sample	US Analysts	European Analysts	Asian Analysts
Category	Mean	Mean	Mean	Mean
Brokerage House Change				
BrokerChange_ttl	0.578	0.742	0.426	0.538
D_BrokerChange_Year	5.15%	5.48%	3.75%	5.75%
Probability That Analyst Moves to Higher-Status Brokerage House				
D_Upgrade	1.946%	2.170%	1.581%	1.954%
D_Downgrade	1.945%	2.107%	1.461%	2.131%
D_Samesize	1.263%	1.200%	0.711%	1.665%
Probability That Analyst Moves to Top5 Brokerage House				
D_Upgrade_top5	0.374%	0.427%	0.357%	0.286%
D_Downgrade_top5	0.283%	0.166%	0.441%	0.145%
D_Samesize	4.497%	4.884%	2.954%	5.318%

- *The characteristics of Top-tier brokerage houses in different regions*

Our findings show a positive correlation between brokerage house size and forecast accuracy globally and regionally. In the United States, analysts at top brokerage houses tend to issue bolder forecasts, follow more concentrated portfolios, and have more bank-specific experience, though they do not necessarily possess high general experience or top past forecast accuracy. Conversely, European analysts exhibit high general experience levels, manage more extensive and complex portfolios, are less bold, and have average past performance records. Asian analysts demonstrate high experience levels, maintain moderate portfolio sizes, are bold, and show good past performance. These results highlight the distinct characteristics and behaviors of analysts across different regions, reflecting the varying dynamics of financial markets and institutional practices (see Appendix C, Table C.1).

2.5.3.2. Past Forecast Accuracy and Career Advancement: High and Low-Experience Analysts

This section explores the relationship between analysts' forecast accuracy and career mobility, including promotions, lateral moves, and exits from the profession. Specifically, we analyze how forecast performance affects the likelihood of analysts transitioning within or between brokerage houses—either moving up to top-tier firms or down to lower-status brokerages. By examining high- and low-experience subsamples, we capture experience-based differences in how forecast accuracy influences these career outcomes. We adopt the methodology outlined by Bolliger (2004), utilizing probit regressions to examine the likelihood of career transitions based on past forecast performance. We estimate separate probit models for each experience subsample, categorized as high or low relative to median experience in each region (8 years in the U.S., 6 years in Europe, and 5 years in Asia). This approach allows us to compare the impact of forecast performance on career mobility between less experienced and more experienced analysts. The model specifications are as follows:

$$Probability\ [Upgrade_{i,t+1}\ = 1]\ = Probit\ (\alpha + \text{ß1 Top\_Performance\_index}_{i,t} +\ \varepsilon_{i,t})$$
$$Probability\ [Downgrade_{i,t+1}\ = 1] = Probit\ (\alpha + \text{ß1 Poor\_Performance\_index}_{i,t}\ \varepsilon_{i,t})$$
(10)

here, "*upgrade*" refers to the likelihood of an analyst moving to a top-tier brokerage, while "*downgrade*" refers to moving to a lower-status brokerage. Past_Per_SCORE represents the analyst's Aggregate Weighted Forecast Performance score, with top-performing analysts (Top_Performance_index) in the top 20th percentile and poor performers marked by the Poor_Performance_index. This approach allows us to capture the extremes of analyst performance and better understand how these factors influence career outcomes across different regions and experience levels. Moreover, the analysis spans a three-year period to determine each analyst's general experience level, classifying them into high- and low-experience groups. This classification enables a nuanced understanding of how career concerns and performance metrics affect career progression, particularly highlighting the varying incentives faced by analysts at different career stages.

Table 2. 9 presents regression results analyzing the effect of past performance on career outcomes, with subsamples for low- and high-experience analysts and distinctions between top and poor performers. The analysis spans the U.S., Europe, and Asia, highlighting regional differences in how past performance influences career trajectories. The findings reveal significant positive relationships in all regions between past performance and the likelihood of promotion to a higher-status brokerage house. Specifically, higher past performance significantly increases the probability of moving up in Europe and Asia, though the effect is smaller in Asia. In contrast, in the U.S., high past performance does not necessarily correlate with promotions to top brokerage firms. Regarding downgrades, the U.S. shows that lower past performance significantly increases the likelihood of downgrading, particularly for less experienced analysts. In Europe, there is no significant relationship between past performance and downgrading overall, though poor past performance among low-experience analysts does increase the likelihood of a downgrade. In Asia, the positive coefficient indicates that market dynamics may interact uniquely with analyst experience level, necessitating further investigation.

Overall, the findings demonstrate that high past performance influences career outcomes, though the effects differ by region. In the U.S., poor past performance, especially for less experienced analysts, increases the likelihood of downgrading, while high past performance alone does not guarantee promotion. In Europe, high past performance is linked to upward mobility, with no significant trend for downgrading except for poor, low-experience performers. In Asia, high past performance boosts advancement to top firms, while lower past performance does not notably increase downgrading risks, highlighting unique market dynamics.

Table 2. 9: Effect of Past Performance on Career Outcomes by Experience

	Probability That Analyst Moves to Top Brokerage House					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
General Experience	US	US	EU	EU	ASIA	ASIA
	<Median	>Median	<Median	>Median	<Median	>Median
Top_Performance_index	-0.0476	-0.391***	0.431***	0.166***	-0.542***	0.0338
	(-1.13)	(-6.03)	-7.91	-2.79	(-4.54)	-0.63
_cons	-2.542***	-2.593***	-2.844***	-2.682***	-2.717***	-2.761***
	(-98.68)	(-118.78)	(-83.33)	(-114.13)	(-92.64)	(-112.28)
Observations	55115	69524	48243	62039	49233	75702
	Probability That Analyst Downgrades to a Lower-Status Brokerage House					
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
	US	US	EU	EU	ASIA	ASIA
	<Median	>Median	<Median	>Median	<Median	>Median
Poor_Performance_index	0.140***	0.0371	0.0952*	0.0523	-0.258***	-0.204***
	-2.72	-0.37	-1.84	-1.31	(-2.83)	(-3.13)
_cons	-2.909***	-3.216***	-2.753***	-2.707***	-2.951***	-2.795***
	(-61.73)	(-43.61)	(-53.29)	(-65.53)	(-46.04)	(-61.00)
Observations	55115	69524	48243	62039	49233	75702

Table 9 presents regression results (Eq. 10) assessing the impact of past performance on analysts' career outcomes. The analysis is structured into two panels: Panel A evaluates the probability of an analyst moving to a top brokerage house, while Panel B examines the likelihood of downgrading to a lower-status brokerage house. Each panel is divided by region and general experience (GEXP) above or below the median. Key variables include Top_Performance_index**,** a dummy set to 1 if the analyst's past performance is in the top 20%, and Poor_Performance_index**,** a dummy set to 1 for the bottom 20%. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

2.5.3.3. Boldness and Career Trajectories: High- and Low-Experience Analysts

Building on herding theories (e.g., Hong et al., 2000), we extend our analysis of career mobility to include forecast boldness as a potential factor influencing job separation probabilities. These models suggest that future career outcomes may be shaped not only by past performance but also by past actions—such as bold or unconventional forecasts that deviate significantly from the consensus—thereby signaling the quality of an analyst's private information. To investigate this, we estimate the relationship between the probability of career advancement or downgrade and forecast boldness, while controlling for forecast accuracy. We specifically explore how the combined effects of forecast accuracy and boldness may vary according to analysts' experience levels. Our model specification builds on Eq. (10), incorporating a dummy variable (BOLDNESS_Top 20%) to capture analysts who rank in the top 20% of the boldness-score distribution in year t. This variable serves as an indicator of bold forecasting behavior[38].

$$Probability\left[Upgrade_{i,t+1} = 1\right] = Probit\,(\alpha + ß1BOLDNESS\_Top\ 20\%_{i,t} + ß2\ Top\_Performance\_index_{i,t} + \varepsilon_{i,t})$$
$$Probability\left[Downgrade_{i,t+1} = 1\right] = Probit\,(\alpha + ß1BOLDNESS_{Top}20\%_{i,t} + ß2\ Poor\_Performance\_index_{i,t} + \varepsilon_{i,t}) \tag{11}$$

This model allows us to analyze how both past performance and boldness influence career mobility, providing insights into the role of unconventional forecasting as a potential driver of career advancement or risk, particularly across varying levels of analyst experience. Table 2. 10 examines how bold forecasts (top 20%) and top performance affect career mobility for analysts with varying experience levels across the U.S., European (EU), and Asian markets. In the U.S., bold forecasts by less experienced analysts correlate with a lower likelihood of advancement to top brokerage houses and a greater probability of downgrade if performance is poor. For experienced analysts, particularly those with robust bank-specific experience (general experience (GEXP) > median (~8 years) and bank-specific experience (BEXP) > mean (~5.1 years)), boldness enhances the likelihood of moving to top firms (see Appendix C, Table C.2). For younger analysts, boldness and strong performance alone do not secure promotions, emphasizing the critical role of experience, especially within specialized sectors, for career growth. Essentially, high performance alone does not ensure advancement without sufficient experience (GEXP> mean (~9.2 years)), while poor performance significantly increases downgrade risk for less experienced analysts (see Appendix C, Table C.3).

In Europe, strong past performance facilitates upward mobility to top brokerage houses, with bold forecasts significantly boosting promotion prospects for less experienced analysts (GEXP < median (~6 years)). Among lower-experience analysts, bold forecasts are associated with better chances of advancing to top firms, though their impact on avoiding downgrades is minimal. For more seasoned analysts, boldness slightly improves promotion prospects, mainly

[38] For our job separation models, we use a cumulative boldness score by averaging each analyst's boldness scores over the current year t and the prior three years, providing a more stable measure of boldness over time. Please see Section 2.3.3.

when coupled with substantial bank-specific experience (BEXP > mean (~4.3 years); see Appendix C, Table C.2). This regional variation highlights the need for further analysis into how boldness affects career trajectories for younger, career-driven European analysts. In Asia, bold forecasts positively impact career advancement across both less and more experienced analysts, with inexperienced analysts benefiting the most from bold moves (GEXP < median (~5 years)). Additionally, bold forecasts reduce the likelihood of downgrades for experienced analysts, suggesting that a combination of high experience and boldness provides resilience and career stability against potential setbacks. These findings underscore the complex interplay between boldness and experience in career mobility, with notable regional differences.

Table 2. 10: Impact of Boldness on Career Advancement Across Regions

	Probability That Analyst Moves to Top Brokerage House					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
General Experience	US	US	EU	EU	ASIA	ASIA
	<Median	>Median	<Median	>Median	<Median	>Median
BOLDNESS_Top 20%	-0.326***	0.159*	0.245**	0.00409	0.742***	0.162*
	(-3.49)	1.83	2.35	0.05	5.71	1.81
Top_Performance_index	-0.0569	-0.429***	0.417***	0.185***	-0.552***	0.000255
	(-1.29)	(-6.12)	7.11	2.8	(-4.13)	0
_cons	-2.456***	-2.618***	-2.902***	-2.656***	-2.931***	-2.773***
	(-74.17)	(-82.89)	(-60.56)	(-75.58)	(-52.32)	(-79.92)
Observations	49787	63137	40470	49341	40688	60571

	Probability That Analyst Downgrades to a Lower-Status Brokerage House					
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
	US	US	EU	EU	ASIA	ASIA
	<Median	>Median	<Median	>Median	<Median	>Median
BOLDNESS_Top 20%	0.356***	-0.3	0.0679	0.271***	-0.0405	-0.324**
	3.41	(-1.20)	0.62	3.29	(-0.27)	(-2.33)
Poor_Performance_index	0.186***	0.0815	0.000908	-0.0832*	-0.308***	-0.136*
	3.41	0.76	0.02	(-1.76)	(-2.97)	(-1.96)
_cons	-2.909***	-3.216***	-2.719***	-2.605***	-2.951***	-2.795***
	(-61.73)	(-43.61)	(-50.23)	(-51.95)	(-46.04)	(-61.00)
Observations	49787	63137	40470	49341	40688	60571

Table 10 presents the regression results (Eq. 11), analyzing the impact of past boldness on the probability that an analyst experiences desirable or undesirable career outcomes, separated by experience levels and across different regions (US, EU, and ASIA). The analysis is structured into two panels: Panel A shows the probability of an analyst moving to a top brokerage house, while Panel B examines the likelihood of an analyst downgrading to a lower-status brokerage house. Each panel is further divided by region and by experience level (general experience (GEXP) above or below the median. The main variable of interest is the Top 20% Boldness: A dummy variable is set to one if the analyst Boldness rank is above 80% and set to zero otherwise. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively.

2.5.3.4. Career Mobility and Strategic Forecasting

Analysts' forecasts are often shaped by brokerage firms' trading incentives, showing increased optimism, boldness, or broader coverage to boost trading volumes and client relationships, even at the risk of reduced accuracy (Lehmer et al., 2022; Ljungqvist et al., 2007; Michaely & Womack, 1999). This analysis explores how portfolio complexity and expanded coverage affect promotion prospects, particularly for career-focused analysts, highlighting how bold forecasting combined with broad coverage can strategically enhance career mobility. The probit model in Eq. (11) is extended to include subsamples for varying levels of portfolio size, complexity, and engagement. Table 2. 11 shows how expanded bank (NBAN) and country coverage (NCOU) amplify promotion probability for bold, career-motivated analysts, while Table 2. 11 examines the marginal effect of increased market activity, with all variables averaged over a three-year window. In the European market, analysts with above-median bank or country coverage who issue bold forecasts experience a significantly higher likelihood of promotion to top brokerage firms, a trend reinforced by positive performance indicators. Active engagement in forecasting further enhances career mobility, as high engagement and broad coverage amplify the benefits of boldness. In contrast, analysts with smaller portfolios have reduced promotion prospects, highlighting the importance of extensive coverage and visibility for advancing in their careers. Unlike Europe, where boldness is rewarded with career mobility, both the U.S. and Asian markets show different dynamic. In Asia, bold forecasts significantly boost promotion prospects, particularly for analysts with moderate portfolio complexity. Analysts with below-median bank or country coverage benefit the most from boldness, while extensive country coverage diminishes its impact, indicating that boldness is more effective when paired with a focused portfolio. In the U.S., however, bold forecasts tend to reduce the likelihood of promotion to top brokerage houses, regardless of whether the analyst's bank coverage is below or above the median. This negative impact is stronger for analysts with higher coverage, suggesting that for less experienced analysts, boldness is not rewarded in the U.S. market and may even be penalized.

These findings indicate that in the European market, less experienced analysts can strategically leverage bold forecasting, extensive portfolio coverage, and active engagement to enhance their career trajectories. However, bold forecasts are often associated with younger analysts, those with lower past performance, and analysts from smaller firms. These analysts tend to cover a broader range of banks and countries, using their diversified portfolios and regional expertise to stand out early in their careers. Notably, bold forecasts in Europe are linked to higher forecast errors, highlighting a trade-off between visibility and accuracy. This trend aligns with theories on economic incentives and strategic forecasting, where bold, optimistic forecasts that drive trading volumes can lead to career advancement, particularly for early-career analysts (Lehmer et al., 2022). This underscores the complex dynamics of boldness, accuracy, and economic motivations in shaping career progression within competitive financial markets.

Table 2. 11: Boldness and Career Advancement by Portfolio Complexity

	Probability That Analyst Moves to Top Brokerage House									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Coverage _ Bank						Coverage _ Country			
	US	US	EU	EU	AS	AS	EU	EU	AS	AS
	<Median	>Median	<Median	>Median	<Median	>Median	<Median	>Median	<Median	>Median
BOLDNESS_Top 20%	-0.258**	-0.525**	-0.112	0.359***	1.190***	0.528***	-0.145	0.317***	0.777***	-0.757
	(-2.49)	(-2.35)	(-0.51)	2.74	-5.18	3.14	(-0.59)	2.65	5.86	(-0.97)
Top_Performance_index	-0.215***	0.631***	0.506***	0.429***	-0.136	0	0.605***	0.345***	-0.551***	0
	(-4.03)	4.83	4.16	6.11	(-0.89)	(.)	4.29	5.27	(-4.05)	(.)
_cons	-2.284***	-3.170***	-3.173***	-2.761***	-3.328***	-2.663***	-3.156***	-2.802***	-2.886***	-3.237***
	(-61.22)	(-28.91)	(-31.67)	(-47.86)	(-27.59)	(-41.23)	(-28.41)	(-51.58)	(-50.18)	(-14.35)
Observations	28451	19360	20541	19929	21478	12704	15141	25329	33705	5360

Table 11 presents the regression results (Eq. 11), evaluating how past boldness influences career outcomes while accounting for portfolio size and complexity across the EU, US, and Asia. The analysis incorporates key portfolio characteristics, including the number of banks covered (DNBAN) and country coverage (DNCOU), to examine the interaction between bold forecasting and portfolio structure on career advancement. The results are further segmented by region and by whether the portfolio size and complexity variables (DNBAN and DNCOU) are above or below the median. All variables are calculated as cumulative averages over a three-year window. The primary variable of interest is the Top 20% Boldness, a dummy variable set to one if the analyst's boldness rank is above the 80th percentile and zero otherwise. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

Table 2. 12: Boldness and Career Advancement by Analyst Engagement

	Probability That Analyst Moves to Top Brokerage House					
	(1)	(2)	(3)	(4)	(5)	(6)
	Active Analyst					
	US	US	EU	EU	AS	AS
	<Median	>Median	<Median	>Median	<Median	>Median
BOLDNESS_Top 20%	0.107	-0.451***	-0.166	0.384***	0.829***	0.161
	-0.59	(-4.11)	(-0.77)	-3.12	-5.84	-0.52
Top_Performance_index	0.468***	-0.190***	0.612***	0.339***	-0.589***	-0.384
	-4.41	(-3.59)	-5.48	-4.78	(-3.93)	(-1.27)
_cons	-2.937***	-2.364***	-3.063***	-2.816***	-2.946***	-2.837***
	(-31.57)	(-66.03)	(-32.33)	(-48.77)	(-47.09)	(-23.91)
Observations	11977	37602	18024	22200	33868	6788

Table 2.12 presents the regression results (Eq. 11), extending the analysis in Table 11 to evaluate the impact of analysts' activity and engagement levels on career outcomes, across EU, US, and Asia. The analysis incorporates the number of all forecasts and revisions issued by analysts in each period (NFALL) as a measure of activity, examining its interaction with boldness and portfolio characteristics on career advancement. The results are segmented by region and by whether NFALL, representing analyst activity levels, is above or below the median. All variables are calculated as cumulative averages over a three-year window. The primary variable of interest remains the Top 20% Boldness, a dummy variable set to one if the analyst's boldness rank is above the 80th percentile and zero otherwise. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

2.6. Summary and Conclusion

This study analyzes the influence of financial analyst characteristics and career motivations on forecast accuracy, boldness, and career trajectories across global regions, focusing on the banking sector. Utilizing the I/B/E/S Detail History Database, we uncover significant regional differences in the factors influencing forecast behavior and career outcomes, highlighting the complexity of financial analysis in a global context. US analysts exhibit lower forecast bias, longer tenure, and higher engagement levels than their European and Asian counterparts, reflecting a more dynamic and competitive environment. European analysts, though slightly more experienced than Asian analysts, show higher optimism and broader geographical coverage, whereas Asian analysts concentrate on more banks within a single country.

We examine determinants of financial analysts' forecast accuracy, revealing that analyst experience, portfolio management, forecasting activity, and institutional resources significantly impact forecast accuracy globally. General experience reduces forecast error across the US, Europe, and Asia, with the US showing the most substantial improvement. Bank-specific experience is particularly impactful in the US and Asia. Larger brokerage houses are associated with lower forecast errors, especially in the US, due to better resources and support. However, this effect is weaker in Europe, indicating regional disparities. Frequent forecasts and revisions correlate with higher accuracy, underscoring the benefits of continuous market engagement. Interestingly, portfolio size enhances accuracy globally but increases errors in Europe due to complexity. This finding contradicts previous studies that linked extensive firm coverage with reduced accuracy, likely due to industry specialization. Higher geographical coverage consistently increases forecast errors across all regions, with Europe being the most affected. Our findings suggest that industry-specialized analysts with large portfolio sizes and limited geographical coverage produce more accurate forecasts. However, this presents challenges for European brokerage houses seeking an optimal research structure. We then explore the dynamics between boldness, ability, and career concerns. Our research reveals regional differences in forecasting behavior, showing how career concerns, boldness, and forecast accuracy interplay. In the US, bold forecasts are more accurate than herding forecasts. Analysts issuing bold forecasts typically have significant bank-specific experience, come from major brokerage houses, and have strong past performance. Career concerns drive less experienced analysts to herd, while experienced analysts make independent, bold forecasts. In Europe, bold forecasts are generally linked with higher forecast errors. Younger analysts, those with less favorable past performance, and those from smaller brokerage houses are more likely to issue bold forecasts.

Boldness here is closely tied to career concerns, with younger analysts taking risks to gain recognition, often compromising prediction accuracy. In Asia, bold forecasts are less accurate overall, though the negative impact is less pronounced for analysts from top brokerage houses and those with focused portfolio coverage who are the main issuers of bold forecasts in Asian markets.

Furthermore, across global financial markets, the interplay between forecasting performance, and career progression reveals distinct regional dynamics that shape analysts' career paths. In the US market, Inexperienced analysts who make bold forecasts generally face challenges in moving to top-tier firms and are more likely to experience downgrades if they perform poorly. However, experienced analysts, particularly those with robust bank-specific expertise, see greater upward mobility when exhibiting boldness, suggesting that boldness combined with experience enhances career prospects in top firms. Essentially, high performance alone does not ensure advancement without sufficient experience, while poor performance significantly increases downgrade risk for less experienced analysts. In the European market, boldness emerges as a key factor for less experienced analysts, markedly enhancing their prospects for advancing to top-tier firms. This finding suggests that early in their careers, European analysts can strategically use bold forecasts, broad portfolio coverage, and active market engagement to advance professionally. Notably, while boldness and extensive coverage increase career mobility, this approach often comes at the expense of forecast accuracy. This trade-off underscores the influence of economic incentives and strategic forecasting behaviors, where bold, optimistic forecasts that drive trading volumes can serve as a powerful catalyst for career growth, especially for ambitious early-career analysts aiming to establish visibility and influence in competitive financial markets. In Asia, bold forecasts significantly enhance career advancement for both experienced and less experienced analysts, with a more pronounced impact on younger analysts. For seasoned analysts, boldness drives career progression and lowers the risk of downgrades, indicating that boldness, when combined with extensive experience, stabilizes career trajectories. Notably, the positive impact of boldness is strongest when analysts maintain a focused portfolio, highlighting the strategic advantage of concentrated expertise in amplifying the benefits of bold forecasts.

Overall, bold forecasts represent a calculated risk that can yield career benefits under certain conditions. In the U.S., experience and strong past performance are prerequisites for leveraging boldness effectively, whereas in Europe, early-career analysts use boldness to stand out but must navigate its trade-offs with accuracy. Asia demonstrates a more consistent advantage of boldness across experience levels, reflecting the regional interplay of market dynamics, institutional structures, and cultural acceptance of risk-taking.

These findings underscore the nuanced and strategic dimensions of analysts' forecasting behaviors, revealing that career progression in financial analysis is influenced not only by traditional skills like forecast accuracy but also by calculated behaviors such as portfolio expansion, optimism, and boldness in predictions. These behaviors are strategically employed, particularly by early-career analysts, to heighten visibility and increase advancement prospects in competitive financial markets. However, such strategies often lead to trade-offs, as boldness and optimism can compromise forecast precision, especially in markets with different regulatory frameworks and economic incentives. By providing valuable insights for investors, financial institutions, and policymakers, this study aims to enhance the integrity and effectiveness of market discipline mechanisms, fostering greater trust and stability in the banking sector.

Our findings collectively illustrate that while experience, firm resources, and specialization contribute to forecast accuracy, the influence of economic incentives—particularly those tied to trading volumes—significantly shapes analysts' forecast behavior. This strategic adjustment of forecasts suggests that analysts may prioritize their brokerage firm's business interests over the provision of unbiased and accurate information.

2.6.1. Policy Implications and Recommendations

The findings in this study underscore the need for comprehensive and harmonized regulations to improve transparency, integrity, and reliability in financial analysis, especially within the opaque banking sector. Current regulations across the U.S., Europe, and Asia show varied strengths and weaknesses: while the U.S. leads in addressing conflicts of interest through clear mandates (e.g., the Global Research Analyst Settlement and Reg BI), Europe focuses on transparency measures, such as unbundling research costs in MiFID II, but faces enforcement challenges due to market fragmentation. In Asia, flexible yet diverse regulations are often inconsistently applied, potentially weakening their effectiveness (see Appendix D). To address these regional disparities, further regulatory efforts should prioritize enhanced disclosure standards, regular independent audits, and mandatory reporting of analysts’ compensation and incentives. Emphasizing ongoing professional development and stringent oversight would help reinforce the quality of financial analysis, ensuring that conflicts of interest are minimized and the integrity of market information is upheld. Strengthening these regulatory frameworks can enhance transparency, reliability, and integrity in financial analysis, reinforcing market discipline and contributing to economic stability and investor trust across key regions.

Appendix II

Appendix A:

Financial Analyst Compensation Package in Global Markets:

Financial analyst compensation varies significantly by region and firm size. In the U.S., salaries typically range from \$60,000 to \$120,000, with top firms offering up to \$150,000. Bonuses generally add 10% to 50% of the base salary, particularly in major financial hubs like New York. In Europe, analysts earn between €50,000 and €90,000, with higher pay in London. Bonuses are also 10% to 50%, though the European Union imposes stricter regulations on bonuses, especially in the financial sector. Analysts in cities like Frankfurt and Paris earn competitive salaries, albeit slightly lower than in London. In Asia, compensation is more variable. Hong Kong and Singapore offer salaries ranging from €47,000 to €100,000, while Japan and China have lower ranges. India is at the lower end of the spectrum. Bonuses across Asia typically range from 10% to 40% of the base salary, with the highest bonuses in Hong Kong and Singapore. Large brokerage firms generally offer higher pay, with U.S. base salaries from \$70,000 to \$90,000 and bonuses up to 100%. These firms provide extensive benefits and greater career growth opportunities. In contrast, smaller firms offer lower salaries, typically \$50,000 to \$70,000 in the U.S., with more modest bonuses, although they may offer faster career progression with broader responsibilities.

Appendix B:

Details On the dataset

Table B.1 Variable definition

Variable	Description
	Experience
GEXP	General Experience: Cumulative years through t in which analyst i has issued forecasts.
CEXP	Country-Specific Experience: Cumulative years through t that analyst i has forecasted for a specific bank.
REXP	Region-Specific Experience: Cumulative years through t that analyst i has issued forecasts for a particular country.
BEXP	Bank-Specific Experience: Cumulative years through t that analyst i has issued forecasts for a particular region.
	Portfolio Complexity
NBAN	This represents the number of banks for which the analyst has supplied at least one forecast during the current year. It indicates portfolio complexity.
NCOU	This number reflects the number of countries for which analysts have supplied at least one forecast during the current year; it provides insight into their specialization in particular countries.
NREG	Indicates the number of regions for which the analyst has supplied at least one forecast during the current year. It reflects the geographic diversification of their portfolio.
	Analysts Engagement
NFB	The number of forecasts/revisions that the analyst supplied for each bank during the current year.
NFCOU	The number of forecasts/revisions that the analyst supplied for each country during the current year.
NFREG	The number of forecasts/revisions that the analyst supplied for each region during the current year.
NFAll	The number of the total forecasts/revisions that the analyst supplied during the current year.
	Forecast Timing
FORD	Forecast order for each analyst during the period. This variable captures the chronological order of analysts' forecasts and revisions
FAGE	Forecast age (in days) represents the number of days between fiscal year-end and forecast date for company j in the year t.
	Analyst Boldness
BOLD	The measure of an analyst's boldness is the deviation from the consensus forecast. The absolute value of the difference between Fi,j,t and F-i,j,t ,If the analyst's current forecast is greater than (less than) the consensus forecast.
BOLDNESS(Score)	Analyst Boldness score: For each bank in each year, rank all the analysts covering a bank by how much they deviate from the consensus forecast of that year (the boldest analyst receives the first rank, the second-boldest, the second rank, etc.). From these rankings, a boldness score for each analyst for each bank is made.
BOLDNESS_Top 20%	A dummy variable is set to one if the analyst Boldness rank is above 80% and set to zero otherwise.
	Brokerage House and Career Movement
BrokerSize	Brokerage size is defined as the number of analysts working for the I/B/E/S brokerage firm that analyst i is associated with in year Y.
BrokerSize_INT	Brokerage houses are ranked yearly according to the number of analysts employed. Small, medium, and large brokers get 1, 2, and 3.
BIG5	A dummy variable is set to one if the analyst is employed by a firm ranked in the top 5% during the current year and set to zero otherwise.
BrokerChange	A number of times analyst has moved to another broker house during his job as an analyst.
D_BrokerChange_Year	A dummy variable is set to one if the analyst has changed the broker in the last 365 days.
D_Upgrade	D_BrokerSize_Change: This dummy variable equals one in case of Upgrade to higher status brokerage house, -1 in case of downgrade, and 0 if there is no change.
D_Upgrade_BIG5	D_BrokerSize_Change: Dummy variable equals one in case of Upgrade to top 5 brokers, -1 in case of downgrade, and 0 if there is no change.
	Analyst Forecast Error & Past Performance
Past_Per	The aggregated forecasting accuracy across all the banks an analyst covers: This represents the weighted average of the analyst's prior period forecast accuracy from the first forecast, assigning higher weights for recent forecasts.
Past_Per_SCORE	Soring and ranking all analysts based on their previous performance and scoring them; the best analyst receives the first rank, the second-best analyst receives the second rank, and onward until the worst analyst receives the highest rank.
Top_Performance_index	A dummy variable is set to one if the analyst's past performance rank is in the top 20% and set to zero otherwise.
Poor_Performance_index	A dummy variable should be set to one if the analyst's past performance rank is down 20% and set to zero otherwise.
AFE	Absolute Forecast error represents the absolute spread between actual earnings per share for stock j and forecasted earnings per share in year t deflated by the actual earnings per share at the end of year t.
PMAFE	IProportional Mean Forecast Accuracy. The ratio of the current year individual analyst's forecast error for a particular firm divided by the mean current year forecast error of all analysts for the firm, minus one.

Table B.2 I/B/E/S Dataset Summary Statistics

Year	TTL Forecasts	Nb. Brokers/year	Nb. Banks/year	Nb. Analyst/year
2000	7,827	297	234	1,073
2001	9,744	296	240	1,033
2002	9,356	259	260	947
2003	11,215	272	278	982
2004	10,558	299	295	916
2005	12,630	313	322	978
2006	12,038	321	335	1,020
2007	13,719	325	354	1,045
2008	17,154	335	351	1,097
2009	18,976	379	377	1,217
2010	18,129	407	382	1,203
2011	22,294	398	400	1,280
2012	22,055	380	410	1,253
2013	21,030	373	421	1,166
2014	20,881	369	439	1,147
2015	21,856	363	448	1,181
2016	22,687	347	466	1,106
2017	21,964	339	485	1,058
2018	21,448	315	504	907
2019	21,458	303	513	835
2020	23,993	282	524	762
2021	20,537	280	529	726
2022	16,626	256	526	653
Total	398,175	901	516	5,647

Total	398,175	29	516	5647	901

Nb. Forecasts represent the number of annual earnings forecasts made each year. Nb. Analysts denote the number of analysts who produced a forecast during fiscal year t. Nb. Brokers refer to the number of brokerage companies for which analysts work each year. Nb. Banks represent the number of banks included in the sample each year. Nb. Countries represent the number of countries included in the sample each year per region.

Table B.3. Geographical distribution of the data

Region/Country	Nb. Forecasts
US	131,962
EU	
United Kingdom	18,105
Italy	13,083
Spain	11,504
Switzerland	10,775
Sweden	10,317
Norway	10,278
Germany	9,453
France	9,197
Denmark	6,822
Netherlands	5,184
Finland	3,573
Austria	3,081
Ireland	2,634
Belgium	2,480
Portugal	726
	117,212
Asia	
India	28,737
China	20,850
South Korea	12,911
Malaysia	11,611
Thailand	10,338
Japan	10,217
Australia	8,378
Indonesia	7,911
Singapore	7,399
Hong Kong	7,136
Taiwan	6,100
Philippines	3,164
	134,752
CA	14,249

Table B.4: Correlation Matrix Relative Forecast Error and Analyst Characteristics (Eq. 7)

	1	2	3	4	5	6	7	8	9	10	11	12
All data												
PMAFE	1											
DGEXP	-0.029	1										
DCEXP	-0.031	0.909	1									
DREXP	-0.029	0.988	0.922	1								
DBEXP	-0.027	0.673	0.750	0.682	1							
DNBAN	-0.022	0.285	0.229	0.281	0.184	1						
DNCOU	0.008	0.127	0.011	0.114	0.031	0.458	1					
DNFB	-0.055	0.197	0.227	0.198	0.356	0.184	0.078	1				
DNFAll	-0.046	0.299	0.262	0.297	0.271	0.752	0.334	0.543	1			
DFORD	-0.167	0.167	0.188	0.167	0.279	0.181	0.061	0.780	0.458	1		
DFAGE	0.245	-0.044	-0.042	-0.042	-0.027	-0.049	0.004	-0.125	-0.120	-0.498	1	
DBIG5	-0.021	0.073	0.019	0.063	0.059	0.060	0.136	0.150	0.153	0.126	-0.063	1
US Sub-sample												
PMAFE	1											
DGEXP	-0.0337	1										
DCEXP	-0.0335	0.991	1									
DREXP	-0.0335	0.991	1	1								
DBEXP	-0.0246	0.5953	0.5996	0.5996	1							
DNBAN	-0.0305	0.2913	0.3006	0.3006	0.1962	1						
DNCOU	0.0227	-0.0245	-0.0311	-0.031	0.0027	0.1041	1					
DNFB	-0.0261	0.0711	0.0683	0.0683	0.2531	0.1231	0.043	1				
DNFAll	-0.0316	0.225	0.2335	0.2335	0.2239	0.7662	0.0739	0.4497	1			
DFORD	-0.1732	0.0633	0.0627	0.0627	0.19	0.1339	-0.0976	0.7363	0.3846	1		
DFAGE	0.2398	0.0224	0.0238	0.0238	0.033	-0.014	0.1323	-0.0905	-0.0987	-0.5112	1	
DBIG5	-0.0233	-0.0791	-0.0852	-0.0853	0.0394	-0.0656	0.0972	0.1802	0.0785	0.14	-0.0501	1

	1	2	3	4	5	6	7	8	9	10	11	12
EU Sub-sample												
PMAFE	1											
DGEXP	-0.030	1										
DCEXP	-0.025	0.808	1									
DREXP	-0.028	0.988	0.818	1								
DBEXP	-0.024	0.689	0.862	0.695	1							
DNBAN	0.009	0.197	0.088	0.188	0.077	1						
DNCOU	0.019	0.120	-0.031	0.114	-0.009	0.776	1					
DNFB	-0.057	0.249	0.333	0.252	0.391	0.124	0.034	1				
DNFAll	-0.033	0.313	0.249	0.308	0.246	0.704	0.508	0.565	1			
DFORD	-0.144	0.213	0.273	0.214	0.308	0.121	0.032	0.809	0.474	1		
DFAGE	0.220	-0.061	-0.056	-0.060	-0.019	0.002	0.034	-0.133	-0.090	-0.484	1	
DBIG5	-0.017	0.108	0.026	0.100	0.025	0.136	0.182	0.123	0.200	0.105	-0.052	1
ASIA Sub-sample												
PMAFE	1											
DGEXP	-0.0315	1										
DCEXP	-0.0392	0.8964	1									
DREXP	-0.0313	0.9902	0.9095	1								
DBEXP	-0.0359	0.7121	0.8002	0.7234	1							
DNBAN	-0.0346	0.3484	0.2712	0.3438	0.2519	1						
DNCOU	0.0016	0.2459	0.0896	0.2305	0.0987	0.4785	1					
DNFB	-0.0709	0.2632	0.2879	0.2605	0.4172	0.2846	0.1396	1				
DNFAll	-0.0669	0.3809	0.3258	0.3725	0.3467	0.7845	0.3958	0.6111	1			
DFORD	-0.1743	0.2247	0.2446	0.2219	0.3376	0.2677	0.1215	0.7861	0.5141	1		
DFAGE	0.2688	-0.0816	-0.0845	-0.0787	-0.0709	-0.0952	-0.0414	-0.1239	-0.1443	-0.4822	1	
DBIG5	-0.0225	0.1776	0.1077	0.1652	0.1084	0.1102	0.1384	0.1528	0.1854	0.1293	-0.0706	1

Table B.4 presents the correlation matrix for the differenced variables in the regression model Eq. (7). *PMAFE* = difference between the absolute forecast error for analyst *i* for firm *j* at time *t* and the mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*.

Table B.5: Spearman Rank Correlation among the regression variables (Eq. 9)

	1	2	3	4	5	6	1	2	3	4	5	6
All data							***EU Sub-sample***					
REXP	1						1					
BEXP	0.7213*	1					0.7453*	1				
BOLDNESS		0.0274*	1				-0.0081*		1			
BOLDNESS_TOP20%		0.0128*	0.7549*	1			-0.0079*		0.7762*	1		
BIG5	0.0435*	0.0529*	0.0043*		1		0.1084*	0.0363*		-0.0219*	1	
Past_Per_Score	0.2447*	0.2130*	-0.0124*		0.0074*	1	0.2292*	0.2282*	-0.0200*	-0.0126*	0.0199*	1
US Sub-sample							***ASIA Sub-sample***					
REXP	1						1					
BEXP	0.6565*	1					0.7511*	1				
BOLDNESS	0.0149*	0.0572*	1				0.0096*	0.0231*	1			
BOLDNESS_TOP20%		0.0158*	0.7503*	1			0.0127*	0.0178*	0.7395*	1		
BIG5	-0.0524*	0.0554*	0.0150*	0.0122*	1		0.0980*	0.0771*		0.0073*	1	
Past_Per_Score	0.0742*	0.0537*		0.0126*	-0.0617*	1	0.3297*	0.3129*			0.0723*	1

Table B.5 presents the Spearman rank correlation coefficients for the variables used in regression model Eq. (9) across different regions. This table provides insights into the relationships between boldness, measured by both BOLDNESS and BOLDNESS_TOP20%, and other analyst characteristics, such as experience, past performance, brokerage affiliation, and portfolio complexity.

Appendix C:

Furthered Analysis:

Table C.1: The Link Between Boldness and Top Brokerage House.

Dependent Variable	Link between Top Brokerage House and Boldenss							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	US	EU	ASIA	All	US	EU	ASIA
BOLDNESS_Top 20%	-0.00349	0.0356***	-0.0663***	0.0183**	-0.00206	0.0348***	-0.0642***	0.0182**
	(-0.73)	-4.36	(-7.85)	-2.25	(-0.43)	-4.25	(-7.60)	-2.24
BEXP	0.0160***	0.0189***	0.00138	0.0269***				
	-27	-20.12	-1.27	-24.51				
Top_Performance_index	-0.0382***	-0.126***	-0.0859***	0.131***	-0.0412***	-0.173***	-0.0580***	0.131***
	(-7.72)	(-16.37)	(-7.93)	-15.27	(-8.31)	(-22.33)	(-5.33)	-15.26
REXP					0.00559***	-0.0183***	0.0181***	0.0338***
					-12.53	(-26.35)	-22.05	-37.52
DNBAN	0.00225***	-0.00446***	0.0490***	0.000945	0.00256***	0.00397***	0.0440***	-0.00480***
	-6.09	(-7.92)	-43.82	-1.22	-6.56	-6.67	-38.64	(-5.98)
_cons	-0.413***	-0.372***	-0.621***	-0.427***	-0.387***	-0.207***	-0.709***	-0.479***
	(-91.52)	(-41.27)	(-68.34)	(-53.74)	(-85.43)	(-22.70)	(-76.64)	(-59.00)
Observations	29775	29775	29775	28559	28559	28559	44809	44809

Table C.1 presents the regression analysis exploring the relationship between boldness and the likelihood of an analyst being associated with a top brokerage house. The dependent variable is the likelihood of being associated with a top brokerage house, with boldness being a key independent variable. Statistical significance is indicated by ***, **, and * for 1%, 5%, and 10% levels, respectively.

Table C.2: Impact of Past Boldness and Performance on Career Outcomes by Bank-Specific Experience

	Probability That Analyst Moves to Top Brokerage House_ Bank-Specific Experience								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank-Specific Experience	US			EU			ASIA		
	<Median	>Median	>Mean(~5.1Y)	<Median	>Median	>Mean(~4.3Y)	<Median	>Median	>Mean(~3.9Y)
BOLDNESS_Top 20%	-0.125*	0.138	*0.387***	0.0762	0.177*	*0.111*	0.644***	-0.0598	*0.00786*
	(-1.75)	0.97	*2.4*	0.89	1.72	*0.96*	6.21	(-0.57)	*0.07*
Top_Performance_index	-0.248***	-0.147*	*-0.223**	0.312***	0.167**	*0.225****	-0.252***	0.111*	*0.0209*
	(-6.35)	(-1.72)	*(-1.89)*	6.02	2.28	*2.62*	(-3.15)	1.87	*0.29*
_cons	-2.351***	-2.970***	*-3.123****	-2.730***	-2.796***	*-2.822****	-2.892***	-2.769***	*-2.788****
	(-91.08)	(-59.35)	*(-49.45)*	(-73.02)	(-65.87)	*(-59.66)*	(-67.34)	(-73.86)	*(-65.70)*
Observations	62846	56971	*48135*	48220	47746	*38937*	55751	54219	*44694*

Table C.2 extends the analysis of Table 10 (Eq. 11) by examining how past boldness and performance influence an analyst's likelihood of moving to a top brokerage house across the US, Europe, and Asia while accounting for varying experience levels. Each region is further categorized into three sub-groups based on whether the analyst's bank-specific experience is above or below the median or above the mean, capturing strong bank-level expertise. The key independent variable, Top 20% Boldness, is a dummy set to 1 if the analyst's boldness rank is above 80% and 0 otherwise. Statistical significance is denoted by ***, **, and * for 1%, 5%, and 10% levels, respectively.

Table C.3: Impact of Past Boldness and Performance on Career Outcomes by General Experience

	Probability That Analyst Moves to Top Brokerage House_ Above the Mean General Experience					
	(1)	(2)	(3)	(4)	(5)	(6)
General-Experience	US	US	EU	EU	ASIA	ASIA
	<Mean(~9.2Y)	>Mean(~9.2Y)	<Mean(~6.5Y)	>Mean(~6.5Y)	<Mean(~6Y)	>Mean(~6Y)
BOLDNESS_Top 20%	-0.175**	-0.224	0.261***	0.0213	0.550***	0.0909
	(-2.35)	(-1.17)	-2.67	-0.24	-4.58	-0.89
Top_Performance_index	-0.247***	0.254***	0.372***	0.199***	-0.111	0.00808
	(-6.17)	-2.94	-6.62	-3	(-1.53)	-0.12
_cons	-2.373***	-3.114***	-2.901***	-2.666***	-2.906***	-2.756***
	(-89.67)	(-46.67)	(-64.76)	(-74.85)	(-62.26)	(-73.75)
Observations	63527	50445	47260	48706	50251	52410

Table C.3 extends the analysis of Table 10 (Eq. 11) by examining how past boldness and performance influence an analyst's probability of advancing to a top brokerage house across the US, Europe, and Asia. This analysis considers variations in general experience, with results categorized into two subgroups: analysts with experience levels above and below the mean within each region. The independent variable of interest, Top 20% Boldness, is a binary indicator equal to one if the analyst's boldness rank is in the top 20% and zero otherwise. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

Appendix D:

Overview of Key Regulations Governing Financial Analysts and Brokerage Firms in Global Markets

Given the vital role that financial analysts play in reducing information asymmetries and bolstering market discipline—especially within the opaque banking sector—robust regulation is essential to ensure transparency, mitigate conflicts of interest, and maintain market integrity. In the U.S., Europe, and Asia, financial analysts and brokerage firms operate under various regulations designed to achieve these goals. Key regulations include the Global Research Analyst Settlement in the U.S., MiFID II in Europe, and various local regulations in Asia. These regulations differ in scope, enforcement strength, and impact, reflecting the distinct market structures and regulatory philosophies of each region (see Appendix D, Table D.1).

- **Comprehensive Separation of Research and Investment Banking (Global Research Analyst Settlement, 2003):** In the U.S., this regulation mandates a strict physical and operational separation between research and investment banking divisions within brokerage firms. This separation prevents investment banking activities from influencing the objectivity of analysts' recommendations, thereby addressing conflicts of interest at their root. In Europe, MiFID II, effective in 2018, enhances transparency and manages conflicts by unbundling research costs from trading fees, but it doesn’t mandate the same strict separation. Similarly, in Asia, while there are guidelines and directives addressing conflicts of interest, they often lack the stringent separation required in the U.S. This leaves more room for potential conflicts to influence analysts' work in both Europe and Asia.
- **Targeted Rules Addressing Conflicts of Interest (FINRA Rule 2241, 2015):** FINRA Rule 2241 in the U.S. provides detailed guidelines for managing conflicts of interest within brokerage firms. It prohibits analysts from being compensated based on specific investment banking activities they might influence. It also requires firms to disclose potential conflicts and ensures that research reports are not compromised by business pressures. While European regulations, such as MiFID II, address conflicts broadly, they lack the detailed, prescriptive measures seen in FINRA Rule 2241. Similarly, Asian regulations, though present, are generally less specific and enforceable.
- **Enforcement Strength and Accountability (Sarbanes-Oxley Act, 2002):** The Sarbanes-Oxley Act (SOX) in the U.S. enhances accountability through stringent internal controls and executive certifications of financial reports, promoting ethical behavior within firms. SOX indirectly influences analysts and research reports by enforcing a broader culture of compliance and integrity. While Europe and Asia have their own regulations, such as CRD IV and MAR in Europe, they do not match SOX's enforcement strength and direct impact on internal firm operations.
- **Investor-Centric Regulation (Regulation Best Interest, 2020):** Reg BI in the U.S. requires broker-dealers to act in the best interest of retail customers, prioritizing client interests over the firm's financial incentives. This helps ensure that analysts' recommendations remain unbiased. While MiFID II in Europe also focuses on investor protection, it does not mandate a "best interest" standard as explicitly as Reg. BI. Asian regulations vary and generally do not enforce a client-first standard to the same extent.

The regulatory frameworks in the U.S., Europe, and Asia each have unique strengths and weaknesses shaped by their market structures and philosophies. The U.S. regulatory framework benefits from a long history of managing conflicts of interest, transparency, and investor protection. It combines broad transparency mandates (Regulation Fair Disclosure, 2000), structural separation (Global Research Analyst Settlement, 2003), detailed conflict management (FINRA Rule 2241, 2015), and strong investor protection (Reg. BI, 2020) to create a robust and comprehensive system, albeit with higher compliance costs and complexity. Europe has strengthened investor protection and transparency with key regulations, including the separation of research and trading fees (MiFID II, 2018) and stringent disclosure rules (Market Abuse Regulation, 2016; ESMA Guidelines, 2013). However, its fragmented market structure challenges consistent enforcement. Asia's regulatory approach, driven by flexibility and rapid development, includes key standards like Japan's Financial Instruments and Exchange Act (2007) and Hong Kong's Securities and Futures Ordinance (2003), which promote transparency and ethical conduct, though inconsistent enforcement across the region can undermine effectiveness. Understanding these differences is essential for developing effective global policies that enhance financial analysis transparency and reliability, particularly in the opaque banking sector.

- **Furthered Enforcements**

Given the strengths and weaknesses of existing regulations, further enforcement is crucial to enhance the reliability of financial analysis and mitigate conflicts of interest, particularly within the opaque banking sector. To strengthen market discipline, policies should mandate standardized disclosures of forecasting assumptions and conflicts of interest supported by rigorous regulatory oversight. This should be coupled with continuous professional development, certification programs, and the promotion of independent analysis to reduce biases. Additionally, regulations could require mandatory disclosure of analyst compensation and incentives, enforce the separation of research and trading activities, and mandate independent audits of research reports. These measures aim to improve transparency, reliability, and integrity in financial analysis across the U.S., Europe, and Asia, ultimately reinforcing the information environment, strengthening market discipline, and contributing to overall economic stability in the banking sector across these key regions.

Table D.1 Key Regulations Governing Financial Analysts and Brokerage Firms in Global Markets

Regulation	Purpose	Date Started
	USA	
Regulation Fair Disclosure (Reg FD)	Prevents selective disclosure of material information, ensuring all investors have equal access.	2000
Sarbanes-Oxley Act (SOX)	Enhances the quality and reliability of corporate financial reporting, including for banks and brokerage firms, requiring stricter internal controls and independent audits.	2002
Global Research Analyst Settlement	Requires separation of research and investment banking within brokerage firms, mandates independent research.	2003
FINRA Rule 2241	Mandates that brokerage firms manage conflicts of interest, separate research from investment banking, and disclose conflicts. No investment banking influence over the compensation of research analysts.	2015
Dodd-Frank Wall Street Reform and Consumer Protection Act	Imposes stricter regulations on financial institutions, including banks and brokerage firms, to improve transparency, accountability, and financial stability.	2010
Volcker Rule (Part of Dodd-Frank)	Restricts proprietary trading by banks and brokerage firms, limits their involvement in hedge funds and private equity.	2013
SEC Regulation Best Interest (Reg BI)	Requires broker-dealers to act in the best interest of retail customers, affecting how brokerage firms conduct business.	2020
Generally Accepted Accounting Principles (GAAP)	Provides a standardized set of accounting principles used by public companies, including banks, to ensure consistency, transparency, and accuracy in financial reporting.	Ongoing
	Europe	
Markets in Financial Instruments Directive II (MiFID II)	Requires unbundling of research costs from trading fees, enhances transparency in financial analysis, and sets standards for conflict of interest disclosures. Impacts brokerage firms by separating research from trading activities.	2018
Market Abuse Regulation (MAR)	Includes measures to prevent market abuse, to ensure the integrity of EU financial markets, and to enhance investor protection and confidence in those markets.	2016
ESMA Guidelines	Provides guidelines for transparency and conflict of interest management in financial analysis.To improve investor protection and promote stable, orderly financial markets.	2013
Capital Requirements Directive IV and Capital Requirements Regulation	Sets stringent capital adequacy standards, risk management requirements, and disclosure obligations for financial institutions to ensure financial stability and transparency in their financial reporting.	2013
Code of Conduct by EFFAS	Promotes integrity, transparency, and professionalism in financial analysis and reporting, indirectly affecting banks' reporting standards.	Widely followed
International Financial Reporting Standards (IFRS)	Mandates standardized financial reporting for banks and other companies, ensuring transparency, comparability, and accuracy in financial disclosures across Europe.	2005 (Ongoing)
	Asia	
Financial Instruments and Exchange Act (FIEA)	Aims to regulate securities markets and financial instruments to ensure investor protection and market transparency. It includes measures to prevent unfair trading practices, enforce corporate disclosure, and oversee financial intermediaries	2007
Securities and Futures Ordinance (SFO)	Ensures transparency and ethical conduct in financial analysis. Sets standards for financial disclosures by financial institutions and banks to prevent market abuse and maintain fair market practices.	2003
Securities and Futures Act (SFA)	Regulates brokerage firms and financial analysts, mandates ethical conduct and transparency, and enforces strict financial reporting standards for banks.	2001
Guidelines for the Conduct of Securities Analysts	Sets standards for brokerage firms, promoting transparency and ethical conduct in financial analysis.	2011
Pan-Asian Regulatory Cooperation	Harmonizes regulations across Asian markets, impacting how banks and financial institutions manage disclosures, transparency, and financial reporting.	Ongoing efforts, varies by country
China Accounting Standards (CAS)	Provides a set of accounting and financial reporting standards for companies, including banks, ensuring high-quality and consistent financial reports. CAS is converged with IFRS but tailored to China's specific needs.	2006 (ongoing updates)
Specific Financial Reporting Requirements by CSRC	Regulates financial reporting by banks and other companies in China, ensuring transparency, accuracy, and compliance with national standards.	Ongoing
International Financial Reporting Standards (IFRS)	Sets standardized financial reporting requirements for banks and financial institutions, ensuring transparency and comparability in financial disclosures across the region.	Adopted different times

Chapter 3

Evolutionary-Based Ensemble Feature Selection Technique for Dynamic Application-Specific Credit Risk Optimization in FinTech Lending

This chapter is based on the paper titled *"Evolutionary-Based Ensemble Feature Selection Technique for Dynamic Application-Specific Credit Risk Optimization in FinTech Lending,"* published in the *Annals of Operations Research* (Received: 20 June 2023 | Accepted: 21 October 2024)
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Abstract

This study introduces EFSGA, an evolutionary-based ensemble learning and feature selection technique inspired by the genetic algorithm, tailored as an optimized application-specific credit classifier for dynamic default prediction in FinTech lending. Our approach addresses existing gaps in metaheuristic applications for credit risk optimization by (i) hybridizing metaheuristics with machine learning to accommodate the dynamic nature of time-evolving systems and uncertainty, (ii) leveraging distributed and parallel computing for real-time solutions in complex risk decision processes, and (iii) enhancing applicability to unbalanced learning scenarios. The proposed model utilizes a heterogeneous ensemble of machine learning algorithms, incorporating a genetic algorithm to simultaneously optimize model hyperparameters and classification thresholds based on decision-maker objectives over time. This approach substantially improves out-of-sample model performance, providing valuable insights for timely post-loan risk management. The feature selection technique contributes to a balanced trade-off between model performance and interpretability—a pivotal consideration in metaheuristic-based models. Results obtained from the EFSGA model applied to a dataset spanning 2007 to 2014 unveiled an average improvement of 23% in application-specific evaluation metrics compared to conventional heterogeneous ensemble techniques across diverse risk-taking scenarios. Noteworthy is the proposed dynamic framework, featuring a tunable class-weighted fitness function, demonstrating significant superiority in delivering real-time solutions adaptable to evolving decision processes. We validate the EFSGA classification model against established credit evaluation models.

JEL classification : C61, C63, G32, E17, G11, G17

Keywords: Decision-Making Optimization, Dynamic Risk Management, Ensemble Learning, Feature Selection Metaheuristic Optimization

3.1.Introduction

The rapid evolution of FinTech credit markets[39] has significantly improved access to financing for households and small enterprises traditionally underserved by conventional banking systems. By leveraging digitization, these platforms have enhanced transparency, reduced costs, and streamlined financial processes (He Li, 2018; Frost et al., 2019). However, the accelerated growth and interconnectedness of these markets have raised concerns regarding information asymmetries and regulatory oversight (FSB, 2019; Abbasi et al., 2021). Despite the initial positive credit performance, empirical evidence points to an increasing risk of delinquency over time, underscoring the need for continuous monitoring and adaptive risk management strategies (Di Maggio & Yao, 2018; Chava et al., 2021). To mitigate these emerging risks, dynamic credit scoring algorithms are crucial for financial institutions (Dia et al., 2022; Granja et al., 2022). The importance of real-time early warning systems in FinTech credit markets, secondary trading, and loan resale markets cannot be overstated. Monitoring borrower behavior and intervening proactively during the repayment process has been shown to significantly reduce delinquencies and minimize financial losses (He Liu, 2018; Wang et al., 2018). However, the complexities of FinTech-driven peer-to-peer (P2P) lending, characterized by high-dimensional and imbalanced credit data, present significant challenges for traditional credit risk models and conventional machine learning algorithms, necessitating advanced statistical and optimization techniques for effective risk assessment (Zhou et al., 2019). Recent advancements in credit risk prediction have focused on three key areas: (i) hybridizing metaheuristics with heterogeneous ensemble machine learning classifiers, (ii) applying hybrid feature selection techniques to balance interpretability and performance, and (iii) developing methodologies to address imbalanced learning scenarios. Metaheuristic algorithms, particularly Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have emerged as powerful tools in computational finance, optimizing complex decision variables and improving the accuracy of credit-scoring models (Goldberg, D. E., 1989; Metawa et al., 2017; Doering et al., 2019; Pławiak et al., 2019). These algorithms are also widely used for feature selection in credit risk analysis (Hall, 1998; Wang et al., 2015; Feng et al., 2019), refining models by identifying key features, removing redundancies, and enhancing interpretability and accuracy (Lappas & Yannacopoulos, 2021; Lu et al., 2022). These methods

[39] The term “FinTech credit” encompasses all credit activity facilitated by electronic platforms that connect borrowers directly with lenders. These entities are commonly referred to as “loan-based crowd funders”, “peer-to-peer (P2P) lenders “or “marketplace lenders”.

are frequently combined with individual machine learning models, neural networks, or ensemble approaches (Calvet et al., 2017; Pławiak et al., 2020), offering enhanced accuracy and reduced computational complexity[40].

Researchers have increasingly focused on advanced techniques to improve model performance in response to the challenges posed by high-dimensional and imbalanced datasets. Such datasets often exhibit a significant bias toward the minority class, requiring refined approaches. Acceptance threshold optimization**,** which adjusts decision thresholds to balance class representation, has proven effective in mitigating this bias. Genetic Algorithms (GA)**,** in particular, excel at optimizing these thresholds in large search spaces with complex performance metrics (Kazemi et al., 2022). Furthermore, cost-sensitive learning plays a crucial role in addressing class imbalances by adjusting thresholds based on the unequal importance of different classes and mitigating the asymmetrical misclassification costs between default and non-default loans (Herasymovych et al., 2019; Junior et al., 2020; Tang et al., 2021; Das, Mullick, & Zelinka, 2022; Jiang et al., 2023; Khalili & Rastegar, 2023).

Despite these advancements, the broader adoption of metaheuristics in credit risk assessment remains constrained by challenges related to model interpretability and handling imbalanced datasets (Dastile et al., 2020). Improving feature extraction methods to balance performance, computational efficiency, and interpretability is critical for the advancement of metaheuristic-based models (Lopez & Maldonado, 2019; Liu et al., 2022c). Additionally, oversized feature sets often lead to overfitting**,** increased computational complexity, and reduced transparency[41]. To address these limitations, more robust methodologies are needed that can integrate dynamic risk factors into decision-making processes while handling imbalanced data classification effectively. Moreover, further exploration of multi-objective optimization strategies is required to simultaneously maximize predictive accuracy while adapting to evolving data environments and financial landscapes. Developing robust methodologies for dynamically adjusting acceptance thresholds in real time is essential to ensure that credit risk models remain adaptive and effective under volatile economic conditions. Addressing these significant gaps is crucial for enhancing credit risk predictions in complex and dynamic financial environments.

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[40] Heterogeneous ensemble machine learning classifiers have become increasingly popular for their superior performance in credit risk prediction and feature selection, as demonstrated in various studies (Jiang et al., 2018; Chen et al., 2020; Mahbobi et al., 2021; Lu et al., 2022; Liu et al., 2022a; Abdoli et al., 2023; Bai et al., 2022; Liu et al., 2022c; Zhang et al., 2023).

[41] Research shows that only 8% of studies focus on model transparency (Dastile et al., 2020), a critical gap given regulatory mandates like the Basel II Accord, which require credit scoring models to be interpretable and explainable. Thus, transparency is not just beneficial but essential for compliance.

Our study pioneers an innovative approach by leveraging metaheuristic-driven ensemble learning and feature selection techniques to advance risk management within the FinTech sector. We propose the EFSGA model—an Evolutionary-based Ensemble Learning and Feature Selection technique inspired by Genetic Algorithms. This approach offers a tailored, application-specific credit risk optimization framework designed for dynamic default prediction and adaptable to imbalanced data environments, aligning with specific management objectives. The EFSGA model integrates a heterogeneous ensemble of machine learning algorithms and uses Genetic Algorithms to simultaneously optimize model hyperparameters and classification thresholds over time, enhancing both performance and decision-maker objectives.

Our research introduces several key innovations to address gaps in the application of metaheuristics for credit risk optimization: (i) the hybridization of metaheuristic algorithms with machine learning techniques to better account for dynamic behaviors and uncertainty in time-evolving systems, (ii) the integration of distributed and parallel computing paradigms to facilitate real-time decision-making in complex risk environments, (iii) the joint application of hybrid feature selection to balance performance, computational complexity, and interpretability, and (iv) the enhanced management of imbalanced learning scenarios through GA-based multi-objective optimization, including dynamic adjustments to decision thresholds. To the best of our knowledge, this study is the first to apply metaheuristics to credit risk optimization using this comprehensive, multi-faceted approach, with a focus on four key areas:

First, Simultaneous Optimization of Ensemble Learning and Feature Selection: Our model pioneers a unique approach by simultaneously optimizing ensemble learning and feature selection using Genetic Algorithms (GA). Unlike conventional methods, which typically require all ensemble classifiers to operate on the same feature set, our model selects distinct feature subsets tailored to each classifier. This optimization technique significantly enhances predictive accuracy and represents an advancement over traditional approaches that, to our knowledge, has not been previously explored in research.

Second, Ensemble Feature Selection with Genetic Algorithm (EFSGA): Our study introduces a novel framework designed to tackle the persistent challenge of balancing performance and interpretability in metaheuristic-driven models. By simultaneously optimizing weights and feature subsets for each base learner, EFSGA enhances the understanding of variable importance, reduces redundancies, and refines the balance between accuracy and transparency, thus advancing metaheuristic applications for credit risk assessment. It delivers valuable implications for risk management and policy decisions by providing deeper insights into variables influencing borrower defaults.

Third, Dynamic Optimized Decision Threshold for Imbalanced Data: Our EFSGA model addresses challenges posed by high-dimensional, imbalanced datasets through a multifaceted strategy. This includes dynamically adjusting the decision threshold using Genetic Algorithms (GA) to account for varying class importance and objectives. Additionally, it integrates a Genetic Class-Weighted, tunable Objective Function that incorporates distinct misclassification costs, enhancing its suitability for application-specific evaluation frameworks[42].

Fourth, Adaptive Framework for Evolving Decision-Maker Needs: Traditional risk assessment methods often face limitations in scenario modeling and accommodating diverse decision-making processes due to their reliance on fixed rules. Our adaptive framework addresses these challenges by offering a dynamic approach that aligns with evolving decision-maker needs and credit risk assessment tasks. Central to this framework is a tunable multi-objective fitness function, enabling customized, real-time risk assessments tailored to specific decision-maker objectives.

Our research provides a nuanced and in-depth analysis of the performance characteristics of diverse machine learning models, from individual classifiers to both homogeneous and heterogeneous ensembles. Rather than focusing solely on minority class identification, we prioritize ensuring model robustness and consistency across a variety of risk scenarios, iterations, and imbalanced datasets, while adhering to computational efficiency. By leveraging real-world P2P lending datasets—well-known for their class imbalance—we employ a metaheuristic algorithm to optimally weigh machine learning classifiers within the ensemble system. This approach enables financial institutions to precisely balance risk mitigation with operational performance, ensuring effective credit risk management across various strategic priorities.

The EFSGA model offers adaptable, real-time solutions for complex risk decision-making, significantly enhancing predictive accuracy and delivering actionable insights. By addressing the limitations of traditional methods, it presents a transformative approach to risk management, capable of adapting to dynamic borrower profiles and shifting macroeconomic conditions. This

[42] Optimizing the decision threshold in credit default identification is pivotal in addressing the disproportionate cost of false negatives compared to false positives. Our method strategically emphasizes recall to reduce the incidence of defaults while ensuring specificity to preserve profitable lending opportunities. This balanced approach not only mitigates risk but also enhances profitability, providing a refined model that aligns risk management with revenue optimization for more effective credit decision-making.

framework enhances credit and post-lending risk management for FinTech firms, banks, and non-bank financial institutions, supporting key areas such as loan approval, portfolio management, regulatory compliance, and risk assessment. Additionally, the model benefits secondary trading and loan resale markets by enabling investors to hedge default risks and adapt to evolving market conditions, making it a versatile tool for diverse financial scenarios. Furthermore, the framework aligns with stringent regulatory requirements, offering transparent and explainable models critical for compliance with standards such as the Basel II Accord, ensuring that financial institutions can meet both operational and regulatory expectations.

The paper is structured as follows: Sect. 3.2 presents the literature review. Section 3. 3 outlines the Proposed EFSGA Model. Section 3.4 details the Empirical Evaluation. Section 3.5 provides the Discussion and Conclusion, and Sect. 3.6 highlights Future Research Directions.

3.2. Related Work

Credit risk prediction has long been a focal point in the financial sector due to its critical role in managing loan portfolios and mitigating potential defaults. Extensive empirical research has explored various modeling techniques, including dynamic credit risk scoring, the integration of metaheuristics with machine learning, feature selection methodologies, and improved strategies for addressing imbalanced data. While substantial progress has been made, several key gaps remain, particularly in the adaptability, accuracy, and interpretability of credit risk models. The following sections review the most relevant work in the field, focusing on dynamic credit risk assessment, ensemble methods, metaheuristic algorithms, feature selection, and imbalanced learning. This review identifies existing limitations and highlights how our approach addresses these challenges.

3.2.1. Dynamic Credit Risk Assessment

In credit risk management, two primary models—credit scoring and behavioral scoring—are traditionally employed to evaluate borrower creditworthiness and repayment potential. However, traditional behavioral models often fail to capture the evolving nature of borrower behavior throughout the loan lifecycle. These static classification approaches may overlook critical changes over time, limiting both predictive accuracy and effectiveness. Recent advancements in credit risk assessment have begun to address these limitations by incorporating dynamic behavioral data into predictive models. This shift involves the use of variables such as repayment history and management interventions, which change over time. Techniques like neural networks, ensemble machine learning models, and continuous-time Markov chains have been particularly effective in capturing the temporal dynamics of borrower behavior, significantly enhancing default risk prediction. For example, Lessmann et al. (2015) underscore the importance of continuously monitoring borrower behavior with machine learning techniques to dynamically adapt credit scoring models. Similarly, Li et al. (2020) propose an ensemble approach that integrates real-time borrower data, improving prediction accuracy in response to changing economic conditions. Chen et al. (2021) also explore continuous-time Markov chains to model the transition probabilities of borrower states, providing deeper insights into credit risk dynamics. Despite these advances, challenges remain in dynamic credit risk assessment. Issues such as data availability and quality, the complexity of modeling dynamic behaviors, and the need to account for macroeconomic conditions and management interventions persist (Foo et al., 2017; Dastile et al., 2020; Li et al., 2020). Overcoming these challenges is essential to further improving the predictive power and generalizability of dynamic credit risk models.

3.2.2. Ensemble of Classifiers in Credit Risk Research Area

Ensemble methods have become a dominant approach in credit risk prediction due to their superior performance over traditional models. Numerous studies (Jiang et al., 2018; Chen et al., 2020; Cao et al., 2021; Mahbobi et al., 2021; Lu et al., 2022; Liu et al., 2022a; Abdoli et al., 2023; Bai et al., 2022; Liu et al., 2022c; Zhang et al., 2023) demonstrate the effectiveness of ensemble techniques in improving credit risk assessment and feature selection. Malekipirbazari and Aksakalli (2015) showed that a random forest-based model outperformed traditional FICO scores in predicting trustworthy borrowers on the Lending Club platform, emphasizing the importance of credit history variables. Kim and Cho (2019) found that an ensemble semi-supervised learning model surpassed the decision tree and support vector machine models for default prediction. Further advancements have included the use of Gradient Boosting Decision Trees (GBDT) and Auto-Encoder in multi-stage ensembles (Chen et al., 2019) and the development of heterogeneous ensemble models for credit scoring, such as the model proposed by Li et al. (2020). Innovations like Xia et al.'s (2020) tree-based ensemble method and Liu et al.'s (2022a) AugBoost-RFS and AugBoost-RFU have further reinforced ensemble methods’ ability to improve accuracy, particularly in handling imbalanced datasets. Research also highlights the importance of data preprocessing, feature selection, and addressing class imbalance to enhance both model performance and interpretability (Galar et al., 2012; Xiao et al., 2016; Wang et al., 2018). Overall, ensemble techniques present a robust solution to credit risk modeling, effectively tackling key issues like feature selection and class imbalance in financial datasets.

3.2.3. Metaheuristic Algorithms in Credit Risk Assessment and Feature Selection

3.2.3.1. Hybrid Approaches with Metaheuristic Algorithms

In recent years, metaheuristic algorithms have garnered significant attention in credit risk assessment due to their ability to handle complex and dynamic datasets. Among these, Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have emerged as effective tools for improving both the accuracy and efficiency of credit-scoring models. These algorithms have been widely employed in hybrid models, often combined with machine learning techniques such as neural networks or ensemble methods. Specifically, GAs have been instrumental in optimizing parameters and enhancing the performance of credit scoring models across various contexts. Several key studies exemplify the application of metaheuristic algorithms in credit risk assessment. Tran et al. (2016) developed a hybrid model integrating Genetic Programming (GP) and Deep Learning (DL), leveraging GAs to optimize neural network architectures. This approach not only improved the model's predictive accuracy but also demonstrated the synergy between evolutionary computation and deep learning in handling complex credit datasets. Similarly, Ye et al. (2018) applied GAs to optimize Random Forest models for Peer-to-Peer (P2P) lending platforms, improving the prediction of loan profitability and refining loan decision-making processes. Moreover, Pławiak et al. (2019) introduced DGHNL, a deep genetic hierarchical network for credit scoring, which combined the strengths of hierarchical learning with genetic algorithm optimization. This model demonstrated superior accuracy compared to traditional deep learning architectures. Soui et al. (2019) further explored the integration of multi-objective evolutionary algorithms in rule-based credit risk models, which enhanced both accuracy and interpretability by optimizing rule extraction and minimizing complexity. These studies collectively highlight the advancements in the application of metaheuristic-driven models for credit risk assessment. However, challenges remain in balancing performance and interpretability, particularly when dealing with complex, high-dimensional datasets. This gap underscores the need for further research into hybrid approaches that integrate metaheuristic optimization with modern machine learning techniques.

3.2.3.2. Feature Selection Using Metaheuristic Algorithms

Feature selection has become a central focus in risk management studies, particularly in identifying key factors influencing credit risk. While model accuracy remains a primary concern, interpretability poses significant challenges in machine learning, deep learning, and ensemble models (Lopez & Maldonado, 2019; Liu et al., 2022c). Efforts to improve interpretability through approaches like LogR (Dumitrescu et al., 2022) or model-agnostic methods such as LIME and SHAP (Bücker et al., 2022) often face challenges, including high computational costs and stability issues (Aas et al., 2021; Slack et al., 2020). Metaheuristic algorithms, including genetic algorithms (GA), particle swarm optimization (PSO), and simulated annealing, are gaining prominence in feature selection for credit risk assessment. These techniques offer more robust solutions compared to traditional methods by effectively identifying influential features (Wang et al., 2015; Feng et al., 2019). For instance, Šušteršic et al. (2009) introduced a hybrid model combining Principal Component Analysis and GAs with neural networks, enhancing feature selection. Similarly, Oreski et al. (2014) developed the Hybrid Genetic Algorithm Neural Network (HGA-NN) to optimize feature subsets for improving classification accuracy. Recent advancements include the use of multi-objective GAs in feature selection, as demonstrated by Deniz et al. (2017), who achieved superior performance over conventional methods like PSO and Greedy algorithms. Hancer et al. (2018) combined differential evolution with information theory to improve feature ranking, while Taradeh et al. (2019) proposed an evolutionary algorithm for more efficient feature selection. Additionally, Lappas and Yannacopoulos (2021) incorporated expert knowledge with GA-based feature selection, improving accuracy in unbalanced credit datasets. Lu et al. (2022) further expanded the field by integrating the binary opposite whale optimization algorithm (BOWOA) with the Kolmogorov–Smirnov (KS) statistic for feature selection in credit risk. Other studies have successfully integrated feature selection algorithms with ensemble classifiers to enhance predictive performance (Tripathi et al., 2019; Nalić et al., 2020). These studies underscore the growing importance of metaheuristic-driven feature selection in credit risk, addressing complex data challenges while balancing interpretability and model accuracy.

3.2.4. Imbalanced Learning and Threshold Optimization Techniques

Imbalanced learning is a persistent challenge in credit risk and default prediction, where datasets often display a significant skew toward one class, such as non-default loans outnumbering defaults. Researchers have developed various techniques to improve model performance under these conditions. A common approach is threshold optimization, which fine-tunes the decision boundary to balance sensitivity (identifying defaults) and specificity (correctly identifying non-defaults). Genetic Algorithms (GAs) have proven effective in this domain by iteratively adjusting thresholds based on performance metrics (Kazemi et al., 2022). Cost-sensitive learning is another critical method, assigning different costs to misclassifications based on their real-world consequences. For example, false positives (approving risky loans) and false negatives (rejecting safe loans) carry different risks. By prioritizing the minority class, cost-sensitive approaches provide a balanced representation of classes (Junior et al., 2020; Tang et al., 2021). In addition, recent studies propose dynamic selection techniques that adapt to varying data characteristics in real time. Junior et al. (2020) introduced dynamic local region selection for imbalanced credit scoring, and Tang et al. (2021) applied a cost-sensitive kernel method with the Blinex loss function to adjust misclassification costs dynamically. Das, Mullick, and Zelinka (2022) reviewed advancements in handling class-imbalanced datasets, emphasizing the importance of these strategies for improving model reliability in real-world scenarios. Khalili and Rastegar (2023) further developed a hybrid metric that integrates traditional and cost-sensitive considerations, enhancing model accuracy while minimizing the financial impact of misclassifications. Kazemi et al. (2022) also demonstrated the efficacy of GAs in optimizing decision thresholds for credit-scoring applications. Their method improved model performance by dynamically adjusting thresholds, which helped balance false positives and negatives, thus enhancing the discriminatory power of credit scoring models.

3.2.5. Our Motivation

While the application of metaheuristics in credit risk assessment has demonstrated significant promise, several critical limitations remain unaddressed in the existing literature. Specifically, the following gaps persist (a) the effective hybridization of metaheuristic algorithms with machine learning techniques to better account for the dynamic behaviors of financial systems and inherent uncertainties, (b) the need for improved feature extraction and selection techniques that balance model performance, computational complexity, and interpretability, (c) the development of flexible frameworks that enable real-time risk decision-making in complex and evolving scenarios, and (d) more robust solutions for handling imbalanced data, including dynamic threshold optimization and the incorporation of broader economic factors into predictive models. To address these limitations, our study introduces a novel hybrid model that combines the strengths of evolutionary algorithms with ensemble learning techniques. By integrating Genetic Algorithms (GAs) for dynamic threshold optimization and feature selection, our approach enhances the adaptability, accuracy, and interpretability of credit risk models. Furthermore, we propose a flexible, real-time decision-making framework that accounts for management objectives and changing risk factors, improving the generalizability of credit risk assessments across diverse economic conditions. Through these innovations, our research aims to advance the field of credit risk modeling and provide more effective solutions for financial institutions facing complex, dynamic credit risk environments.

3.3. Proposed EFSGA Model

Generally, in pattern recognition systems, an optimal feature subset is chosen from a set of original features to maximize system performance. Indeed, the system eliminates unnecessary and redundant features that may be represented as continuous or discrete binary variables. Hence, the selected feature set constitutes the "features vector" (Ansari et al., 2017). Each machine learning classifier has advantages and disadvantages in classifying samples into different classes based on a distribution of data samples in an N-dimensional feature space. Therefore, an ensemble of heterogeneous classifiers may result in better performance. Moreover, each classifier can achieve the best accuracy via a specific feature subset. In other words, the optimal feature subset for a classifier may differ from another classifier. Therefore, the feature selection procedure is also a classifier-dependent problem. Fig.1 illustrates the simplified flow diagram representing the " Data, Methodology, and Output " structure of the proposed combined evolutionary-based ensemble learning and ensemble feature selection technique for early credit risk warning systems in P2P lending. The proposed EFSGA utilizes a hybrid ensemble learning and feature selection technique based on GA. This optimized application-specific loan classifier compromises an ensemble of heterogeneous machine learning structures as base learners. The GA is employed to simultaneously optimize the weights and feature subsets for each base learner within the ensemble model. Additionally, the GA optimizes the classification decision threshold to address the misclassification challenge associated with imbalanced datasets with varying class importance, particularly for the minority class (the default class in this study).

3.3.1. Ensemble Learning and Feature Selection

The optimization process of the EFSGA model is facilitated through the collective learning system within the proposed ensemble model. Our study utilizes a parallel, heterogeneous ensemble learning algorithm to enhance performance and reduce overfitting. Therefore, using GA enhances result interpretability and improves system performance by individually selecting the most compelling features for each classifier. The feature selection process eliminates redundant and unnecessary features, leading to a simplified model that maximizes system accuracy.

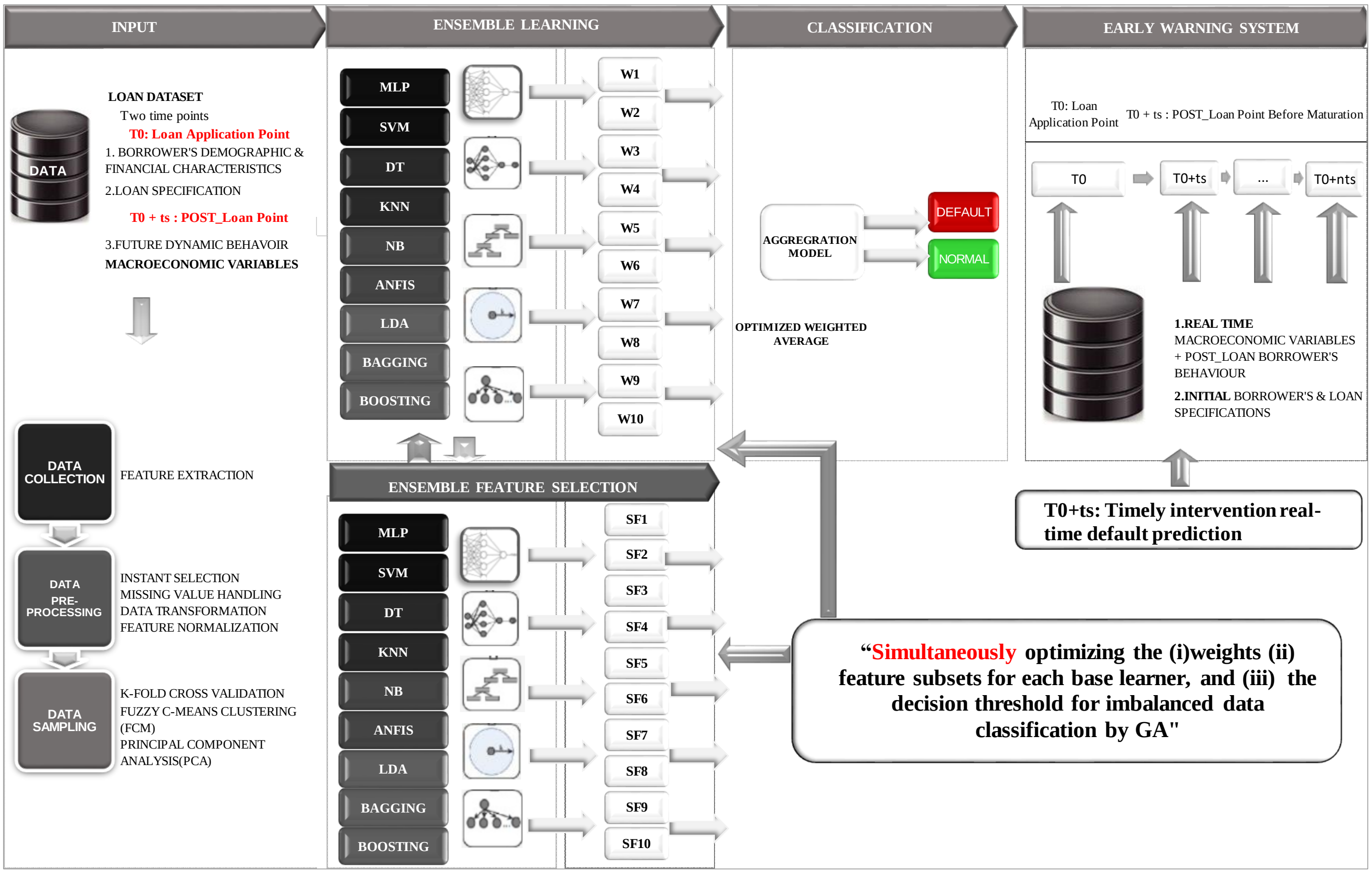

Fig. 3.1. The simplified flow diagram representing the " Data, Methodology, and Output " structure of the proposed EFSGA model.

3.3.1.1. Heterogeneous Ensemble Model

Our Heterogeneous Ensemble Model integrates high-performing machine learning algorithms through a rigorous performance evaluation process. This evaluation encompasses individual models as well as homogeneous and heterogeneous ensembles, with a specific focus on identifying minority classes. To ensure robustness, stability, and consistency, we assess model performance across multiple iterations, varied risk modeling scenarios, and imbalanced data distributions while adhering to computational constraints. The evaluation leverages real-world P2P lending datasets, known for their imbalanced nature, across two critical prediction periods: the loan application stage and the post-loan repayment period. A Genetic Algorithm (GA) is employed to optimize key parameters, including algorithm weights (ranging from 0 to 1), feature subsets, and classification thresholds for each classifier to enhance the ensemble's overall performance. The assigned weights reflect the contribution of each algorithm to the final ensemble model, where values closer to 1 signify a higher impact on the model's predictions, and values closer to 0 indicate a more limited role. This adaptive weighting system enables the model to effectively balance the contributions of individual algorithms, prioritizing those that perform consistently well while down-weighting less effective ones. By ranking classifiers based on weighted averages across multiple genetic iterations, the GA provides critical insights into their consistency and effectiveness across diverse risk scenarios. The initial selection of algorithms for integration into the ensemble model was driven by their demonstrated ability to address data imbalance challenges. Prior research highlights substantial differences in the performance, strengths, and limitations of various machine learning algorithms for identifying default instances. While some models excel in predicting minority classes, their applicability in broader or imbalanced contexts remains under scrutiny, especially given the computational demands of certain algorithms[43]. In response, our approach strategically balances the selection of initial ensemble models by incorporating a diverse set of individual algorithms—both linear (e.g., Linear Discriminant Analysis, Naïve Bayesian) and non-linear (e.g., K-Nearest Neighbors, Adaptive Neuro-Fuzzy Inference System)—along with homogeneous ensemble models (e.g., Random Forest, AdaBoost, LogitBoost, Random Subspace). This comprehensive strategy harnesses the diverse strengths of each model, reduces computational complexity, and enhances overall predictive performance (Altman, 1992; Jang et al., 1991; Winterfeldt et al., 1986; Detlof et al.,1986; Breiman, 2001; Ernst & Wehenkel, 2006; Freund et al., 1999; Friedman et al., 2000). These algorithms were tested on real-world, imbalanced P2P lending datasets across two key stages: loan application and post-loan repayment. The development of the ensemble learning model followed a systematic selection process based on three core criteria: (i) classification performance, particularly in identifying minority classes, aligning with our main objectives (ii) consistency and stability across different data imbalance ratios and risk scenarios, and (iii) computational efficiency, achieved through hyperparameter tuning to ensure optimal resource use.

[43] Linear models like Logistic Regression (LR) and Support Vector Machines (SVMs) with linear kernels are widely used for their simplicity, ease of implementation, and good classification accuracy in balanced datasets. They work well when the relationship between predictors and the target is linear, making them fast and reliable. In contrast, non-linear models such as Decision Trees, k-Nearest Neighbors (KNN), and SVMs with non-linear kernels excel in handling imbalanced datasets, where minority class instances are fewer but crucial, as they capture complex relationships better than linear models. However, ensemble methods like Boosting (e.g., AdaBoost, XGBoost) and Bagging (e.g., Random Forest) outperform both linear and non-linear models for predicting minority classes. These methods reduce bias and variance by combining multiple models, improving accuracy in imbalanced datasets despite higher computational costs (Kim & Cho, 2019; Liu et al., 2022a; Malekipirbazari & Aksakalli, 2015; Chen et al., 2019; Xia et al., 2020). This underscores the trade-offs between model complexity, efficiency, and performance, with ensemble methods consistently offering superior results for minority class predictions.

3.3.1.2. Ensemble Feature Selection

Furthermore, to enhance the interpretability of the results, build a simpler model, maximize system performance, and eliminate unnecessary and redundant features, we have developed the ensemble feature selection and feature importance analysis technique using a genetic algorithm. The proposed ensemble feature selection analysis technique aims to determine each feature subset's predictive power and significance as significant predictors of default. It selects the most efficient features for each classifier separately (as the optimal feature subset for a classifier may differ from another classifier due to their different classification algorithms). It performs weighted optimization of collective learning coefficients for all heterogeneous machine learning classifiers accordingly.

The output of the proposed EFSGA system for i^{th} input sample is expressed as a weighted average of the outputs of M different classifiers, represented as follows:

$$Output(i) = \frac{\sum_{k=1}^{M} w_k Out_k^i(SF_k)}{\sum_{k=1}^{M} w_k} \tag{1}$$

where w_k is the weight of the k^{th} classifier in the proposed ensemble learning model, SF_k is the selected features for the k^{th} classifier, and Out^i_k is the output of the k^{th} classifier for the i^{th} input sample.[44]

Moreover, in a binary classification problem, the output of a model is a probability score indicating the likelihood of the instance belonging to the positive class. The decision threshold separates the positive and negative classes based on the model's probability scores. Typically, a threshold of 0.5 is used. However, in imbalanced data, since the probability distribution tends to be biased toward the minority class, the default classification threshold of 0.5 may not be the best choice. The choice of threshold depends on the problem and the importance of false positives and false negatives. We employ a Genetic Algorithm (GA) to optimize the threshold, which mimics natural selection to find the most suitable value. The GA is a powerful approach to finding an optimal threshold value, especially when the search space is large or the relationship between the threshold and performance is complex. The GA generates a population

[44] We utilized ten individual machine learning algorithms and homogeneous ensemble methods to construct our collective heterogeneous ensemble learning model (M = 10). Furthermore, our loan dataset comprises 47 features, encompassing loan characteristics, borrower demographics and financial records, as well as macroeconomic characteristics (N = 47)

of thresholds, evaluates their performance, selects the best ones, and creates new populations. This systematic approach using a GA provides a powerful tool for improving the performance of machine learning models.

$$Solution.T = T, \quad T \in [0,1] \tag{2}$$

$$Label(i) = \begin{cases} Default & if\ Output(i) \geq T \\ Normal & if\ Output(i) < T \end{cases} \tag{3}$$

Where T is the optimized threshold by genetic algorithm, and Label (i) is a final decided class (Default, Non-default) for each i^{th} input sample. Further details are provided in Appendix A.

3.3.2. Optimization of EFSGA Model

3.3.2.1. Problem Representation

A genetic algorithm (GA) is an efficient optimization procedure. The mechanisms of biological evolution inspire the basic principle of the GA. GA uses a set of genetic-inspired operators to evolve an initial population of solutions into a new population. Each population comprises chromosomes representing genetically encoded solutions to a specific problem. Each individual has a fitness score _ based on the GA fitness function_ assigned to them, which represents their ability in terms of a solution. A new population is evolved by using operators of crossover, mutation, and selection, where selection is based on the individual's fitness and influences the ability to reproduce into the next generation (Mitchell,1996; Michalewicz,1996; Šušteršic et al., 2009; Kozeny, 2015). The process begins with producing a random population of chromosomes (Feasible Solution). For many optimization problems, GA does not operate directly on the solutions for the problems. Instead, they make use of problem-specific representations of the solutions. The genetic operators modify the representation, which is then transformed into a solution using a decoding procedure. More specifically, each chromosome can be represented as a hybrid structure containing an integer vector W of length 1*M (weights of M Machine learning classifiers of the heterogeneous ensemble learning) and a binary matrix F of dimension M*N (each raw represents the feature selection for each classifier from N original features). In reference to Eq. (1), if the j attribute is present in class i, the i, j derivative in a binary matrix is equal to "1", and if the j attribute for class i is eliminated in the corresponding solution, the derivative i, j is equal to "0". Also, the weight coefficients of different classes are expressed according to Eq. (4).

Solution. W:
Heterogeneous Regressors

w_1	w_2	w_3	…	W_M

Solution. F :
Heterogonous Feature extraction

f_{11}	f_{12}	f_{13}	…	f_{1N}
f_{21}	f_{22}	f_{23}	…	f_{2N}
f_{31}	f_{32}	f_{33}	…	f_{3N}
:	:	:	…	:
F_{C1}	F_{C2}	F_{C3}	…	F_{MN}

Solution. T:
Optimized Decision Threshold

T

Fig. 3.2. Representation of a feasible solution (chromosome encoding) for optimizing the EFSGA model.

$$\text{Solution.W}(k) = w_k \in [0,1]; \quad \forall k = 1, 2, \ldots, M$$

$$\text{Solution.F}(k, j) = f_{kj} \in \{0,1\}; \quad \forall k = 1, 2, \ldots, M \ , \forall j = 1, 2, \ldots, N \tag{4}$$

$$f_{kj} = \begin{cases} 1 & if \ \ j^{th} \ feature \ is \ selected \ for \ k^{th} \ classifier \\ 0 & otherwise \end{cases} \tag{5}$$

In each iteration of the GA, there are two general steps. The first is to evaluate the competence of the solutions produced, and the second is to update the population (generate a new population). These two consecutive steps are performed repeatedly until the termination criterion is satisfied. The final condition in this study is to determine the number of repetitions of the algorithm.

3.3.2.2. Proposed Fitness Function

This paper introduces a class-weighted, multi-objective function (ObjF) in the GA framework as a tunable, application-specific evaluation metric for optimizing the EFSGA model. To enhance interpretability, our initial evaluation applies weighted aggregation of precision, accuracy, and recall rates within the genetic objective function. The objective function (ObjF) is defined as the minimization of the weighted sum of the overall error (1 - Accuracy), imprecision (1 - Precision), and missed predictions (1 - Recall):

$$Minimize\ ObjF\ =\ w_{cf1} \times (1 - Accuracy) + w_{cf2} \times (1 - Precision) + w_{cf3} \times (1 - Recall) \tag{6}$$

where w_{cf1}, w_{cf2}, and w_{cf3} are constant weights that regulate the influence of each metric, ensuring the sum equals 1. Further details are provided in Section 3. 4.2.

We use K-fold cross-validation to compute the fitness function, averaging accuracy, precision, and recall across folds for evaluation. Our model prioritizes minimizing the false negative rate to mitigate financial loss from defaulted loans, even with a minor trade-off in overall accuracy. Additionally, we aim to sustain an optimal true negative rate (specificity) to preserve potential revenue from performing loans. Our model's design reflects this dual objective—minimizing defaults while maximizing profit. Recognizing the limitations of single-metric evaluations in imbalanced datasets, which can bias results toward minority classes, our approach incorporates a suite of performance measures, including the Fß-Score, for a more comprehensive evaluation.

The optimization process is tailored to accommodate varying risk strategies through a customizable genetic cost function that reflects management objectives (e.g., risk tolerance, trade-offs between risk and profit). By adjusting the weights in the GA cost function, the model adapts to diverse risk preferences. Our approach prioritizes recall and the F2-Score, particularly in scenarios requiring high recall while maintaining sufficient accuracy and precision for practical decision-making. The model's optimization balances objectives such as maximizing recall with minimal precision loss, balancing recall with modest accuracy and precision trade-offs, and achieving optimal performance across all metrics. These objectives shape the weightings in the GA's cost function, enabling the model to strike a balance between minimizing defaults and maximizing profits, ensuring its flexibility across different risk management contexts.

3.3.2.3. GA Optimization Process

The Genetic Algorithm (GA) begins by generating a randomly initialized population. This initial stage is followed by an iterative cycle of two key processes: fitness evaluation and population updating, which continue until the predefined number of iterations is reached. In each iteration, the fitness of the current population is evaluated, and a subset of high-performing chromosomes is selected as parents for the next generation. These selected parents undergo a crossover operation to produce offspring, ensuring genetic diversity and enabling the exploration of new solutions within the search space. Following the creation of the offspring, a mutation operator is applied to introduce random alterations to certain genes, which helps prevent premature convergence and fosters a broader exploration of the solution space. The optimization process is guided by the objective of improving model performance at each iteration, ensuring the population evolves toward optimal solutions. The overall structure of the proposed hybrid GA-based optimization algorithm is illustrated in Fig. 5, which outlines the following key steps:

Generating a Random Initial Population: Population initialization marks the first step in the GA process. The population represents a subset of solutions in the current generation, with each solution encoded as a chromosome. The initial population P (0), or the first generation, is generated randomly. Each chromosome is represented as a binary matrix and a quantitative vector, expressed as a vector of length M X N + MT. The M X N portion corresponds to the feature selection phase, while MT represents the collective learning segment. Each gene within a chromosome has an equal probability of being "0" or "1," ensuring randomness in the initial population.

Assessing the competence of the proposed solutions: Following the population update, the solutions are evaluated based on a fitness score. This score guides the evolutionary process. If necessary, the weights of the error components in the objective function (ObjF) are tuned to improve optimization. The fitness evaluation plays a crucial role in determining the quality of each chromosome.

Population update: The GA iteratively generates new populations by applying genetic operators to the current population. The population update consists of three stages: recombination, crossover, and mutation. The proportions of the new generation produced using these three operators are defined as PRecombination, PCrossover, and PMutation, respectively. In this study, these values are set to 0.1, 0.5, and 0.4. This balanced approach facilitates exploration while preserving optimal genetic material.

Parent selection: Parent selection is critical to the GA's convergence rate, as it determines which chromosomes will combine to form offspring for the next generation. Following the research by Li Zhan et al. (2021), we utilize the Roulette Wheel selection method, which has shown superior optimization capabilities. In this approach, the probability of selecting a chromosome is proportional to its fitness, as determined by the objective function (ObjF). The Roulette Wheel selection with power two is applied in this study to ensure effective parent selection.

Combination Operator (Crossover): The crossover operator combines the genetic material from two selected parents to produce a new generation (offspring). In this study, we use the Uniform Crossover method, where genes from the offspring are randomly selected from either parent with a probability of *PCrossover*. For example, in Fig. 3, specific genes (second, fourth, sixth, and ninth) are inherited from the first parent, while the remaining genes come from the second parent. This process ensures diversity and enhances the search for optimal solutions.

Parent 1	1	0	1	1	0	0	1	0	1	0
Parent 2	0	0	1	0	1	0	1	1	1	0

Child	0	0	1	1	1	0	1	1	1	0

Fig.3.3 Population updating in GA: Uniform Crossover Operator.

Mutation operator: The mutation operator introduces random variations to the offspring's genes to prevent premature convergence. In this study, we apply Binary Swap mutation for the feature selection structure (FS) and Evolution Strategies (ES) for the other components. The mutation operator alters genes with a probability P_m (Mutation probability), ensuring that new genetic material is explored. In the Binary Swap mutation, two randomly selected genes are interchanged to maintain diversity, as illustrated in Fig. 4. This process allows the algorithm to explore a wider range of potential solutions while preserving essential features of the parents.

Before Mutation Operation	1	0	1	1	0	0	1	0	1	0
After Mutation Operation	1	0	1	1	1	0	1	0	1	0

Fig. 3.4: Population updating in GA: Binary Swap Mutation Operator.

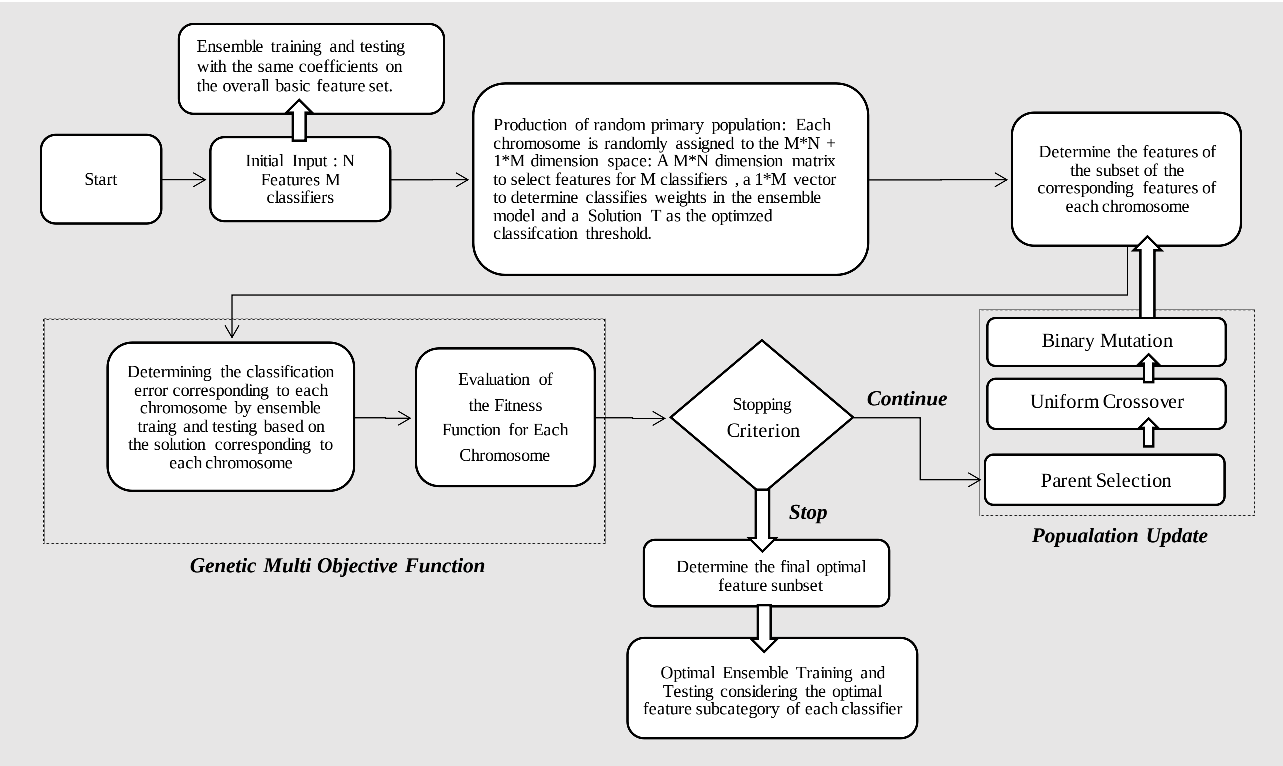

Fig. 3.5 Flowchart of the proposed hybrid method for Ensemble Feature Selection using the genetic algorithm.

3.4. Empirical Evaluation of Proposed Method

All experiments reported in this section have been executed in MATLAB R2018b on a PC with a 1.80 GHz Intel® Core™ i5-8250U CPU and 12 GB of RAM using the Windows 10 operating system.

3.4.1. Data Collection

3.4.1.1. P2P Lending Dataset

The dataset for this study was sourced from "Lending Club," a leading P2P lending platform in the US, in November 2019. It includes both defaulted and non-defaulted loans issued between Q3 2007 and the end of 2018[45]. After excluding non-funded loans, the dataset contains 622,682 observations, with 24% representing defaults and 76% non-defaults. The raw data is divided into four feature groups, comprising 128 attributes relevant to loan applications: Group 1 includes borrower financial characteristics (76 attributes), Group 2 encompasses loan attributes

[45] https://www.lendingclub.com/info/statistics.action .Since 2019, Lending Club has modified its download policies and data accessibility, now exclusively offering data on accepted loans while removing information on rejected loans. Additionally, a new copyright notice has been introduced. It's important to note that data collection is currently restricted to US residents.

(18 attributes), Group 3 captures post-loan performance (34 attributes), and Group 4 incorporates macroeconomic indicators. Each feature group contributes essential data for evaluating borrower credit risk and predicting default probability (Appendix B provides detailed feature descriptions).

Additionally, to ensure the robustness and generalizability of our findings, we performed a robustness test using data from Mintos, a European marketplace lending platform. This analysis covers loans issued across the US and various EU countries, incorporating recent economic disruptions, such as the COVID-19 pandemic and the Russia-Ukraine war, thus providing a broader perspective on the study's implications.

3.4.1.2. General Economy data collection

This study examines the real-time influence of macroeconomic factors on borrower risk behavior, particularly during periods of financial crisis and market instability. Departing from prior P2P lending research, which primarily focused on individual factors like interest rates or default probabilities, we aim to establish a direct connection between default risk and broader economic conditions (Foo et al., 2017). Our analysis incorporates six key macroeconomic indicators: the unemployment rate, stock market performance (total shares), consumer price index (CPI), household debt, GDP growth, and the TED spread. These variables provide a comprehensive view of economic health and its relationship to credit risk. The data on Treasury yields and general economic indicators were retrieved from the FRED database of the Federal Reserve Bank of St. Louis.

3.4.2. Simulation Settings

The implementation of the EFSGA model's assessment involves multiple stages: (i) data pre-processing, (ii) adjustments to the real-time prediction framework, (iii) configuring data sampling for training, validation, and testing using techniques like FCM, K-Fold Cross-validation, and PCA, and (iv) hyperparameter tuning of EFSGA through the Genetic Algorithm (GA).

3.4.2.1. Data Pre-processing

The first stage in the process is data pre-processing, which includes instance selection, missing value imputation, data transformation, feature normalization, outlier detection, and data randomization. These steps ensure that the data is properly formatted for model training and evaluation. Detailed information on the pre-processing procedures is provided in Appendix C.

3.4.2.2. Real-Time Prediction Framework

The next phase involves generating a real-time loan default prediction framework. The model is designed to operate at two prediction points: at the loan application stage and during post-loan repayment before maturity. The model uses Feature Groups 1, 2, and 4 for loan applications, while post-loan predictions utilize all Feature Groups. The system dynamically updates borrower information, such as repayment history and total paid amounts, to capture delayed payments and their durations. The framework tracks each borrower's progress every three months, refining the prediction based on updated macroeconomic factors and allowing for a real-time, adaptive risk prediction during the loan settlement period.

3.4.2.3. Representative Data Selection and Training

A key component of the EFSGA implementation is the selection of representative data for training, validation, and testing. We employ the Fuzzy C-Means (FCM) algorithm, configured with specific parameters (e.g., an exponent for the membership matrix of 1.2, a maximum of 50 iterations, and a minimum improvement of 1e-5). To ensure generalizability, we employ a 10-fold cross-validation approach. Initially, the dataset is divided into training and test sets, comprising 60% and 40% of the data, respectively. The training set is then partitioned into 10 equal-sized folds, with the model trained on 9 folds and validated on the remaining fold during each iteration. This iterative process ensures the model is exposed to diverse data subsets, improving robustness and reducing the risk of overfitting. As a result, this method enhances the model's ability to generalize effectively to new, unseen data.

Additionally, we apply Principal Component Analysis (PCA) to reduce data dimensionality while retaining 95% of the explained variance (Li et al., 2023). PCA is performed separately on the training, validation, and test sets to prevent information leakage and maintain model integrity. By eliminating noise and irrelevant features, PCA enhances model efficiency and improves predictive accuracy, making it particularly valuable in optimizing credit risk assessment models.

3.4.2.4. GA Simulation Settings

In optimizing the EFSGA model, several GA parameters were fine-tuned to achieve optimal performance. After experimenting with various parameter values, the best results were selected based on the objective function (ObjF) performance in the final simulations. The specific parameters for the EFSGA algorithm are outlined in Table 3. 1. For instance, the next-generation chromosomes were produced using PRecombination, PCrossover, and PMutation values of 0.1, 0.5, and 0.4, respectively. The population size and maximum iterations were set to 50 and 200. These configurations allowed us to refine the model's ability to predict default probability over time while improving generalization to new datasets. Notably, the EFSGA can be customized based on specific application needs by adjusting the weights assigned to objectives in the multi-objective function (Eq. 6). We conducted multiple simulations across different settings for w_{cf1}, w_{cf2}, w_{cf3} and varied data imbalances to evaluate model consistency. Results are based on the average outcome over ten iterations.

After completing data pre-processing, system tuning, and parameter optimization, the full implementation involved two main steps: first, we developed a collective learning system integrating heterogeneous machine learning classifiers; second, we fine-tuned the ensemble learning approach using a metaheuristic algorithm. This process enhanced performance, enabling an effective real-time early credit risk warning system.

Table 3. 1. Setting the controllable parameters of GA.

Parameter	Value
Maximum Iteration	200
Population	50
Selection Method	Roulette Wheel
Crossover Operator	Uniform
PRecombination %	10%
PCrossover %	50%
PMutation %	40%
Mutation Operator	Binary Swap & Value
P_m	0.02
Wcf_1	0.25
Wcf_2	0.15
Wcf_3	0.60

3.4.3. Performance Comparison of Individual and Homogenous Ensemble Algorithms

To construct our ensemble learning model from the best-performing individual and homogenous ensemble algorithms, in this stage, we evaluated the classification performance of several diverse individual linear non-linear machine learning algorithms (KNN, LDA, NB, ANFIS, SVM, MLP & DT) and homogenous ensemble models (RF, AdaBoost, LogitBoost, TotalBoost, and Random Subspace) on real datasets of P2P lending with imbalanced data, in two prediction periods including the loan application point and the post-loan repayment period. The spot-check criteria include evaluating (i) overall classification performance focusing on identifying the minority class, aligning with our main objectives, (ii) the consistency and stability of their performance across different data imbalance ratios and different risk modeling scenarios, and

(iii) computational complexity using hyperparameter tuning with a limited need for computational resources. Our principal objective is to achieve the lowest false negative rate while maintaining the true negative rate and system accuracy at optimized levels. We prioritize selecting algorithms that yield the highest recall and Fß-Score (ß=2) without sacrificing accuracy and precision rates. Refer to Appendix D for a detailed presentation of our crucial evaluation metrics. The summarized out-of-sample results are shown in Table 3. 2.

3.4.3.1. Individual Linear Models

Linear algorithms, such as LDA and NB, are extremely fast and simple to implement, with an average computation time of just 3.48 seconds. These models provide good overall classification performance, delivering an average accuracy of 84.62% and precision of 96.48%. However, despite their speed and accuracy, linear models struggle to effectively capture minority class instances, as indicated by their lower average recall of 70.25% and F2-Score of 74.29%. This reflects a trade-off between computational efficiency and their ability to handle imbalanced datasets, particularly in identifying the minority class, where recall and F2-Score are critical. Linear models are useful for quick and efficient classification tasks, but they are less effective in scenarios requiring high recall, such as those dealing with imbalanced data. Their high precision is offset by the reduced ability to detect minority class instances, making them less suitable for tasks where identifying minority class events is crucial.

3.4.3.2. Individual Non-Linear Models

Regarding computational efficiency, KNN, ANFIS, and DT significantly outperform SVM and MLP. The average computation time for KNN, ANFIS, and DT is 56 seconds, while SVM (both Polynomial and Linear Kernels) and MLP require much more time, with an average of 2,311 seconds. SVM models, particularly SVM Polynomial and Linear, are the slowest due to the complexity of kernel operations. MLP also demands considerable time, primarily because its computational complexity depends on the depth and size of the neural network layers. When optimizing KNN, increasing the value of k generally improves accuracy, precision, and specificity by reducing noise in the classification. However, larger values of k led to less distinct boundaries between classes, reducing the recall rate. KNN tends to be biased towards the majority class, especially with smaller k values (e.g., k=1) because of its majority voting mechanism. Decision Trees (DT), while showing the highest recall rates, deliver relatively lower accuracy than other models. The trade-off here is between capturing more true positives at the expense of overall prediction accuracy.

Across all non-linear algorithms—KNN, ANFIS, SVM, MLP, and DT—the average accuracy and precision rates are 82.75% and 89.2%, respectively. These non-linear models also demonstrate superior performance in handling imbalanced classes, with an average recall of 74.2% and an F2-Score of 76.56%, outperforming linear models in recall and F2-Score. This suggests that non-linear models are well-suited for addressing class imbalances.

3.4.3.3. Homogenous Ensemble Algorithms

Homogeneous ensemble algorithms, including boosting and bagging, demonstrated superior overall performance compared to individual models (both linear and non-linear). The average accuracy for boosting, bagging, and individual models was 85.23%, 85.22%, and 83.02%, respectively. In terms of precision, bagging performed the best with 95.92%, followed by boosting at 90.68% and individual models at 90.24%. Boosting methods, however, excelled in the more critical metrics for imbalanced datasets—recall and F2-Score. Boosting achieved an average recall of 77.14% and an F2-Score of 79.36%, surpassing bagging (recall: 71.91%, F2-Score: 75.7%) and individual models (recall: 71.63%, F2-Score: 76.24%). This makes boosting particularly effective in addressing the challenge of identifying minority classes in highly imbalanced datasets. Among bagging methods, Random Forest (RF) improved precision over individual decision trees, making it highly effective at identifying borrowers with strong credit profiles (Breiman et al., 1996). However, RF struggled to detect the minority class, resulting in a lower recall rate. This limitation arises because RF, like other bagging methods, treats all samples equally during classification, which diminishes its ability to focus on minority class instances. In contrast, boosting algorithms like AdaBoost and LogitBoost consistently outperformed RF and other bagging techniques in minority class detection. Boosting assigns higher weights to minority class samples during each iteration, increasing the sensitivity of the model towards those harder-to-detect instances. As a result, these algorithms achieved better recall and F2-Scores than bagging techniques, making them ideal for imbalanced datasets. TotalBoost, which initially demonstrated the highest recall rate among boosting algorithms, was excluded due to its prohibitively high computational cost. AdaBoost and LogitBoost performed similarly, with AdaBoost minimizing exponential loss and LogitBoost focusing on logistic loss. Both are particularly effective in improving minority class prediction when paired with tree-based weak learners, which perform well in imbalanced classification tasks.

In summary, boosting algorithms, particularly AdaBoost and LogitBoost, consistently outperformed both individual models and bagging techniques in predicting minority class instances. Their superior recall and F2-Score metrics demonstrate their effectiveness in handling imbalanced datasets, making them more suitable for applications where identifying the minority class is critical (Liu et al., 2022a).

3.4.3.4. Analysis of Algorithm Performance On Varied Imbalanced Ratios

This analysis reveals notable variations in algorithm performance on imbalanced datasets. While some algorithms show promise, their superiority is not necessarily universal or consistent across all imbalance scenarios. To investigate this further, datasets were intentionally balanced, starting with an initial 25%-75% imbalance ratio, followed by simulations at a more severe 15%-85% ratio. The focus remained on evaluating the classification performance of these algorithms in identifying default cases, prioritizing recall as the key metric.

The outcomes of these simulations are presented in Table 3. 3 and Table 3. 4 As the imbalance ratio became more severe, new insights emerged regarding algorithm performance. Boosting algorithms maintained their maintained superiority, except for TotalBoost. Interestingly, Random Forest's (RF) ranking in terms of recall decreased as the imbalance ratio increased, highlighting its struggle to adapt to more extreme data imbalances. In contrast, Decision Trees (DT) continued to excel in recall but showed a drop in precision. MLP and ANFIS performed consistently well across different imbalance ratios, while SVMs displayed mixed results. Notably, RBF-SVM showed relative stability. KNN, while achieving a comparatively high precision score, suffered from a lower recall, demonstrating its weakness in classifying risky loans under severe imbalanced conditions (Liu et al., 2022a). This analysis highlights different algorithms' diverse strengths and weaknesses across varying imbalanced scenarios. The performance of each model fluctuated based on the severity of the data imbalance, reinforcing the need for targeted algorithm selection based on specific classification objectives.

Table 3. 2. An Empirical Comparison of Individual and Homogenous Ensemble Algorithms_ Post–Loan Repayment Period[46]

			Post-Loan Repayment Period						
			Standard Classification				Imbalanced Classification		
Algorithm	**Specification**		**Accuracy**	**Recall**	**Precision**	**Specificity**	**F2-Score**	**B.Accuracy**	**Time(s)**
Linear Discriminant Analysis (LDA)			85.5	70.31	98.92	99.45	74.65	84.88	2.77
Naïve Bayesian (NB)			83.74	70.19	94.04	95.98	73.94	83.08	4.2
K-Nearest Neighborhood (KNN)	K	1	81.19	77.37	81.98	84.64	78.25	81.005	52
		7	84.34	72.57	92.88	94.98	75.89	83.775	54
		9	84.47	71.98	93.89	95.77	75.5	83.875	56
		19	84.96	70.78	96.64	97.78	74.78	84.28	52
Adaptive Neuro-Fuzzy Inference System (ANFIS)	Membership simulations	3	84.01	73.78	90.8	93.25	76.65	83.515	115.5
Support Vector Machine (SVM)		Linear	85.38	69.51	99.94	99.96	74.02	84.735	2930
		RBF	85.33	71.67	97.73	98.55	75.7	85.11	1715
		Polynomial	70.54	82.12	65.02	60.08	78.02	71.1	4860
Multi-Layer Perceptron (MLP)	Hidden layers	[35 20 5]	84.93	73.04	93.8	95.63	76.42	84.34	1855
		[30 10 25]	84.24	74.68	90.99	93.32	77.46	0.00	1270
Decision Tree (DT)			79.09	79.55	77.12	80.44	79.05	79.995	6.6
Ensemble Algorithms	Random Forest NumTree: #100	Bagging	85.22	71.91	95.92	97.24	75.7	84.575	141
	Tree	LogitBoost	85.3	76.31	91.3	93.43	78.9	84.43	81
	Tree	TotalBoost	80.73	81.28	78.79	80.23	80.77	80.755	3493
	Tree	AdaBoostM1	85.15	77.98	90.07	92.31	79.83	84.77	81
	KNN	Random.Subspace	72.5	76.79	69.16	68.55	75.13	72.67	121
	Discriminants	AdaBoostM1	85.11	69.35	99.06	99.35	73.77	84.35	24

Table 3. 3. Analysis of Algorithm Performance in Varied Imbalanced Ratios

		Algorithms													
Imbalanced Ratio	**Metrics**	LDA	NB	NN	KNN	ANFIS	SVM-L	SVM-RBF	SVM-P	MLP	DT	RF	LogitBoost	Total Boost	AdaBoostM1
25%-75%	Gen. ObjF	0.216	0.228	0.210	0.214	0.211	0.220	0.210	0.233	0.205	0.209	0.212	0.192	0.192	0.184
	Recall	70.31	70.19	77.37	72.57	73.78	69.51	71.67	82.12	74.68	79.55	71.91	76.31	81.28	77.98
	F2-Score	74.65	73.94	78.25	75.89	76.65	74.02	75.70	78.02	77.46	79.05	75.70	78.90	80.77	79.83
15%-85%	Gen. ObjF	0.206	0.232	0.250	0.220	0.218	0.204	0.207	0.500	0.200	0.252	0.209	0.201	0.228	0.214
	Recall	68.99	69.62	77.22	73.51	74.46	68.63	70.78	60.05	75.85	79.30	71.60	75.90	79.93	75.91
	F2-Score	73.30	71.74	71.07	73.94	74.28	73.20	74.01	42.00	74.48	70.55	74.20	76.24	73.58	74.99

Table 3. 4. Analysis of Algorithm Rankings in Varied Imbalanced Ratios

		Algorithms													
Imbalanced Ratio	**Rank**	LDA	NB	NN	KNN	ANFIS	SVM-L	SVM-RBF	SVM-P	MLP	DT	RF	LogitBoost	Total Boost	AdaBoostM1
25%-75%	Recall	12	13	5	9	8	14	11	1	7	3	9	6	2	4
	F2-Score	12	14	5	9	8	13	11	6	7	3	10	4	1	2
15%-85%	Recall	12	11	3	8	7	13	10	14	6	2	9	5	1	4
	F2-Score	9	11	12	7	4	10	6	14	3	13	5	1	8	2

3.4.4. Results of the Heterogeneous Ensemble Model

Following the comprehensive evaluation of individual models and homogeneous ensembles in earlier stages, the Heterogeneous Ensemble Model was constructed by integrating the top-

[46] Table E.1. in Appendix E shows the performance of each individual and homogenous classifier in the loan allocation period.

performing algorithms. The selection was based on each algorithm's ability to consistently classify risky loans while maintaining manageable computational demands and stability across various imbalance ratios. The final model combined linear, non-linear, and boosting algorithms, all of which surpassed traditional bagging methods in predicting minority class instances. Each algorithm in the final ensemble was carefully configured to optimize performance and minimize complexity.

From the linear models, LDA and Naive Bayes (NB) were included for their simplicity and precision. Among the non-linear models, K-Nearest Neighbors (KNN) was selected with configurations of k=1 and k=9, offering a balance between noise reduction and localized decision-making. Decision Trees (DT), powered by the CART (Classification and Regression Trees) algorithm, were included for their strong recall, particularly in identifying defaulted loans. However, DT required careful tuning to avoid overfitting, a common challenge with tree-based models. ANFIS (Adaptive Neuro-Fuzzy Inference System) was incorporated to model complex relationships, and to address its computational cost, Principal Component Analysis (PCA) was used to enhance performance and speed. For Support Vector Machines (SVM), the RBF (Radial Basis Function) kernel was chosen after eliminating Polynomial and Linear kernels due to inefficiency. The RBF kernel handled the complexities of imbalanced data effectively while maintaining robustness and computational efficiency. Multi-Layer Perceptron (MLP), using a two-layer network configuration ([30, 10]), was also integrated, offering a good balance between complexity and performance.

The inclusion of AdaBoost and LogitBoost was critical for improving the model’s ability to detect risky loans. These boosting algorithms are particularly suited to imbalanced datasets, as they assign greater weight to minority class instances during training. AdaBoost, by minimizing exponential loss, and LogitBoost, by minimizing logistic loss, significantly enhanced recall and the F2-Score. TotalBoost, which initially showed the highest recall, was excluded from the final model due to its prohibitive computational cost, making AdaBoost and LogitBoost the most effective trade-offs between computational efficiency and predictive power. The integration of diverse classifiers, each with its own strengths, created a model that was both flexible and powerful in tackling the complexities of imbalanced datasets.

The performance of the ensemble model was evaluated during two critical prediction periods: the loan application point and the post-loan repayment period, using a weighted average strategy to aggregate results. As indicated in Table 3. 5, during the loan application phase, the ensemble model outperformed individual and homogeneous models in terms of predictive accuracy. However, the model's true strength became apparent in the post-loan repayment period, where it achieved an overall accuracy of 85.89%, a precision rate of 98.9%, and a recall rate of 71.95%. These results highlight the ensemble's ability to effectively identify high-risk loans with minimal false positives, a crucial factor in credit risk prediction. The recall rate of 71.95% and the F2-Score of 75.28% further underscore its capacity to detect defaulted loans, particularly within the minority class, where accurate prediction is most critical. Although there remains room for improvement, particularly in reducing false negatives, the ensemble's ability to surpass both individual and homogeneous models demonstrate its robustness and efficiency in managing imbalanced datasets.

Table 3. 5. Ensemble of collective learning from heterogeneous individual and ensemble algorithms

		Standard Classification				Imbalanced Classification			
Algorithm	**Specification**	**Accuracy**	**Recall**	**Precision**	**Specificity**	**F2-Score**	**B.Accuracy**	**Time(s)**	**Gen. ObjF**
Ensemble of the collective base learners (weighted average)	Loan Allocation Period	82.76	55.85	94.79	98.23	60.85	77.04	230	0.316
	Post Loan Repayment Period	85.89	71.95	98.9	99.11	75.28	85.44	116	0.205

3.4.5. Performance Evaluation of the Proposed Application-Specific EFSGA Model

To enhance the ensemble's overall performance, a Genetic Algorithm (GA) was employed to optimize key parameters, including algorithm weights, feature selection, and classification thresholds. The weights, ranging from 0 to 1, reflect each algorithm's relative contribution to the final model, with higher values indicating greater influence on predictions. This adaptive weighting framework ensures the ensemble prioritizes the most effective classifiers while attenuating the impact of less reliable ones. By iterating across multiple genetic cycles, the GA systematically ranks classifiers based on their weighted contributions, offering critical insights into their stability and performance across various risk scenarios. This process ensures a finely-tuned, balanced model with optimized predictive accuracy.

The GA optimizes the ensemble by fine-tuning each classifier's weight according to predefined objectives tied to varying risk and profit scenarios. By iterating through multiple genetic cycles, the GA systematically ranks classifiers based on their contributions, providing critical insights into their stability and effectiveness across different risk environments. This process ensures that the model is well-calibrated for diverse situations, with optimized predictive accuracy. The primary goal of the EFSGA model optimization was to enhance recall and F2-Score, prioritizing these metrics over accuracy and precision. This approach ensures that the model minimizes defaults (false negatives) while maintaining an acceptable true negative rate (specificity) to avoid overlooking potential revenue from good loans. This dual optimization strategy focuses on balancing the reduction of defaults and maximizing profit.

The EFSGA model was simulated under three distinct risk-taking strategies, each with different weighted coefficients to reflect the importance of accuracy, precision, and recall in the GA objective function: *[wcf1, wcf2, wcf3]*.

- Scenario 1: Prioritizing maximum recall, even at the expense of some loss in precision: *[0.25,0.1,0.65]*.
- Scenario 2: Maximizing recall without significantly sacrificing accuracy and precision: *[0.25,0.15,0.6]*.
- Scenario 3: Achieving an optimal balance between all performance metrics: *[0.35,0.15,0.5]*.

3.4.5.1. EFSGA Classification Results

The final EFSGA model exhibited marked advancements across all key performance metrics, decisively surpassing the ensemble models from earlier stages. As detailed in Table 3. 6, the EFSGA model achieved a 29% improvement in the genetic fitness function, alongside a 24% increase in recall and a 14% enhancement in the F2-Score when compared to traditional heterogeneous ensemble techniques. These results underscore the model's exceptional capability to effectively manage imbalanced datasets and dynamically adjust to varying risk-taking scenarios, demonstrating its robustness and adaptability in high-stakes predictive environments.

Notably, the EFSGA model demonstrated an impressive out-of-sample sensitivity, achieving an 88.20% recall rate, a 24% improvement over the previous Ensemble of Collective Top Learners. With an F2-Score of 86.17%—representing a 14% increase—the model exhibited a remarkable ability to minimize both false positives and false negatives. This performance illustrates the model's proficiency in accurately identifying genuine risks without over-triggering unnecessary alarms, ensuring both risk minimization and revenue maximization from loans.

The results affirm the value of leveraging a metaheuristic algorithm to optimize ensemble learning and feature selection techniques, yielding substantial performance gains. The robustness of the EFSGA model was consistently demonstrated across various test scenarios. Moreover, the model's computational efficiency far exceeded that of prior ensembles. For example, in Scenario No. 1, the EFSGA required just 55 seconds to execute, significantly outperforming the previous top algorithms, which required 230 seconds during the Loan Allocation Period and 116 seconds during the Post Loan Repayment Period.

The proposed dynamic flexible risk decision-making framework, driven by the Genetic Algorithm, further enhanced real-time default prediction accuracy, especially during the post-loan repayment period. The EFSGA model's combination of superior optimization and computational efficiency positions it well ahead of the ensemble models developed earlier, with consistently lower execution times and more favorable general objective values across all tested scenarios. Additionally, the model's flexibility allows it to be seamlessly adapted to the specific goals of decision-makers, making it both an effective and efficient solution for real-world applications where accuracy and operational costs are critical. For the sake of visualization, we summarize our results in Fig. 6.

The comparative results presented in Table 3. 7 validate the EFSGA model's performance, clearly establishing its superiority over other leading algorithms in key metrics such as the genetic objective function, recall, and F2-Score. These findings solidify the EFSGA model's status as the optimal choice for handling imbalanced datasets and ensuring high-quality predictive performance.

Table 3. 6. EFSGA prediction performance based on different risk-taking scenarios – Post-Loan repayment prediction

		Evaluation Metrics							
		Standard Classification				Imbalanced Classification			
Algorithm	**Specification**	**Accuracy**	**Recall**	**Precision**	**Specificity**	**F2-Score**	**B.Accuracy**	**Time(s)**	**Gen. ObjF**
EFSGA	Scenario no.1	74.69	92.04	68.63	56.79	86.16	74.42	55	0.146
	Scenario no.2	82.63	88.20	78.9	76.55	86.17	82.38	75	0.146
	Scenario no.3	83.62	84.94	81.88	79.22	84.31	82.08	51	0.160

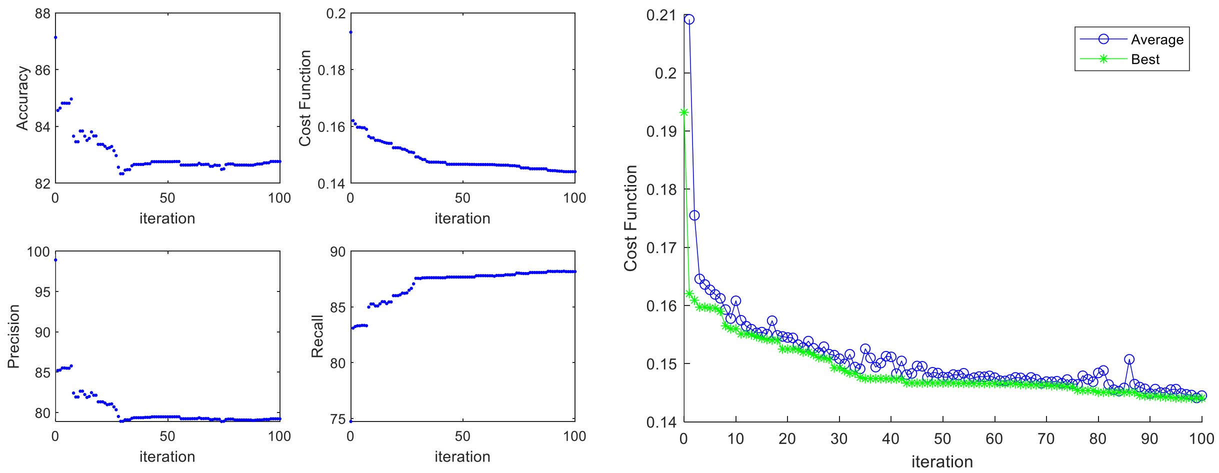

Fig. 3.6. Post-loan repayment prediction result by EFSGA

Table 3. 7. EFSGA prediction performance comparison against top selected and heterogeneous ensemble algorithms

		Algorithms								
Imbalanced Ratio	**Metrics**	EFSGA	ANFIS	SVM-RBF	MLP	DT	RF	LogitBoost	AdaBoostM1	Het.Ensemble
25%-75%	Gen. ObjF	0.146	0.211	0.210	0.205	0.209	0.212	0.192	0.184	0.205
	Recall	88.20	73.78	71.67	74.68	79.55	71.91	76.31	77.98	71.95
	F2-Score	86.17	76.65	75.70	77.46	79.05	75.70	78.90	79.83	75.28
	Precision	78.90	90.80	97.73	90.99	77.12	95.92	91.30	90.07	98.90
	Accuracy	82.63	84.01	85.33	84.24	79.09	85.22	85.30	85.15	85.89

3.4.5.2. Optimized Weights of Classifiers in the Ensemble Model

Our ensemble model employs a metaheuristic algorithm to optimize the weight of each classifier within the collective learning system[47]. These weights, tailored to different risk-taking scenarios, are presented in Table 8**.** Classifiers were further ranked based on their average weights across ten genetic iterations, providing insights into their stability and effectiveness across multiple iterations and risk scenarios, as shown in Table 3. 9**.**

In the second scenario (the prefered scenrio) , which focused on maximizing recall while maintaining accuracy and precision, the Genetic Algorithm (GA) assigned higher weights to advanced classifiers such as LogitBoost, SVM-RBF, MLP, and ANFIS. Simpler algorithms, including KNN, LDA, and Naive Bayes (NB), received lower weights. Decision Trees (DT) ranked highest in the first scenario, where recall was prioritized. However, in the third scenario, which focused on precision, DT lost its top position. In contrast, MLP and LogitBoost consistently secured the top ranks, demonstrating superior performance in identifying risky credits with minimal loss of good credits. SVM-RBF maintained a strong position across all scenarios, reflecting its robust and stable performance. MLP proved to be particularly reliable and effective, consistently ranking among the top five classifiers. ANFIS also performed well, especially in the recall-focused first scenario, though DT, while effective, was slightly less competitive when compared to the leading classifiers.

These results highlight the efficacy of advanced classifiers—LogitBoost, SVM-RBF, MLP, ANFIS, and DT—in managing credit risk by accurately identifying high-risk loans while preserving the integrity of low-risk classifications. A more detailed analysis of these top-performing classifiers can be found in Fig. E.1 in Appendix E.

[47] Specifically, the Genetic Algorithm (GA) generated an integer vector, W, with a length of 1*M, representing the weights of M machine learning classifiers in the heterogeneous ensemble.

Table 3. 8. Optimized weights of each ML classifier by GA based on the genetic objective function

		Solution W: Optimized Weights of the Ensemble Model									
Algorithm	**Specification**	LDA	NB	NN	KNN	ANFIS	SVM-RBF	MLP	DT	LogitBoost	AdaBoostM1
EFSGA	Scenario no.1	0.14	0.01	0.05	0.03	0.17	0.12	0.09	0.18	0.12	0.09
	Scenario no.2	0.09	0.01	0.10	0.06	0.11	0.13	0.13	0.10	0.14	0.11
	Scenario no.3	0.06	0.07	0.07	0.09	0.04	0.17	0.17	0.05	0.19	0.10

Table 3. 9. Top Ranked algorithms based on GA-assigned weights

		Solution W: Algorithm Ranking (1~10)									
Algorithm	**Specification**	LDA	NB	NN	KNN	ANFIS	SVM-RBF	MLP	DT	LogitBoost	AdaBoostM1
EFSGA	Scenario no.1	3.0	9.0	5.4	7.3	3.3	5.0	5.0	4.3	4.0	5.1
	Scenario no.2	5.4	9.0	5.2	6.3	4.4	3.2	3.6	4.9	3.2	4.6
	Scenario no.3	6.5	6.0	7.0	5.0	7.0	2.0	2.0	7.0	1.0	4.0

3.4.5.3. Dynamic Optimized Decision Threshold

Optimizing the decision threshold in credit default identification is vital due to the higher cost associated with false negatives than false positives. While lowering the decision threshold improves recall, it may compromise precision. Striking an optimal balance between recall and precision is crucial. Our proposed model leverages a Genetic Algorithm (GA) as a search heuristic to optimize the decision threshold. The model employs a class-weighted, tunable objective function in the GA to address imbalanced datasets and varying class importance. This function prioritizes recall, which is especially critical in credit default identification while maintaining an optimal true negative rate (specificity) to prevent overlooking potential revenue from good loans. This dual objective ensures a balanced optimization focus on minimizing defaults while maximizing profit. The GA fine-tunes the classification threshold to achieve an optimal balance, considering specific problem goals and trade-offs. The model's performance is rigorously assessed using imbalanced classification metrics to ensure robust identification of both majority and minority classes.

We fine-tune the weighted coefficients (wcf1, wcf2, and wcf3) in the GA objective function to determine the optimized decision threshold, influencing the trade-off between accuracy, precision, and recall. The optimal thresholds for three risk strategy scenarios are as follows: 0.1 in scenario 1, maximizing recall and F2-Score; 0.18 in scenario 2, maximizing recall while maintaining balanced accuracy and precision; and 0.25 in scenario 3, achieving a balance between recall, precision, and accuracy. Fig. 7 illustrates these results. Our proposed model effectively addresses the challenges associated with high-dimension imbalanced datasets, optimizing credit default identification by minimizing the risk of misclassifying normal credits while maximizing expected profit. Leveraging a class-weighted, tunable objective function, optimizing the classification threshold, and utilizing imbalanced classification metrics for evaluation, our model attains a high level of sensitivity and precision in credit default identification problems.

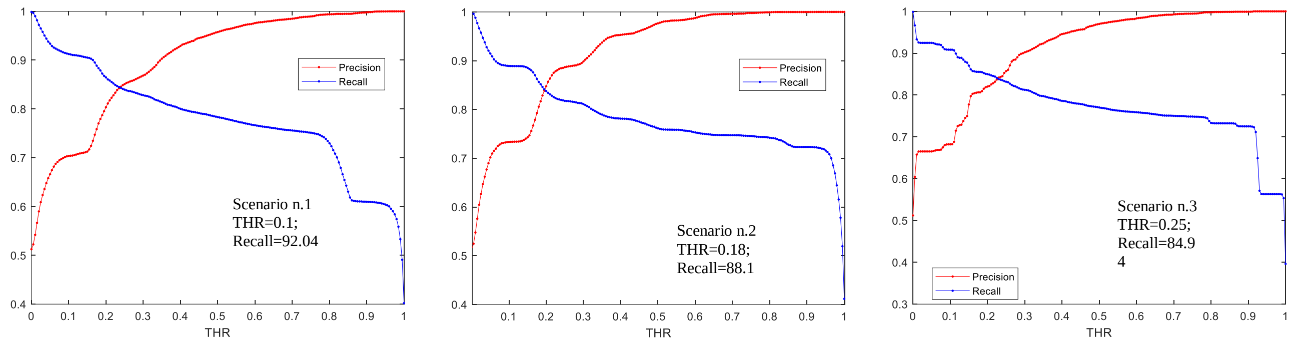

Fig.3.7: Optimized threshold according to genetic objective function parameter adjustment.

3.4.5.4. Ensemble Feature Importance Analysis - Model Interpretability

To improve interpretability, simplify the model, and eliminate redundancy, we applied an ensemble feature selection approach using a genetic algorithm (GA). This method simultaneously optimizes both feature subsets and weights for each base learner within the ensemble model. The GA autonomously selects the most relevant features for individual classifiers while optimizing collective learning coefficients across all heterogeneous classifiers[48]. Our findings demonstrate that the EFSGA model effectively extracts critical features, reduces overfitting, and significantly outperforms both individual classifiers and homogeneous ensemble methods. Notably, the GA reduced the number of selected features by over 50%, from 47 to 24, without sacrificing model performance[49]. In the context of achieving optimal recall rates (our second scenario), we prioritize the contribution of each variable to defaults rather than overall accuracy. This approach provides valuable insights into which variables most strongly predict borrower default, supporting risk management and policy decisions. By running the GA 10 times, we calculate the importance of each feature based on its selection frequency across iterations.

The results, shown in Table 3. 6, reveal the following key findings: Key insights reveal that loan characteristics, such as maturity and interest rate, play a crucial role in predicting defaults. Borrowers opting for longer loan terms, such as five years, tend to have lower credit scores, face higher interest rates, and are more likely to default. The purpose of the loan is also significant, with small business loans presenting the highest risk, as default rates surpass 73%,

[48] Optimizing Performance and Cost: Base learners are categorized into two groups based on training speed and complexity. Feature selection is applied to the first group, comprising NN, KNN, LDA, NB, and DT.
[49] Number of selected features = [NN:24, KNN:26, LDA:24, NB:25, DT:24]

while wedding loans carry the lowest risk. In contrast, loan amounts and installments are found to be less impactful. Socioeconomic characteristics also provide valuable predictive insights. Homeownership and annual income stand out as strong indicators of credit risk, whereas employment length shows minimal effect. Renters, compared to homeowners, exhibit a higher likelihood of default, with default rates exceeding 45%. In terms of Borrower's financial profile and credit history, critical predictors include delinquencies, public records (such as overdue accounts), debt-to-income ratio, and credit utilization. Additionally, the number of satisfactory bankcard accounts, the average balance across all accounts, recent trade activity, and total revolving credit balance significantly influence default risk. Lastly, macroeconomic variables, those associated with actual economic activity such as inflation rates, GDP, and stock market indices, consistently emerged as key contributors to default rates across all scenarios.

Table 3. 6. Feature Importance Scores from Iterative Genetic Algorithm Optimization

Attributes	*Feature Importance Rank*	Occurrence %			Genetic Solutions				
		AVG %	*Selected by X% of Classifers*		*NN*	*KNN*	*DA*	*NB*	*DT*
			>80%	*>60%*	*24*	*26*	*24*	*25*	*24*
delinq_2yrs	*1*	64%	50%	70%	0.9	0.7	0.4	0.6	0.7
delinq_amnt	*2*	64%	50%	80%	0.7	0.6	0.6	0.6	0.7
num_bc_sats	*3*	62%	50%	70%	0.6	0.7	0.6	0.4	0.7
avg_cur_bal	*4*	62%	30%	80%	0.4	0.9	0.4	0.9	0.7
annual_inc	*5*	62%	40%	60%	0.4	0.6	0.9	0.6	0.7
term	*6*	62%	40%	70%	0.7	0.6	0.9	0.7	0.3
acc_open_past_24mths	*7*	62%	30%	60%	0.6	0.6	0.4	0.7	0.7
purpose	*8*	62%	30%	60%	0.4	0.7	0.7	0.6	0.6
TTL All Shares	*9*	61%	30%	70%	0.7	0.4	0.4	0.7	0.9
acc_now_delinq	*10*	60%	30%	60%	0.7	0.6	0.7	0.6	0.4
dti	*11*	59%	10%	70%	0.6	0.6	0.6	0.4	0.7
revol_bal	*12*	59%	30%	60%	0.1	0.7	1.0	0.7	0.3
revol_util	*13*	59%	30%	60%	0.7	0.3	0.9	0.6	0.4
bc_open_to_buy	*14*	58%	40%	60%	0.7	0.3	0.4	0.6	0.7
home_ownership	*15*	58%	20%	50%	0.6	0.7	0.4	0.6	0.6
Inflation (cpi)	*16*	58%	20%	50%	0.4	0.6	0.6	0.6	0.7
mths_since_last_delinq	*17*	57%	20%	50%	0.7	0.4	0.7	0.4	0.6
sub_grade	*18*	56%	20%	60%	0.4	0.4	0.6	0.7	0.6
bc_util	*19*	56%	0%	60%	0.6	0.6	0.6	0.6	0.3
num_rev_tl_bal_gt_0	*20*	54%	0%	70%	0.6	0.6	0.6	0.4	0.6
mths_since_recent_inq	*21*	54%	20%	50%	0.4	0.4	0.4	0.6	0.7
installment	*22*	53%	20%	70%	0.4	0.6	0.4	0.4	0.7
int_rate	*23*	53%	40%	40%	0.7	0.4	0.4	0.4	0.6
TED	*24*	52%	10%	60%	0.6	0.6	0.3	0.9	0.3
num_tl_op_past_12m	*25*	52%	0%	60%	0.4	0.6	0.4	0.6	0.4
GDP Growth	*26*	52%	30%	50%	0.7	0.6	0.4	0.4	0.4
Income status _ verified	*27*	52%	30%	50%	0.3	0.6	0.6	0.6	0.4
pub_rec	*28*	51%	20%	50%	0.4	0.9	0.6	0.3	0.4
Loan_Amnt	*29*	51%	20%	50%	0.3	0.4	0.7	0.3	0.7
tax_liens	*30*	51%	20%	60%	0.7	0.7	0.6	0.3	0.4
total_bal_ex_mort	*31*	51%	10%	70%	0.4	0.7	0.6	0.4	0.4
Unemployment rate	*32*	50%	10%	40%	0.4	0.6	0.7	0.6	0.1
pct_tl_nvr_dlq	*33*	50%	20%	50%	0.6	0.3	0.4	0.6	0.4
num_sats	*34*	50%	20%	50%	0.4	0.7	0.4	0.6	0.6
inq_last_6mths	*35*	50%	10%	50%	0.4	0.6	0.4	0.4	0.6
mort_acc	*36*	49%	10%	40%	0.1	0.6	0.6	0.6	0.7
HH Debt	*37*	49%	20%	50%	0.7	0.4	0.4	0.6	0.6
pub_rec_bankruptcies	*38*	49%	10%	50%	1.0	0.6	0.3	0.6	0.1
open_acc	*39*	48%	20%	30%	0.6	0.1	0.7	0.4	0.4
emp_length	*40*	46%	10%	50%	0.1	0.6	0.6	0.4	0.4
num_actv_bc_tl	*41*	46%	10%	50%	0.6	0.6	0.1	0.7	0.3
num_bc_tl	*42*	46%	20%	40%	0.4	0.6	0.7	0.4	0.3
num_rev_accts	*43*	44%	10%	40%	0.4	0.6	0.1	0.6	0.6
chargeoff_within_12_mt	*44*	44%	20%	30%	0.6	0.4	0.4	0.4	0.4
percent_bc_gt_75	*45*	41%	10%	40%	0.3	0.4	0.4	0.4	0.6
month(earliest_cr_line)	*46*	32%	10%	20%	0.1	0.3	0.6	0.3	0.3

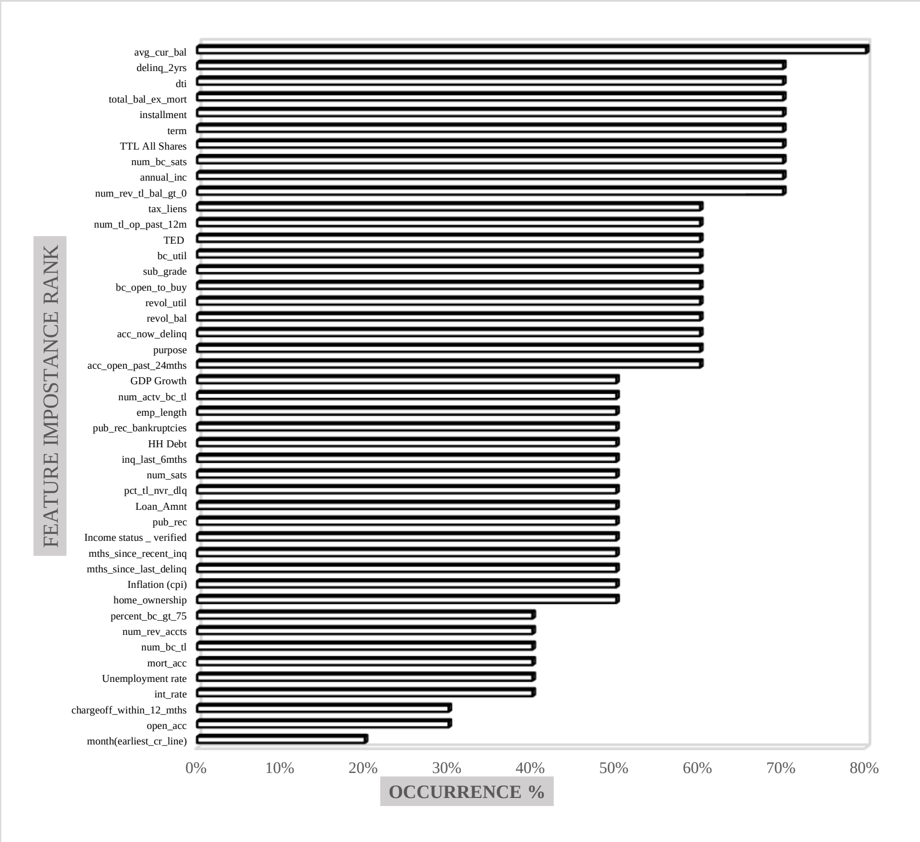

Fig. 3.8 ***Top*** features contributing to default risk selected by EFSGA

3.4.6. Optimization of Credit Risk Management

The proposed approach has the potential to revolutionize credit risk optimization in FinTech lending by employing evolutionary algorithms to optimize feature scaling, classifier weights, and decision thresholds within a collective learning framework. Traditional risk assessment models, often constrained by fixed rules, fail to adapt to the dynamic nature of borrowers and overlook critical factors such as macroeconomic conditions and management interventions. These limitations can be particularly problematic in complex risk decision-making processes where risk tolerance levels and objectives may vary. Our study introduces a flexible and dynamic decision-making framework that addresses these shortcomings by offering tailored, real-time risk assessments. By leveraging distributed and parallel computing paradigms, this approach provides timely solutions, particularly valuable in the fast-paced FinTech industry. The framework's adaptability ensures that decision-makers receive customized risk insights, aligning with specific management goals and evolving market conditions. This high level of customization is crucial for enhancing credit risk management, as it allows organizations to make more informed decisions across diverse sectors and risk scenarios, ultimately improving decision-making processes in industries beyond FinTech.

3.4.7. Robustness Tests

To ensure the reliability and broader applicability of our findings, we conducted a robustness test using data from Mintos, a European marketplace lending platform. This dataset, spanning loan listings from January 2018 to September 2023 across 10 European countries, captures the effects of economic fluctuations, including the COVID-19 pandemic and the Russia-Ukraine war. Detailed information on the dataset and variables is provided in Appendix F, with Table F.1 offering a comprehensive description. After preprocessing, the dataset included 23 variables and 484,912 loan listings, with 19% defaulted loans and 81% non-defaulted loans. The data underwent a similar preprocessing procedure as described in Section 3. 4-2, except for utilizing alternative configurations[50] . All detailed results are presented in Appendix F (Tables F2 to F6), covering individual and homogeneous ensemble algorithm performance (Table F.2), results from the heterogeneous ensemble model (Table F.3), EFSGA model classification results (Table F.4), optimized classifier weights (Table F.5), and feature selection analysis (Table F.6).

The key findings from the robustness tests are as follows: Firstly, the proposed EFSGA model demonstrates sustained robustness across various scenarios. Notably, the model achieved a 14% improvement in recall, a 9% increase in F2-Score, and a 3% boost in balanced accuracy compared to the previous Ensemble of Collective Top Learners[51]. Secondly, compared with the previous results, where the optimized weights and rankings of machine learning classifiers were detailed, the current analysis shows consistency in the top five ranked classifiers across different risk-taking scenarios. Although the specific order of rankings has changed, boosting algorithms, ANFIS, SVM-RBF, Decision Trees (DT), and MLP consistently occupy the leading positions. This stability reinforces the robustness of our findings and the effectiveness of these classifiers, even with varying emphases on recall, precision, and accuracy. Lastly, the EFSGA model excels in extracting valuable features, surpassing alternative methods, and notably reducing the number of features while maintaining superior model performance. Detailed insights into the significance of features regarding borrower credit default are available in Appendix F.

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[50] For this new dataset, we employed a distinctive train-test split, allocating 70% for training and 30% for testing to rigorously assess model performance. Additionally, we introduced a different imbalanced ratio of 20-80. PRecombination, PCrossover, and PMutation operators were set to 0.2, 0.4, and 0.4, respectively. The Genetic Algorithm parameters included a population size of 30 and a maximum of 100 iterations.

[51] The Mintos dataset differs from typical credit risk datasets by excluding borrower personal information, focusing only on loan-related data such as Issue Date, Rate, Term, and Type. This divergence results in lower classification accuracy for individual and ensemble algorithms compared to the results from our primary dataset.

3.5. Discussion and Conclusion

The EFSGA methodology introduces a novel approach to credit risk optimization, addressing challenges faced by traditional metaheuristics in dynamic default prediction for FinTech lending. The Evolutionary-based Ensemble Feature Selection with a Genetic Algorithm (EFSGA) leverages diverse machine learning structures, optimizing both hyperparameters and classification thresholds through a Genetic Algorithm. This dual optimization enhances the model's performance, offering a comprehensive and efficient solution. Our approach fills the gap in metaheuristic applications for credit risk optimization by hybridizing with machine learning, utilizing distributed and parallel computing for real-time solutions, and enhancing adaptability to unbalanced learning scenarios.

The proposed "dynamic flexible risk decision-making framework," inspired by GA, has significantly improved real-time default prediction during the post-loan repayment period. The EFSGA model shows superior computational efficiency and optimization compared to the ensemble of top algorithms, with notably lower execution times and general objective values across various scenarios. It demonstrated substantial improvements in overall model performance during the post-loan repayment period, including a 29% improvement in the genetic fitness function, a 24% boost in recall, and a 14% increase in F2-Score, outperforming conventional heterogeneous ensemble techniques across diverse risk-taking scenarios. Moreover, the framework is highly flexible and can be adapted to the specific objectives of decision-makers. Our ensemble feature selection and analysis technique, driven by a genetic algorithm, achieves a balanced trade-off between model performance and interpretability. By simultaneously optimizing weights and feature subsets for each base learner within the ensemble model, the proposed technique extracts valuable features, reduces overfitting, and outperforms other classifiers. It significantly reduces the feature set from 47 to 24 while maintaining superior performance. We conducted ten iterations of the GA to comprehensively assess feature importance, deriving scores from the occurrence rates across iterations. The EFSGA model adeptly addresses challenges associated with the misclassification of imbalanced datasets and variable class importance through dynamic decision threshold adjustments using a Genetic Algorithm. Employing cost-sensitive learning algorithms prioritizes the minority class, optimizing a class-weighted objective function for a balanced recall-precision trade-off.

Our research thoroughly assesses the performance dynamics of diverse machine learning algorithms, spanning individual models and homogeneous and heterogeneous ensembles.

Emphasizing the identification of minority classes, we ensure robustness, stability, and consistency across multiple iterations, varied risk modeling scenarios, and different imbalanced data distributions, all while adhering to computational constraints. This evaluation leverages real-world P2P lending datasets known for their imbalanced nature across two key prediction periods: the loan application stage and the post-loan repayment period. To further optimize the ensemble, a Genetic Algorithm (GA) is employed to determine the optimal weights for each classifier based on predefined objectives across different risk scenarios. This approach enabled the model to adapt to various conditions by balancing the contribution of each algorithm. The Genetic Algorithm (GA) strategically allocated higher weights to advanced classifiers such as LogitBoost, SVM-RBF, MLP, and ANFIS, while simpler algorithms like KNN, LDA, and NB received lower weights. These findings indicate that boosting algorithms, particularly LogitBoost, which consistently holds the first rank, followed by SVM-RBF, MLP, ANFIS, and DT, are the most effective in identifying risky credits while maintaining optimal accuracy and minimizing the loss of good credits. These insights can guide financial institutions in selecting appropriate machine-learning models to minimize credit risk while maintaining optimal performance across different operational priorities. The proposed "flexible, dynamic decision-making-based framework" with its tunable class-weighted fitness function offers transformative potential for risk management in the FinTech sector. Providing real-time, adaptable solutions for complex decision-making processes, this approach enhances risk management and offers valuable insights across industries where diverse risk tolerances and objectives necessitate adaptable strategies.

3.6. Future Research Directions

While the EFSGA model marks a significant advancement in credit risk optimization, several avenues for further exploration remain. First, the reliance on Genetic Algorithms (GA) for optimization can be expanded by exploring alternative metaheuristics, such as Grey Wolf Optimization or the Aquila Optimizer, to enhance flexibility and efficiency (Mirjalili et al., 2014; Abualigah et al., 2021). Additionally, integrating advanced deep learning techniques like deep neural networks or reinforcement learning could improve the model’s ability to manage complex, imbalanced datasets. Another limitation is the restricted access to post-loan borrower data, which limits real-time risk monitoring. Future research should incorporate richer datasets, such as borrower payment histories and behavioral patterns, to refine dynamic predictions. Furthermore, although the EFSGA model has shown promise in FinTech, its application in traditional banking and high-risk finance requires further exploration. Evaluating the model in volatile, high-risk environments will help assess its scalability and robustness across diverse credit risk settings. Incorporating EFSGA into decision support systems (DSS) with scenario-based simulations would further enhance its practical utility for decision-makers managing complex risk profiles. Altogether, advancing the EFSGA model through alternative metaheuristics algorithms, richer data integration, and broader application will enhance its adaptability and effectiveness in diverse financial contexts.

Appendix III

Appendix A

Threshold Optimization Method Based On Genetic Algorithms: This framework outlines the basic steps for optimizing the classification threshold using a genetic algorithm. Here is a brief explanation of each step:

(i) Objective function: The objective function is a metric that measures the model's performance at different threshold values. We used accuracy, precision, and recall in this study and analyzed them based on F2-Score.

(ii) Initial population: The initial population is a set of potential threshold values that the objective function will evaluate. These values are typically chosen randomly.

(iii) Fitness evaluation: The fitness of each potential threshold value in the population is evaluated using the objective function. This determines how well each threshold value performs on the classification problem.

(iv) Selection: The best-performing threshold values with the highest fitness scores are selected to move on to the next generation. This process is repeated until specific threshold values have been set.

(v) Reproduction and mutation: New threshold values are created by combining the selected individuals and introducing random mutations to promote diversity. This creates a new population of potential threshold values. So, the fitness of the new population is evaluated, and the process is repeated until a termination criterion is met. This could be a certain number of generations or a specific fitness level.

(vi) Solution: Once the genetic algorithm has converted to a solution, the threshold value with the highest fitness score is chosen as the optimized threshold. This threshold value can predict new data in the classification problem.

Appendix B

Lending Club Lending Dataset

Table B.1. Overview of Lending Club Features and Associated Economic Indicators

Attributes		*Description*	*Summary Statistics*			
			Min	*Max*	*Mean*	*SD*
Loan Indicators						
term		The number of payments on the loan.	36.0	60.0	42.2	10.5
int_rate		Interest Rate on the loan	0.1	0.3	0.1	0.0
installment		The monthly payment owed by the borrower .	21.6	1408.1	428.7	244.2
purpose		A category provided by the borrower for the loan request. House, education , Small buisness,… (1~14)	1.0	14.0	4.7	2.8
Loan_Amnt		The listed amount of the loan applied for by the borrower.	1,000	35,000	13,866	8,186
LC sub_grade		Lending Club assigned loan subgrade, A1~G5 , codes (1~35)	1.0	35.0	13.1	6.7
Loan_status		Current status of the loan: Fully paid, Charged off, Default, In grace period, Late ,…	0	5	1	1.41
Borrower's Financial Characteristics and Credit History indicators						
Demographics						
home_ownership		The home ownership status provided by the borrower including Own, Mortgage, Rent (Codes: 1,2,3)	1.0	3.0	2.3	0.6
emp_length		Employment length in years.	0.0	10.0	5.7	3.7
annual_inc		The self-reported annual income provided by the borrower during registration.(*1000)	4	1	70	46
Income status _ verified		Income verification status by LendingClub :Verified, Source verified, Not verified (Codes: 1,2,3)	1.0	3.0	1.8	0.86
Credit Hisory & Performnce						
dti	Indebtedness level	Borrower's total monthly debt payments on the total debt obligations,excluding mortgage, divided by his self-reported monthly income.	0	35	17	8
percent_bc_gt_75	Indebtedness level	Percentage of all bankcard accounts > 75% of limit.	0	100	46	37
bc_util	Indebtedness level	Ratio of total current balance to high credit/credit limit for all bankcard accounts.	0	340	57	34
inq_last_6mths	Indebtedness level	The number of inquiries in past 6 months (excluding auto and mortgage inquiries)	0	8	1	1
mths_since_recent_inq	Indebtedness level	Months since most recent inquiry.	0	24	6	6
mort_acc	Indebtedness level	Number of mortgage accounts.	0	24	2	2
revol_util	Indebtedness level	The amount of credit the borrower is using relative to all available revolving credit.	0	148%	57%	0
acc_now_delinq	Delinquencies & Public records	The number of accounts on which the borrower is now delinquent.	0	5	0	0
delinq_2yrs	Delinquencies & Public records	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 year	0	18	0	1
delinq_amnt	Delinquencies & Public records	The past-due amount owed for the accounts on which the borrower is now delinquent.	0	63,453	8	527
mths_since_last_delinq	Delinquencies & Public records	The number of months since the borrower's last delinquency.	1	151	35	22
pub_rec	Delinquencies & Public records	Number of derogatory public records	0	9	0	0
pub_rec_bankruptcies	Delinquencies & Public records	Number of public record bankruptcies	0	5	0	0
chargeoff_within_12_mths	Delinquencies & Public records	Number of charge-offs within 12 months	0	4	0	0
pct_tl_nvr_dlq	Delinquencies & Public records	Percent of trades never delinquent	0	100	78	38
acc_open_past_24mths	Length of Credit History	Number of trades opened in past 24 months.	0	40	4	3
month(earliest_cr_line)	Length of Credit History	The month the borrower's earliest reported credit line (LOC) was opened - Loan Issue date	36	683	174	80
num_tl_op_past_12m	Length of Credit History	Number of accounts opened in past 12 months	0	25	2	2
total_bal_ex_mort	Accounts _ Balance	Total credit balance excluding mortgage	0	1,924,200	37,502	41,092
revol_bal	Accounts _ Balance	Total credit revolving balance	0	1,743,266	15,237	18,955
avg_cur_bal	Accounts _ Balance	Average current balance of all accounts	0	958,084	11,273	16,327
bc_open_to_buy	Accounts _ Balance	Total open to buy on revolving bankcards.	0	278,899	6,828	12,329
open_acc	Number of Accounts	The number of open credit lines in the borrower's credit file.	0	53	11	5
num_rev_accts	Number of Accounts	Number of revolving accounts	0	63	12	9
tax_liens	Number of Accounts	Number of tax liens	0	9	0	0
num_sats	Number of Accounts	Number of satisfactory accounts	1	53	11	5
num_bc_tl	Number of Accounts	Number of bankcard accounts	0	44	9	5
num_actv_bc_tl	Number of Accounts	Number of currently active bankcard accounts	0	22	3	2
num_bc_sats	Number of Accounts	Number of satisfactory bankcard accounts	0	29	5	3
num_rev_tl_bal_gt_0	Number of Accounts	Number of revolving trades with balance >0	1	30	5	3
Macroeconomic indicators						
Unemployment rate		The number of unemployed as a percentage of the labor force.	25.5	33.6	29.9	2.2
TTL All Shares		Total Share Prices for All Shares for the United States	-22.5	12.7	0.4	3.7
Inflation		Inflation as measured by the consumer price index.	-0.4	3.8	2.2	1.0
HH Debt		Household Debt Service Payments as a Percent of Disposable Personal Income	9.7	13.2	11.3	1.2
GDP Growth		The inflation adjusted value of the goods and services produced by labor and property located in the US.	-1.9%	2.4%	1.0%	0.7%
TED		The spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill.	0.1	3.4	0.4	0.4
Post Loan Performance						
Loan_Paid %		Total paid amount at loan maturation or closure	1	1.4	0.79	0.3
Loan_last_first Payment		Months before loan maturation or closure(last_pymnt_d)-(Issue_d)	1	60	11	6
Recovery		Recovery plan for problematic loans	0	1	0.15	0.35
3M_interval_loan status		Timing every 3 Months before loan maturation				

Appendix C

We meticulously conducted the following critical steps in data preprocessing to ensure the data is well-suited for effective utilization in our prediction model.

(i) Instance selection:

- The data set is filtered to select only the loans issued between 2007 and 2014, as we choose only finished credits that have reached their final state during the standard term of the credit – 36 or 60 months.
- Eliminating features and rows with more than 5 percent missing values.
- Removing categorical variables with only one possible value and irrelevant variables such as member ID, URL, emp_title, grade, description, address, etc. As a result, 64 variables have been dropped.

(ii) Handling missing values:

- Various techniques, including mean, mode, and KNN imputations, are employed to address missing values. In a comprehensive experiment involving 1000 samples, KNN imputation demonstrated superior performance, yielding the smallest values for rmse (root mean squared error), mse (mean squared error), and mae (mean absolute error). Consequently, KNN imputation has been chosen as the preferred method over alternative approaches.

(iii) Data transformation:

- Categorical variables are encoded using one-hot encoding, and date variables are transformed into numerical features. In this step, several variables are transformed into new forms:
- The loan status attribute describes the current state of the loan and has the following values: “Current,” “Fully Paid,” “Default,” “Charged Off,” “In Grace Period,” “Late (16 - 30 days)”, and “Late (31 – 120 days)”. These statuses are transformed to a binary classification problem, i.e., the loan with the status “Charged Off,” “Late (31 – 120 days)”, and “Default” will be changed into “Default” and loan with the status “Fully Paid” will be transformed into “Normal.” Loans with statuses “In Grace Period,” “Current,” and “Late (16 – 30 days)” will be filtered out because those loans are considered immature or do not have final statuses.
- Nominal variables such as subgrade, employment length, Loan Purpose, Term, Home Ownership, Verification status, … are transformed into continuous variables.
- Some new variables have been calculated, such as Credit history_ yrs by subtracting Loan application date from earliest_cr_line (The month the borrower's earliest reported credit line (LOC) was opened).

(iv) Normalization of features:

- The features are normalized and standardized through the Min-Max Scaling Standardization/Variance Scaling

(v)Data randomization:

- After normalization and before the dataset is divided into training and validation sets, deliberate data randomization has been implemented, prioritizing a randomized arrangement over an ordered one. This approach is crucial for mitigating potential biases arising from inherent order or patterns in the data. We aim to foster a diverse and representative training experience by opting for randomization, enhancing the model's ability to generalize effectively across different scenarios.

(vi) Handling Outliers:

- To ensure dataset quality, a rigorous outlier treatment has been implemented. Various methods, including outlier removal, capping, and discretization, have been selectively applied to specific variables based on the percentage and distribution of outliers detected.

After completing these comprehensive preprocessing steps, our final dataset comprises 84,440 observations and 49 variables. This refined dataset is primed for optimal utilization in building an accurate and robust prediction model.

Appendix D

Fitness evaluation

Table D. CONFUSION MATRIX

		Predicted Class	
		Positive (Default)	Negative(Normal)
Actual Class	Positive (Default)	**True positive** (TP)	**False Negative** (FN)
	Negative(Normal)	**False Positive** (FP)	**True Negative** (TN)

Precision Rate *= TP / (TP+FP) *100%*
Accuracy Rate *= (TP+TN) / (TP+FP+TN+FN) *100%*
Recall (Sensitivity) Rate *= TP / (TP+FN) *100%*
Specificity Rate *= TN / (TN+FP) *100%*
F ß Score *= (1+ ß^2)*(Precision*Recall)/(ß^2*Precision + Recall)*100%*
G_mean *=0.5*((Recall* specificity)*
Balanced_Accuracy *=0.5*(Recall+ specificity)*

A confusion matrix is a summary of prediction results on a classification problem. In the above confusion matrix, TP is the number of test samples with a default class tag that are properly assigned to a default class. TN is the number of test samples with the Normal class tag that are correctly placed in the Normal class. FP is the number of samples with a Normal label mistakenly classified by the classification system. Finally, FN is the number of samples with a Default label incorrectly identified by the system as default.

Appendix E

Table E. An Empirical Comparison of Individual and Homogenous Ensemble Algorithms_ Loan Allocation Period

			Loan Allocation Period						
			Standard Classification				Imbalanced Classification		
Algorithm	**Specification**		**Accuracy**	**Recall**	**Precision**	**Specificity**	**F2-Score**	**B.Accuracy**	**Time(s)**
Linear Discriminant Analysis (LDA)			82.62	57.43	91.96	97.11	74.65	84.88	2.77
Naïve Bayesian (NB)			81.25	54.21	90.7	96.8	73.94	83.08	4.2
K-Nearest Neighborhood (KNN)	K	1	77.6	65.47	70.94	84.57	66.49	75.02	52
		7	81.43	58.03	86.71	94.98	62.14	76.46	54
		9	81.61	56.74	88.89	95.77	61.16	76.33	56
		19	82.15	54.43	94.26	97.78	74.78	84.28	52
Adaptive Neuro-Fuzzy Inference System (ANFIS)	Membership simulations	3	81.22	57.58	86.48	94.82	76.65	83.515	56.9
Support Vector Machine (SVM)		Linear	85.38	69.51	99.94	99.96	74.02	84.735	2930
		RBF	82.4	53.16	97.51	99.22	75.46	85.11	225
		Polynomial	77.74	65.51	71.23	84.78	78.02	71.1	503
Multi-Layer Perceptron (MLP)	Hidden layers	[35 20 5]	78.49	65.22	72.99	86.12	76.42	84.34	1160
		[30 10 25]	80.14	62	79.08	90.56	64.80	76.28	340
Decision Tree (DT)			75.72	68.07	66.32	80.11	79.05	79.995	6.6
Ensemble Algorithms	Random Forest NumTree: #100	Bagging	82.59	55.92	93.95	97.93	75.7	84.575	67
	Tree	LogitBoost	82.77	62.43	86.67	94.47	78.9	84.43	81
	Tree	TotalBoost	80.73	81.28	78.79	80.23	80.77	80.755	3493
	Tree	AdaBoostM1	82.9	63.51	86.01	94.05	79.83	84.77	81
	KNN	Random.Subspace	72.5	76.79	69.16	68.55	75.13	72.67	121
	Discriminants	AdaBoostM1	85.11	69.35	99.06	99.35	73.77	84.35	24

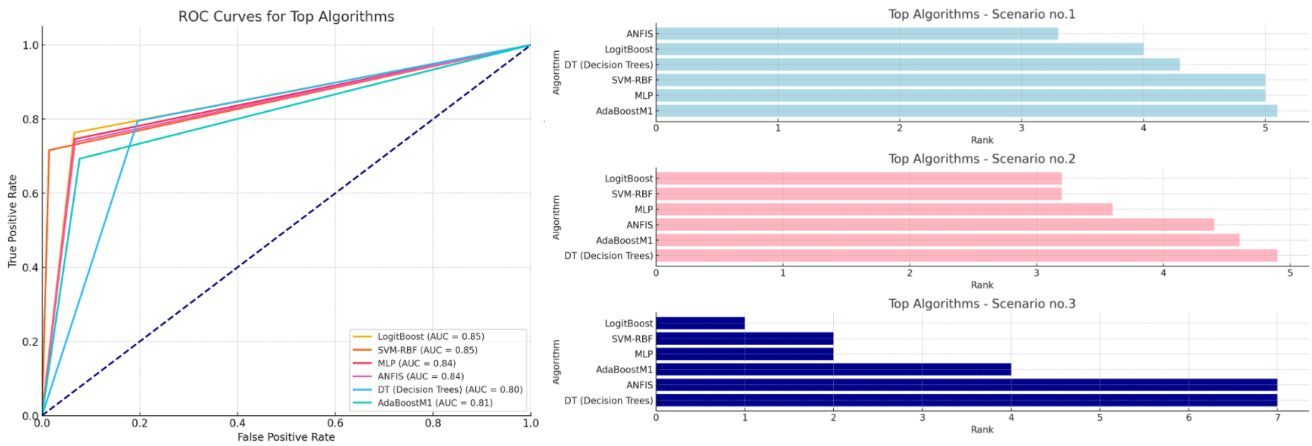

Fig. E.1. Top Algorithms Performance Based On Each Scenario

Appendix F

Mintos Lending Dataset:

The countries included in the database are Bulgaria, Denmark, Estonia, Finland, Latvia, Lithuania, Poland, Spain, Romania and the United Kingdom. These countries are similar in their regulatory framework and business environment and represent an excellent opportunity for analyzing the current tendencies in marketplace lending markets. We combine each loan recorded in the database with the country-specific economic variables and variables representing COVID-19 risk and the Russia-Ukraine war. The loan status attribute describes the current state of the loan and has the following values: “Current,” “Bad debt or Default,” “finished (as scheduled or prematurely),” “In Grace Period,” and “Late” loans. These statuses are transformed to a binary classification problem, i.e., the loan with the status “Bad debt or Default,” “finished prematurely_ Buyback Guarantee,” “Late (31 – 60)”, and “Late (60+)” will be changed into “Default.” Loans with the status “finished as scheduled” and “finished prematurely due to early repayment” will be transformed into “Normal.” Loans with statuses “In Grace Period,” “Current,” and “Late less than 30 days will be filtered out because those loans are considered immature or do not have final statuses.

Table F.1. Description and Summary Statistics of Mintos Features and Associated Economic Indicators

Attributes	*Description*	*Summary Statistics*				
		Min	*Max*	*Mean*	*SD*	*Count*
Loan indicators						
Loan Type	A category provided by the borrower for the loan request. 1-Business Loan, 2-Car Loan, 3-Invoice Financing, 4-Mortgage Loan, 5-Pawnbroking Loan, 6- Personal Loan, 7-Shert-Term Loan	1.00	8.00	7.44	0.75	484,912
Loan Rate%	Interest Rate on the loan	4.00	18.50	11.67	2.81	484,912
Term	Duration of loan	1.00	238.00	3.89	10.52	484,912
Initial LTV	Initial Loan-to-Value (LTV) Ratio	0.00	650.00	8.51	23.84	484,912
LTV	Final Loan-to-Value (LTV) Ratio	0.00	99.00	1.08	8.84	484,912
Initial Loan Amount	The listed amount of the loan applied for by the borrower.	12.59	70000.00	424.81	593.70	396,536
Collateral	Dummy variable representing the loan type in terms of a provision of collateral. Equal to 1 if the loan is collateralised, 0 otherwise	0.00	1.00	0.12	0.32	484,912
Loan Status	Current status of individual loan.Dummy variable equal to 1 if the loans is overdue, defaulted or buyback and 0 otherwise (current or repaid)	0.00	1.00	0.19	0.42	484,912
Borrower's Financial Characteristics						
Mintos Risk Score	Mintos assigned Rating’ ranging between A+ (1) and D (7)	5.50	8.60	6.80	0.60	412,813
Macroeconomic indicators						
Covid_DUM	Dummy variable equal to 1 for the dates between March 11, 2020 & Jan 2021 and 0 otherwise	0.00	1.00	0.18	0.38	484,912
War_DUM	Dummy variable equal to 1 for the dates later than Feb. 24th 2022 and 0 otherwise	0.00	1.00	0.55	0.50	484,912
GDP	Gross domestic product (GDP)	-20.32	16.78	0.76	0.99	484,912
unemployment rate	Country based Unemployment rateTotal, % of labour(Monthly)	2.70	16.50	9.21	4.30	484,912
Inflation	Inflation as measured by the consumer price index.(CPI monthly Growth)	-1.68	21.84	6.89	6.69	484,912
HH debt	Household Debt Service Payments as a Percent of Disposable Personal Income	36.90	256.86	84.14	34.07	484,912
Stcok Mkt index	Dow Jones EURO STOXX indices - Benchmark - Broad Index	308.5	478.7	422.9	38.8	484,912
Death_cases	Number of WHO reported daily COVID-19 related deaths in country i at time t (Monthly acc.)	0	121,852	60,941	50,473	484,912
Post Loan						
In Recovery	Recovery plan for problematic loans	0.00	1.00	0.07	0.26	484,912
Extendable schedule	Dummy variable representing the restructuring of a loan. Equal to 1 if the original maturity date of the loan has been increased by more than 60 days, 0 otherwise	0.00	1.00	0.78	0.42	484,912
Buyback	Dummy variable Equal to 1 if the loan uses buyback guarantee, 0 otherwise	0.00	1.00	0.65	0.48	484,912
Loan Originator Status	Timing every 3 Months before loan maturation					

Table F.2. An Empirical Comparison of Individual and Homogenous Ensemble Algorithms_ Post–Loan Repayment Period

			Post-Loan Repayment Period						
			Standard Classification				Imbalanced Classification		
Algorithm	**Specification**		**Accuracy**	**Recall**	**Precision**	**Specificity**	**FBScore**	**B.Accuracy**	**Time(s)**
Linear Discriminant Analysis (LDA)			80.85	74.22	83.01	84.23	75.82	79.22	0.32
Naïve Bayesian (NB)			81.25	73.58	86.24	88.96	75.81	81.27	4.2
K-Nearest Neighborhood (KNN)	K	1	77.64	77.65	76.01	77.85	74.10	77.75	149
		7	78.74	76.54	77.64	79.64	77.73	78.09	152
		9	79.75	76.28	79.60	81.44	76.92	78.86	52
Adaptive Neuro-Fuzzy Inference System (ANFIS)	Membership simulations	3	79.80	75.92	79.44	78.65	76.60	77.29	2050
Support Vector Machine (SVM)		Linear	85.38	71.51	86.97	88.23	74.15	79.87	3150
		RBF	79.50	75.86	84.13	85.09	77.38	80.48	210
		Polynomial	52.44	57.15	65.56	83.08	58.65	70.12	3780
Multi-Layer Perceptron (MLP)	Hidden layers	[35 20 5]	76.94	75.32	76.04	78.42	75.47	76.87	18
		[25 5 15]	78.29	75.68	87.24	88.20	77.45	81.94	1270
Decision Tree (DT)			76.82	79.73	77.29	78.95	79.23	79.34	54
Ensemble Algorithms	Random Forest [NumTree, #100]	Bagging	77.08	76.85	79.13	80.99	77.30	78.92	567
	Tree	LogitBoost	77.98	77.19	80.64	82.56	77.86	79.87	256
	Tree	TotalBoost	73.95	73.05	72.47	74.76	72.94	73.91	4835
	Tree	AdaBoostM1	78.30	76.26	81.01	82.39	77.16	79.32	287

Table F.3. Ensemble of collective learning from heterogeneous individual and ensemble algorithms

		Evaluation Metrics							
		Standard Classification				Imbalanced Classification			
Algorithm	**Specification**	**Accuracy**	**Recall**	**Precision**	**Specificity**	**FBScore**	**B.Accuracy**	**Time(s)**	**Gen. ObjF**
Ensemble of the collective base learners	Loan Allocation Period	75.26	70.02	78.56	77.88	73.29	73.03	226	0.274
	Post Loan Repayment Period	78.92	76.26	81.27	82.65	76.78	78.36	258	0.223

Table F.4. EFSGA prediction performance based on different risk-taking scenarios – Post-Loan repayment prediction

		Evaluation Metrics								
		Standard Classification				Imbalanced Classification				
Algorithm	**Specification**	**Accuracy**	**Recall**	**Precision**	**Specificity**	**FBScore**	**B.Accuracy**	**Time(s)**	**Gen. ObjF**	**Decision Threshold**
EFSGA	Scenario no.1	71.22	92.54	63.57	75.01	84.81	83.78	55	0.316	0.100
	Scenario no.2	76.05	87.02	71.33	74.69	83.35	80.86	75	0.181	0.130
	Scenario no.3	82.350	83.48	80.31	81.31	82.83	82.40	51	0.185	0.210

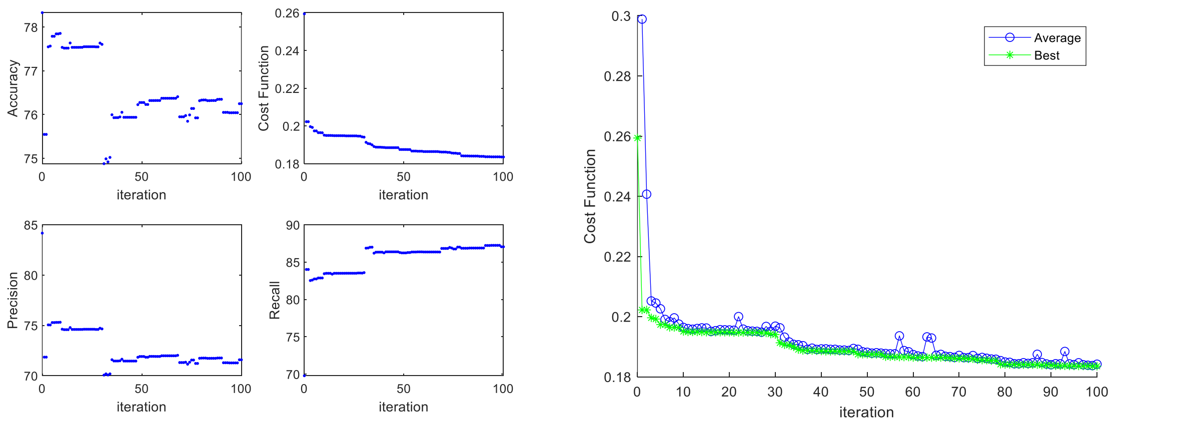

Fig. F.1. *Post-loan repayment prediction result by EFSGA*

Table F.5. Optimized weights of each ML classifier by GA based on the genetic objective function

		Solution W: Optimized Weights of the Ensemble Model									
Algorithm	**Specification**	LDA	NB	NN	KNN	ANFIS	SVM-RBF	MLP	DT	LogitBoost	AdaBoostM1
EFSGA	Scenario no.1	0.05	0.02	0.06	0.06	0.12	0.15	0.13	0.18	0.13	0.08
	Scenario no.2	0.06	0.07	0.07	0.08	0.10	0.12	0.13	0.12	0.14	0.12
	Scenario no.3	0.07	0.09	0.05	0.08	0.10	0.11	0.13	0.12	0.14	0.11

Table F.6. Feature Importance Scores from Genetic Algorithm Optimization

Attributes		*Feature Selection by ML Classifiers*				
		NN	*KNN*	*DA*	*NB*	*DT*
	TTL #	*14*	*17*	*15*	*16*	*14*
Loan Chracteristics						
Loan Type	3		1	1	1	
Loan Rate%	5	1	1	1	1	1
Term	4	1		1	1	1
Initial LTV	3	1		1	1	
LTV	2			1		1
Initial Loan Amount	5	1	1	1	1	1
Loan Originator	3	1	1		1	
Loan Originator Status	4	1	1		1	1
Collateral	3		1		1	1
Mintos Risk Score	3		1	1		1
Macroeconomic indicators						
Covid_DUM	4	1	1		1	1
War_DUM	3		1		1	1
GDP	5	1	1	1	1	1
unemployment rate	4	1	1	1	1	
Inflation	5	1	1	1	1	1
HH debt	3	1	1			1
Stcok Mkt index	2			1	1	
Death_cases	3		1	1		1
Post Loan						
In Recovery	3	1		1		1
Extendable schedule	2		1	1		
Buyback	4	1	1	1	1	
Loan Originator Status	3	1	1		1	

The EFSGA model effectively extracts valuable features and outperforms other methods, significantly reducing the number of features. The key findings are as follows:

- Loan Specific Characteristics: Essential factors, such as loan maturity and interest rates, carry significant weight for classifiers. Our analysis reveals a notable correlation: borrowers opting for higher loan amounts (averaging 40% higher) and longer loan terms generally face elevated interest rates (approximately 10% higher) and an increased propensity for default. Loan purpose is another determinant; invoice financing and pawnbroking loans present the lowest risk, while business and car loans bear the highest risk, with default rates exceeding 75% and 69%, respectively. The loan originator, Creditstar, primarily offers various short-term loans (mostly less than one year), with only approximately 25% classified as favorable. A more appealing option could be Everest Finanse, exhibiting a superior rate of non-delinquent short-term loans. Additionally, riskier borrowers tend to exhibit higher loan-to-value (LTV) ratios. Examining the binary variable "Buyback," 65% of loans entail the buyback obligation, with 70% classified as good borrowers and 30% categorized as riskier. Similar trends are observed in loans with an "extendable schedule." Mintos' estimated credit scores show that 69% fall into the mid-risk range, 16% in the low-risk range, and 15% as Score Withdrawn (SW). Significantly, the default risk does not necessarily increase as Mintos' estimated loan risk transitions from the low to medium-risk range.

- Macroeconomic Variables and Default Risk: The primary drivers of default rates encompass elements tied to actual economic activity, inflation rates, and GDP. Notably, the impact of European stock market indexes on credit risk is less pronounced compared to our observations in the US. More precisely, our analysis reveals that a decline in GDP is associated with an increase in default probabilities within the Euro area, mirroring a similar pattern observed for the inflation rate. This aligns with well-established findings in the existing literature. The effect of stock market indexes varies across sectors, prompting scrutiny regarding its effectiveness in elucidating credit quality trends in the present dataset.
- COVID-19 Pandemic Risk and Default Risk: While a limited number of studies have delved into early-stage implications of the pandemic on risk levels and defaults in FinTech lending markets (Baig et al., 2020; Demirguc-Kunt et al., 2020b; Najaf et al., 2021), our study extends the horizon (2018–2023) to capture the full extent after the easing of government restrictions. The pandemic's influence on credit risk becomes evident by late 2021 as short-term liquidity challenges transform into insolvency for businesses and households. Our analysis reveals a delayed yet impactful rise in default risk from the second half of 2021, persisting until the first quarter of 2022. Borrower risk profiles notably deteriorated during the pandemic, with the two pandemic risk proxies (Covid_DUM and Death_cases) consistently selected by classifiers. Specifically, the surge in COVID-19-related deaths significantly increases the likelihood of default. The probability of default, late payments, and the inclusion of 'buyback' guarantees for loans increases from 22% pre-pandemic to 26% post-pandemic. We emphasize a decline in loan quality amid the pandemic, with the loan ratings shifting from low risk to the middle to near low-risk range (8.3 to 6.8). It can be asserted that the decrease in loan ratings inherently leads to changes in default or overdue loans. Furthermore, we uncover variations in the magnitude of COVID-19 risk impact based on borrower credit score and country, providing nuanced insights into the evolving landscape of default risk in Europe.
- Effect of Russia–Ukraine War on Default Risk: Following the Russia-Ukraine invasion, we observed a notable uptick in default risk during the first six months, as opposed to the preceding period. Our analysis reflects a gradual change in defaulted loans, instances of significant repayment delays, and the use of a buyback guarantee. The overall incidence has increased from 20% before the invasion to 23% after, with some countries experiencing rates surpassing 40%.

General Conclusion

This thesis aims to investigate the complex interplay between bank opacity, the role of financial analysts, and risk optimization within the banking and FinTech sectors. It explores how opacity influences stability, how financial analysts can both mitigate and exacerbate risks in different market environments, and introduces innovative approaches to credit risk management in FinTech lending. Through these objectives, the research seeks to provide policymakers and financial institutions with actionable insights to foster systemic resilience in an increasingly interconnected financial landscape.

The findings challenge the traditional perception of financial analysts as purely stabilizing agents in the financial ecosystem, revealing a dual role where analysts, especially in opaque institutions, can inadvertently amplify risk. This thesis identifies specific conditions—such as economic uncertainty and market overvaluation—under which analyst coverage may heighten instability rather than reinforce discipline. By highlighting these dynamics, the research calls for a more nuanced regulatory approach, recognizing the situations where analysts might unintentionally serve as catalysts for risk. Furthermore, the thesis underscores the often-overlooked systemic implications of opacity in financial institutions. Rather than being a localized issue, opacity has far-reaching consequences that, when compounded by market pressures, can destabilize entire financial systems. The findings suggest a need for enhanced transparency measures and adaptive regulatory frameworks capable of responding to evolving market conditions, thereby minimizing the destabilizing potential of opacity across highly opaque sectors.

The research also sheds light on the implications of dividend policies in opaque banks, revealing that excessive payouts can exacerbate the negative impact of opacity, particularly within U.S. markets. This insight suggests that dividend policies should be reconsidered as regulatory tools, as they may not only signal financial strength but also indicate vulnerability in certain contexts. Policymakers are encouraged to view dividend restrictions as a strategic mechanism to mitigate instability where opacity and market pressures converge.

The comparative analysis of financial analysts' behavior across the U.S., Europe, and Asia illustrates significant regional variations in forecasting accuracy, boldness, and career motivations. These differences underscore the importance of region-specific regulatory approaches that address the distinct incentives, experience levels, and affiliations influencing analysts' behaviors. Such tailored oversight can help mitigate the potential risks of overly optimistic or bold forecasts that may prioritize career advancement over market discipline, ensuring that the regulatory environment aligns with the unique characteristics of each region's financial landscape.

In the FinTech sector, this thesis introduces the EFSGA model, a dynamic, evolutionary-based ensemble learning technique tailored for real-time credit risk optimization. By integrating genetic algorithms with machine learning, EFSGA provides adaptive solutions to the specific challenges of FinTech lending, such as unbalanced datasets and rapidly shifting risk profiles. This model demonstrates the potential of evolutionary-based algorithms to enhance credit risk management, setting a foundation for future research in machine learning applications within finance and underscoring the value of adaptable frameworks that can meet evolving market needs.

Ultimately, this research bridges traditional banking and FinTech risk management, proposing that key principles such as transparency and market discipline can be adapted to bolster stability in FinTech platforms. This cross-sector perspective supports a unified regulatory approach that addresses both traditional and digital financial institutions, fostering systemic stability through a holistic framework. As a crucial recommendation, the thesis advocates for transparency as a cornerstone of financial stability. Opacity not only obscures risks but also creates vulnerabilities to market shocks, making transparency essential in an interconnected global financial system. This emphasis on transparency calls for policy reforms at both national and international levels, ensuring that financial stability is underpinned by clear, reliable, and comprehensive information across diverse sectors.

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Table of contents

Acknowledgements i
Summary iii
General Introduction 1
Chapter 1. Opacity, Financial Analysts and Bank Risk: Evidence from US and European Publicly Traded Banks 4
1.1. Introduction 6
1.2. Related Work and Hypothesis Development 10
1.2.1 Bank Opacity, Risk, and Earnings Volatility 11
1.2.2 The Role of Financial Analysts in the Nexus Between Bank Opacity and Risk 13
1.2.3 The Moderating Effect of Bank Dividend Payout Policy on Opacity and Risk 15
1.2.3.1 Other Considerations: Bank vs. Market-Driven Environments 16
1.3. Econometric Specification and Methodology 16
1.4. Measurement and Data 18
1.4.1 Measuring Bank Risk 20
1.4.2 Measuring Opacity Using Analyst EPS Forecasts 20
1.4.3 Measuring Analyst Pressure: Coverage Effect 21
1.4.4 Measuring Analyst Pressure: Informational Effect 21
1.4.5 Measuring Dividend Payouts 21
1.4.6 Control Variables 21
1.4.7 Data Collection and Preprocessing 22
1.4.8 Summary Statistics and Correlation Matrix 23
1.5. Empirical Findings and Analysis 27
1.5.1 Opacity, Analyst Influence, and Bank Risk -Taking 27
1.5.1.1 Alternative Measures for Analyst Coverage 29
1.5.1.2 Threshold Effects of Dividend Payouts and Analyst Coverage on Stability 30
1.5.1.3 Employing Market-Based Risk Metrics for Robustness 31
1.5.1.4 Contextual Drivers of Bank Risk: Impacts of Valuation, Volatility, and Size 33
1.5.1.5 Interactions between Analyst Coverage, Dividend Policies, and Bank Risk 35
1.5.2 Comparative Analysis: Opacity-Risk Dynamics Across Bank vs. Market-Driven Financial Systems 38
1.5.2.1 Differences in Analyst Properties and Risk Profiles 38
1.5.2.2 Information, Analyst, Dividend Distribution and Risk-taking – U.S. vs. Europe 39
1.5.2.3 Threshold Effects of Dividend Policies and Analyst Pressure 43
1.5.2.4 Contextual Influences of Volatility, Valuation, and Size on Opacity-Risk 44
1.5.2.5 Interactions and Extensions: Analyst Coverage, Dividend Policies, and Bank Risk 45
1.5.3 Extended Robustness Analyses 49
1.5.3.1 Opacity and High Default Probability (Merton's Model) 49
1.5.3.2 Market Systematic Risk and Price Volatility Analysis 52
1.6. Summary and Conclusion 53
Appendix I 55

Chapter 2. The Influence of Financial Analyst Characteristics on Forecast Accuracy: A Comparative Analysis Across Global Banking Markets 64
2.1. Introduction 66
2.2. Related Work 69
2.2.1 Determinants of Financial Analysts' Forecast Accuracy 69
2.2.2 Forecast Accuracy, Boldness, and Career Outcome 71
2.2.2.1 Economic Incentives and Analyst Behavior 72
2.3. Research Design and Methodology 73
2.3.1 Measurement of the Proportional Mean Forecast Accuracy 73
2.3.2. Measures of Analyst General Characteristics 74
2.3.2.1 Measurement of Experience 74
2.3.2.2 Measurement of Portfolio Complexity 75
2.3.2.3 Analyst Engagement Metrics 75
2.3.2.4 Measuring Brokerage House Size: 76
2.3.2.5 Control Variables 77
2.3.3 Measures of Analyst Forecast Boldness and Past Performance 77
2.3.3.1 Forecast Boldness Measurement 77
2.3.3.2 Analyst Past Performance Measurement: 78
2.3.4 Estimation Methodology 79
2.4. Research Data 80
2.4.1 Data Collection 80
2.4.2. Descriptive Statistics of Raw Variables 81
2.5. Empirical Result 84
2.5.1 Analyst Characteristics and Relative Forecast Accuracy 84
2.5.1.1.Regression variables 84
2.5.1.2 Regression Result 85
2.5.1.3 Determinants of Forecast Accuracy Across Regions 87
2.5.1.4 Portfolio Complexity and Regional Disparities 89
2.5.2 Boldness, Forecast Accuracy, and Career Concerns 90
2.5.2.1 Boldness and Relative Forecast Error 91
2.5.2.2 Forecast Boldness and Analyst Characteristics 93
2.5.3. Labor Market Incentives and Boldness 96
2.5.3.1 Measures of Job Movements 96
2.5.3.2 Past Forecast Accuracy and career Advancement : High- and Low-Experience Analysts 98
2.5.3.3 Boldness and Career Trajectories: High- and Low-Experience Analysts 100
2.5.3.4 Career Mobility and Strategic Forecasting 103
2.6. Summary and Conclusion 105
1.6.1 Policy Implications and Recommendations 107
Appendix II 108

Chapter 3. Evolutionary-Based Ensemble Feature Selection Technique for Dynamic Application-Specific Credit Risk Optimization in Fintech Lending 116
3.1. Introduction 118
3.2. Related Work 122
3.2.1 Dynamic Credit Risk Assessment 122
3.2.2 Ensemble Of Classifiers In Credit Risk Research Area 123
3.2.3 Metaheuristic Algorithms In Credit Risk Assessment And Feature Selection 124
3.2.3.1 Hybrid Approaches With Metaheuristic Algorithms 124
3.2.3.2 Feature Selection Using Metaheuristic Algorithms 124
3.2.4 Imbalanced Learning And Threshold Optimization Techniques 125
3.2.5 Our Motivation 126
3.3. Proposed EFSGA Model 127
3.3.1 Ensemble Learning And Feature Selection 127
3.3.1.1 Heterogeneous Ensemble Model 128
3.3.1.2 Ensemble Feature Selection 130
3.3.2 Optimization Of EFSGA Model 131
3.3.2.1 Problem Presentation 131
3.3.2.2 Proposed Fitness Function 132
3.3.2.3 GA Optimization Process 133
3.4. Empirical Evaluation Of The Proposed Method 136
3.4.1 Data Collection 136
3.4.1.1 P2P Lending Dataset 136
3.4.1.2 General Economy Data Collection 136
3.4.2 Simulation Settings 137
3.4.2.1 Data Pre-Processing 137
3.4.2.2 Real-Time Prediction Framework 138
3.4.2.3 Representative Data Selection And Training 138
3.4.2.4 GA Simulation Settings 138
3.4.3 Performance Comparison Of Individual And Homogenous Ensemble Algorithms 139
3.4.3.1 Individual Linear Models 140
3.4.3.2 Individual Non-Linear Models 140
3.4.3.3 Homogenous Ensemble Algorithms 141
3.4.3.4 Analysis Of Algorithm Performance On Varied Imbalanced Ratios 142
3.4.4 Results Of The Heterogeneous Ensemblemodel 143
3.4.5 Performance Evaluation Of The Proposed Application-Specific Efsgamodel 145
3.4.5.1 EFSGA Classification Results 146
3.4.5.2 Optimized Weights Of Classifiers In The Ensembe Model 148
3.4.5.3 Dynamic Optimized Decision Threshold 149
3.4.5.4 Ensemble Feature Importance Analysis—Model Interpretability 150
3.4.6 Optimization Of Credit Risk management 152
3.4.7 Robustness Tests 153
3.5. Discussion And Conclusion 154
3.6. Future Research Directions 155
Appendix III 157
General Conclusion 166
Bibliography 168
Table of contents 180
List of tables and figures 183

List of tables and figures

Chapter 1. Opacity, Financial Analysts and Bank Risk: Evidence from US and European Publicly Traded 4
Table 1.1: Variables Definition and Summary Statistics 25
Table 1.2: Correlation Matrix 26
Table 1.3: Opacity and Bank Risk-Taking – Fixed Effect Estimation Results 29
Table 1.4: Threshold Effects of Dividend Payout and Analyst Coverage on Stability 31
Table 1.5: Opacity and Bank Risk – Employing Alternative Risk Metrics for Robustness 33
Table 1.6: Contextual Drivers of Bank Risk: Impacts of Valuation, Volatility, and Size 35
Table 1.7: Interactions between Analyst Coverage, Dividend Policies, and Bank Risk 37
Table 1.8: Marginal Effects of Opacity, Analyst Pressure, and Dividend Payout Policy 37
Table 1.9: Opacity, Analyst Pressure, and Bank Risk – U.S. vs. Europe 42
Table 1.10: Threshold Effects of Dividend Payouts and Analyst Coverage 43
Table 1.11: Contextual Influences of Volatility, Valuation, and Size on Opacity-Risk – U.S. vs. Europe 44
Table 1.12: Interactions and Extensions: Analyst Coverage, Dividend Policies, and Opacity-Risk – U.S. vs. Europe 47
Table 1.13: Analyst Coverage, Dividend Policies, and Opacity-Risk – Segmentation by Bank Size 47
Table 1.14: Marginal Effects of Analyst Coverage, Dividend Policies on Opacity-Risk Nexus – by Bank Size 48
Table 1.15: Opacity and High Default Probability: Evidence from Merton's Model 51
Table 1.16: Market Systematic Risk and Price Volatility Analysis 53
Fig. 1.1: Scatter Plot of Detrended Opacity (Forecast Dispersion) and Risk-Taking 26
Fig. 1.2: Scatter Plot of Detrended Opacity (Forecast Error) and Risk-Taking 26
Fig. 1.3: Scatter Plots of Detrended Opacity (Forecast Error) and Risk Indicators (PD_Mert and DD_Mert) 50
Chapter 2. The Influence of Financial Analyst Characteristics on Forecast Accuracy: A Comparative Analysis Across Global Banking Markets 64
Table 2. 1: Descriptive Statistics for the Raw Variables 84
Table 2. 2: Relative Forecast Error and Individual Analysts' Characteristics 86
Table 2. 3: Determinants of Forecast Accuracy Across Regions 88
Table 2. 4: Relative Forecast Error and Portfolio Complexity 90
Table 2. 5: Boldness and Relative Forecast Error 92
Table 2. 6: Marginal Effects of Experience, Brokerage, and Portfolio Size on Boldness 93
Table 2. 7: The Link Between Analysts' Experience, Past Performance, and Boldness 96
Table 2. 8: Summary Statistics of Job Movements Dataset 98
Table 2. 9: Effect of Past Performance on Career Outcomes by Experience 100
Table 2. 10: Impact of Boldness on Career Advancement Across Regions 102
Table 2. 11: Boldness and Career Advancement by Portfolio Size 104
Table 2. 12: Boldness and Career Advancement by Analyst Engagement 104

Chapter 3. Evolutionary-Based Ensemble Feature Selection Technique for Dynamic Application-Specific Credit Risk Optimization in Fintech Lending 116

Table 3. 1 Setting the controllable parameters of GA 139

Table 3. 2 An empirical comparison of individual and homogenous ensemble algorithms_ post–loan repayment peroid 143

Table 3. 3 Analysis of algorithm performance in varied imbalanced ratios 143

Table 3. 4 Analysis of algorithm rankings in varied imbalanced ratios 143

Table 3. 5 Ensemble of collective learning from heterogeneous individual and ensemble algorithms 145

Table 3. 6 EFSGA prediction performance based on different risk-taking scenarios—post-loan repayment prediction 147

Table 3. 7 EFSGA prediction performance comparison against top selected and heterogeneous ensemble algorithms 148

Table 3. 8 Optimized weights of each ML classifier by GA based on the genetic objective function 149

Table 3. 9 Top Ranked algorithms based on GA-assigned weights 149

Table 3. 10. Feature Importance Scores from Iterative Genetic Algorithm Optimization 151

Fig. 3.1 The simplified flowdiagram representing the "Data, Methodology, and Output" structure of the proposed EFSGA model 128

Fig. 3.2 Representation of a feasible solution (chromosome encoding) for optimizing the EFSGA model 132

Fig. 3.3 Population updating in GA: Uniform Crossover Operator 135

Fig. 3.4 Population updating in GA: Binary Swap Mutation Operator 135

Fig. 3.5 Flowchart of the proposed hybrid method for Ensemble Feature Selection using the genetic algorithm 136

Fig. 3.6 Post-loan repayment prediction result by EFSGA 147

Fig. 3.7: Optimized threshold according to genetic objective function parameter adjustment. 150

Fig. 3.8. Top features contributing to default risk selected by EFSGA 152

Abstract

This thesis examines the interplay between bank opacity, financial analyst influence, and risk optimization in banking and FinTech. It comprises three studies exploring systemic stability, analyst behaviors, and innovative credit risk management tools. Chapter one focuses on U.S. and European banks, demonstrating how opacity, measured via analyst forecast errors and dispersion, exacerbates risk, particularly in smaller, opaque U.S. banks. Analyst coverage amplifies market sensitivity to negative signals, while high dividend payouts intensify opacity-driven risks. Chapter two analyzes global forecasting behaviors, revealing that experience, portfolio breadth, and regional incentives shape accuracy and boldness. U.S. analysts show accuracy and boldness, while European analysts prioritize boldness, often sacrificing precision. Chapter three introduces EFSGA, an evolutionary-based ensemble learning model for dynamic credit risk optimization in FinTech, balancing accuracy and interpretability. This thesis advances understanding of opacity, analyst behavior, and adaptive risk assessment, offering critical insights for resilience in modern finance.

Résumé

Cette thèse explore l'interaction entre l'opacité bancaire, l'influence des analystes financiers et l'optimisation du risque dans les secteurs bancaire et FinTech. Le premier chapitre révèle que l'opacité, mesurée par les erreurs et dispersions des prévisions des analystes, accroît les risques, notamment dans les petites banques opaques américaines, où la couverture par les analystes amplifie la sensibilité du marché. Le deuxième chapitre analyse le rôle des analystes à l'échelle mondiale, montrant que l'expérience, les portefeuilles et les incitations régionales influencent précision et audace des prévisions. Enfin, le troisième chapitre introduit EFSGA, un modèle d'apprentissage évolutif pour l'optimisation dynamique du risque de crédit dans les FinTech, équilibrant précision et interprétabilité. Cette thèse éclaire l'impact de l'opacité et des pressions des analystes sur la stabilité financière, tout en proposant des outils innovants pour gérer les risques dans les marchés modernes.