Experience, Bias and the Evolving Role of Human Capital in the Age of AI

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Expérience, biais et rôle évolutif du capital humain à l'ère de l'intelligence artificielle

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Résumé

Cette thèse examine comment le capital humain — en particulier l'expérience — interagit avec l'intelligence artificielle (IA) dans l'élaboration de prévisions et la prise de décision experte. À mesure que l'IA prend en charge des tâches traditionnellement réalisées par des humains, comprendre l'évolution du rôle de l'expérience devient essentiel. En s'appuyant sur le contexte empirique des analystes financiers, cette recherche explore trois questions : (1) comment l'expérience influence les biais cognitifs dans les prévisions, (2) si et comment l'expérience humaine contribue à la performance de l'IA, et (3) comment l'adoption de l'IA affecte les capacités prédictives organisationnelles et le rôle de l'expérience humaine dans ce cadre.

La première étude examine si l'accumulation d'expérience atténue ou renforce les biais dans les évaluations des analystes concernant des entreprises adoptant des stratégies controversées, en prenant les SPAC (Special Purpose Acquisition Companies - Société d'Acquisition à Vocation Spécifique) comme cadre d'analyse. Les résultats montrent que les analystes manifestent initialement un biais d'optimisme envers les SPAC, mais que ce biais diminue avec l'expérience, soulignant la fonction corrective de l'expérience dans des contextes incertains.

La deuxième étude s'intéresse à l'interaction entre intelligence humaine et intelligence artificielle. En comparant les erreurs de prévision des analystes avec celles de modèles d'apprentissage automatique, l'étude révèle un paradoxe : si l'expérience spécifique à un domaine peut réduire la précision des prévisions humaines par rapport à celles de l'IA, cette même expérience améliore la performance de l'IA lorsqu'elle est intégrée dans les données d'apprentissage. L'expérience généraliste, bien qu’elle n’améliore pas significativement les prévisions humaines, accroît considérablement la précision de l’IA dans des environnements volatils. Ces résultats démontrent que l’expérience humaine, même si elle est sous-optimale pour des prédictions individuelles, reste un atout précieux lorsqu’elle est exploitée par l’IA.

La troisième étude explore les implications organisationnelles de l’adoption de l’IA. À l’aide d’une mesure des investissements en IA dans les entreprises, l’étude montre que l’adoption de l’IA réduit les erreurs de prévision, notamment lorsqu’elle est associée à des analystes généralistes plutôt qu’à des spécialistes d’un domaine précis. Cela suggère que, l’IA devenant de plus en plus performante dans les tâches spécialisées, la valeur du capital humain se déplace vers une expérience plus large et généraliste, favorisant l’adaptabilité, le raisonnement contextuel et la supervision stratégique.

Ensemble, ces études offrent une compréhension plus nuancée de la complémentarité entre humains et IA. Plutôt que de considérer l’IA comme un substitut à l’expertise humaine, les résultats soulignent l’importance de l’expérience comme un atout dynamique et dépendant du contexte : parfois une faiblesse dans une prise de décision exclusivement humaine, mais une force lorsqu’elle est intégrée à l’IA. Cette thèse contribue aux théories de l’apprentissage par l’expérience, des biais cognitifs et de la transformation technologique dans la prévision experte, et propose des pistes concrètes pour aider les organisations à adapter, requalifier et repenser le capital humain à l’ère de l’IA.

Mots-clés : Capital humain, Intelligence artificielle, Prévision, Biais cognitifs, Accumulation d’expérience, Complémentarité humain–IA

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Abstract

This dissertation investigates how human capital, specifically experience, interacts with artificial intelligence (AI) in shaping forecasting accuracy and expert decision-making. As AI increasingly takes over tasks traditionally performed by humans, understanding the evolving role of human experience becomes critical. Drawing on the empirical context of financial analysts, the dissertation explores three questions: (1) how experience influences cognitive biases in forecasting, (2) whether and how human experience contributes to AI performance, and (3) how AI adoption affects organizational predictive capabilities and the role of human experience in that context.

The first study examines whether accumulated experience mitigates or reinforces bias in analysts' evaluations of firms employing controversial strategies, using SPACs (Special Purpose Acquisition Companies) as the setting. Results show that analysts initially display optimism bias toward SPAC firms, but this bias diminishes with accumulated experience, highlighting the corrective function of experience in uncertain contexts.

The second study focuses on the interplay between human and machine intelligence. By comparing human analysts' forecast errors with those of machine learning models, the study reveals a paradox: while domain-specific experience may reduce the relative accuracy of human forecasts compared to AI, the same experience enhances AI performance when incorporated into training data. Generalist experience, although not significantly improving human predictions, substantially increases AI accuracy in volatile environments. These findings demonstrate that human

experience, even when suboptimal for individual prediction, remains a valuable asset when leveraged through AI.

The third study investigates the organizational implications of AI adoption. Using a measure of AI investment across firms, the study shows that AI adoption reduces forecast errors overall, particularly when paired with generalist, rather than firm-specific, analyst experience. This suggests that as AI increasingly excels at deep, domain-specific tasks, the value of human capital shifts toward broader, generalist experience that enables adaptability, contextual reasoning, and strategic oversight.

Together, these studies contribute to a more nuanced understanding of human-AI complementarity. Rather than framing AI as a substitute for human expertise, the findings underscore the importance of experience as a dynamic, context-dependent asset: potentially a liability in human-only decision-making, but a strength when integrated with AI. The dissertation advances theory on experiential learning, cognitive biases, and technological transformation in expert forecasting, offering practical insights into how organizations can adapt, reskill, and rethink human capital in the age of AI.

Keywords: Human Capital, Artificial Intelligence, Forecasting, Cognitive Bias, Experience Accumulation, Human-AI Complementarity

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Chapter 1 - General Introduction

Objective and Research Questions

When high-impact strategic decisions rely on a single forecast, even minor errors can have massive consequences. Across industries, from finance and supply chain to healthcare and tech, experts with years of accumulated experience suddenly find themselves "competing" with artificial intelligence (AI) tools that promise fast, seemingly objective analysis, forecasts and decisions. This tension between human expertise and AI is reshaping how organizations need to think about decision-making, forecasting and evaluation under uncertainty.

Human capital, defined as the skills, experience, and judgment embedded within individuals, is crucial for strategic advantage in knowledge-intensive industries (Becker, 1994). In roles that require forecasting, evaluation and judgment, especially those surrounded with uncertainty and ambiguity, organizations traditionally relied on human capital and its experience (Durand, 2003). The logic is simple: more experience leads to better decisions through experiential learning (Argote, 2012; Reagans et al., 2005).

Yet the reality is more complicated. While experience often enhances judgment, it can also exacerbate cognitive biases (Kahneman, 2011), amplify overconfidence (Gaba et al., 2022), or reinforce outdated mental models (March, 2010). So, while experience is valuable, it is also fallible.

At the same time, AI has emerged as a transformative force in organizational decision-making. As a general-purpose technology (Agrawal et al., 2019), AI is increasingly embedded into processes across finance, logistics, medicine, and more (Brynjolfsson & Mitchell, 2017). It promises to identify patterns in massive datasets, offering speed, scale, and consistency beyond human capabilities. Some scholars view AI as a substitute for human capital (Yilmaz et al., 2023), while others argue it can complement and extend human expertise (Allen & Choudhury, 2022; Krakowski et al., 2022).

This duality-AI as both complement and competitor to human capital, raises more pressing questions than which side “wins”. What happens to the value of human experience when AI starts taking over more of the work? Under what conditions can human experience add, or even enhance, value in AI-augmented decision-making? And how should organizations adapt their strategies for recruiting, training, and leveraging human capital in a world where machines play a central role in judgment?

In this dissertation I explore how accumulated experience influences forecasting performance, whether it mitigates or magnifies cognitive biases, and when it complements the capabilities of AI. Specifically, I investigate whether and how human expertise remains relevant (or even essential) in a landscape where AI’s role continues to expand. In doing so, I also examine how organizational adoption of AI should drive shifts in the kinds of experience and skill sets that matter most, potentially favoring broad, adaptable knowledge over deep, domain-specific expertise.

More specifically, I focus on three research questions:

RQ1. How does accumulated experience influence cognitive biases in expert forecasting?

RQ2. In what ways can human experience enhance the performance of AI systems, and under what conditions is this contribution most valuable?

RQ3. How does AI adoption transform organizational predictive capabilities, and what role does human experience play in this transformation?

To address these questions, this dissertation draws insights from various streams of literature. The next section provides an overview of four key areas of literature: the performance implications of human experience, the cognitive biases that challenge human judgment, the transformative role of AI in prediction and decision-making, and the use of financial analysts as a context in which to study these changes caused by advent of AI. Together, these literatures provide the groundwork for the research questions explored in this dissertation.

Theoretical Foundation

Human Capital and Experience in Knowledge Work

Human capital, defined as the collective knowledge, skills, experience and capabilities of an organization's members, is acknowledged as a key predeterminant of organizational success (Becker, 1994). Within strategic management, human capital is viewed as a key intangible resource that organizations can leverage to differentiate themselves from competitors. According to the resource-based view (RBV) of the firm, when an organization is able to attract and retain human capital that is valuable, rare, inimitable, and non-substitutable, it possesses a strategic asset capable of generating sustained competitive advantage (Barney, 1991).

According to RBV, experienced and knowledgeable human capital constitutes a core competence of an organization. Extensions of the resource-based view of the firm, such as knowledge-based view of the firm, further argue that knowledge is the most significant resource in the possession of the organizations, and this knowledge is largely embedded within the human capital (Grant, 1996). This knowledge, if effectively integrated and leveraged correctly, will yield competitive advantage by fostering the firm's ability to recombine and exploit it (Szulanski et al., 2016).

One key characteristic of human capital is the experience embedded within human capital. A large body of research in strategic management examines the correlation between key members of the organizations and overall firm performance. For example, prior experience of firm founders has been shown to be associated with the higher chances of survival (Bruderl et al., 1992). Similarly, prior experiences of top management teams has been shown to result in sustained growth in the long term (Kor, 2003). In addition, such factors as top managers' experience of being on multiple company boards, industry-specific managerial experience, and firm-specific founding experience have been shown to affect positively the firm growth (Kor & Sundaramurthy, 2009).

Learning by doing literature also highlights the benefits of experience accumulation (Arrow, 1962). The underlying idea is that the repeated execution of a task leads to improved performance. This process, often referred to as learning curve (Argote, 2012), shows that as individuals gain experience while performing a task, their efficiency and effectiveness at that task increases. This phenomenon has been documented across a variety of contexts: software developers (Narayanan et al., 2009), surgeons (Hopper et al., 2007), financial analysts (Clement, 1999) - all tend to get faster, better, more accurate or more productive with accumulated experience.

One key idea associated with experience accumulation is the development of expertise and tacit knowledge. Tacit knowledge is defined as know-how that is hard to codify or explain, but results in performance improvement (Polanyi, 1966). As Michael Polanyi (1966) put it, "we can know more than we can tell". Tacit knowledge is developed through hands-on experience: as humans accumulate experience, they gain intuitive insights, skills and habits that are associated with improved performance. Nonaka (1994) further extends this idea by bringing it to organizational level and highlighting how individuals share tacit knowledge and convert it into explicit knowledge to drive innovation.

Despite all the benefits of experience accumulation and learning, the extant literature highlights also its potential pitfalls. At organizational level, learning processes can become shortsighted - a phenomenon known as myopia of learning (Levinthal & March, 1993), where firms overemphasize recent successes and fail to explore alternative strategies. March (2010) further highlights that experience is ambiguous, and it does not necessarily provide clear and reliable lessons.

All in all, the literature on human capital and experience underscores its critical role as a source of competitive advantage. Experience accumulation and learning by doing allow individuals and organizations to achieve better performance and develop greater efficiency. However, despite all the benefits, learning from experience is an ambiguous process, offering lessons that are not always clear and applicable and in some cases, potentially reinforcing cognitive biases that distort judgment rather than improve it.

Biases and Bounded Rationality in Expert Judgment

While human capital and its experience accumulation are associated with performance improvement, organizational success and growth in the long term, human judgment is not necessarily optimal. Human decision-making is limited by bounded rationality (Simon, 1955). Rather than being perfectly rational and striving for optimal decision, even experienced individuals look for “good enough” options rather than optimal ones. Simon described this process as “satisficing” - humans look for optimal decision until they are satisfied with it, and do not necessarily strive for the optimal one (Simon, 1991).

In addition to bounded rationality, cognitive biases and heuristics have also been shown to affect human decision-making, particularly under the conditions of uncertainty and ambiguity (Tversky & Kahneman, 1974). Cognitive biases negatively impact decision-making across contexts such as strategic choices (Schwenk, 1984), investments (Blohm et al., 2020), risk assessment (Kahneman & Lovallo, 1993; McNamara & Bromiley, 1997), and forecasting (Hilary

& Menzly, 2006). While cognitive biases are widespread in human judgment (Kahneman, 2011), strategy research has specifically examined how they manifest within the context of strategic decision-making (Das et al., 1998). Das et al (1998) provide examples of common cognitive biases that are “ever-present ingredients of strategic decision making” - prior hypothesis bias, limited search, insensitivity to probabilities, and illusion of control.

However, despite large body of literature analyzing the negative impact of biases and heuristics, it is important to mention that an opposing viewpoint emerges in the literature. This perspective suggests that heuristics, often seen as decision-making flaws, can serve as valuable mental shortcuts enhancing human predictions and judgments (Gigerenzer & Todd, 1999). Gigerenzer claims that heuristics are “fast and frugal” decision rules, that, while simple, are quite effective. Particularly in dynamic contexts characterized by evolving environments and incomplete information, where traditional rationality falls short, relying on heuristics enables humans to forecast swiftly and accurately (Gigerenzer & Gaissmaier, 2011).

Given the performance improvement and learning associated to experience accumulation, prior studies have analyzed whether experience can potentially mitigate human cognitive biases. There is evidence that suggests that biases tend to diminish with experience, as individuals learn from repeated exposure and feedback (e.g. Christoffersen & Sarkissian, 2011). For example, Gort et al. (2008) show that highly educated people with more experience tend to be significantly less biased compared to those with less experience and education. Nevertheless, the opposite effect has also been demonstrated. For example, one of the most prevalent cognitive biases - overconfidence, defined as the overestimation of one’s knowledge, abilities, or predictive accuracy, has been shown to be predominantly present among experts (Sanchez & Dunning, 2023). Moreover, it has been shown not only to persist despite experience accumulation, but to be even more pronounced among seasoned professionals (Gaba et al., 2022).

Thus, extant literature provides mixed finding on cognitive biases and experience's role in mitigation of biases. While cognitive biases are largely recognized to distort human judgment, accumulated experience's impact on this can act as a double-edged sword, both by mitigating and amplifying it, depending on the context. As Kahneman and Klein (2009, p. 515) put it, "professional intuition is sometimes marvelous and sometimes flawed": its reliability depends on boundary conditions, such as high-validity environment, opportunities for regular practice, timely and accurate feedback, and sufficient exposure that allows learning. Absent these conditions, even expert judgment can be systematically biased.

As organizations confront the limitations of human decision-making, many are turning to AI as a means to improve performance. This has sparked growing interest in human–machine complementarity: how AI systems can work alongside human experts to reduce bias, increase efficiency, and adapt to dynamic environments. The literature now increasingly asks not whether AI will replace human judgment, but how the two can be effectively integrated.

In what follows, I review the emerging literature on AI adoption and human–machine complementarity, with a focus on how these technologies interact with and reshape the role of human capital and experience.

AI Adoption, Human-AI Complementarity and Implications for Labor

AI is widely regarded as a general-purpose technology (GPT) (Agrawal et al., 2019) capable of performing a wide range of tasks traditionally carried out by human capital, particularly in knowledge-intensive sectors. As Brynjolfsson and Mitchell (2017) discuss, AI and particularly its subfield of machine learning, have found successful applications in areas such as medical diagnostics, fraud detection, image recognition, and customer service automation. These systems excel in tasks where large datasets exist, outcomes are clearly defined, and decisions can be learned from patterns in data rather than explicit programming (Agrawal et al., 2018). AI adoption has been shown to result in higher growth in sales, employment, and market valuation - effects primarily attributed to product innovation (Babina et al., 2024).

Given the promise of this technology, considerable scholarly attention has been devoted to comparing the performance of AI and humans across wide range of tasks. Interestingly, when compared in relatively static and predictable environments, even early generations of most basic predictive models, well before the capabilities of modern AI, have been shown to outperform human judgment (Grove et al., 2000; Meehl, 1954). As the technology has continued to evolve, fueled by advances in computational power and the growth of data generation and storage (Agrawal et al., 2018), newer iterations of AI have been able to outperform human judgment in increasingly complex tasks. For example, studies have shown that AI can outperform humans in a variety of contexts, including investment decision-making (Blohm et al., 2020), medical image recognition (Killock, 2020), and estimating the time required to complete tasks (Ibrahim & Kim, 2019).

Nevertheless, despite its vast potential, AI is not a universal solution, and its performance can vary significantly depending on the context. It is not always optimal or superior to human judgment. AI's performance is highly dependent on the quantity of training data (Sambasivan et al., 2021). When data is limited, algorithms often struggle to identify meaningful patterns and may produce inaccurate or misleading outputs. Moreover, if the data used to train algorithms is of poor quality, it can lead to biased outcomes. For instance, when training data includes existing human biases, AI models are likely to replicate those biases, and may even amplify them, thereby reinforcing rather than correcting underlying biases (Cowgill, 2018; Cowgill & Tucker, 2019).

To address these challenges and leverage the strengths of both human and artificial intelligence, recent literature has begun exploring ways to effectively combine the two. A growing body of work highlights that the most promising outcomes often arise not from substitution but from complementarity between AI and human capital. For instance, algorithm-augmented work has been shown to outperform manual work for individuals with moderate domain experience, where users possess enough ability to interpret AI output but not so much experience that they develop aversion to it (Allen & Choudhury, 2022). Similarly, in complex tasks like patent examination, domain experts can correct for algorithmic bias, such as that caused by strategically manipulated inputs, outperforming AI-only or human-only approaches (Choudhury et al., 2020). In competitive and strategic contexts, the combination of human and machine intelligence has been shown to create a new source of competitive advantage, emerging when human judgment is paired with the speed and consistency of algorithms (Krakowski et al., 2022).

More theoretical work has advanced the concept of human-AI ensembles, where humans and AI both tackle the same task, and their predictions are aggregated rather than divided by specialization. This setup can improve decision accuracy, even when neither humans nor AI are individually superior (Choudhary et al., 2023; Puranam, 2021).

This literature also warns against the risks of over-reliance on automation. While research has demonstrated that AI can effectively substitute for human labor, especially in analytical and language-intensive tasks (Yilmaz et al., 2023), other studies caution that full automation may lead to the erosion of critical human skills over time. A more sustainable approach may lie in embracing the automation–augmentation paradox (Raisch & Krakowski, 2021), which argues that exclusively focusing on automation or on augmentation is suboptimal, and that the balance of both is the best solution.

Based on this, recent studies started questioning the implications of advent of AI on labor market, and reskilling of human capital that becomes increasingly crucial. Autor (2015) emphasizes that while automation substitutes for certain human tasks, it cannot automate all of the tasks, particularly those requiring adaptability, problem-solving, and interpersonal judgment. Yet, the pace and scope of recent AI advances have raised concerns about whether displaced workers can transition smoothly into new roles. Acemoglu et al. (2022) find that AI exposure is associated with reduced hiring in non-AI roles, suggesting displacement effects without immediate offsetting gains from productivity or complementarity.

At the same time, scholars have developed measures to assess occupational exposure to AI, revealing that high-wage and high-skill occupations, such as legal services, finance, and post-secondary education, are increasingly exposed to Large Language Models (LLMs) like ChatGPT (Felten et al., 2023). These trends underline the need for proactive reskilling strategies. As Furman and Seamans (2019) argue, the rapid deployment of AI risks outpacing workers' ability to adapt. A key policy challenge, therefore, lies in enabling workers to develop the complementary skills needed to thrive alongside AI rather than be displaced by it.

Together, these bodies of literature highlight a critical tension that organizations face today: while human capital, particularly its experience, remains a cornerstone of expertise and learning, it is also prone to cognitive limitations that can affect decision-making. At the same time, AI emerges as a powerful tool with a potential of replacing human intelligence, but its effectiveness depends on how it is integrated with human judgment within organizations. This raises questions about how AI adoption reshapes the value of human experience, the performance of knowledge workers, and organizations in general.

By focusing on the intersection of human judgment, machine intelligence, and evolving experience, this dissertation investigates the dynamics that shape predictive accuracy in strategic settings where expert judgment is critical. Forecasts are a particularly valuable outcome to study because they serve as a forward-looking input to organizational decision-making. Accurate forecasts enable firms to navigate uncertainty, align expectations, and respond proactively to environmental changes (Durand, 2003; Makadok & Walker, 2000). At the same time, forecasting draws heavily on both human experience and analytical tools, making it an ideal setting to explore how expertise, bias, and technology interact. As organizations increasingly incorporate AI into evaluative and predictive processes, understanding how these forecasts are produced offers key insights into the evolving role of human capital in strategic decision-making. This dissertation thus extends existing research by analyzing whether experience helps overcome bias and how that relationship evolves in the context of AI adoption.

To explore these dynamics, I focus on the empirical context of financial analysts: a highly relevant group of knowledge workers whose forecasts are observable, comparable, traceable throughout time. Moreover, these forecasts can have a significant impact on firm valuation and strategic decisions. Analysts operate in an increasingly data-driven environment, where both human expertise and AI play a growing role. In the next section, I review the literature on financial analysts to position them as a context for exploring how human expertise interacts with the integration of artificial intelligence.

Financial Analysts

Financial analysts are professionals employed by investment banks, brokerage firms, and equity research institutions who evaluate publicly listed companies and issue forward-looking assessments to guide investor decision-making. A central part of their job is forecasting a firm's earnings per share (EPS) - a key financial metric that reflects a company's profitability. These EPS forecasts are typically released ahead of a firm's earnings announcements and are used by investors, fund managers, and other stakeholders to form expectations and make investment decisions. Analysts rely on a mix of financial modeling, industry knowledge, company disclosures, and increasingly, AI tools to produce these forecasts.

As such, financial analysts represent a highly relevant setting to examine the dynamics of human expertise, judgment, and the integration of AI. As external evaluators and information intermediaries, analysts play a critical role in capital markets by shaping investor perceptions, monitoring firms, and influencing strategic decisions through their earnings forecasts and stock recommendations (Brauer & Wiersema, 2018; Jensen & Meckling, 1976). Their assessments help reduce information asymmetry, guide investment decisions of investors, and ultimately affect firm valuation, reputation and access to capital (Hayward & Boeker, 1998; Stickel, 1992; Zuckerman, 1999).

What makes analysts especially valuable for research on expertise is the measurable and repeatable nature of their forecasting tasks. Earnings forecasts provide observable outcomes that can be systematically compared against actual results, allowing to quantify performance, detect bias, and assess the influence of both individual and organizational factors. This makes the analyst context particularly well-suited for evaluating how judgment and forecasting accuracy evolve with experience (Clement, 1999; Mikhail et al., 1997), and how these dynamics shift in response to organizational changes such as AI adoption.

In addition, analysts have been shown to be subject to various cognitive biases (Hilary & Menzly, 2006). Moreover, analysts operate under unique institutional and social pressures that affect their judgment. Prior research has shown that their forecasts may reflect reputational concerns, conflicts of interest tied to employer incentives, or social proximity to management (Brauer & Wiersema, 2018; Dechow et al., 2000).

Moreover, when it comes to AI, investment banks employing financial analysts have been shown to increasingly invest in AI tools to support forecasting (KPMG, 2023). In addition, existing research comparing AI systems to human analysts suggests that AI has the potential to outperform them in certain forecasting and decision-making tasks (Ball & Ghysels, 2018; Cao et al., 2024).

As such, the setting of financial analysts and their forecasts provides a rich and measurable context for exploring how the value of human capital, particularly accumulated experience, evolves in response to the growing use of artificial intelligence. In these increasingly data-driven environments, analysts must interpret complex information, navigate algorithmic inputs and make judgments. This makes them an ideal setting to examine how AI adoption reshapes the role of expertise, learning, and decision-making in organizational contexts.

Structure of the Dissertation

Building on the theoretical foundations and empirical setting outlined above, this dissertation examines how the interplay between human capital, specifically accumulated experience, and AI adoption shapes forecasting performance, both for humans and AI. It does so through three empirical studies, each focusing on a distinct yet connected dimension of this relationship: bias, learning, and organizational transformation.

Chapter 2 addresses the first research question: How does accumulated experience influence cognitive biases in expert forecasting? It explores the behavioral foundations of analyst judgment, specifically investigating how accumulated experience influences the emergence and persistence of cognitive biases in forecasting. While prior research acknowledges experience as a critical component of human capital, evidence on its relationship with cognitive bias remains inconclusive: some studies suggest experience mitigates bias through learning (Gort et al., 2008), while others find it can entrench overconfidence or reliance on heuristics (Gaba et al., 2022). This chapter aims to clarify the nature of that relationship by examining whether and how experience affects bias in complex evaluative contexts. Focusing on the financial analysts' assessment of firms that go public via SPACs, a highly controversial practice used to circumvent regulatory checks of traditional initial public offerings (IPO), it analyzes a large panel of earnings forecasts to test how analyst behavior changes with experience accumulation. The findings reveal that while analysts initially exhibit optimism toward SPAC firms, this bias diminishes as they gain firm-specific and practice-specific experience. Experience, in this case, has a corrective function, enhancing judgment by reducing biases.

Chapter 3 explores the second research question: "In what ways can human experience enhance the performance of AI systems, and under what conditions is this contribution most valuable?" Focusing on AI-augmented forecasting, it builds on prior research, which has been inconclusive about whether experience improves or impairs predictive performance. While some studies suggest experience leads to cognitive biases, others highlight its value in navigating complex environments. This chapter aims to resolve that tension by exploring how both general and domain-specific experience influence human prediction accuracy relative to AI, and whether these experiences can enhance AI's predictive performance when incorporated into algorithmic training data. Drawing on a dataset of analyst earnings forecasts and using Random Forest models, the study finds that domain-specific experience can decrease human predictive accuracy compared to AI, yet the same experience can improve AI performance in volatile environments. In contrast, general experience does not improve human prediction directly but significantly boosts AI's accuracy when integrated into its learning process. These findings reveal a paradox: experience may hinder human judgment compared to AI, while simultaneously enriching AI's capabilities, particularly under uncertainty. The chapter thus reframes experience not as a static predictor of performance, but as a dynamic resource that can be strategically leveraged to improve AI-driven forecasting.

Chapter 4, addressing the third research question- "How does AI adoption transform organizational predictive capabilities, and what role does human experience play in this transformation?"- shifts the focus from task-level analysis to the organizational level. It examines how AI adoption shapes predictive accuracy and redefines the value of human capital within firms. While earlier research has provided mixed evidence on how experience influences forecasting performance, this chapter addresses that ambiguity by examining how different types of experience, general versus domain-specific, interact with organizational-level AI adoption. Using a dataset that combines analyst earnings forecasts with LinkedIn data-based measures of AI investment across investment banks, the study finds that AI adoption significantly reduces forecast errors, particularly when paired with generalist human capital. In contrast, firm-specific experience is associated with higher errors and appears to constrain the benefits of AI. These findings suggest that AI not only enhances organizational forecasting capabilities but also reshapes the strategic value of expertise, favoring broad, adaptive experience over narrow, domain-specific knowledge.

Chapter 5 serves as the concluding chapter of this dissertation, drawing together the theoretical and empirical insights developed throughout. It addresses a critical moment of transformation in how organizations understand, deploy, and evaluate human expertise in the context of AI integration. As artificial intelligence becomes more deeply embedded in predictive processes, its relationship with human capital becomes increasingly multifaceted. This chapter argues that experience should not be viewed as inherently beneficial or detrimental in the age of AI. Rather, its value depends on the evolving interplay between individual cognitive capabilities, organizational context, and the extent of technological integration

This dissertation makes three central contributions. First, it provides evidence on when and how experience corrects for bias in judgment, expanding our understanding of the conditions under which learning contributes to more accurate predictions. Second, it moves beyond performance comparisons between humans and machines to explore how human experience can inform and enhance AI systems, revealing new forms of human-AI complementarity. Third, it examines how AI adoption at the organizational level reconfigures the value of human capital, offering insight into how firms can strategically leverage expertise in an increasingly data-driven world. In doing so, it contributes to the broader conversation on how expert judgment, learning, and decision-making adapt to the rise of Artificial Intelligence.

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Chapter 2 - Biased at First Sight: How Analyst Experience Shapes Evaluations of Controversial Practices

Abstract

This chapter addresses the following research question: "How does accumulated experience influence cognitive biases in expert forecasting?" It examines how experience shapes and potentially mitigates bias in stakeholder evaluations in uncertain, high-stakes environments. The analysis is done within the context of financial analysts' forecasts of firms going public via controversial SPAC mergers versus traditional IPOs. While analysts initially display optimism toward SPACs, despite their governance concerns and poor performance, this bias fades with accumulated experience. Both firm-specific and SPAC-specific experience increase the likelihood of more conservative, realistic forecasts. These findings highlight experience as a key mechanism through which human capital corrects cognitive biases over time. By showing how experiential learning refines judgment, the study contributes to research on bias, human capital, and stakeholder evaluation in contexts where uncertainty and controversy increase susceptibility to evaluative error and biases.

Note on co-authored research and inclusion in this dissertation

This chapter emerged from the initial version of this research that later evolved into a collaborative project with Woodrow Matthews, a fellow PhD candidate at SKEMA Business School/Université Côte d'Azur (GREDEG), and our advisor, Professor Francesco Castellaneta. As Woodrow and I developed our respective dissertation chapters, we realized there were strong overlaps in our data and research interests. That led us to join forces on a co-authored article, which we are now preparing for submission. While the empirical core is partially shared, this chapter is adapted to reflect my own theoretical framing and the specific focus of my dissertation.

In our collaboration, I took the lead on the theoretical development related to financial analysts and human experience, while Woodrow focused on SPACs and the IPO process. We divided the data collection based on our respective areas of expertise and worked closely together on the empirical analysis. The interpretation and narrative presented here represent my own perspective, independent of the co-authored paper and Woodrow's dissertation.

Introduction

Human capital, encompassing the collective knowledge, skills, abilities, and experience of an organization's members, is widely recognized as a critical driver of organizational success (Becker, 1994). In the strategic management literature, it is considered a key intangible resource that enables firms to differentiate themselves and sustain a competitive advantage over time (Barney, 1991). The importance of human capital is particularly pronounced in knowledge-intensive industries, where the expertise and capabilities of individuals are central to value creation and innovation (Mayer et al., 2012).

Despite its advantages, human capital is not without limitations: human decision making and judgment are tainted by bounded rationality (Simon, 1955). In addition, a large body of work across disciplines highlights how even highly trained professionals are subject to systematic cognitive biases, such as anchoring, confirmation bias, and availability heuristics (Bazerman & Moore, 2012; Tversky & Kahneman, 1974). These biases impair decision-making in contexts ranging from strategic choices (Schwenk, 1984), investments (Blohm et al., 2020), risk assessment (Kahneman & Lovallo, 1993) to earnings forecasting (Hilary & Menzly, 2006). In addition to biases, emotions have been shown to have a considerable impact on human decisions (Delgado-García & De La Fuente-Sabaté, 2010).

Human susceptibility to biases and resulting suboptimal decision-making is particularly relevant when considering one of the key dimensions of human capital: experience. Extant literature has established a positive relationship between the experience of key individuals within organizations and overall organizational performance. This link has been demonstrated in various contexts, including founders' prior experience and its impact on firm performance and survival (e.g. Dencker & Gruber, 2015; Hashai & Zahra, 2022), as well as the experience of board members (e.g. Kor, 2003; Kor & Sundaramurthy, 2009) and top management teams (Hamori & Koyuncu, 2015; Weterings & Koster, 2007).

While the accumulation of experience is generally associated with improved performance, there is mixed evidence regarding its impact on cognitive biases. On one hand, there is a stream of literature that suggests that biases tend to diminish with experience, as individuals learn from repeated exposure and feedback (e.g. Christoffersen & Sarkissian, 2011; Gort et al., 2008). On the other hand, there are studies that show that experience accumulation might result in amplification of biases. For instance, it has been demonstrated that as managers accumulate more experience and knowledge in a specific domain, they also tend to become more overconfident, hindering firm's performance as a result (Gaba et al., 2022). Additionally, there is evidence that by relying on experience, individuals might rely on outdated mental models or underweight new information (March, 2010). Moreover, this might be further amplified in highly uncertain environments, as experts have been shown to demonstrate higher reliance on heuristics and mental shortcuts under these conditions (Einhorn & Hogarth, 1981; Hayward & Hambrick, 1997).

Thus, while experience generally enhances performance, its effect on bias is ambiguous: it can either mitigate or exacerbate cognitive biases depending on the context. Although the strategic management literature has long acknowledged the value of experience, there is a lack of empirical evidence on how experienced individuals perform in complex, high-stakes decision-making contexts, especially when judgment may be influenced by bias.

To explore this, we focus on the context of financial analysts, who represent a critical group of firms' external stakeholders who significantly influence firms' strategic choices. Often described as market watchdogs (Coffee, 2006), analysts act as external monitors by generating information that helps other stakeholders assess managerial performance. This, in turn, influences managerial decisions by increasing managers' accountability to external stakeholders (Jensen & Meckling, 1976). As external evaluators and information intermediaries, analysts shape how organizational practices are perceived, legitimized, or challenged in the market (Brauer & Wiersema, 2018; Zuckerman, 1999). Through their unique dual role as both information intermediaries and external monitors, analysts can thus influence firms' reputation, investor behavior, and access to capital (Hayward & Boeker, 1998; Stickel, 1992).

Given their influence, the quality of analysts' evaluations is especially consequential. Financial analysts are knowledge workers with substantial variation in experience and expertise, ranging from novices to highly regarded "star " (Groysberg et al., 2008). However, as noted by sociologists and behavioral finance scholars, analysts are not perfectly rational and are subject to systematic biases that can influence their judgments (Brauer & Wiersema, 2018).

These biases become particularly consequential when firms adopt controversial practices - actions that deviate from accepted legal, regulatory, or socio-cultural norms, and violate societal expectations around fairness, transparency, and accountability (Naumovska & Harmon, 2024). In such contexts, analysts' evaluations are even more influential, as other stakeholders may rely heavily on them to make sense of norm-defying or ambiguous organizational behavior. Analysts' assessments can effectively legitimize or delegitimize such practices, thereby shaping public perception and stakeholder response. Yet the very ambiguity and uncertainty that characterize controversial practices also increase the likelihood of bias in analyst decision-making.

Analysts are both critically important and susceptible to biases in the face of controversial organizational practices. This makes them a particularly valuable setting to examine how experience and bias interact to influence evaluative outcomes in uncertain, high-stakes environments.

Extant research indicates that analysts frequently penalize firms for adopting controversial practices (Bednar et al., 2015; Briscoe & Murphy, 2012). One explanation for this tendency lies in reputational concerns: analysts may adjust their forecasts to align with dominant investor sentiments, which are frequently critical of controversial actions, in order to preserve their own credibility (Meng, 2015; Morris, 2001). In this light, pessimistic forecasts can serve as a form of reputational risk management.

However, from a behavioral perspective, analysts' responses are not shaped by reputational concerns alone. Other institutional and social pressures can push them in the opposite direction. For instance, conflicts of interest: investment banks employing analysts can incentivize them to provide more favorable evaluations of firms engaged in controversial practices, as optimistic forecasts may support client relationships or future deals (Dechow et al., 2000; Michaely & Womack, 1999). Additionally, analysts' professional or social ties with firm management may further bias their judgments, encouraging more lenient evaluations to preserve these connections (Brauer & Wiersema, 2018).

Taken together, these competing pressures create a complex evaluative context where analysts must navigate reputational risks, institutional incentives, and personal relationships, often under conditions of uncertainty that amplify cognitive biases. This underscores the need for empirical research to disentangle how experience, bias, and institutional context jointly influence analysts' evaluations of controversial organizational practices.

Studying how analysts evaluate controversial organizational practices requires a setting where norm violations are clear, strategically important, and traceable over time. We identify an suitable empirical context to address this issue: special purpose acquisition companies (SPACs), which have existed for over two decades but have only recently gained widespread attention for the controversy that surrounds them. As a strategic practice that fundamentally challenges established norms of organizational legitimacy, SPACs enable us to observe how stakeholders respond to firms' engagement in these kinds of actions.

SPACs represent a controversial alternative to traditional IPOs, allowing private firms to go public through a merger with a shell company while bypassing standard due diligence processes of IPOs (Naumovska, Gaba, et al., 2021; Naumovska & Harmon, 2024). There are various aspects of the use of SPACs that make this practice controversial. First, SPACs circumvent the rigorous screening and legitimization procedures that characterize traditional IPO processes by avoiding expert scrutiny and reducing organizational transparency (Coates, 2022; Naumovska & Harmon, 2024). Second, SPACs introduce misaligned incentives that enable insiders to capture substantial value regardless of post-merger organizational performance (Gahng et al., 2023; Klausner et al., 2022), which creates potential conflicts of interest between investors and SPAC sponsors. Third, unlike IPOs, SPACs can issue projections of future earnings which can attract potential investors. However, empirical evidence shows that these projections are systematically overoptimistic and rarely achieved (Blankespoor et al., 2022).

Combined with the broader ambiguity surrounding analyst perceptions of controversial practices, it is unclear how analysts will respond to firms going public via SPACs: will they view them with skepticism, or interpret them as legitimate strategic alternatives? This uncertainty creates conditions under which cognitive biases are more likely to influence judgment. Analysts may rely on heuristics or reputational concerns, leading to more conservative or pessimistic forecasts. To examine this, we compare analysts' evaluations of firms that go public through SPACs versus traditional IPOs. We hypothesize that analysts' forecasts for firms that went public through SPACs (hereafter SPAC firms) will be more pessimistic than for those that used IPOs (hereafter IPO firms).

Moreover, while experience is typically seen as improving forecast accuracy, it may also reinforce preexisting beliefs in judgments. Thus, we hypothesize that greater analyst experience with SPACs, whether firm-specific or SPAC specific, will further amplify this pessimistic stance towards these firms.

To test these hypotheses, we analyze a sample of analysts' estimates for 289 SPAC firms and 728 IPO firms over the period from 2004 to 2022. Our findings reveal a nuanced picture of how external stakeholders respond to controversial practices. First, contrary to our expectation that analysts would penalize SPAC firms, we find consistent evidence of greater optimism in their forecasts for SPAC firms relative to traditional IPO firms. This suggests that, in the face of evaluative ambiguity, analysts may rely on heuristics or biased mental shortcuts when evaluating SPACs early on that lead them to view SPACs more favorably than expected.

However, we also find that analyst experience with SPACs-either through continued coverage of a specific firm or broader exposure to SPAC firms, lowers this initial optimism. As analysts gain experience, they are more likely to issue negative coverage, suggesting that experience may help mitigate bias by yielding more realistic assessments.

Our findings make several important theoretical contributions. First, we contribute to theories of learning and experiential judgment by demonstrating that experience plays a critical role in mitigating cognitive biases. Rather than viewing analyst assessments as fixed or uniformly rational, we uncover a dynamic learning process: analysts initially exhibit overly optimistic evaluations of controversial practices—likely influenced by cognitive biases such as framing effects, over-optimism, or reputational concerns. However, as they accumulate direct experience, this bias diminishes, and their evaluations become more critical. This shift underscores the corrective nature of experience, showing how repeated exposure to novel practices enables analysts to refine their mental models, overcome biased heuristics, and arrive at more accurate assessments. These findings extend prior research on the interplay between experience and bias (Gaba et al., 2022; March, 2010) by highlighting the bias-mitigating role of experience in complex and uncertain decision-making environments. They also add to existing work on analyst experience and forecast accuracy (Brauer & Wiersema, 2018; Clement, 1999; Mikhail et al., 1997), showing that accumulated exposure not only enhances accuracy but also helps correct initial evaluative biases.

Second, we extend theories of stakeholder evaluation by challenging the assumption that external evaluators consistently penalize norm-violating behaviors (Bednar et al., 2015; Wiersema & Zhang, 2011). Our findings suggest that in the presence of uncertainty, controversial practices may initially avoid sanction and even gain temporary legitimacy in the eyes of key stakeholders. This highlights the importance of experience as a moderating force in stakeholder judgment, revealing how evaluators learn to navigate ambiguity and refine their assessments over time.

Empirically, to the best of our knowledge, we provide the first systematic evidence of how financial analysts evaluate SPACs relative to traditional IPOs. Given the growing prevalence and contentious nature of SPACs (Blankespoor et al., 2022; Gahng et al., 2023; Naumovska, Zajac, et al., 2021), our study offers important insights into how key market intermediaries strategically interpret and respond to novel market entry mechanisms.

Theoretical Background

Human Experience and Biases

Accumulated experience has been shown to be associated with improved organizational performance (e.g. Dencker & Gruber, 2015; Kor & Sundaramurthy, 2009). Existing research has sought to identify the link between experience accumulation and performance outcomes. The learning literature suggests that individuals acquire valuable insights and capabilities through their prior experiences (Argote et al., 2021; Castanias & Helfat, 2001; Jain, 2013). Repeated task engagement allows individuals to refine technical skills and absorb tacit, context-specific knowledge (Argote, 2012; Reagans et al., 2005). This phenomenon has been observed across a variety of contexts. For instance, in software development, it has been shown that seasoned developers often achieve faster development times (Narayanan et al., 2009). Similarly, in forecasting, there’s a noted correlation between task-specific experience and prediction accuracy (Clement et al., 2006). Collectively, this body of research underscores a central insight: "previous experience empowers individuals to acquire and construct pertinent knowledge and skills that they can subsequently effectively apply in their decision-making and tasks" (Gaba et al., 2022, p. 2).

In the meantime, a vast body of literature documents the prevalence of various cognitive biases that affect human decision making and judgment (Kahneman & Lovallo, 1993; Tversky & Kahneman, 1974). What is more important, the evidence on the impact of experience accumulation on biases is inconsistent. There are studies showing that biases decline as individuals accumulate experience (Christoffersen & Sarkissian, 2011; Locke & Mann, 2003). For example, Gort et al. (2008) show that highly educated people with more experience tend to be significantly less overconfident compared to those with less experience and education. On the other hand, there are studies showing that experience accumulation might result in amplification of human biases (Heath & Tversky, 1991). For example, experienced managers tend to become overconfident in their decisions and fail to take action in case of poor performance (Gaba et al., 2022; Schumacher et al., 2020). The biases also do not get mitigated as a result of learning, suggesting that the learning process fails to correct for preexisting biases (Bukszar & Connolly, 1988).

Hence, the impact of experience accumulation on cognitive biases remains both ambiguous and underexplored. It is still unclear whether experience amplifies or mitigates bias in decision-making. To investigate this question, we examine the context of financial analysts and their earnings forecasts for companies that go public via special purpose acquisition companies (SPACs) - a controversial mechanism for entering public markets.

Financial Analysts

Financial analysts serve as critical information intermediaries in markets, transforming complex financial data into actionable insights that guide investment decisions (Brauer & Wiersema, 2018). Analysts' assessments play a crucial role in shaping market perceptions of firms and their strategic decisions, with empirical research showing that their recommendations can drive significant market responses (Stickel, 1992; Womack, 1996). Beyond their informational role, analysts also serve as external monitors, exerting influence over corporate governance and strategic choices through their evaluations (Bradley et al., 2017; Jensen & Meckling, 1976). Their monitoring role becomes particularly significant when firms engage in practices that diverge from conventional norms, as analysts can either legitimize or oppose the engagement in such practices by affecting firm's reputation, investor behavior, and access to capital (Hayward & Boeker, 1998).

Although analysts strive to deliver accurate forecasts, since consistent inaccuracy can jeopardize their careers (Clement, 1999), extant literature acknowledges that they are not perfectly rational and remain subject to a variety of cognitive and social biases that can shape their judgment (Brauer & Wiersema, 2018). A multitude of factors can influence analysts' decisions and contribute to biased forecasts. For instance, reputational concerns may lead analysts to align their forecasts with prevailing investor sentiment, even when it contradicts their private assessments, in an effort to maintain credibility (Meng, 2015; Morris, 2001). Additionally, analysts often maintain ongoing relationships with firm management to secure access to critical information that enhances forecast accuracy. However, these ties can also create subtle pressures to issue favorable evaluations that preserve these relationships—sometimes at the expense of objectivity (Brauer & Wiersema, 2018).

Given these tensions, it is hard to theoretically predict analysts' reaction towards firms' engagement in controversial practices. Extant literature has shown that analysts can react to these cases by influencing management's reputation (Bednar et al., 2015) or by downgrading stock recommendations (Briscoe & Murphy, 2012), thus penalizing firms who engage in these practices. These findings align with the theoretical view that analysts strive to deliver accurate forecasts and serve as objective information intermediaries. Furthermore, considering the widespread opposition to such practices from investors, the public, and the media, these results also support the notion that analysts adjust their coverage to reflect prevailing sentiment, thereby mitigating the risk of reputational backlash.

However, there are also strong countervailing incentives that may bias analysts toward endorsing, or at least not penalizing firms engaged in controversial practices. Analysts often maintain important social ties with firm insiders to secure access to privileged information, and these relationships can subtly pressure them to provide more favorable coverage to avoid jeopardizing those ties (Brauer & Wiersema, 2018). In addition, analyst coverage has been shown to become increasingly positive as firm management engages in verbal impression management (Westphal & Graebner, 2010). Moreover, analysts have been shown to become increasingly optimistic as environmental uncertainty increases (Ackert & Athanassakos, 1997), which are often present in the context of controversial practices. These conditions can lead analysts to rely more heavily on heuristics or reputational cues, further increasing the risk of biased judgment. Finally, institutional pressures from investment banks, particularly when covered firms are seen as potential clients, can incentivize analysts to issue overly optimistic forecasts to strengthen client relationships (Dechow et al., 2000; Michaely & Womack, 1999).

SPACs as Controversial Corporate Practice

Also referred to as blank check companies, SPACs have existed since 2003 (Kolb & Tykvova, 2016) but have exploded in popularity in recent years. In 2020, the number of SPACs to list on US stock markets were nearly double that of operating companies (Blankespoor et al., 2022). SPACs raised over $162 billion in 2021 alone – more than all other years combined.

A SPAC is formed by one or several individuals, called sponsors, who are often high-profile, celebrity, or otherwise highly successful figures in venture capital, private equity, or industry (Harris, 2022). The firm forms to serve no other purpose than to conduct an initial public offering (IPO) and become traded on a stock market without conducting any true operations until a privately held target firm is identified and merged with. This is openly declared in the required filings for the IPO; investors, whether individuals or institutional, can invest in the company as they would in any other.

The SPAC has up to 24 months to identify its target firm, present it to shareholders, hold a vote on whether to approve or reject it, and complete the acquisition in the form of a reverse merger (Naumovska, Zajac, et al., 2021). Shareholders are presented with basic information about the target firm such as its history, industry analysis, financial situation, management team, and more. The SPAC and its target also have the unique capability of offering future financial projections should the merger take place - something not possible in an IPO but allowed by the SEC in the case of SPACs, as they fall in the context of mergers and acquisitions rather than new securities (Blankespoor et al., 2022; Coates, 2022). With the aid of all this information, shareholders vote on the acquisition. If approved, the SPAC acquires the privately held target - but changes its name, status, and business to that of the target. The whole process is a vehicle to bypass a traditional IPO and provide funding and public listing to the target (Matthews et al., 2023).

The controversy of such a practice is both obvious and hidden. For one, the system is designed to allow a firm to bypass the IPO process - a significant milestone in a firm's life that represents a critical step for its development (Certo, 2003) and provides a sort of "stamp of approval" for it (Cirillo et al., 2018). Much of this is a result of the "roadshow" a firm undergoes in the IPO process, which opens it to intense scrutiny by bankers, regulators, and experts. However, in a SPAC transaction, however, this due diligence is conducted by the SPAC team itself (Naumovska & Harmon, 2024). This is a serious conflict of interest due to the fact that SPAC sponsors have been shown, in many studies, to be highly incentivized to complete a merger regardless of target quality and post-deal performance (e.g. Feng et al., 2022; Gahng et al., 2023; Lakicevic & Vulanovic, 2013). Sponsors invest their own funds in the SPAC for a tiny fraction of the units price and are compensated with shares upon deal completion (Naumovska & Harmon, 2024). And as long as the stock price trades at more than $1 after the merger, sponsors are set to make profits (Lakicevic & Vulanovic, 2013).

For all of this, it is reasonable to classify public listing via a SPAC as a controversial practice – as Naumovska, Zajac, and Lee (2021) do when they use reverse mergers to study the diffusion of controversial practices.

Analyst Evaluations of SPACs

Analysts' evaluation of firms that engage in controversial practices such as SPACs remains theoretically ambiguous, given the conflicting cognitive, social, and institutional biases that shape their decision-making.

Drawing on existing theory and the documented controversial nature of SPACs, we propose that analysts are likely to adopt a negative stance toward firms that go public via SPACs. Prior research has shown that analysts often penalize firms for engaging in controversial practices (Bednar et al., 2015; Briscoe & Murphy, 2012), suggesting a similar pattern may emerge in the SPAC context. Moreover, given the reputational concerns of the analysts, they may be inclined to issue forecasts that align with dominant market sentiment, even when such forecasts deviate from their private assessments (Meng, 2015; Morris, 2001). This tendency can introduce biases into their evaluations, as analysts may prioritize preserving their credibility over providing fully objective forecasts, particularly when assessing firms involved in controversial practices like SPACs. Given the documented poor post-merger performance of SPACs (Blankespoor et al., 2022), significant regulatory concerns (Bazerman & Patel, 2021) and critical assessments by the media and general public, analysts would face substantial reputational risks by issuing optimistic forecasts for SPAC firms. Consequently, even if analysts possess insights into the SPACs' optimal performance, they are likely to adjust their earnings projections downward to match investor expectations, thereby safeguarding their own reputation.

Thus, we hypothesize that compared to IPO firms, analysts are more likely to adopt negative stance towards the firms that use SPACs to go public.

Hypothesis H1: *Financial analysts' forecasts will be systematically more pessimistic for firms going public through SPACs compared to those opting for IPOs.*

Analyst experience

Given that accumulation of experience is associated with improvement of performance, we also investigate how analyst evaluations evolve as gain experience with SPAC firms. Analysts exhibit significant heterogeneity in experience levels, from novices to renowned "star analysts" (Groysberg et al., 2008), and this variation substantially influences forecast accuracy (Brauer & Wiersema, 2018). Two specific dimensions of experience are particularly relevant to evaluations of controversial practices: firm-specific experience and practice-specific experience.

This question is especially relevant given the ambiguous role of experience in bias formation. While some research suggests that experience can reduce bias through learning, other studies argue that experience can entrench biases. Thus, investigating how experience shapes analysts' evaluations of SPAC firms provides a unique opportunity to assess whether experience mitigates biases, or whether it amplifies them in the context of controversial practices.

One dimension of analyst experience that the extant literature has focused on is firm-specific experience, which has been shown to be associated with greater forecasting accuracy (Clement, 1999; Mikhail et al., 1997). The more experienced an analyst is in covering a particular firm, the more knowledge and understanding they accumulate, which in turn enhances the accuracy of their earnings projections. Moreover, the augmentation of firm-specific experience not only enriches knowledge about a firm's operations but also fosters closer social ties with firm management, allowing analysts access to valuable insights and information (Brauer & Wiersema, 2018).

Since the extant literature provides mixed evidence on the impact of experience on biases, we cannot rely on existing evidence to theoretically justify whether analysts' biases will become more or less pronounced with accumulation of biases. However, given the controversial nature of SPACs, we hypothesize that as analysts' firm-specific experience with these firms increases, their forecasts will become more conservative. With greater exposure to these firms, analysts will acquire a deeper understanding of their business models and operational nuances. Since SPACs bypass the extensive due diligence required for traditional IPO firms, certain operational shortcomings may not be apparent to the general public. However, these deficiencies are likely to become more evident to financial analysts over time as they deepen their knowledge of the firm.

By contrast, IPOs undergo a more rigorous evaluation process and tend to be more transparent, leaving fewer undisclosed issues to influence analysts' optimism.

Additionally, evidence shows that SPAC projections are often overly optimistic, with only 35% being met (Blankespoor et al., 2022). As analysts get to know the SPAC firms, they become aware of the frequent gaps between projected and actual performance for most SPACs, which may increase their pessimism about future earnings. In contrast, this mismatch is less relevant for analysts covering IPOs, as they cannot make earnings projections, reducing the impact of missed expectations.

Hypothesis H2a: *As their firm-specific experience increases, financial analysts will issue increasingly more pessimistic forecasts for SPAC firms compared to IPO firms.*

Beyond firm-specific experience, analysts' practice-specific experience - prior exposure to the particular practice itself - should significantly shape their evaluations. While firm-specific experience focuses on deepening understanding of a particular firm's internal operations, practice-specific experience involves broader insights developed through consistent exposure to multiple firms engaging in the same controversial strategy. This distinction is theoretically critical, as analysts covering multiple instances of a controversial practice gain valuable insights into systematic challenges, performance patterns, and governance idiosyncrasies common to that practice.

Practice-specific experience is particularly relevant in the context of SPACs because of the unique governance conflicts and performance outcomes associated with this listing mechanism. Analysts with extensive experience evaluating multiple SPAC entities develop proficiency in identifying recurring patterns that are not idiosyncratic to individual firms but are intrinsic to the structural and operational framework of SPACs as a listing mechanism. Prior exposure to SPAC firms would make it more evident to analysts that SPAC transactions systematically bypass the rigorous scrutiny and due diligence characteristic of traditional IPO processes, leading to weaker governance structures and exacerbated conflicts of interest between investors and sponsors (Dimitrova, 2017; Klausner et al., 2022). Experienced analysts understand that the merged entity consistently and overwhelmingly underperforms post-merger (Gahng et al., 2023). They may recognize that all the while, SPAC sponsors frequently profit significantly not matter the performance, reinforcing concerns regarding structural misalignment of incentives (Dimitrova, 2017; Kolb & Tykvova, 2016).

With repeated exposure to the practice, analysts become better at assessing potential governance conflicts and questioning the reliability of financial projections, thereby becoming more cautious and conservative. Thus, experience specifically tied to the controversial practice of SPAC listings acts as a countervailing force to the institutional pressures encouraging optimism, such as maintaining relationships with firm management or investment banking incentives (Brauer & Wiersema, 2018; Michaely & Womack, 1999).

In sum, while firm-specific experience deepens knowledge of individual firm operations, practice-specific experience provides analysts with broader, systematic insights into the legitimacy challenges and risks associated with controversial practices such as SPACs. This enhanced experiential knowledge should enable analysts to anticipate and discount overly optimistic projections more effectively, leading to increasingly cautious and skeptical forecasts for SPAC firms compared to IPO firms. Hence, we propose the following hypothesis:

Hypothesis H2b: *Financial analysts with prior SPAC experience will issue more pessimistic forecasts for SPAC firms compared to IPO firms.*

Data

Sample Selection

We obtain the population of SPAC firms that successfully completed a deal on US stock markets for the period of 2004 to 2022 from Refinitiv, which denotes deals with a "blank check company" flag. We match this sample with data on financial analysts' earnings per share forecasts from IBES. IBES provides analyst estimates for various time periods, ranging from forecasts for the next quarter to long term forecasts. Given the relatively short time span for most of the firms in our sample, we retain only quarterly forecasts in the scope of this analysis.

We use data from Compustat to obtain the sample of firms who had an initial public offering (IPO) in the same period as the firms in the SPAC sample. We match these companies with IBES to obtain the forecasts of financial analysts for these firms. The final dataset comprises a total of 135,524 analyst estimates, contributed by 3,497 analysts, covering 289 SPAC and 728 IPO firms, spanning the period from 2004 to 2022.

Variables

Dependent variable

Our dependent variable, *Negative error*, is a binary variable which operationalizes whether the analysts penalize the firms with their estimates. This variable takes the value of 1 if the analyst's prediction error is negative, indicating that the analyst's expectation for the firm's performance was lower than the firm's actual achieved performance. The variable takes the value of 0 otherwise. A positive error signifies an analyst's optimism, reflecting high expectations of the firm's earnings and the identification of clear signals of business growth. Conversely, a negative error in forecasts signifies an analyst's pessimism, suggesting the identification of signals indicative of a potential decline in future earnings and overall firm performance.

Independent variables

SPAC. To test variability of results between SPACs and IPO firms, we construct a dummy variable which indicates whether the company used SPAC to go public or underwent an IPO. This variable is equal to 1 when the company uses SPACs and 0 otherwise.

Analyst's firm-specific experience. Following Clement (1999), we calculate analyst firm level experience as the number of years during which analyst had at least one forecast for the focal firm. This measure captures the analyst's familiarity with the unique characteristics and operations of the firm, as well as the experience and potential access to private information accumulated over time.

To ensure accuracy, we exclude forecasts made within the final month of the fiscal period, as these forecasts are often less indicative of close firm monitoring. Analysts issuing forecasts near period-end are more likely to replicate estimates from other analysts, rather than conduct in-depth analysis of the firm Clement (1999). By excluding these end-of-period forecasts, this measure better reflects the analyst's genuine experience and expertise with the firm.

SPAC experience. This is a binary variable that operationalizes analyst's practice experience with SPACs. It is equal to 1 when analyst had previously covered any SPAC firm when estimating the focal firm, and 0 otherwise.

Controls

Following Clement (1999), we measure *Analyst's general experience* as the number of years during which the analyst has issued at least one forecast for any firm. This measure captures the analyst's breadth of experience with the forecasting process across various firms and industries. This accumulated experience reflects increasing expertise in interpreting diverse financial information, recognizing industry-specific patterns, and adjusting forecasts based on shifting market conditions. As with firm-specific experience, forecasts issued within the final month of the forecasting period are excluded to avoid inflating the measure with forecasts that may rely on replication rather than original analysis. This exclusion ensures that the measure more accurately reflects the analyst's expertise developed over time.

Number of companies covered. Following Clement (1999), we operationalize this measure as the number of distinct companies that an analyst covers during the forecasting period. This reflects the complexity of the analyst's portfolio, as a larger set of firms implies more diverse information to process and greater difficulty in closely monitoring each firm. Given the constraints on analysts' time and attention, covering a larger number of companies may reduce the depth of analysis on each, potentially impacting forecast accuracy.

Number of industries covered. Similarly, this measure is calculated as the number of distinct industries that an analyst covers during the first 11 months of the focal year. This measure captures the complexity of the analyst's portfolio from an industry perspective: an increased number of industries can limit the analyst's ability to focus on each sector's unique factors, potentially affecting forecast accuracy.

Top size bank. We add a dummy indicating whether the analyst was employed by a top investment bank, measured in terms of the number of analysts employed by the bank. This measure proxies for the resources that were available to the analyst in the process of forecasting. The underlying assumption is that larger investment banks give analysts a larger set of resources which can facilitate and improve the process of forecasting firm earnings.

Forecast age. We also control for the length of the forecasting horizon, which shows the number of days between the date when the forecast was announced and the date for which the forecast is issued. The underlying assumption is that the longer the forecasting horizon, the less information is accessible to the analyst. Hence, the forecast's quality will be affected by this.

In addition to these, we also control for the following firm level characteristics: *total assets, revenue, number of employees* and *net income*. These controls are used to disentangle the idiosyncrasies of firms which might affect the degree of optimism of analysts. We obtain these measures from Compustat.

Table 2.1 provides summary statistics and correlations of these measures.

Table 2.1 - *Summary statistics and correlation table*

	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1.	*Negative error*	0.59	0.49	0.00	1.00												
2.	*SPAC*	0.08	0.28	0.00	1.00	-.10											
3.	*Firm experience*	1.79	1.93	0.00	18.00	.04	-.08										
4.	*General experience*	9.50	6.69	0.00	38.00	.05	-.02	.34									
5.	*SPAC experience*	3.02	10.12	0.00	133.00	-.05	.35	.16	.06								
6.	*N. of companies covered*	19.56	9.32	0.00	73.00	.00	-.03	.19	.33	.14							
7.	*N. of industries covered*	4.85	2.61	0.00	18.00	.03	.08	.10	.26	.09	.44						
8.	*Top size bank*	0.61	0.49	0.00	1.00	.02	-.08	.04	.00	-.02	.15	.10					
9.	*Forecast horizon*	31.97	30.40	-377.00	344.00	.07	-.07	.08	.10	-.08	.07	.09	.01				
10.	*Total assets*	6983.75	24676.44	0.23	277149.41	.02	-.05	.11	.02	-.01	-.04	-.04	.03	-.04			
11.	*Net income*	34.58	455.88	-6674.52	12460.45	.07	-.03	.03	-.02	-.02	-.05	.00	-.01	-.02	.43		
12.	*Revenue*	662.00	2404.12	-2039.67	44948.97	.04	-.06	.09	-.01	-.04	-.08	.00	.01	-.05	.55	.52	
13.	*Number of employees*	6.39	23.26	0.00	385.36	.04	-.06	.09	-.01	-.05	-.09	.02	.01	-.03	.36	.30	.87

Methodology

To test the first hypothesis on whether analysts are generally less optimistic about SPACs relative to IPOs, we use a logistic model with *Negative error* as dependent variable and *SPAC* dummy as independent variable. In addition, we incorporate a set of controls for analyst characteristics and various characteristics of the firms. Consistent with H1, we expect the coefficient for SPACs to be positive and significant.

To test the hypotheses on the impact of firm-specific experience and prior SPAC experience on analysts' perception of the use of SPACs, we use the *Negative error* as independent variable and measure the interaction of *firm experience* and *SPAC experience* with *SPAC* dummy. In line with H2a and H2b, our expectation is that the increase in *firm experience* and *SPAC experience* should have a positive effect on the likelihood of penalizing the firms' use of SPACs.

Results

Table 2.2 displays the regression results of the use of a SPAC on likelihood of having negative coverage by analysts. H1 states that analysts will tend to underestimate the earnings of the SPAC firms relative to IPO firms, thus penalizing these firms for being engaged in this controversial practice. Model 1 shows the direct effect of the use of SPAC on the likelihood of having a negative estimate error. Model 2 includes analyst characteristics and forecasting horizon. Model 3 provides the results of the regression which controls for firm characteristics and the forecasting horizon. Finally, Model 4 provides the results of the specification with all the above-mentioned controls. Contrary to our expectation, the sign for the coefficient of SPAC dummy is consistently negative and significant. The coefficient for SPAC in Model 4 (-0.6606, $p < 0.01$) suggests 51.6% lower odds of being undervalued for SPAC firms compared to IPO firms. In other words, analysts, on average, are less likely to have lower expectation of earnings of SPAC firms in comparison with IPO firms. This result is significant across all model specifications, with minor variation in the coefficients. This consistent pattern of higher expectations for SPAC firms, despite their controversial nature and documented underperformance, suggests that analysts may be exhibiting biased evaluations. Rather than penalizing SPAC firms, analysts appear to overestimate their prospects, potentially due to cognitive biases, or biases caused by external pressures that distort objective judgment.

In addition, given the small magnitude of the coefficients of firm level controls, these results indicate that firm level characteristics do not have major impact on the likelihood of analysts' negative coverage of the firms. This hints that firm fundamentals are not primary drivers for analysts' decision-making process, at least in the contexts of the firms which recently were listed on the markets, either through the use of IPOs or SPACs.

Table 2.2 - *Likelihood of undervaluing SPACs relative to IPOs*

	Negative error			
Variables	1	2	3	4
SPAC	-0.6716***	-0.6495***	-0.6740***	-0.6606***
	(0.0273)	(0.0274)	(0.0276)	(0.0277)
General experience			0.0253***	0.0288***
			(0.0034)	(0.0035)
Firm experience			0.0097**	0.0081*
			(0.0042)	(0.0042)
Number of companies covered			-0.0012	-0.0008
			(0.0015)	(0.0015)
Number of industries covered			0.0107*	0.0078
			(0.0062)	(0.0062)
Top size bank			0.0195	0.0229
			(0.0312)	(0.0313)
Forecast age		0.0011***	0.0010***	0.0010***
		(0.0002)	(0.0002)	(0.0002)
Total assets		-0.0000***		-0.0000***
		(0.0000)		(0.0000)
Total revenue		-0.0001***		-0.0001***
		(0.0000)		(0.0000)
Net income		0.0008***		0.0008***
		(0.0000)		(0.0000)
Number of employees		0.0048***		0.0053***
		(0.0008)		(0.0008)
Constant	-0.7985**	-0.8962**	-1.4392***	-1.5616***
	(0.4014)	(0.4018)	(0.4085)	(0.4088)
Observations	135,524			
Analyst FE	Yes			

The coefficients of *Number of companies covered, Number of industries covered,* and *Top size bank* are insignificant, indicating that the portfolio complexity and diversion of analyst attention, as well as availability of resource do not have an impact on their likelihood of undervaluing firms. The coefficients for *Firm experience* and *General experience* are positive, thus hinting that the accumulation of experience results in more pessimism towards future earnings about the firms. Hence, more experienced analysts tend to be less optimistic. Finally, the coefficient for *Forecast age* is positive and significant, indicating that the larger is the forecasting horizon, the less optimistic the analysts are.

We next present the results of our analysis evaluating the impact of firm experience accumulation and prior SPAC experience on the likelihood of undervaluing SPAC firms relative to IPO firms. The initial results in Table 2.2 already show that the accumulation of both firm specific and general experience result in higher likelihood of underestimating future earnings. Table 2.3 reports the results of additional analyses tackling this question.

Model 1 provides the results for the direct impact of *Firm experience* on the likelihood of providing *Negative error*. Model 2 provides the results for the interaction of *Firm experience* with *SPAC* dummy, as well as controls for firm and analyst characteristics. Model 3 provides the results for the direct impact of *SPAC experience* on the likelihood of providing *Negative error*. Model 4 provides the results for the interaction of *SPAC experience* with *SPAC* dummy, as well as controls for firm and analyst characteristics. Finally, Model 5 reports the results for both interaction with all the above-mentioned controls.

In line with the results from Table 2.2, the direct impact of *Firm experience* is positive and significant. The coefficient of interaction of *Firm experience* with *SPAC* dummy is significant and positive across various specifications of the models. The coefficient in Model 5 (-0.0490, $p < 0.01$) implies that for each unit increase in firm experience, the odds of undervaluation for SPACs increase by approximately 5%, holding other variables constant.

Despite the fact that the direct impact of *SPAC experience* dummy is insignificant, its interaction with *SPAC* is positive and significant, indicating that the forecasts from analysts who had prior experience with SPAC firms are more likely to be negative. The coefficient of interaction in Model 5 (0.2778, $p < 0.01$) implies that the odds of undervaluation for SPACs are approximately 32% higher when analysts with prior SPAC experience issues the forecast.

Table 2.3 - *Effect of firm and SPAC experience on likelihood of undervaluing SPACs relative to IPOs*

	Negative error				
Variables	1	2	3	4	5
SPAC	-0.6537***	-0.7358***	-0.6792***	-0.9566***	-0.9545***
	(0.0274)	(0.0324)	(0.0292)	(0.0810)	(0.0813)
Firm experience	0.0272***	0.0032			0.0033
	(0.0036)	(0.0044)			(0.0044)
SPAC experience			0.0210	-0.0863***	-0.0700**
			(0.0286)	(0.0309)	(0.0311)
Firm experience X *SPAC*		0.0591***			0.0490***
		(0.0131)			(0.0135)
SPAC experience X *SPAC*				0.3478***	0.2778***
				(0.0851)	(0.0870)
Total assets		-0.0000***		-0.0000***	-0.0000***
		(0.0000)		(0.0000)	(0.0000)
Total revenue		-0.0001***		-0.0001***	-0.0001***
		(0.0000)		(0.0000)	(0.0000)
Net income		0.0008***		0.0008***	0.0008***
		(0.0000)		(0.0000)	(0.0000)
Number of employees		0.0054***		0.0054***	0.0054***
		(0.0008)		(0.0008)	(0.0008)
Forecast age		0.0010***		0.0010***	0.0010***
		(0.0002)		(0.0002)	(0.0002)
General experience		0.0298***		0.0336***	0.0311***
		(0.0035)		(0.0030)	(0.0035)
Number of companies covered		-0.0007		-0.0006	-0.0005
		(0.0015)		(0.0015)	(0.0015)
Number of industries covered		0.0069		0.0082	0.0075
		(0.0063)		(0.0063)	(0.0063)
Top size bank		0.0235		0.0218	0.0219
		(0.0313)		(0.0314)	(0.0314)
Constant	-0.8211**	-1.5799***	-0.7985**	-1.6682***	-1.6135***
	(0.4014)	(0.4089)	(0.4014)	(0.4075)	(0.4092)
Observations			135,524		
Analyst FE			Yes		

Moreover, it is worth mentioning the difference in magnitudes of two interactions: the coefficient of interaction of *SPAC experience* with *SPAC* is several times larger than that for *firm experience* with SPAC. This means that the analysts who had prior experience with SPACs have a substantial drop in their optimism about the firms that use SPACs and are more likely to penalize them. In addition to this, as their firm-specific experience with the given SPAC firm increases, this effect becomes stronger, even though at more marginal rate.

These results suggest that as analysts accumulate both firm-specific and broader SPAC-related experience, their initial optimism fades, indicating that experience plays a de-biasing role by enabling more critical and objective evaluations over time.

All in all, analysts in general become less optimistic about future earnings of the SPAC firms when they have prior SPAC experience and as they accumulate firm-specific experience, in line with our expectations for Hypotheses 2a and 2b.

Robustness Checks

We run a set of robustness checks to ensure the validity of our findings. To corroborate the findings regarding Hypothesis 2a, we use another measure to proxy for analyst's firm-specific experience. In addition to counting the number of years an analyst provided forecasts for the focal firm, we also measure experience as the *Number of forecasts* issued for the firm. This alternative measure captures not only the span of time an analyst has followed the firm but also the intensity of their engagement, as a higher frequency of forecasts may indicate closer monitoring and deeper familiarity with the firm's operations, as well as stronger ties to company management. By using both the duration (years) and frequency (forecast count) of coverage, we aim to account for variations in how consistently and closely analysts follow a firm, thereby enhancing the robustness of our results related to firm-specific experience.

Table 2.4 reports the results when *Number of estimates* is used instead of *Firm experience.* Model 1 accounts for the direct effect of *Number of estimates* on the likelihood of undervaluing SPACs relative to IPOs. Models 2 provides the results of interaction of *Number of estimates* with *SPAC*, as well as a vector of controls. Finally, Model 3 reports the results of interactions of *Number of estimates* and *SPAC experience* with *SPAC,* as well as a vector of controls.

Table 2.4 - *Robustness check: Firm experience as number of estimates provided*

	Negative error		
VARIABLES	1	2	3
SPAC	-0.6551***	-0.7208***	-0.9506***
	(0.0274)	(0.0340)	(0.0812)
Number of forecasts	0.0044***	0.0011	0.0012*
	(0.0006)	(0.0007)	(0.0007)
SPAC X Number of forecasts		0.0070***	0.0049**
		(0.0023)	(0.0023)
SPAC experience			-0.0761**
			(0.0312)
SPAC experience X *SPAC*			0.2986***
			(0.0876)
General experience		0.0290***	0.0303***
		(0.0034)	(0.0034)
Number of companies covered		-0.0007	-0.0005
		(0.0015)	(0.0015)
Number of industries covered		0.0069	0.0075
		(0.0063)	(0.0063)
Top size bank		0.0222	0.0207
		(0.0313)	(0.0314)
Forecast age		0.0010***	0.0010***
		(0.0002)	(0.0002)
Total assets		-0.0000***	-0.0000***
		(0.0000)	(0.0000)
Total revenue		-0.0001***	-0.0001***
		(0.0000)	(0.0000)
Net income		0.0008***	0.0008***
		(0.0000)	(0.0000)
Number of employees		0.0054***	0.0054***
		(0.0008)	(0.0008)
Constant	-0.8137**	-1.5632***	-1.5986***
	(0.4014)	(0.4085)	(0.4088)
Observations		135,524	
Analyst FE		Yes	

The results are consistent with those for *firm experience.* The higher the *Number of estimates*, the higher the likelihood that the analysts would penalize the firm using SPACs. The coefficient for interaction of *SPAC* with *Number of forecasts* (0.0049, $p < 0.05$) in Model 3 shows that with each additional forecast that analyst issues for the focal firm, the odds of undervaluing SPACs increase by 0.5%.

Thus, whether we measure firm-specific experience by duration (years of coverage) or by frequency (number of forecasts), the results are consistent: as analysts deepen their familiarity with these firms, the likelihood increases that their initial optimistic outlook will diminish, leading them to adopt a more conservative perspective on the firms' prospects.

In addition to this, we employ two alternative measures for SPAC experience to further corroborate H2b. To operationalize one of these measures, we take an approach similar to that for calculation of *Firm experience* and *General experience* and calculate this measure as number of years during which the analyst had at least one forecast for any SPAC firm. Similar to the other measures, the forecasts within 30 days from forecast period end date are not taken into calculation. We call this variable *SPAC experience (years).*

The other variable, *SPAC experience (forecasts)*, is calculated as the number of forecasts that analysts had for any SPAC firm as of the time when they predict the focal firm earnings. Similar to the case of firm experience, by adopting these differing measures, we aim to account both for duration and intensity of analysts' engagement with the firm and obtain more precise proxies for SPAC-specific experience.

Table 2.5 reports the results of regression models where *SPAC experience (years)* and *SPAC experience (forecasts)* are used instead of *SPAC experience*. Model 1 accounts for the direct effect of *SPAC experience (years)* on the likelihood of undervaluing SPACs relative to IPOs. Models 2 provides the results of interaction of *SPAC experience (years)* with *SPAC*. Finally, Model 3 reports the results of interactions of *SPAC experience (years)* and *Firm experience* with *SPAC*. Model 4 accounts for the direct effect of *SPAC experience (forecasts)* on the likelihood of undervaluing SPACs relative to IPOs. Models 2 provides the results of interaction of *SPAC experience (forecasts)* with *SPAC*. Finally, Model 3 reports the results of interactions of *SPAC experience (forecasts)* and *Firm experience* with *SPAC*.

Table 2.5 - *Robustness check: Alternative operationalizations of SPAC experience*

	Negative error					
Variables	1	2	3	4	5	6
SPAC	-0.6720***	-0.7379***	-0.7340***	-0.6897***	-0.7363***	-0.7441***
	(0.0273)	(0.0351)	(0.0358)	(0.0275)	(0.0343)	(0.0351)
SPAC experience (years)	0.0617***	0.0087	0.0108			
	(0.0086)	(0.0108)	(0.0109)			
SPAC X SPAC experience (years)		0.0395***	0.0068			
		(0.0118)	(0.0173)			
SPAC experience (forecasts)				0.0054***	0.0003	0.0005
				(0.0010)	(0.0012)	(0.0012)
SPAC X SPAC experience (forecasts)					0.0045***	0.0012
					(0.0014)	(0.0018)
Firm experience			0.0037			0.0036
			(0.0044)			(0.0044)
Firm experience X SPAC			0.0485**			0.0502***
			(0.0200)			(0.0168)
General experience		0.0294***	0.0279***		0.0305***	0.0290***
		(0.0033)	(0.0038)		(0.0031)	(0.0036)
Number of companies covered		-0.0006	-0.0005		-0.0006	-0.0006
		(0.0015)	(0.0015)		(0.0015)	(0.0015)
Number of industries covered		0.0062	0.0061		0.0065	0.0065
		(0.0063)	(0.0063)		(0.0063)	(0.0063)
Top size bank		0.0234	0.0233		0.0226	0.0230
		(0.0313)	(0.0313)		(0.0313)	(0.0313)
Forecast age		0.0010***	0.0010***		0.0010***	0.0010***
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
Total assets		-0.0000***	-0.0000***		-0.0000***	-0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Total revenue		-0.0001***	-0.0001***		-0.0001***	-0.0001***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Net income		0.0008***	0.0008***		0.0008***	0.0008***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Number of employees		0.0054***	0.0054***		0.0054***	0.0054***
		(0.0008)	(0.0008)		(0.0008)	(0.0008)
Constant	-0.7985**	-1.5684***	-1.5373***	-0.7985**	-1.5937***	-1.5622***
	(0.4014)	(0.4086)	(0.4104)	(0.4014)	(0.4079)	(0.4096)
Observations	135,524					
Analyst FE	Yes					

Overall, the results are consistent with the findings in main specifications. The coefficients of interactions of both measures of SPAC experience with SPAC dummy are positive and significant. However, they become insignificant when *Firm experience's* interaction with SPAC is added to the models. This loss of significance may be because aspects captured by the alternative SPAC experience measures overlap with information already embedded in the Firm-Specific

Experience measure. Consequently, the addition of *Firm experience* could absorb some explanatory power, resulting in diminished significance for the *SPAC experience* interactions. Nonetheless, the overall findings remain consistent with our expectations and corroborate the results presented in the main analysis. Accumulation of experience coincides in drop of optimism towards the use of SPACs, hinting on debiasing effect of experience.

Additional Analyses

To further validate our findings about how analysts evaluate SPACs, and how their experience shapes them, we conducted additional analyses examining whether these relationships hold under different market conditions. First, we split our sample into high and low uncertainty periods and re-estimated our main models. We define uncertainty as standard deviation of analyst forecasts for a given firm and period, following (Bromiley, 1991). Tables 2A.1 and 2.A2 in the appendix reports the results of this analysis.

These results reinforce our core findings. Analysts maintain a generally optimistic view of SPACs compared to IPOs under both high and low uncertainty conditions (coefficients: -0.7479 and -0.6129, $p < 0.01$). Importantly, these coefficients are different ($p < 0.01$ for the test of coefficient difference). Interestingly, the SPAC dummy coefficient is larger under low uncertainty. Our central theoretical proposition posits that analysts may face lower reputational penalties under uncertain conditions. This is because market participants recognize the inherent challenges of forecasting in such environments and are more lenient, assigning lower reputational penalties to analysts. The observed difference in coefficients supports this proposition, as analysts exhibit greater optimism toward SPACs when uncertainty is higher.

The split-sample regression results for H2 offer a more nuanced understanding. First, the interaction coefficient between firm experience and SPACs under high uncertainty (0.0372, p <

0.1) is smaller ($p < 0.01$ for the test of difference of coefficients) than under low uncertainty (0.0829, $p < 0.01$). This suggests that the previously observed learning effect is weaker under high uncertainty. Facing lower reputational penalties, analysts do not adjust their positive stance toward SPACs as strongly as they do under low uncertainty. Second, the interaction coefficient between SPAC experience and the SPAC dummy is insignificant under low uncertainty, indicating that prior SPAC experience does not influence analysts' SPAC forecasts in these conditions.

We also conducted a split-sample analysis based on analysts' historical accuracy, measured as the average accuracy of all their forecasts up to the time of the focal forecast. Since accuracy serves as a key market signal of reliable judgment, we assume higher historical accuracy correlates with higher analyst reputation.

The results corresponding to H1, presented in Table 2.A3 of Appendix, show that the SPAC coefficient is smaller ($p < 0.01$ for the test of difference of coefficients) in the high-accuracy sample (-0.5915, $p < 0.01$) than in the low-accuracy sample (-0.7598, $p < 0.01$), suggesting that historically more accurate analysts are less optimistic about SPACs. Additionally, the results corresponding to H2, reported in Table 2.A4 of the Appendix reveal minimal evidence of a learning effect for these analysts. The interaction coefficient between SPAC experience and the SPAC dummy is insignificant, while the interaction between firm experience and SPACs (0.03, $p < 0.1$) is less significant but not statistically different in the low-accuracy sample (0.0701, $p < 0.01$).

Overall, these findings suggest that more accurate analysts exhibit greater skepticism toward SPACs, likely as a strategy to protect their credibility. Their limited adjustment of forecasts with experience further implies an inherently cautious stance toward these firms, reinforcing their conservative approach in an effort to protect their reputation.

Finally, we also run split sample analysis in high versus low growth industries. The growth is measured in terms of EPS. We aggregate the EPS growth across industries based on SIC code. The underlying idea is that analysts might be more likely to be optimistic about SPACs in higher growth industries, as these companies will be more likely to yield better results within growing industries.

Tables 2.A5 and 2.A6 in the appendix present the results of this analysis. The SPAC dummy coefficient is smaller ($p < 0.01$ for the test of difference of coefficients) in high-growth industries (-0.4871, $p < 0.01$) than in low-growth industries (-0.8249, $p < 0.01$), implying greater analyst optimism toward SPACs operating in low-growth industries. This suggests that the observed optimism is not driven by industry growth prospects but rather is specific to the SPAC structure. Furthermore, the interaction coefficient between SPACs and firm experience is smaller ($p < 0.01$) in high-growth industries (0.0614, $p < 0.01$) than in low-growth industries (0.0847, $p < 0.01$), indicating a stronger learning effect in low-growth industries. Finally, the interaction coefficient between prior SPAC experience and the SPAC dummy is insignificant in high-growth industries, suggesting that prior SPAC experience does not influence analyst optimism in these industries. Taken together, these findings suggest that optimism toward SPACs is not attributable to their operation in high-growth industries, but rather to their inherent nature as SPACs.

Conclusion

This study shows the complex and evolving role of human capital in shaping human judgment, particularly under the conditions characterized by high uncertainty and controversy.

While prior literature highlights experience as a key component of human capital that enhances performance (e.g. Kor, 2003; Kor & Sundaramurthy, 2009), our findings reveal that its influence on judgment and biases is more nuanced. Despite the documented and generally agreed controversy surrounding the SPACs (Naumovska, Zajac, et al., 2021), analysts initially exhibit overall optimism towards this practice. This is initial optimism likely stems from cognitive biases combined with institutional and social pressures that affect analyst judgment. However, as analysts accumulate firm and practice specific experience, these initial optimism starts to fade away, resulting in more controversial estimates for firms using SPACs. Combined, these results suggest that human capital is biased, but experience can mitigate the effect of biases.

We make several contributions. First, the diminishing optimism associated with the experience accumulation adds to our understanding of how experience affects human biases. So far, literature provides mixed findings on this topic: some papers show that biases tend to get amplified as a result of experience accumulation (Gaba et al., 2022; Heath & Tversky, 1991), while others conclude that experience can result in debiasing of judgment (Christoffersen & Sarkissian, 2011; Gort et al., 2008). We add to this discussion by analyzing human biases in the context of corporate use of highly controversial practices – a setting where biases are expected to be present as a result of surrounding uncertainty and various institutional and social pressures. Our results show that experience accumulation results in mitigation of these biases. This suggests that experience does not merely represent task-related accumulated knowledge, but also serves to reduce biases over time, as repeated exposure allows individuals to refine their judgment and adjust for initial distortions. In this way, experience emerges as a means through which human capital enhances judgment through reduction of biases, even in uncertain and high-pressure environments.

In addition to this, our study advances strategic management theory by revealing the learning processes through which analyst evaluations evolve. While existing research recognizes that stakeholder support can change over time (Naumovska, Gaba, et al., 2021; Sanders & Tuschke, 2007), the theoretical mechanisms driving these shifts remain underexplored. We observe a consistent pattern where analysts' initial assessments change over time as they directly experience practice outcomes. This process creates a gradual shift in evaluation, shaping how the practice is perceived and legitimized. This finding extends strategic management theory by showing how stakeholder learning operates as a distinct mechanism separate from traditional explanations based on institutional pressures or social influence. Specifically, we demonstrate that analysts' accumulated experience leads to progressively refined evaluations that fundamentally alter how they assess controversial practices. This theoretical insight helps explain why seemingly stable patterns of stakeholder support can unexpectedly shift as they gain experience, contributing to our understanding of the dynamic nature of practice legitimation.

Our third contribution addresses the question of why do controversial practices persist despite stakeholder resistance? Prior research has shown that stakeholders discourage controversial practices through reduced valuations (Mahoney & Mahoney, 1993), negative media coverage (Bednar et al., 2015), and reputational damage (Briscoe & Murphy, 2012) - mechanisms that should theoretically prevent their adoption. Yet these practices continue to emerge and diffuse across organizations. Our study adds to the understanding of this theoretical puzzle by revealing how financial analysts, as influential market intermediaries, can enable controversial practices to gain legitimacy through biased evaluations. This finding advances strategic management theory by demonstrating how heterogeneity in stakeholder responses—particularly initial optimism from influential intermediaries—helps explain the persistence of practices that appear to violate institutional norms. Our theory thus moves beyond simple stakeholder penalty models to reveal the complex dynamics through which controversial practices persist, despite general resistance towards them.

Our findings have important managerial implications. First, we show that stakeholder evaluations of corporate actions are affected by cognitive biases, particularly in the early stages, when ambiguity surrounding these actions is high. For managers, this means that early stakeholder support may not reflect a fully informed or objective assessment, but rather a biased interpretation shaped by limited exposure and uncertain contexts. This should be taken into consideration in stakeholder relationship management activities. For example, early positive reactions might encourage managers to push forward with bold initiatives, while signs of growing doubt could signal a need for greater transparency or strategic adjustments. This approach helps maintain trust and credibility with stakeholders, even as their views change. These insights are particularly consequential in emerging sectors characterized by novel business models and unconventional strategic approaches.

At the same time, it is important to recognize that the initial optimism we find creates a temporary "legitimacy window". This creates a unique opportunity for managers, especially those with opportunistic or unethical motives, to strategically exploit the reduced scrutiny and advance counternormative actions. These actions, while initially supported by positive stakeholder sentiment, may conceal significant risks, including governance breakdowns, misaligned incentives, or eventual financial underperformance. This dynamic presents a pressing challenge for regulatory bodies responsible for safeguarding market integrity and investor interests. The temporary legitimacy window allows controversial practices to gain momentum and spread quickly, often before their full implications, either positive or negative, are understood by the market. Regulatory agencies, such as the Securities and Exchange Commission (SEC), must therefore adopt a proactive stance to identify and address these windows of opportunity that could otherwise enable harmful practices to take root under the guise of legitimacy.

In addition, the evolving nature of stakeholder perceptions carries significant implications for investors. Initially, key stakeholders like financial analysts may exhibit optimism toward novel or unconventional strategies, such as firms going public via special purpose acquisition companies (SPACs), creating a temporary perception of legitimacy. This early positivity is not always rooted in objective analysis but can be shaped by cognitive biases—such as over-optimism, framing effects, or reputational concerns - that distort judgment in uncertain or unfamiliar contexts. These biased evaluations can influence investor decisions, encouraging participation in opportunities that appear promising based on favorable forecasts or prevailing sentiment. However, investors must recognize that such perceptions are neither static nor purely rational; as analysts accumulate experience with a firm or its practices, their assessments often shift from enthusiasm to skepticism, revealing risks like governance misalignments or unmet projections, that were not initially evident. Understanding this dynamic, and the biases that fuel it, is crucial for investors to avoid over-relying on early hype and to make more informed, resilient, and long-term investment choices.

Limitations and Future Research

While this study provides valuable insights into interplay between experience and biases, as well as the dynamics of stakeholder evaluations and the process of legitimization of controversial practices, it also has some limitations.

First, we rely on analysts' earnings forecasts as the primary measure of stakeholder evaluations. While this offers quantifiable insights into analysts' expectations, it captures only one dimension of their assessments. Future research could complement these findings by incorporating textual data, such as analyst reports or media narratives, to explore how language and framing influence the legitimacy of controversial practices over time. A qualitative study that conducts interviews with analysts could yield some especially intriguing and reliable insight, which could confirm the quantitative results or raise new points entirely.

Second, our focus on financial analysts highlights their importance as intermediaries, but other stakeholders—such as institutional investors, regulators, or media outlets—may play equally significant roles. Future studies could examine how these groups interact to shape the adoption and persistence of controversial practices. A multi-stakeholder approach would offer a more comprehensive understanding of how legitimacy is co-constructed across diverse actors.

Third, while we examine how analysts' evaluations evolve over a specific period, longer-term dynamics remain underexplored. Future research could adopt longitudinal designs to study how stakeholder learning and regulatory responses interact over time to influence the lifecycle of controversial practices. This would shed light on how legitimacy is sustained, transformed, or eroded in different phases.

Finally, this study emphasizes market-based mechanisms, such as earnings forecasts, in shaping legitimacy. However, controversial practices also rely on non-market mechanisms, such as cultural acceptance, regulatory alignment, or societal perceptions. Future work could explore how non-market actors, such as advocacy groups or policymakers, contribute to the legitimacy or resistance of such practices, broadening the scope of legitimacy research beyond financial markets.

This study shows that experience accumulation is associated with reduction in cognitive biases, particularly in contexts characterized by novel and controversial practices surrounded by uncertainty. We find that stakeholder evaluations are not purely rational or static; instead, they are influenced by biases, especially when evaluators face uncertainty or limited information. These biases can lead to premature legitimacy for practices that deviate from established norms, only for that legitimacy to erode as stakeholders gain experiential knowledge and reassess earlier judgments. Although focused on the distinctive empirical context of SPACs, our findings illuminate broader theoretical puzzle about how legitimacy emerges. In doing so, we challenge the assumption that stakeholder evaluations are consistently negative toward controversial practices, revealing instead a more dynamic process. These insights open up fertile ground for future research on how biases and experiential learning interact to shape institutional outcomes, advancing both strategic management theory and our understanding of institutional change in evolving and uncertain environments.

To conclude, this study highlights the importance of human capital and the role of experiential learning in shaping biases in decision-making. While our findings suggest that accumulated experience can help mitigate biases over time, the process of gaining that experience is itself prone to various biases. The transition from novice to expert does not happen overnight; it unfolds gradually, and during this period, human capital is vulnerable to biased judgments. Moreover, despite mitigation of biases associated with experience accumulation, even experienced human capital is not completely immune to bias. This raises a fundamental question: if human judgment is prone to biases, and experience does not completely eliminate them, how can organizations obtain better, more accurate decisions, particularly in volatile environments?

One potential solution lies in the integration of AI, which is considered to be more robust and more immune to biases. However, this introduces new questions about the evolving role of human capital in decision-making. If algorithms can outperform humans in certain tasks, what value does human expertise continue to hold? How should we rethink the role of experience in an era where machines increasingly augment, or even substitute human judgment? These are the questions explored in the next chapters of this dissertation.

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Chapter 3 - The Role of Human Experience in Enhancing AI's Predictive Accuracy

Abstract

This chapter addresses the following research question: "In what ways can human experience enhance the performance of AI systems, and under what conditions is this contribution most valuable?" As firms increasingly adopt AI, exploring its synergy with human expertise becomes a crucial area of research. This chapter suggest that to manage the challenges of AI implementation, firms should rely on the experience of individuals. The study examines how individual experience interacts with AI. It uncovers an intriguing paradox: while individual experience does not uniformly improve human prediction accuracy, integrating it with AI models significantly enhances predictive accuracy, especially in volatile conditions. These findings contribute to strategic management theory by revealing the context-dependent nature of human-AI complementarities. We offer a novel framework for understanding how firms can leverage human capital to enhance AI-driven competitive advantages. This study provides insights into the strategic value of human expertise in an AI-driven era, with important implications for competitive strategy.

Note on co-authored research and inclusion in this dissertation

This chapter is based on a joint work with my dissertation advisors, Francesco Castellaneta and Bruno Cirillo.

Introduction

Predictive capability is crucial for firms to secure long-term success and a competitive edge in a dynamic business environments (Barney 1986; Durand 2003; Eisenhardt and Martin 2000; Makadok and Walker 2000). Faced with the uncertainties and complexities of internal and external factors in many industries, firms are turning to Artificial Intelligence (AI) to improve their predictive capabilities. AI can mitigate the biases and limitations of individual judgment (Kleinberg et al., 2017), which often result in erroneous predictions (Durand, 2003). Consequently, AI can outperform individual decision-makers, even in complex decisions of a strategic nature, thereby assisting firms in adapting their strategies and resources. Thus, many firms have reevaluated the role of humans and individual decision-makers (Krakowski et al., 2022; Shrestha et al., 2019). For example, in January 2024, the German software giant, SAP, announced a "transformation program" involving an investment of more than $2 billion to integrate artificial intelligence into its business, which led to the restructuring of 8,000 roles, with some workers being laid off and others re-trained to work with AI (Cerullo, 2024).

Despite the growing trend of enhancing the role of AI in decision-making, AI is not a flawless substitute for humans, particularly in highly volatile contexts. The predictive performance of AI relies on the availability and quality of training data (Choudhary et al., 2023), which may be scarce, unrepresentative, or biased in some contexts (Sambasivan et al., 2021). These are scenarios in which humans are anticipated to significantly complement AI. This is particularly true for tasks that necessitate a subtle comprehension of complex systems. In such contexts, individual experience has demonstrated its crucial role in fully leveraging the potential of AI (Choudhury et al., 2020; Krakowski et al., 2022). Acknowledging this, firms reallocate their human capital, which includes retraining existing employees and restructuring roles, to efficiently support and adapt to the integration of AI. This aims to optimize the synergies between AI's proficiency in processing and analyzing large volumes of data swiftly and accurately, and the human’s competence in understanding and navigating complex contexts.

Despite significant progress in understanding human-AI complementarities (e.g. Choudhary et al., 2023; Choudhury et al., 2020; Krakowski et al., 2022; Puranam, 2021), most research has focused on specific tasks within certain decision-making contexts. For example, studies have explored these synergies in activities like application reviews and archival searches during patent approval processes (Choudhury et al., 2020). However, a critical gap persists in our understanding of how firms can strategically leverage human-AI complementarities to enhance their predictive performance and, consequentially, competitive edge. This gap significantly limits our theoretical understanding of how firms should reallocate and utilize their human capital when adopting AI, particularly in volatile environments.

To address this gap, we propose a framework that goes beyond the conventional approach of merely reskilling employees for AI adoption. Our study aims to develop a more nuanced and comprehensive theoretical understanding of how firms can strategically deploy a diverse spectrum of human experiences - ranging from general to domain-specific - to effectively leverage AI and enhance predictive capabilities. Crucially, we investigate the underexplored question of whether and how incorporating human inputs into AI training sets can improve its predictive capabilities. This approach not only bridges a significant gap in the literature but also offers a new theoretical lens through which to view the strategic value of human capital in the age of AI. By examining these dynamics in the context of environmental volatility, we provide a more robust and context-sensitive theoretical framework, advancing our understanding of the complex interplay between human expertise, AI capabilities, and environmental factors in shaping firm performance and competitive advantage.

Given these, we adopt question-based approach without formal hypothesis formulation (Graebner et al., 2023) and address three questions: How does individual experience—both general and domain-specific—affect human predictive performance when compared to AI? To what extent can integrating input from individuals with different types of experience improve the predictive accuracy of AI? Finally, does the degree to which human experience enhances AI performance depend on the level of volatility in the decision-making environment?

To answer these questions, we examine the context of analysts employed by investment banks, tasked with predicting the performance (Earnings Per Share) of publicly listed firms on the New York Stock Exchange (NYSE). We compiled a longitudinal dataset from the I/B/E/S estimates data, the WRDS Financial Ratios Suite, and data from the Federal Reserve Bank of Philadelphia. This dataset spans from 1983 to 1998 with estimates from 6,729 analysts for 8,074 NYSE-listed firms. This context suits well for answering these questions. First, it predates the widespread use of AI; hence analysts' predictions are based on human judgment and do not involve any AI predictions. Second, this context is characterized by varied levels of generic and firm-specific experience of analysts, which is crucial to answer these questions.

We run two tests. For the first test, we train a Random Forest (RF) algorithm on firm and macroeconomic data. For the second test, we train another RF algorithm, which, in addition to firm and macroeconomic data, also receives inputs from humans in the form of analysts' predictions for the same firm and period as the algorithm aims to predict. This allows us to assess whether these algorithms could effectively leverage human inputs to enhance their predictive accuracy, and how this is dependent on the level and type of individual experiences.

To address our first research question regarding the effect of experience on individual predictive performance relative to AI, in the first test we conducted a comparison between the predictions provided by analysts for a specific firm-year and those generated by the first RF model for the same firm-year. This allowed us to examine how the analyst's predictive performance compares against that of an RF algorithm, considering two aspects of individual experience: the individual's experience in predicting a particular firm' performance (i.e., their domain-specific experience), and the individual's experience within the broader context of EPS predictions (i.e., their general experience). We also conducted additional tests to determine how an analyst's predictive accuracy compares to AI algorithms under varying levels of volatility.

To address our second research question - how incorporating inputs from individuals with varying types of experience influences the predictive accuracy of AI - we conducted a second set of analyses. Specifically, we examined the effect of both domain-specific and general experience on the performance of a random forest (RF) model that integrated analyst inputs. This analysis aimed to identify the relationship between the type and level of experience and the final predictions generated by the model. As in our first test, we also conducted additional analyses to evaluate how different levels of volatility impact the model's predictive performance.

Our analysis yields two primary insights. First, we find that the accumulation of domain-specific experience correlates with a higher human predictive error compared to that of RF algorithms. However, we do not observe a similar effect for general experience. As volatility increases, the gap between an individual's predictive error and that of RF algorithms shrinks as the levels of both domain-specific and general experience increases. Second, we find that incorporating predictions from the individuals with extensive domain-specific experience into the RF training algorithm does not significantly alter the RF algorithm's predictive accuracy. Conversely, the RF's predictive accuracy improves when the training algorithm includes predictions by individuals with substantial general experience. Moreover, in situations of high volatility, both types of experience correlate with a reduction in the RF's predictive error.

These findings reveal a paradoxical insight: the accumulation of experience can have opposing effects depending on the context. For human predictors, more experience may correlate with decreased predictive accuracy when compared to AI, while simultaneously enhancing the performance of AI models that incorporate human inputs. Thus, while experience accumulation might impede human predictive abilities, it holds the potential to improve AI predictions. Even more intriguingly, in both humans and AI, experience accumulation reduces the adverse impact of environmental volatility on predictive accuracy.

Our study makes several significant contributions to strategic management theory and practice. First, we extend the strategic human capital literature and the ongoing discourse on job automation (e.g. Autor, 2015; Felten et al., 2021; Frey & Osborne, 2017; Raisch & Krakowski, 2021) by revealing the context-embedded nature of human-AI complementarity. We demonstrate that the effectiveness of AI integration is contingent upon both the level of human expertise and the degree of environmental volatility - critical boundary conditions often overlooked in existing literature. This nuanced understanding challenges simplistic notions of AI replacing human labor, instead pointing towards a strategic division of labor (Puranam 2021) where AI and human expertise synergistically enhance firm performance. Our findings suggest that firms should reevaluate their talent acquisition and seek to attract human capital which can provide expertise and insights to enhance AI performance.

Second, this study adds to ongoing discussion on human-AI complementarities (e.g. Choudhary et al., 2023; Choudhury et al., 2020; Krakowski et al., 2022) by inverting the typical perspective. While most studies explore how AI augments human decision-making, we demonstrate a reciprocal relationship where human experience significantly enhances AI performance. This novel approach offers a new theoretical lens for understanding the strategic value of human capital in an AI-driven era and opens new avenues for research on how firms can systematically leverage human insights to improve AI-driven strategic decisions.

Third, these findings have important implications for competitive strategy and resource-based view of the firm (J. Barney, 1991) particularly. As Krakowski et al. (2022) show, AI adoption alone may erode competitive advantage since AI is not an inimitable resource. However, through human-AI complementarity and a system in which humans provide inputs to AI, a new source of hard-to-imitate resources is created.

Our study thus reveals the type of human capital and the conditions under which firms should rely on it to maximize the complementarities between human expertise and AI, enhancing their predictive capabilities. This approach can enable firms to develop distinctive, hard-to-imitate capabilities that lead to sustained competitive advantage in AI-augmented contexts.

Theoretical Background

AI has emerged as a powerful tool for prediction across diverse domains (Yu et al., 2021), excelling in tasks like credit card fraud detection (Agrawal et al., 2018), airport operation optimization through precise aircraft arrival estimates and personalized customer promotion tailoring (McAfee et al., 2012). It even assists judicial decision-making by assessing detainees' future criminal risk (Kleinberg et al., 2017). AI's potential is constantly improving, with error rates in predictions declining significantly, sometimes even surpassing individual accuracy in terms of predictive accuracy in specific contexts (Agrawal et al., 2018; Allen & Choudhury, 2022; Kellogg et al., 2020).

AI biases and the synergies with humans

AI's effectiveness in predictive tasks depends on the quantity and quality of its training data, with algorithms exhibiting predictive power in "data-rich contexts" (Choudhary et al., 2023). However, firms and decision-makers often struggle with accessing information, frequently encountering issues of information asymmetry. These problems can undermine the quantity and quality of data utilized in AI predictions, thereby affecting their reliability and precision (Cowgill & Tucker, 2019; Sambasivan et al., 2021). Insufficient or suboptimal data can drastically reduce algorithmic accuracy, potentially leading to flawed strategic decisions based on erroneous predictions. This vulnerability underscores the importance of human-AI collaboration in contexts with volatile and rapidly changing external and internal environments. Humans, with their ability to interpret, analyze, and apply expert judgment, can address information asymmetry by critically evaluating the data, identifying gaps or inconsistencies, and seeking additional information. This ensures a more balanced and accurate foundation for AI predictions. Thus, firms have a crucial need to reevaluate the role of their human capital as a foundation for their predictive capability and gain a deeper understanding of how human-AI synergies can help them navigate these challenges.

Research increasingly emphasizes the importance of human experience in maximizing AI's potential (Choudhury et al., 2020; Krakowski et al., 2022). However, while extant research demonstrates the efficacy of AI in accomplishing specific tasks within constrained decision-making environments—e.g., application reviews, patent searches (Choudhury et al., 2020)—a critical gap persists in our comprehension of how firms can harness human-AI synergies in complex decisions of a strategic nature, thus helping them to cultivate a competitive advantage. This gap extends beyond the context of task-specific applications; the entire spectrum of human capabilities, encompassing general problem-solving and domain-specific knowledge, represents a valuable resource (Argote et al., 2021; Castanias & Helfat, 2001; Jain, 2013). Prior experiences equip individuals with invaluable insights and competencies (Castanias and Helfat 2001). Iterative engagement with tasks fosters the development of these experiences (Reagans et al., 2005), which are subsequently instrumental in creating synergies within human-AI collaborative endeavors. Domain expertise enables individuals to provide context and interpretation for the large datasets analyzed by AI. This ensures that the algorithms incorporate nuanced factors that extend beyond historical trends, thereby mitigating potential biases in some AI algorithms. Human oversight remains indispensable, particularly in contexts fraught with potential algorithmic biases, where individual input can provide guidance to AI-driven predictions, consequently contributing to the continuous refinement and improvement of AI models.

This evolving understanding of human-AI synergies necessitates a strategic reallocation of human capital to maximize the value of human experience. The key challenge, and the main motivation for our study, lies in determining how to best leverage diverse individual experiences to enhance the predictive precision of AI algorithms.

The role of individual experience

The role of individual experience in predicting, decision making, and firm's competencies has been extensively explored by extant research. However, the specific ways in which experience can enhance predictive capabilities remain somewhat unclear and, at times, contradictory. One of the key findings from these studies is the development of cognitive biases and heuristics because of individual experiences (Argote, 2012; Reagans et al., 2005). As individuals interact with their environment and gain experience, they form heuristics (Bingham & Eisenhardt, 2011), which, over time, become part of an individual's cognitive process and influence their decision-making. These biases and heuristics can sometimes undermine rationality (Simon, 1955; Tversky & Kahneman, 1974). For example, they have been shown to negatively impact decision-making across contexts such as strategic choices (Schwenk, 1984), investments (Blohm et al., 2020), risk assessment (Kahneman & Lovallo, 1993; McNamara & Bromiley, 1997), and earnings predictions (Hilary & Menzly, 2006). Despite these potential pitfalls, heuristics have also been shown to enhance individual predictions and judgments in some contexts (Gigerenzer & Todd, 1999). In particular, heuristics are important for predictions in complex systems, because these mental shortcuts allow individuals make swift and accurate predictions, especially in dynamic contexts characterized by incomplete information (Gigerenzer & Gaissmaier, 2011). In such situations, traditional rationality may fall short, and relying on heuristics enables individuals to navigate the complexity effectively.

In addition, learning from experience is not a straightforward process. It involves the transformation of raw experience into meaningful knowledge, which can be a complex and demanding process (March 2010). Moreover, cognitive limitations and biases can intensify due to the accumulation of experience (Gaba et al., 2022). Overall, the evidence is inconclusive regarding whether the accumulation of experience leads to improved predictive performance in individuals. Consequently, this uncertainty extends to AI systems that receive human inputs.

Experience can be divided into two primary categories: specific and generic. Specific experience is derived from repeated, direct interactions within a particular domain, invaluable for detailed, domain-specific tasks (Narayanan et al., 2009). In contrast, generic experience arises from exposure to a variety of situations, challenges, and contexts over time, offering adaptability, versatility, and the ability to connect seemingly disparate dots (Clement et al., 2006).

In the context of individual predictions, both these types of experiences placritical roles. While specific experience can provide detailed insights into patterns and trends of a particular domain, generic experience can offer overarching strategies and approaches adaptable to multiple prediction scenarios.

Human-AI synergies in volatile environments

The challenges and complexities of harnessing human-AI synergies are highlighted by the constraints of individual experience in decision-making. The synergy between individual and machine capabilities is gaining recognition (e.g. Choudhary et al., 2023; Choudhury et al., 2020; Puranam, 2021). However, the effective utilization of individual experiences, often linked with biased decision-making, for human-AI synergies is less clear. This introduces an additional layer of complexity to the question of how to optimally integrate individual experience and AI algorithms (Allen & Choudhury, 2022; Krakowski et al., 2022).

In highly volatile contexts, data variability and instability can result in inconsistent decision-making outcomes. Experienced individuals often resort to their heuristics in such situations. Despite having incomplete representations of a volatile problem environment, these heuristics can simplify the decision-making process (Gigerenzer & Gaissmaier, 2011) in unfamiliar or unstable scenarios by providing unique perspectives or solutions that may not be evident from the available data. Recognizing the potential of individual heuristics to enrich AI with a more robust and relevant training set, particularly when AI faces challenges due to scarce or inconsistent data, our aim is to examine whether the incorporation of diverse types of individual experiences, both generic and domain-specific, into AI training data can boost its predictive accuracy. Individuals, through their unique experiences, have the potential to mitigate AI biases and augment its predictive capabilities when these experiences are incorporated into the training data. AI, with its inherent strengths, can evolve into a more robust predictive model when combined with insights derived from a wide array of individual experiences. While extant research has examined AI's capacity to augment individual performance, the influence of various types of experience on individual and AI performance in strategic contexts, such as firm performance prediction, remains somewhat unclear and largely unexplored. Therefore, we pose the following questions:

Research question 1. *What is the effect of experience, both generic and domain-specific, on individual predictive performance relative to AI?*

Research question 2. *If and how can the integration of inputs from individuals with various types of experience, both generic and domain-specific, into AI enhance the predictive precision of AI?*

Research question 3. *Does the enhancement of AI predictive accuracy by individual experience vary depending on the levels of volatility present within the decision-making environment?*

Data and Methods

Research context

To address our research questions, we focus on the context of equity research analysts employed by investment banks and brokerage firms. The investment banking industry is an ideal setting for our research questions, for several reasons. First, there is significant variation in individual experience within the industry. Experienced analysts, including successful star analysts (Groysberg et al., 2008), generally exhibit higher accuracy in their predictions (Stickel, 1992). In contrast, novice analysts, who lack experience, tend to have less accurate predictions than their more seasoned counterparts (Mikhail et al., 1997).

Second, existing studies indicate that financial analysts are susceptible to various cognitive biases, such as overoptimism (e.g. Kim et al., 2001). They are also influenced by managerial tactics and engage in impression management (Cohen et al., 2012; Washburn & Bromiley, 2014; Westphal & Clement, 2008). Their estimates are influenced by conflicting interests as they seek to present a favorable image of the firms, aiming to enhance the probability of their investment banks receiving underwriting or M&A deals from the companies they are covering (Michaely & Womack, 1999). Analysts often exhibit tendencies to disregard private information while imitating their peers

(Lieberman & Asaba, 2006). These traits make them pertinent to heuristic decision-making, a topic of utmost relevance to our investigation.

Third, in the banking and finance industry AI is increasingly replacing humans in predictive tasks (e.g. Agrawal et al., 2018; Shrestha et al., 2019), making it particularly relevant for our study. In fact, some investment banks and hedge funds are already undertaking projects where they try to create AI “mimicking their employees’ brains” (Copeland & Hope, 2016), in line with our proposition.

Dataset

We constructed a longitudinal dataset by utilizing data from I/B/E/S Estimates dataset. We focus on analysts’ projections for the full fiscal year and the corresponding actual EPS released by the firms for the same period. This approach allows for a comprehensive assessment of the analysts’ predictive accuracy over a complete fiscal cycle, thereby providing a more robust analysis of their performance and the factors influencing their projections.

Our dataset comprises EPS predictions from 6,729 analysts for 8,074 firms listed on the NYSE for the period of 1983 to 1998, resulting in 660,379 observations at the firm-year-analyst level. We intentionally selected this timeframe to isolate “human predictions,” While the theoretical foundations of machine learning and artificial intelligence had been established earlier, their practical application in financial analysis was not feasible during this period. The viability of these technologies for widespread use in predictive tasks only materialized after significant advancements in methodologies, computing power, and data availability in the mid-2000s (Lee, 2018)(Agrawal et al., 2018). By terminating our dataset in 1998, we ensure that the estimates in our study stem purely from individual analysts' judgments, uninfluenced by any machine learning or AI-generated predictions.

To train AI models, we merge this estimates sample with firm data from the WRDS Financial Ratios Suite and macroeconomic data from the Federal Reserve Bank of Philadelphia. We ensure that algorithms only receive the information available to analysts at the time of their projections, preventing any future data from being included into training set and preserving the robustness of our findings.

Dependent variables

To operationalize our dependent variables, we used predictions from Random Forest (RF) models. Below, we provide the rationale for choosing this algorithm and describe the procedure for training the RF models.

Algorithm Choice

We choose Random Forest (RF) algorithm (Choudhury et al., 2021) for its several key advantages over other machine learning models. First, RF handles complex, high-dimensional datasets effectively (Breiman, 2001). Second, RF is generally less prone to overfitting compared to other ML algorithms (Tidhar & Eisenhardt, 2020). Overfitting occurs when a model learns the noise in the training data and performs poorly on new data. RF mitigates this by building multiple decision trees on different subsets of the data and averaging their predictions, reducing the model's variance and improving its generalizability. Third, RF is particularly effective with highly nonlinear data, providing precise estimates and highlighting the variables that most influence estimation accuracy, as evidenced by Tidhar and Eisenhardt (2020).

RF Training

While training RF algorithms for this study, we aimed to replicate the analysts' task of predicting EPS. Consequently, the algorithms were trained specifically to predict EPS. For each prediction made by the analysts in our sample, we obtained a corresponding prediction from the

RF algorithms, targeting the same firm's earnings for the same period. By using the approach suggest by Van Binsbergen et al. (2023), we trained two different algorithms to separately assess the impact of individual experience and environmental volatility on: a) the predictive performance of analysts compared to RF, and b) the predictive performance of the RF algorithm when it receives inputs from analysts.

The first algorithm was trained using firm performance metrics data and macroeconomic data. For past performance metrics of the firms, we utilized pre-computed financial ratios from the Wharton Research Data Services, which include various performance measures such as valuation, liquidity, and profitability indicators. We used data from Federal Reserve Bank of Philadelphia to get macroeconomic measures that influence markets and directly impact firms' earnings. Key variables include consumption growth (logarithmic difference in consumption of goods and services), GDP growth (logarithmic difference in real GDP), industrial production growth (logarithmic difference in the Industrial Production Index, IPT), and unemployment rate. To ensure the RF models accurately mimicked the analysts' prediction process, we provided the algorithms with the most recent data available to the analysts when they made their predictions.

In addition to these variables, we included the analysts' predictions for the same firm and period in the training dataset of the second RF algorithm. This allows us to explore how analyst inputs can influence the performance of machine learning models. While the RF algorithms use the same quantitative data available to analysts at the time of their projections, they lack the qualitative insights from experience, direct communication with company management, and other subjective factors that analysts might consider. By incorporating analysts' predictions into the training set, we aim to give the algorithm access to these qualitative aspects and assess their impact on the algorithm's predictive performance. Additional details on the training process of the RF models are provided in Appendix A.

Based on the predictions from these two RF models we develop the following measures.

Error difference. Our first dependent variable, error difference, is measured as the absolute difference between the error made by the analyst and the error made by the RF algorithm's first specification in predicting the actual EPS of the focal firm for the focal year. Specifically, it measures the difference between the analyst's prediction error (the difference between the analyst's EPS prediction and the actual EPS) and the RF's prediction error (the difference between the RF's EPS prediction and the actual EPS). Since EPS values can vary significantly across firms, we divided the error difference by the stock price in the month preceding the estimation date to ensure comparability across predictions for different firms. The resulting numbers are often close to zero. To enhance interpretability of the results, we multiply measure by 10,000. The measure is calculated using the following formula:

$$\text{Error difference}= \frac{|\text{Analyst EPS prediction-Actual EPS}| - |\text{RF EPS prediction-Actual EPS}|}{\text{Stock price at the end of the month preceding the prediction}} * 10{,}000$$

RF error. Our second dependent variable is measured as the difference between the EPS prediction by the second specification of RF algorithm which received inputs in the form of analyst predictions and the actual EPS disclosed by the firm for a given fiscal year. Like the error difference metric, this measure is normalized by the stock price in the month preceding the estimation date and multiplied by 10,000 for interpretability of results.

$$\text{RF error}= \frac{|\text{RF (with analyst inputs) prediction of EPS - Actual EPS}|}{\text{Stock price at the end of the month preceding the prediction}} * 10{,}000$$

To minimize the impact of outliers, we winsorize the actual values and EPS predictions at the 99% level when calculating these measures. Additionally, we winsorize the error difference measure at the 99% level.

Independent variables

Analyst's firm-specific experience. This measure proxies for domain-specific experience. Following Clement (1999), we calculate the number of years an analyst has issued at least one forecast for the focal firm, from the first forecast year until the focal forecast year. This calculation requires the analyst to produce at least one forecast within the initial 11 months of each fiscal year. The 11-month period is chosen to ensure that analysts develop their own predictions independently, without being influenced by the forecasts of others. By the 11th month of the fiscal year, most analysts would have already published their forecasts, increasing the chances that predictions made in the final month are simply mirroring those of their peers. This widely adopted approach helps to capture the analyst's true forecasting ability, rather than their ability to conform to existing estimates, as is standard in many studies within this domain. Firm-specific experience measures the analyst's familiarity with the firm's unique characteristics and reporting practices, as well as the extent to which the analyst has cultivated relationships with firm insiders, gaining access to potentially private information. This measure aligns with the theoretical premise that specific domain expertise is crucial for nuanced interpretations of information in the process of predicting.

Analyst's general experience. We measure an analyst's general experience by calculating the number of years during which an analyst has made forecasts for any firm, from their first active forecast year until the focal forecast year. This measure assumes the analyst generates at least one forecast during the initial 11 months of the fiscal year for any company. General experience serves as a proxy for the analyst's overall proficiency and ability to assimilate diverse information, applying it effectively across various forecasting scenarios (Clement et al., 2006). This broad experience is theorized to enhance adaptability and versatility, enabling analysts to contribute valuable insights that improve AI predictive accuracy.

Volatility. Reflecting the concept of environmental volatility and its impact on decision-making (Levinthal & March, 1993), we measure volatility in accordance with Agle et al. (2006). Specifically, we use the annual standard deviation of daily stock returns for a firm, adjusted for average industry volatility in the same period. This measure captures the collective assessment of uncertainty by stock market participants and serves as a proxy for the complexity and unpredictability of the forecasting environment. The role of volatility underscores the necessity of human-AI synergies in volatile contexts, where human heuristics can offer unique advantages despite data fluctuations (Gigerenzer & Gaissmaier, 2011).

Control variables

To isolate the effects of our independent variables on predictive accuracy, we control for several factors that might influence both the analyst's and the RF algorithm's predictive abilities. We include the *number of analysts following the firm*, a measure used in line with Lys and Soo (1995) and Mikhail et al. (1997). A higher number of analysts increases the amount of information available publicly, potentially enhancing the accuracy of both human and AI predictions, while fewer analysts reduce the information pool, complicating the forecasting task.

Following Clement (1999), we also control for the complexity of an analyst's portfolio by considering the number of firms and industries they cover. The *number of firms covered* is the count of firms for which an analyst provided at least one forecast during the initial 11 months of a fiscal year. The *number of industries covered* is the count of two-digit SICs (Standard Industrial Classification) for which the analyst issued at least one forecast within the same period. This control accounts for the cognitive load and potential information dilution faced by analysts covering a broad and diverse portfolio.

Additionally, we include a binary indicator, *top size bank*, to account for the resources and information access available to analysts affiliated with major banks. This variable takes the value of one if the analyst works for a firm in the top decile of employee count (Clement, 1999), positing that larger institutions provide analysts with superior support and data access, potentially improving forecast accuracy.

Forecast age is another critical variable, measuring the length of the forecasting horizon, calculated as the number of days between the forecast formulation date and the date to which the forecast pertains to (Clement, 1999). A shorter forecasting horizon generally implies less uncertainty and more accurate predictions. Notably, some EPS predictions are submitted after the forecast period has ended but before firms release actual numbers, which can result in negative values for this variable.

To further control for unobserved heterogeneity, we include firm fixed effects to account for firm-specific characteristics that might influence EPS predictions. Analyst fixed effects are utilized to control for individual analyst characteristics and inherent biases. Lastly, investment bank fixed effects are incorporated to mitigate potential biases arising from analysts' affiliations with specific banks.

Statistical approach

As an initial step to address our first research question, we employ a T-test to compare the average prediction errors between financial analysts and the first RF algorithm. This comparison helps us understand the relative predictive performance of humans versus AI. For our subsequent analyses, aimed at exploring our second and third research questions, we use ordinary least squares (OLS) regression to examine the relationships between our dependent variables—error difference and RF error—and the predictor variables. Errors are clustered at the analyst level in all models.

We utilize two main analytical specifications in our study, each corresponding to different research questions. The first specification addresses our first research question by focusing on the error difference (the difference between the prediction errors of financial analysts and the RF algorithm) as the dependent variable. This model includes measures of analyst experience, control variables, and fixed effects. For this specification, it is crucial to note that the RF model's training data includes only the firm's financial information and broader macroeconomic indicators. This approach examines the relative predictive accuracy of financial analysts compared to the RF algorithm, evaluating the impact of both firm-specific and general experience, as well as the role of environmental volatility, on individual accuracy.

The second specification is designed to explore our second and third research questions. It focuses on regressing RF error against the independent variables and control variables. This analysis assesses how firm-specific and general experience influence the performance of the RF algorithm. Additionally, this specification explores how the impact of these experiences is conditioned by the levels of volatility present within the decision-making environment.

Results

We start our analysis by comparing the average accuracy of analysts to that of the RF algorithm trained exclusively on firm data and macroeconomic variables. Table 3.1 presents the results of a T-test comparing the average error of financial analysts and the first RF algorithm. The p-value for the left-tailed test is 0, indicating that the predictive error of the RF algorithm is significantly smaller than that of financial analysts. This supports the proposition that the RF algorithm generally outperforms individual analysts in prediction accuracy, even without any inputs from humans.

Table 3.1 - *T-test comparing average estimate error of analysts and RF*

	Mean	SD
RF	0.028	0.234
Analyst	0.043	0.368
Difference	-0.015	
p-value	0	

Table 3.2 provides descriptive statistics and correlation matrix.

Table 3.2 - *Summary statistics and correlations*

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9
1.	*Error difference*	78.34	725.82	- 2,292.05	5,127.90									
2.	*RF error*	260.78	2274.11	0.00	641,465.50	.24								
3.	*Analyst's firm-specific experience*	2.68	2.70	0.00	16.00	-.01	-.03							
4.	*Analyst's general experience*	5.46	3.65	0.00	16.00	-.03	-.02	.57						
5.	*Volatility*	0.77	0.28	0.07	7.75	.14	.17	-.06	-.01					
6.	*N. of analysts following the firm*	13.96	9.29	0.00	48.00	.01	-.08	.20	-.02	-.21				
7.	*Forecast age*	124.69	86.31	- 30.00	358.00	.06	.03	.09	.06	-.02	-07			
8.	*Top size bank*	0.49	0.50	0.00	1.00	.01	-.01	.11	.14	.01	-08	.03		
9.	*Number of firms covered*	68.73	58.08	0.00	739.00	.01	.02	.14	.17	.01	.03	.04	-.08	
10.	*Number of industries covered*	5.72	4.21	0.00	46.00	-.01	.02	.04	.11	.03	-.13	-.02	-.21	.53

Table 3.3 presents the estimates of the effect of analyst's *firm-specific* and *general experience* on *error difference* and *RF error*. We conduct distinct regressions to estimate the effects of firm-specific and general experience measures. This approach is taken due to the correlation between these two measures (0.57) and combining them within a single regression would introduce multicollinearity.

Columns 1 and 3 of Table 3.3 reveal the effects of firm-specific experience and general experience on individual accuracy relative to AI. The coefficient for firm-specific experience is significantly positive, indicating that greater firm-specific experience is associated with higher predictive errors. In contrast, the coefficient for general experience is negative but not significant. These findings indicate that while accumulating firm-specific experience is associated with higher prediction errors, similar effect is not observed in case of general experience. In addition, the coefficient for volatility is positive and significant in both models. This means that higher environmental volatility is associated with higher prediction errors by individuals compared to AI models.

Table 3.3 - *Regression Analysis*

Dependent variable:	*Error difference*				*RF error*			
VARIABLES	1	2	3	4	5	6	7	8
Analyst's firm-specific exp.	2.69***	8.96***			1.45	50.34***		
	(0.64)	(2.09)			(1.27)	(17.81)		
Analyst's general exp.			-0.95	9.89***			-10.24***	47.01*
			(0.78)	(1.74)			(2.01)	(27.67)
Volatility	344.55***	367.67***	345.77***	421.94***	1,330.55***	1,510.85***	1,336.26***	1,738.30***
	(14.89)	(16.32)	(14.91)	(19.85)	(220.02)	(280.06)	(220.50)	(407.11)
Analyst's firm exp. X *Volatility*		-8.36***				-65.19***		
		(3.09)				(24.19)		
Analyst's general exp. X *Volatility*				-13.93***				-73.52**
				(2.36)				(37.00)
N. of analysts following the firm	7.72***	7.72***	7.49***	7.60***	-11.19***	-11.16***	-11.91***	-11.32***
	(0.40)	(0.40)	(0.41)	(0.41)	(1.27)	(1.27)	(1.31)	(1.25)
N. of firms covered	0.23***	0.23***	0.25***	0.25***	0.16	0.15	0.27	0.26
	(0.09)	(0.09)	(0.09)	(0.09)	(0.24)	(0.24)	(0.24)	(0.24)
N. of industries covered	-1.53	-1.52	-1.50	-1.43	-3.35	-3.25	-3.14	-2.74
	(1.09)	(1.09)	(1.10)	(1.09)	(2.68)	(2.65)	(2.67)	(2.58)
Top size bank	2.41	2.75	8.75	9.16	-22.19	-19.55	6.14	8.32
	(7.62)	(7.62)	(7.92)	(7.88)	(13.61)	(13.42)	(13.82)	(13.71)
Forecast age	0.54***	0.54***	0.55***	0.55***	1.08***	1.08***	1.10***	1.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)
Constant	-377.87***	-395.85***	-368.78***	-430.19***	-730.61***	-870.83***	-690.11***	-1,014.27***
	(14.08)	(14.82)	(14.15)	(17.10)	(152.36)	(199.13)	(149.17)	(299.55)
R-squared	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	660,379							

Columns 2 and 4 of Table 3.3 examine the interaction between experience metrics and level of environmental volatility. Both interaction terms are negative and significant, showing that while firm-specific experience generally correlates with reduced predictive performance, its benefits increase under higher volatility. This suggests that firm-specific experience becomes particularly valuable in volatile conditions. Moreover, even though general experience does not directly improve predictive accuracy, it helps mitigate the negative impact of volatility. Thus, greater volatility enhances the value of both types of experience, narrowing the accuracy gap between analysts and the RF algorithm.

Next, we explore the impact of individual experience on the performance of the second RF algorithm that was trained on inputs from analysts together with firm and macroeconomic data (Columns 5-8 of Table 3.3). The dependent variable in these models is the RF algorithm's predictive error. Columns 5 and 7 show the direct effects of experience metrics on RF accuracy. Firm-specific experience does not significantly influence algorithm accuracy ($p > 0.1$), while increase in general experience is associated with significant improvement of algorithm's predictive performance ($p < 0.01$). The significant positive coefficient for environmental volatility indicates that the RF algorithm's performance deteriorates under volatile conditions. These results suggest that integration of inputs from individuals with high general experience is associated with significant enhancement of AI accuracy, while inputs from those with firm-specific experience do not have the same effect.

Columns 6 and 8 present the interaction effects between experience metrics and volatility. Both coefficients are negative and significant ($p < 0.01$), indicating that the experience of individuals providing inputs to the RF algorithm mitigates the adverse impact of volatility. The accumulation of both firm-specific and general experience is linked to improvement of predictive accuracy of the algorithm in volatile environments.

The economic significance of these findings is substantial. The average error of the algorithm in our sample is 260.78. The interaction coefficient for firm experience with volatility is -65.19, implying around 25% reduction in average error with a one-point increase in firm experience, all else constant. Similarly, for general experience, this reduction is around 28%.

To contextualize the magnitude of these coefficients, consider Apple's earnings report for Q4 of 2022. When a firm's earnings surpass or fall short of analyst expectations, it tends to significantly impact subsequent stock performance, potentially resulting in outperforming or underperforming relative to the market (Kinney et al., 2002). In this case, Apple's EPS for Q4 2022 exceeded analysts' consensus expectation by 2 cents, leading to over a 1% rise in Apple shares (Leswing, 2022). Adjusting this 2-cent difference relative to the stock price at the previous month's end and scaling it by 10,000 (for comparability with our measure), yields a value of 1.44. This minor 1.44 discrepancy had a substantial effect on stock price performance. Given that our study finds an average improvement in algorithm accuracy that is significantly larger than the 1.44 discrepancy seen in Apple's case, the potential real-world economic impact of enhancing predictive accuracy is substantial.

In summary, these results provide interesting insights. Increase in domain-specific experience is associated in lower predictive performance of individuals relative to AI. Increase in general experience is associated with higher predictive performance of AI. Depending on type of experience, these are somewhat paradoxical results: while experience accumulation might affect negatively the performance of humans, it affects positively AI models that receive inputs from these humans. In addition, as environmental volatility increases, accumulation of both types of experience mitigates the negative impact of volatility, both in case of human predictors and AI that receives inputs from them.

Robustness checks

To confirm the robustness of our main findings, we undertook a series of additional analyses. The tables reporting the robustness checks are available in the Appendix.

First, we incorporate a broader set of control variables. These additional controls are designed to capture various dimensions of analyst experience more comprehensively. Specifically, we introduced a measure for the cumulative number of estimates made by analysts within their specific industry, categorized at the 4-digit Standard Industrial Classification (SIC) level. This measure aims to account for the depth of the analyst's familiarity with industry trends. Furthermore, we considered the average error and the standard deviation of these errors over the last five years (from prediction time) for each analyst. The average error provides insight into the overall accuracy of an analyst's predictions, while the standard deviation captures the consistency of their prediction performance over time. By incorporating these measures, we sought to have a more wholistic view on various aspects of analysts' job that can provide a more wholistic view on the dimensions of their domain-specific and general experience.

The results, detailed in Table 3.B1 and 3.B5 of the Appendix, show that the sign and the significance of main coefficients remains unchanged because of addition of these controls, indicating that these results are not driven by industry experience of the analysts and their past forecasting performance.

Second, in our primary analysis, we clustered standard errors by analyst. To test the robustness of our findings against the assumptions that estimation errors might be driven by grouping at firm or investment bank level, we conducted further analyses with standard errors clustered at these levels. This approach allows us to control for shared biases within banks and firm-specific effects that might influence predictions across analysts, ensuring our results are not sensitive to the initial choice of clustering method. Results reported in Tables 3.B2, 3.B3, 3.B6, and 3.B7 of the Appendix show that the results are not determined by the choice of clustering method and are consistent across various clustering approaches.

Thirdly, we refined our analysis by winsorizing the volatility measure at the 1% and 99% levels. This step was taken to minimize the impact of outliers, ensuring a more accurate reflection of volatility's effect on our results. The robustness of our findings after this adjustment is documented in Tables 3.B4 and 3.B8 of the Appendix, indicating that the main specification results are not dependent on outliers in the volatility measure.

Fourth, to further account for the potential impact of outliers on the predictive performance of the Random Forest (RF) model, we applied the logarithmic transformation to the dependent variable, the RF error. This adjustment was made to mitigate the influence of outliers on our results. The findings, as detailed in Table 3.B9 of the Appendix, show that the results in the main specification are not dependent on the outliers in the dependent variable.

Additional analysis

To further examine the impact of analyst experience on the accuracy of RF predictions, we visualized the relationship between the log of RF error and varying levels of uncertainty. Figures 2.1 and 2.2 plot firm-specific and general experience, respectively, on the x-axis against the log of RF error on the y-axis, under three levels of volatility: average volatility, average minus 1 standard deviation, and average plus 1 standard deviation.

Figure 2.1

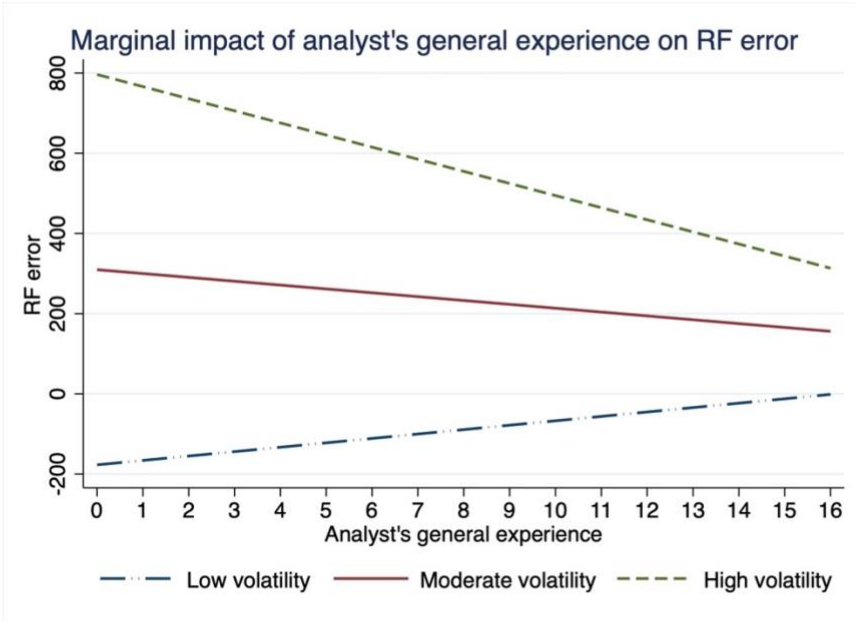
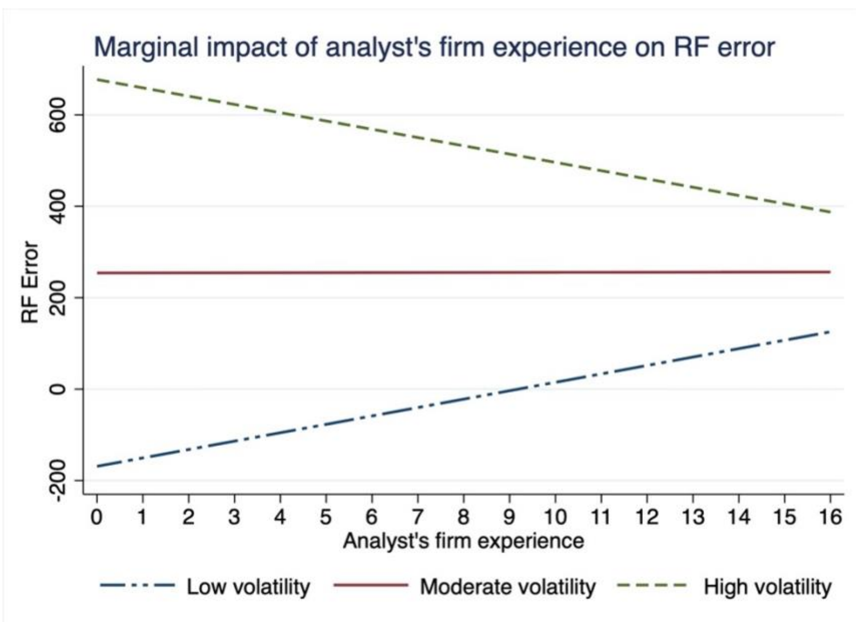


Figure 2.2



The results highlight a nuanced impact of individual experience on the predictive performance of the RF algorithm. When volatility is low, an increase in both firm-specific and general experience is associated with an increase in the RF's predictive error. This finding suggests that under stable and predictable conditions, when volatility is minimal, predictive algorithms might already exhibit optimal performance. Consequently, the supplementary insights derived from human experience do not necessarily improve accuracy and could potentially lower the performance of these algorithms.

At moderate levels of volatility, the graphs indicate a minimal impact of firm-specific experience and a marginal impact of general experience on the predictive error of the algorithm. This generally flat trend suggests that neither general experience nor firm-specific experience significantly affects AI's predictive performance under these conditions. It appears that the AI is adequately versatile to undertake the task, or it might be incapable of extracting any supplementary insights from human experience that could be utilized to enhance its predictive efficiency under the condition of moderate level of volatility.

Interestingly, at higher levels of volatility, an increase in both firm-specific and general experience is associated with a decrease in RF error. This finding indicates that in a volatile environment, individual experience becomes a valuable asset for the RF algorithm. The rich insights drawn from years of handling diverse and complex situations provide a crucial edge to AI models, helping them navigate the ambiguity of such environments.

These visualized results underscore the importance of considering the context in which AI and human experience interact. While human experience might not always enhance AI performance in stable environments, it becomes indispensable in more volatile settings. This dynamic interplay highlights the necessity of integrating varied types of human experience into AI training processes to optimize predictive accuracy, particularly when facing uncertain and rapidly changing conditions.

Discussion and Conclusion

This study investigates the complex interplay between human experience and AI, focusing on how domain-specific and general human experience influence both individual predictive performance relative to AI and the performance of AI models augmented with human inputs. We also explore the moderating role of environmental volatility in this context. The findings underscore the context-dependent nature of the effect of human expertise in AI-augmented decision-making environments, particularly in volatile conditions.

Implications for strategic human capital literature

The advent of AI, catalyzed by the fusion of increasing computational resources, growing amount of data and the evolution of algorithms (Agrawal et al., 2018), is transforming strategic management across various sectors. This transformation is compelling firms to integrate AI into their organizational processes, intensifying concerns about the potential redundancy and obsolescence of human roles in areas traditionally dominated by human experts (e.g. Autor, 2015; Felten et al., 2021; Frey & Osborne, 2017; Raisch & Krakowski, 2021). Our study contributes to this ongoing debate about the possibility of replacing human labor with AI.

First, we advance the discourse on job automation by highlighting its context embedded nature. Our findings reveal that the feasibility and effectiveness of automation are contingent upon both the level of human expertise and the degree of environmental volatility. These critical boundary conditions, often overlooked by existing literature, have profound implications for both strategic human capital research and practice. By elucidating how environmental volatility moderates the effectiveness of human-AI integration, our research provides a theoretical foundation for understanding when and how firms should combine human capital and AI to enhance their predictive capabilities. This intricate understanding not only addresses the ongoing debate about the role of human expertise in an AI-driven era but also offers practical implications for firms seeking to optimize their strategic decision-making processes in varying environmental conditions.

In addition, our study contributes to this debate by showing that despite the relative superiority of AI, human expertise is still relevant and can be used to further improve AI's predictive performance. Despite this, as AI continues to advance, humans might increasingly need to undergo reskilling – a process where they will need to develop new skills to stay relevant in the evolving labor market. The new roles taken by humans are expected to be the ones that require interpersonal interactions, tacit knowledge, social skills, and creativity, where humans will have competitive advantage over AI (Agrawal et al., 2018; Choudhury et al., 2020; Yilmaz et al., 2023). For instance, in the context of this study, the role of financial analysts is likely to evolve with AI adoption, exemplifying a broader trend in human-AI collaboration. This evolution reflects a strategic division of labor (Puranam 2021) where AI handles quantitative analysis, freeing analysts to focus on high-value activities that leverage uniquely human skills. These activities include cultivating relationships with firm management (Brauer & Wiersema, 2018), interpreting qualitative information, and applying tacit industry knowledge - tasks where human judgment and interpersonal skills remain critical for generating strategic insights.

This evolving landscape of human-AI collaboration necessitates a shift in firms' talent acquisition strategies. Organizations now need to focus on recruiting and developing individuals who possess not only technical proficiency but also the ability to effectively interface with AI systems (Choudhury et al., 2020; Krakowski et al., 2022). These sought-after talents should bring "human touch" (Raisch & Krakowski, 2021) to AI-augmented environments by demonstrating strong interpersonal skills, adaptability, and the capacity for critical thinking. Moreover, firms must prioritize acquiring and nurturing human capital that can provide expertise and insights that enhance AI performance, particularly in volatile contexts. This strategic approach to talent management is crucial for organizations aiming to create and sustain competitive advantages in an increasingly AI-driven business world.

Implications for Human-AI capital complementarity literature

Our study contributes to the growing body of literature on integrating humans and AI to achieve improved performance (Choudhary et al., 2023; Choudhury et al., 2020; Krakowski et al., 2022; Puranam, 2021). Building on existing research, we highlight the importance of human experience in human-AI complementarities within a novel context. We demonstrate that various dimensions of human experience are crucial for maximizing the complementarity between humans and AI and that this impact is influenced by external factors such as environmental volatility.

Importantly, we contribute to strategic management theory by inverting the typical perspective on human-AI integration. While most strategy studies explore how AI can augment human decision-making, our research unveils a reciprocal relationship: human capital can significantly enhance AI performance by integrating experiential insights into strategic decision-making processes. This approach presents a novel method for enhancing organizational predictive capabilities, thereby offering a new lens through which to view the strategic value of human capital in an AI-driven era.

This theoretical contribution challenges conventional wisdom about the role of human expertise in AI-augmented environments and opens new avenues for strategic human capital research. By demonstrating how human insights can be systematically leveraged to improve AI-driven strategic decisions, we provide a more nuanced understanding of human-AI complementarity. This perspective enriches our theoretical understanding of how firms can combine human and artificial intelligence to create unique, hard-to-imitate capabilities that drive competitive advantage, by illustrating how the integration of human experience with AI can form a complex, socially embedded resource.

Implications for competitive strategy literature

Our study advances the understanding of competitive advantage in AI-augmented contexts by revealing the complex interplay between human expertise, AI capabilities, and environmental volatility. We add to the resource-based view of the firm (J. Barney, 1991) by demonstrating that the integration of human expertise and AI can constitute a valuable, rare, and difficult-to-imitate resource. Our results validate the proposition by Krakowski et al. (2022) that AI adoption alone may erode competitive advantage, as AI itself is not an inimitable resource. However, through human-AI complementarity, a new source of hard-to-imitate resources is created. This synergy suggests a pathway to developing distinctive capabilities that may lead to sustained competitive advantage in AI-augmented contexts.

What is more important, our findings reveal a context-dependent framework for obtaining competitive advantage. In stable environments, increased human experience is associated with higher AI error, contradicting traditional learning curve hypotheses. This phenomenon extends our understanding of core rigidities (Leonard-Barton, 1992) into the domain of human-AI interaction, suggesting that deeply ingrained expertise can potentially impede AI performance under certain conditions. In moderately volatile contexts, we observe a 'zone of indifference' where the effect of experience on AI performance is minimal, suggesting AI's inherent capabilities may suffice. However, in highly volatile environments, both types of human experience significantly enhance AI performance. This volatility-dependent relationship prompts a reconsideration of experience as a strategic resource, challenging the notion of sustained competitive advantage based solely on accumulated experience (J. Barney, 1991). Our findings point towards a more nuanced conceptualization of complementarities between human and artificial intelligence in strategic decision-making processes, emphasizing the critical role of environmental context in determining the value of human experience in AI-augmented strategic decision-making. This framework has important practical implications as firms can use it to identify what kind of human capital they need to rely on and complement with AI to sustain competitive advantage in long run.

Implications for organizational learning literature

Our study contributes to the ongoing discourse about AI's impact on organizational learning dynamics, particularly addressing concerns about learning myopia (Balasubramanian, Ye, and Xu 2022) and potential human "deskilling" (Raisch & Krakowski, 2021). Building on our findings, we propose an extension to organizational learning theory in AI-augmented contexts. Our results suggest that the integration of human expertise with AI can potentially enhance organizational learning, particularly in volatile environments. This insight points towards a dual-learning model where machine learning capabilities and human experiential learning might complement each other. Human experts may offer crucial strategic interpretation and contextual understanding, especially in highly uncertain situations, which complements AI's data processing capabilities. This perspective opens new avenues for exploring how organizations can potentially maintain and enhance their learning capabilities in an increasingly AI-driven business landscape, balancing the strengths of both AI and human learning processes.

Limitations

We acknowledge several limitations of this paper. First, our analysis is situated within a context enriched with historical, codified data, ideal for training AI algorithms. However, such data abundance might not be universally accessible, potentially altering the dynamics and effectiveness of AI and its interaction with human experience in different settings.

Second, our research utilizes the Random Forest algorithm, the benefits of which we discuss in methodology section. However, with current rate of AI technology development, introduction of newer generation of algorithms could unveil enhanced performance and possibly affect the intricacies of how individual experience complements AI. Additionally, the tests we conducted can only provide indirect evidence of RF learning from individuals and their experience, yet it does not help identify the exact mechanisms through which such forms of experience influence machine learning in the RF. To mitigate these limitations, future studies could consider a varying set of contexts with heterogeneous amounts of historical data and use various AI algorithms to deepen our understanding of the complexity of the interplay between individuals and AI.

Conclusion

In conclusion, this study underscores the importance of human-AI collaboration in achieving competitive advantages, demonstrating that the interplay between human experience and AI is context dependent. Our findings challenge the assumption of AI's superiority over human expertise and show the importance of relying on human experience, advocating for a more integrated approach where the strengths of both human judgment and AI are leveraged to achieve superior predictive performance and sustained competitive advantage. Our nuanced understanding suggests that firms should adopt a strategic approach to integrating human expertise with AI systems, moving beyond simple reskilling programs. Organizations should develop tailored talent management strategies that identify and nurture key human competencies that complement AI capabilities. This could involve creating specialized roles or cross-functional teams where human judgment and AI-driven insights are combined to tackle complex, high-stakes decisions. Additionally, firms operating in volatile environments should prioritize the development of adaptive frameworks that allow for dynamic interaction between human experts and AI, ensuring that both can effectively respond to rapid changes and uncertainties.

This study emphasizes the contextual nature of human-AI interactions, particularly the overlooked boundary conditions of environmental volatility. Nevertheless, other external factors can influence human-AI synergies, which warrant further investigation. We hope this study paves the way for more in-depth analyses of these conditions.

The findings in Chapter 2 show that while artificial intelligence can outperform analysts in predictive accuracy on average, human experience continues to play a critical role, particularly in complex or volatile environments. This suggests that rather than replacing human capital, AI functions as a complementary force - augmenting expertise rather than substituting for it. However, these results are based on task-level comparisons between analysts and algorithms, and do not reflect how organizations themselves adopt and integrate AI technologies into their decision-making processes.

Chapter 3 builds on this by shifting the focus to the organizational level, examining how AI adoption within firms, specifically within investment banks, affects the performance of their analysts. It investigates whether the presence of AI tools within an organization changes not only the average quality of forecasts, but also the role of analyst experience in shaping that performance. In doing so, Chapter 3 addresses the broader question of how AI reshapes the value and structure of human capital in knowledge-intensive work.

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Chapter 4 - AI Adoption and the Evolving Value of Human Experience

Abstract

This chapter addresses the following research question: *"How does AI adoption transform organizational predictive capabilities, and what role does human experience play in this transformation?"* It explores how artificial intelligence (AI) adoption transforms firms' predictive capabilities and the role of human experience in this process. Using data from investment banks' earnings forecasts, the study shows that AI adoption significantly improves predictive capabilities of organizations. However, the extent of this improvement depends on the composition of human capital. General experience - broad and cross-contextual, enhances the benefits of AI, while domain-specific experience, deep and narrowly focused, diminishes them. These findings suggest that AI not only augments or substitutes human judgment at the task level but also transforms the value of different types of expertise within organizations. The study offers insights into how firms can align talent strategies with AI investments to unlock competitive advantage through improved forecasting and decision-making.

Introduction

Artificial Intelligence (AI) is experiencing rapid growth, driven by increasing investment and widespread adoption across industries (Furman & Seamans, 2019). It is widely recognized as a general-purpose technology with the potential to enhance both productivity and creativity (Agrawal et al., 2019, 2022). AI has been shown to complement human capital (Choudhury et al., 2020; Krakowski et al., 2022), and potentially even substitute it (Balasubramanian et al., 2022). At the organizational level, it has been shown that firms investing in AI tend to experience higher growth in sales, employment, and market valuation - effects primarily attributed to product innovation (Babina et al., 2024).

Despite its versatility and wide range of applications, AI is fundamentally a prediction technology designed to generate estimates about unknown outcomes based on historical data (Agrawal et al., 2018). As Babina et al. put it, “as a prediction technology, AI allows firms to learn better and faster from vast quantities of data, with the potential to significantly improve business decision-making” (2024, p. 1). Even Large Language Models (LLMs), known for their ability to generate creative solutions (Boussioux et al., 2024) and evaluate strategic decisions (Doshi et al., 2025), ultimately operate on a predictive process: they estimate the most relevant next output based on prior context (Chang et al., 2023).

Yet, despite significant progress in research on AI and its organizational implications, the question of how AI influences organizations’ predictive capabilities remains open. This gap is particularly important given that predictive capability is critical to organizational success: only by making more accurate predictions can organizations improve strategic decision-making and gain a sustained competitive advantage (Barney 1986; Durand 2003; Eisenhardt and Martin 2000; Makadok and Walker 2000).

While AI may enhance forecasting performance, it is not the only source of predictive capability. Prior to the advent and development of AI, human capital and its accumulated expertise were the "traditional" source of forecasts (Durand, 2003). What is more important, as experienced professionals are assumed to have deeper understanding of contexts, better pattern awareness and more refined judgment, expertise and experience accumulation have been shown to be associated with increased forecasting performance (Clement, 1999; Mikhail et al., 1997). However, there is also contradictory evidence that experience accumulation might have also negative effect on performance (e.g. Gaba et al., 2022).

In addition, human experience has also been demonstrated to have effect on successful implementation of AI. There is a body of literature analyzing the complementarities between human capital and AI (e.g. Choudhury et al., 2020; Krakowski et al., 2022), and how the successful combination of these elements is dependent on the level and type of human expertise. For example, successful implementation of AI systems has been shown to be associated with higher levels of vintage-specific skills of human capital – "the skills and knowledge accumulated through prior familiarity of tasks with the technology" (Choudhury et al., 2020, p. 1383).

The second chapter of this dissertation showed that human experience has the potential to augment the performance of AI at the task level, but it remains unclear how this complementarity evolves when AI is embedded in organizational process. Extant research has focused on isolated comparisons of substitutability and complementarity between human capital and AI (e.g. Choudhury et al., 2020; Krakowski et al., 2022). However, AI is rarely deployed in isolation. In practice, it is embedded into organizational processes. Thus, the impact of AI adoption may go beyond simply substituting or complementing human capital and might be associated with fundamental shifts in how organizations utilize and leverage human expertise.

To address these possible changes, in this chapter I shift from task-level analysis and comparison of human experts and AI models and look at this from the viewpoint of firm level AI adoption. More specifically, I investigate whether firms with higher levels of AI adoption achieve lower forecast errors, and more importantly, what is the role of human experience in improvement of organizational predictive capabilities through incorporation of AI tools. By doing so, this chapter seeks to provide a more nuanced understanding of AI's strategic role - not simply as a tool for substituting or complementing human expertise, but as a catalyst for reshaping the structure and value of human expertise within organizations.

I use the context of investment banks, where financial analysts are tasked with forecasting the earnings of publicly listed companies. This setting offers a unique opportunity to directly evaluate the predictive output of organizations and examine how the increasing adoption of AI influences the quality of these forecasts. Although these earnings estimates do not directly concern firms' strategic choices, they serve as a proxy for the process of forecasting the external environments - an essential input into strategic decision-making.

Through integration of data on analyst forecasts of earnings per share (EPS) of publicly listed companies with LinkedIn profiles data to measure organizational AI adoption, the findings of this study reveal that AI significantly improves predictive accuracy in knowledge-intensive sectors, particularly investment banking. Hence, AI adoption is associated with improved predictive capabilities at the organizational level, and it can become a new source of competitive advantage if deployed correctly and paired with human expertise.

Moreover, the results indicate that the type of human capital present within organizations substantially influences the extent of the benefits derived from AI. Specifically, general human capital—characterized by broad experience—amplifies the predictive advantages offered by AI adoption. In contrast, firm-specific human capital, which involves deep expertise within a particular task or organization, appears to limit these predictive benefits.

These findings contribute to the ongoing discussion on the implications of AI adoption for organizational performance (Babina et al., 2024), as well as to the debate on the complementarity and substitutability between human capital and AI (e.g. Allen & Choudhury, 2022; Choudhury et al., 2020). By clearly outlining how the benefits of AI adoption vary depending on the types of human expertise, the study highlights the nuanced and contingent nature of AI-human capital relationships.

These insights open up a discussion on the best strategies for adopting AI, depending on the characteristics of the human capital embedded within organizations. Furthermore, the findings have important implications for the evolving role of human capital: narrow, domain-specific, and deep expertise appears to be becoming increasingly less relevant in the age of AI, as this technology excels at deriving insights traditionally associated with such expertise. In contrast, breadth of experience seems to complement AI and enables organizations to fully harness its potential benefits.

Finally, these findings have important implications for how organizations should approach talent acquisition—suggesting that attracting broadly experienced individuals may be more beneficial in maximizing the returns from AI adoption.

Theoretical Background

Artificial Intelligence (AI) is recognized as a general purpose technology (Agrawal et al., 2019, 2022) with the potential of disrupting businesses across various industries (Felten et al., 2021). As such, AI is increasingly viewed as a source of firm-level competitive advantage (Krakowski et al., 2022). Moreover, a growing body of literature highlights the fact that it can increasingly perform task that were traditionally performed exclusively by human capital, especially in knowledge-intensive contexts (Acemoglu et al., 2022; Autor, 2015; Felten et al., 2023).

Recent advancements in this technology have drawn increasing scholarly interest, particularly around the question of whether AI will substitute or complement human capital. Depending on the context and the nature of task that is being performed by human capital and AI, this body of literature has document potential for both outcomes (Allen & Choudhury, 2022; Balasubramanian et al., 2022; Choudhury et al., 2020). These outcomes vary based on factors such as context complexity and the extent to which human judgment, social cognition, tacit knowledge or intuition is required (Raisch & Krakowski, 2021; Yilmaz et al., 2023).

Despite its wide range of applications, AI is fundamentally a prediction technology that aims to generate estimates based on historical data. As Agrawal et al. put it, "the new wave of artificial intelligence does not actually bring us intelligence but instead a critical component of intelligence – prediction" (Agrawal et al., 2018, p. 2). Extant research has analyzed the feasibility of using AI for the purpose of obtaining better predictions. For example, it has been demonstrated that AI can outperform humans in the context of analysis of loan applications and default prediction (Brynjolfsson & Mitchell, 2017). Similarly, in the field of medical diagnostics, AI has achieved high accuracy in detecting conditions such as skin cancer from medical images, often matching or surpassing the diagnostic performance of experienced professionals (Esteva et al., 2017). AI has also been shown to outperform human capital in investment decision-making on average (Blohm et al., 2020). Notably, only highly experienced humans who managed to suppress their cognitive biases (Tversky & Kahneman, 1974) managed to outperform AI.

Even though AI draws increasingly larger interest in strategy research, most of the studies are comparing the performance of AI to that of human capital at the task level. However, AI is increasingly being embedded into various organizational processes and workflows (Agrawal et al., 2022). Nevertheless, despite this widespread adoption, there is a relative scarcity of studies examining the broader implications of AI at the firm level. One study addressing this issue has shown that increased adoption of AI by organizations is associated with higher growth in sales, employment, and market valuation (Babina et al., 2024). The effects are primarily due to increased product innovation stemming from larger adoption of AI.

Despite growing scholarly interest in this area, we still lack a more complete understanding of what are the organizational level implications of AI adoption, particularly in the context of firms' predictive capabilities. From a strategic perspective, predictive capabilities are essential, as they allow firms to anticipate future trends in the external environments and better align their strategic choices (Durand, 2003; Eisenhardt & Martin, 2000; Makadok & Walker, 2000). As such, from the perspective of resource based view of the firms, predictive capabilities can act as a core competence of the firms which could potentially lead to sustained competitive advantage through superior strategic decisions (Barney, 1986).

Within the context of the task of forecasting, even the most basic quantitative models have long been shown to outperform human judgment (Meehl, 1954). As AI technologies have advanced, modern systems now demonstrate a clear competitive edge over human decision-makers (Agrawal et al., 2018). The predictive superiority of AI has been evidenced across a range of domains, including judicial bail decisions (Kleinberg et al., 2017) and the prediction of surgery durations in medical settings (Ibrahim & Kim, 2019). In addition to outperforming human judgment, AI has also been shown to augment and complement human decision-making (Allen &

Choudhury, 2022; Choudhury et al., 2020; Krakowski et al., 2022). Moreover, AI adoption has been linked to improved firm-level outcomes such as innovation and growth (Babina et al., 2024).

Building on these findings, I posit that AI adoption will be positively associated with firm-level predictive performance. Specifically, I hypothesize that as firms increase their investment in and adoption of AI, their forecasting errors will decline.

Hypothesis H1: *Higher levels of AI adoption within firms will be associated with lower average forecasting error.*

Prior to the introduction of AI, organizations historically relied primarily on human capital and individual judgment to come up with forecasts. One crucial aspect of human capital is its experience. Indeed, extant literature has documented that accumulation of experience is associated with better task performance (e.g. Argote et al., 2021; Reagans et al., 2005). The benefits of experience have also been shown within the context of forecasting: humans tend to have lower forecasting errors as they accumulate experience (Clement, 1999; Mikhail et al., 1997). However, experience can also have negative impact on forecasting performance. First, the process of learning from experience is not straightforward, and it is not guaranteed that experiential learning will always yield better performance (March, 2010). In addition, since cognitive biases are very likely to be present within context of forecasting (Tversky & Kahneman, 1974), accumulation of experience might manifest in the amplification of biases rather than mitigation (Gaba et al., 2022).

Given the ambiguity surrounding the role of experience and its effect on predictive performance, organizations adopting AI might reconsider how human experience is being leveraged. For example, the adoption of AI might be used to mitigate the amplification of human biases stemming from accumulation of experience, or AI might be used to further enhance the strengths of human insights derived from experience.

In addition, experience might affect the extent to which AI adoption improves predictive capabilities. For example, Allen and Choudhury (Allen & Choudhury, 2022) found that individuals with moderate levels of domain-specific experience are best positioned to fully leverage algorithmic tools. Similarly, individuals possessing higher levels of vintage-specific skills - skills and knowledge acquired through prior exposure to similar tasks or technologies - have been shown to collaborate more effectively with AI systems, leading to greater human-AI complementarity and improved performance (Choudhury et al., 2020). Moreover, within the context of the game of chess, Krakowski et al. (2022) show that human-machine capabilities are unrelated, or even negatively related, to humans' traditional chess playing capabilities. Hence, increased domain experience might have a negative impact on human-AI complementarity.

Moreover, it is important to differentiate between types of experiences that humans accumulate. The tension between having broad experience across different areas and deep expertise in a specific domain has been a longstanding topic in strategic management, since both can have their potential benefits. Deep expertise in narrowly defined domains is often linked to higher productivity in stable and structured environments, where domain-specific knowledge and finely tuned problem-solving skills offer a clear advantage (e.g. Ferguson & Hasan, 2013; Jain & Mitchell, 2022). However, this kind of deep expertise involves important trade-offs: individuals with narrow specialization may find it difficult to apply their knowledge across domains, are more vulnerable to disruption from new technologies (Marx et al., 2009), and can be resistant to organizational change that challenges their established skill set (Leonard-Barton, 1992). Moreover, AI excels in the same structured and well-defined settings where deep expertise is required, given its strength in recognizing patterns and optimizing decisions based on large volumes of historical data (Agrawal et al., 2018; Felten et al., 2021).

In contrast, individuals with broader skill sets draw on diverse knowledge across domains, enabling them to solve problems creatively, coordinate effectively, and contribute to strategic decisions in rapidly changing environments (Byun et al., 2018). Their flexibility allows them to shift between roles and functions, making them especially valuable in sectors undergoing technological transformation (Byun & Raffiee, 2023).

Taken together, these considerations suggest that the effectiveness of AI adoption may depend not only on the presence of human expertise, but also on the type of experience individuals bring. Since AI performs best in structured and narrowly defined settings, it may overlap with the strengths of deeply specialized individuals, potentially limiting complementarity and even creating redundancy. In contrast, employees with broad experience are more likely to contribute contextual understanding, flexibility, and integrative thinking that complements AI's predictive capabilities. Therefore, I propose that AI adoption will yield greater improvements in forecasting accuracy when paired with individuals possessing broad experience across domains, whereas its benefits may be more limited when paired with narrowly focused, domain-specific expertise. Hence, I suggest the following hypotheses:

Hypothesis H2: *General human capital experience positively moderates the effectiveness of organizational AI adoption in lowering forecast errors, whereas domain-specific human capital experience negatively moderates this relationship.*

Data And Methods

Research context

For this study, I focus on the context of investment banks and the earnings forecasts produced by their financial analysts for publicly listed firms. The investment banking industry provides an ideal setting for testing the hypotheses for several reasons. First, it offers a unique opportunity to longitudinally track forecasts over time - an advantage rarely available in other organizational contexts. Second, the setting is particularly well-suited for examining the role of experience in the context of AI adoption, as financial analysts represent a highly heterogeneous pool of human capital with varying levels and types of experience (Brauer & Wiersema, 2018). Third, the investment banking industry is known for its substantial investment in AI technologies (KPMG, 2023), making it a relevant and timely context for studying the intersection of human expertise and algorithmic decision-making.

Data

I obtain financial analysts' earnings forecasts from the Institutional Brokers' Estimate System (I/B/E/S) database, which provides detailed and time-stamped analyst-level data. Measuring organizational-level AI adoption presents a methodological challenge (Babina et al., 2024). To address it, I follow the approach proposed by Babina et al. (2024), estimating AI adoption as the annual ratio of AI-related employees to the total number of employees within each investment bank. To construct the measure of AI adoption, I merge the I/B/E/S dataset with LinkedIn data to obtain information on the human capital employed by each investment bank. Further details on calculation of the measure are provided in the Appendix.

I aggregate the estimates at the investment bank level. More specifically, for each investment bank, I calculate the average earnings forecast for a given covered firm - that is, the firm for which the analysts are making predictions, by aggregating the forecasts of all analysts employed by that bank within a given year. The final dataset consists of 157,015 aggregated forecasts issued by 90 investment banks for 7,084 publicly listed companies over the period from 2005 to 2016.

Dependent Variable

To evaluate the impact of AI adoption on organizational predictive capability, I use forecast error as the primary outcome variable. Specifically, I use *Average error* as the dependent variable, calculated as the mean of individual forecast errors at the investment bank–firm–year level. Individual errors are measured as the absolute difference between the analyst's earnings per share (EPS) forecast for a firm and the actual realized EPS. To ensure comparability of forecast errors across firms of varying sizes, I scale this difference by the firm's stock price at the beginning of the forecast year. Taking the absolute value of the error ensures that positive and negative forecast errors do not offset each other in the regressions.

Independent Variables

As mentioned earlier, I follow the approach of Babina et al. (2024) to measure AI adoption at the organizational level. Specifically, *AI adoption* is calculated as the ratio of AI-related roles to the total number of employees at each investment bank in a given year. This ratio captures how much of the bank's workforce is focused on developing and implementing AI technologies and serves as a proxy for extent to which the organization is investing in AI. A higher ratio suggests a stronger commitment to building AI capabilities within the bank.

In order to proxy for the experience of human capital within investment bank, following Clement (1999) I calculate two measures: *Average firm-specific experience* and *Average general experience.* After calculating both experience measures for each analyst as of the time of providing estimates, I aggregate them at investment bank-firm-year level by calculating the averages of these measures.

Analyst's firm-specific experience reflects an analyst's narrow, domain and task-specific experience, as well as familiarity with a company's distinctive attributes and reporting practices, as well as the strength of their relationships with firm insiders (Brauer & Wiersema, 2018), which may provide access to private information. This measure is based on the idea that having deep, specific knowledge about a firm helps analysts better understand and interpret complex information when making forecasts. It is operationalized as the number of years an analyst has issued at least one forecast for a given firm, from their first forecast year up to the year of the current forecast. To be counted for a given year, the analyst must have issued at least one forecast within the first 11 months of the fiscal year. This cutoff helps ensure that the forecast reflects the analyst's own judgment, rather than being influenced by the predictions of others, which are more likely to appear in the final month of the year.

General experience is measure in a similar fashion: it is the number of years an analyst has issued at least one forecast for any firm, from their first forecast year up to the year of the current forecast. Similar to firm experience, only the forecasts issues within first 11 months are taken into calculation, to make sure forecasts are not affected by the forecasts of other analysts. General experience reflects how skilled an analyst is overall, including their ability to understand different types of information and use it effectively when making forecasts in a variety of contexts. This measure captures the breadth of an analyst's experience across different firms, industries, and forecasting situations.

Controls

To rule out alternative explanations, I use a vector of controls in my analysis. The descriptions of these controls are provided below.

Number of employees: I obtain this measure from LinkedIn data by counting the distinct number of users who reported working for the focal investment bank in a given year. This variable serves as a proxy for the overall size of the bank. Larger institutions may have more resources, more diversified operations, and greater capacity to invest in predictive analytics - factors that could independently influence forecasting performance.

Number of analysts: I measure this as the number of distinct analysts employed by the focal bank who issued at least one forecast in a given year. This variable helps control for the scale of the bank's forecasting operations, as a higher number of analysts may contribute to improved predictive accuracy through specialization, collaboration, and broader coverage.

Number of companies covered by bank: I operationalize this as the number of distinct companies for which the focal investment bank issued at least one forecast in a given year. This measure captures the breadth of the bank's forecasting activities and serves as a control for workload and attention scope. Wider coverage may affect the depth of analysis as well as pool of resources assigned to the coverage of each company, consequently, the accuracy of forecasts.

Number of industries covered: I define this as the number of distinct industries for which the focal investment bank issued at least one forecast in a given year. This variable controls for the diversity of the bank's forecasting portfolio, as covering a broader set of industries may introduce varying levels of complexity and uncertainty that can influence forecasting performance.

Number of estimates by the bank for the focal firm: This variable captures the total number of forecasts issued by the focal investment bank for a given firm within a year. It serves as a proxy for the bank's attention to and familiarity with the firm, as more frequent forecasting may reflect deeper engagement, improved information flow, and potentially more accurate predictions.

Table 4.1 provides summary statistics and correlation tables for the measures used in analysis.

Table 4.1 - *Summary statistics and correlation table*

Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8
1. *Average error*	0.06	0.21	0	1.69								
2. *AI Adoption*	0.92	2.04	0	25	.01							
3. *Average firm-specific exp.*	2.24	2.77	0	32	-.04	-.04						
4. *Average general exp.*	7.62	6.08	0	34	-.03	-.05	.45					
5. *N. of employees*	12926.54	25270.17	1	130898	-.04	-.15	.02	.01				
6. *N. of analysts*	61.23	38.97	1	202	-.05	-.19	.04	.01	.37			
7. *N. of companies covered*	350.26	192.44	1	749	-.05	-.18	.04	.02	.43	.87		
8. *N. of industries covered*	146.99	73.29	1	310	-.06	-.15	.03	0	.43	.85	.96	
9. *N. of estimates for the focal firm*	2.76	2.12	1	94	-.01	-.06	.02	0	.05	.05	.07	.06

Results

I use ordinary least squares (OLS) regression for the analysis. In all model specification, I also add firm and year fixed effects to control for unobserved heterogeneity across firms and time-specific factors that might influence forecasting errors. Table 4.2 presents the results of regression analyses.

Model 1 shows the direct impact of AI adoption on average error. Model 2 adds the vector of controls to this specification. Across both models, the coefficient for AI adoption is negative and statistically significant (−0.0007, $p < 0.01$), indicating that higher levels of AI adoption at the firm level are associated with lower average predictive error. Given that the mean forecast error is 0.06, a one-unit increase in AI adoption corresponds to an approximate 1.2% reduction in average forecasting error. These results provide strong support for Hypothesis 1, suggesting that AI adoption contributes to improved predictive performance at the organizational level.

Table 4.2 – *Regression Analysis*

	Average error			
VARIABLES	1	2	3	4
AI Adoption	-0.0007***	-0.0007***	-0.0010***	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Average firm-specific experience		0.0016***	0.0013***	
		(0.0002)	(0.0001)	
Average general experience		-0.0002***		0.0002***
		(0.0001)		(0.0001)
AI Adoption X Average firm-specific experience			0.0001*	
			(0.0001)	
AI Adoption X Average general experience				-0.0001**
				(0.0000)
Number of employees		-0.0000**	-0.0000**	-0.0000*
		(0.0000)	(0.0000)	(0.0000)
Number of analysts		-0.0001***	-0.0001***	-0.0000**
		(0.0000)	(0.0000)	(0.0000)
Number of companies covered by bank		0.0000*	0.0000*	0.0000
		(0.0000)	(0.0000)	(0.0000)
Number of industries covered		-0.0000	-0.0000	-0.0000
		(0.0000)	(0.0000)	(0.0000)
Number of estimates for the focal firm		-0.0001	-0.0001	-0.0001
		(0.0002)	(0.0002)	(0.0002)
Constant	0.0558***	0.0534***	0.0525***	0.0542***
	(0.0004)	(0.0011)	(0.0010)	(0.0011)
R-squared	0.6408	0.6411	0.6411	0.6408
Firm FE	Yes	Yes	Yes	Yes
Yeat FE	Yes	Yes	Yes	Yes
Observations	156,489			

The coefficients for average firm-specific experience and average general experience exhibit opposite signs. An increase in average firm-specific experience is associated with higher forecast errors (coefficient = 0.016, $p < 0.01$), whereas an increase in average general experience is associated with a reduction in forecast errors (coefficient = −0.0002, $p < 0.01$).

Models 3 and 4 present the results for the interaction effects between AI adoption and two types of human capital experience: average firm-specific experience and average general experience, respectively. The coefficient of interaction of AI adoption with average firm-specific experience is positive and significant (0.0001, $p < 0.1$), suggesting that error reducing effect of AI adoption gets smaller as the level of firm-specific experience within the human capital of the bank increases. On the contrary, the coefficient of interaction of general experience with AI adoption is negative and significant (-0.0001, $p < 0.05$), implying that the benefits in terms of error reduction of AI adoption get even stronger as the average level of general experience of the human capital increases.

Taken together, these results support Hypothesis 2, which posited that the effectiveness of AI adoption in enhancing predictive capability is contingent on the composition of human capital. Specifically, higher levels of general experience are associated with lower forecast errors and appear to strengthen the beneficial impact of AI adoption. In contrast, greater firm-specific experience is linked to higher forecast errors and appears to diminish the performance gains associated with AI adoption.

Robustness Checks

While the results of this analysis provide a solid understanding of the moderating role of human capital experience on the positive impact of AI adoption on organizational predictive capabilities, the experience measures used are aggregated at the investment bank level. This aggregation may remove important variation, potentially masking the heterogeneity in individual analysts' experience. Therefore, to address this concern, I also conduct an additional analysis at forecast level, which allows me to capture each analyst's individual experience at the time of producing a given forecast, and how they affect the organizational predictive capabilities. This approach provides a more granular assessment of human capital experience and enables a more nuanced examination of how the interaction between organizational AI adoption and individual-level experience influences forecasting performance.

The forecast-level dataset comprises 425,771 observations of earnings forecasts made by 6,758 financial analysts. In this analysis, I include a different set of control variables specifically aimed at capturing analyst-level characteristics. A detailed description of these control variables is provided below.

Number of firms covered: This is defined as the number of distinct firms for which an analyst issued at least one forecast during the first 11 months of the fiscal year.

Number of industries covered: This refers to the number of distinct industries represented among the firms for which the analyst provided forecasts in the same period. Together, these variables control for the cognitive demand and attention span of analysts managing a broad and diverse coverage portfolio, which may impact their forecasting performance.

Top size bank: This a binary indicator of whether the analyst is employed by large investment bank, defined as being in the top decile of banks by employee count. This control accounts for the greater resources, support infrastructure, and information access typically available at larger firms, which may enhance analysts' ability to produce more accurate forecasts.

Forecast age: This variable captures the forecasting horizon by measuring the number of days between the forecast date and the end date of the period being forecasted. Shorter horizons are typically associated with reduced uncertainty and greater forecast accuracy.

For this analysis, I again use ordinary least squares (OLS) regression. Consistent with the main analysis, I include firm and year fixed effects to control for unobserved heterogeneity across firms and time periods. Table 4.3 provides the results of this analysis.

Table 4.3 - *Robustness Checks*

	Forecast error			
VARIABLES	1	2	3	4
AI Adoption	-0.0007***	-0.0007***	-0.0010***	-0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Analyst's firm-specific experience		0.0013***	0.0012***	0.0013***
		(0.0001)	(0.0001)	(0.0001)
Analyst's general experience		-0.0002***	-0.0002***	-0.0002***
		(0.0000)	(0.0000)	(0.0000)
AI Adoption X Firm-specific experience			0.0001**	
			(0.0001)	
AI Adoption X General experience				-0.0001***
				(0.0000)
Number of firms covered		-0.0001*	-0.0001*	-0.0001*
		(0.0000)	(0.0000)	(0.0000)
Number of industries covered		0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)
Forecast age		0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)
Constant	0.0550***	0.0343***	0.0345***	0.0339***
	(0.0002)	(0.0007)	(0.0007)	(0.0007)
R-squared	0.5965	0.5998	0.5998	0.5998
Firm FE	Yes	Yes	Yes	Yes
Yeat FE	Yes	Yes	Yes	Yes
Observations	425,771			

Model 1 presents the results for the direct effect of AI adoption on individual forecast error, while Model 2 includes the full set of control variables. Models 3 and 4 examine the interaction effects between AI adoption and analysts' firm-specific and general experience, respectively.

The results are consistent with the findings from the main analysis. AI adoption is significantly associated with lower forecast error (coefficient = −0.0007, $p < 0.01$). Firm-specific experience is positively related to forecast error (coefficient = 0.0013, $p < 0.01$), indicating reduced predictive accuracy as this type of experience increases. In contrast, greater general experience is associated with lower forecast error (coefficient = −0.0002, $p < 0.01$), suggesting improved predictive performance.

The interaction terms further reinforce the main findings. The interaction between firm-specific experience and AI adoption is positive and significant (coefficient = 0.0001, $p < 0.1$), indicating that higher firm-specific experience weakens the beneficial effect of AI. Conversely, the interaction between general experience and AI adoption is negative and significant (coefficient = −0.0001, $p < 0.01$), suggesting that general experience enhances the positive impact of AI adoption on forecasting accuracy. In sum, this robustness checks confirm the findings of the main analysis.

Discussion and Conclusion

This paper investigates how the adoption of artificial intelligence (AI) within organizations affects predictive accuracy, specifically within investment banks' earnings forecasts. Results provide empirical support for two hypotheses: first, increased AI adoption significantly reduces forecast errors, enhancing organizational predictive capability. Second, the effectiveness of AI adoption in improving predictive accuracy is contingent on the experience composition of human capital within the organization. Specifically, higher general experience amplifies the beneficial effects of AI adoption, whereas greater domain-specific experience diminishes these advantages, highlighting nuanced interactions between AI and human expertise in predictive tasks.

These findings have important theoretical implications. First, they extend prior research on AI and human capital by illustrating that AI does not merely substitute or complement human judgment at the task level (Allen & Choudhury, 2022; Choudhury et al., 2020; Krakowski et al., 2022; Raisch & Krakowski, 2021; Yilmaz et al., 2023) but fundamentally reshapes the strategic value of different forms of human expertise at the organizational level. While previous studies predominantly focus on isolated tasks or controlled experimental settings, this study provides insights into the broader implications of AI as embedded within organizational processes.

Second, the divergent roles of general versus domain-specific experience highlighted in this research contribute to the ongoing debate in the literature about the nuanced impacts of experience on performance (Argote et al., 2021; Gaba et al., 2022; March, 2010). Our results suggest that general experience, characterized by diverse, context-independent skills, is complementary to AI systems and can augment their predictive benefits. Conversely, firm-specific, that is deeper and context-specific experience, appears to diminish in relative importance as AI increasingly handles data-intensive predictive tasks.

This study makes several contributions. First, it advances our understanding of how AI adoption influences firm-level outcomes beyond the direct productivity and innovation effects previously documented (Babina et al., 2024). By explicitly examining predictive accuracy, a crucial component of strategic decision-making (Durand, 2003; Makadok & Walker, 2000), this study offers insights into how AI reshapes a core organizational capability. As such, by relying on AI organizations can potentially increasingly improve their core competence of predicting, which can yield superior performance and competitive gains.

Second, this study adds to the discourse on the complementarity and substitutability of AI and human expertise (Allen & Choudhury, 2022; Choudhury et al., 2020; Krakowski et al., 2022). The findings illustrate that AI adoption not only impacts predictive accuracy but also will result in a situation, where organizations need to reassess and strategically manage their human capital, emphasizing the synergies between AI technologies and general human expertise while reconsidering the value of firm-specific experience in predictive contexts.

Finally, this research has practical implications for management. As organizations continue to integrate AI into their decision-making processes, these findings suggest that strategic human capital management must evolve accordingly. Firms investing in AI technologies should also strategically develop and leverage general human expertise, which appears to synergistically enhance predictive performance when combined with advanced predictive technologies. Conversely, reliance on firm-specific experience alone may become less strategically advantageous in an AI-enabled environment. Combined with the findings of the second chapter of this thesis, these findings also have important implications in terms of recruitment strategies of the organizations: they will increasingly need to attract human capital characterized by more generic experience – one that would allow them to complement AI systems, as well as enhance the positive effects derived from AI adoption and implementation.

This study has certain limitations that may affect the generalizability of its findings. First, although the measure of AI adoption based on the proportion of employees in AI-related roles has been used in prior research (Babina et al., 2024), it captures organizational investment in AI only indirectly. It does not account for the actual intensity or effectiveness of AI usage within firms. Future research could address this limitation by leveraging internal firm-level data to more precisely measure AI deployment and usage.

Second, due to data availability, this study focuses on the period from 2005 to 2016. While AI technologies began gaining momentum during the 2010s, driven by advances in computational power and machine learning algorithms. Nevertheless, this field continues to evolve rapidly. As such, it remains uncertain whether the findings presented here will fully extend to more recent periods marked by widespread AI integration. Future studies could explore this by examining updated datasets that capture more contemporary developments in AI adoption and its organizational impacts.

In summary, this paper deepens our understanding of AI's organizational implications, providing a nuanced perspective on how AI adoption reshapes the strategic role and composition of human capital in achieving competitive advantage through improved predictive capabilities.

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Chapter 5 - Discussion and Conclusion

Overview

The rise of AI marks a profound transformation in how expert knowledge is produced, accessed, and applied across industries. As organization increasingly integrate AI into decision-making processes, fundamental questions about the role of human capital rise: How do the cognitive limitations of human experts evolve alongside AI systems? What is the value of human experience when algorithms are increasingly taking over roles traditionally performed by humans? Does human experience still matter, and if so, under what conditions?

This dissertation addresses these questions by examining how human experience and cognitive biases operate in complex forecasting tasks, and how these dynamics evolve in the presence of AI tools. The work proceeds in three empirical chapters, each contributing to our understanding of expert forecasting in the age of AI.

Chapter 2 addresses the following research question: "How does accumulated experience influence cognitive biases in expert forecasting?" It sets the empirical and conceptual foundation for this dissertation by examining how analysts behave when forecasting earnings for controversial firms operating in uncertainty environments, specifically, those going public through SPACs. The study shows that analysts exhibit systematic optimism bias in these contexts, but also that experience, both at the firm level and with the SPACs in general, mitigates this bias. This chapter establishes the importance of experience in shaping forecasting accuracy, independent of any AI involvement, and highlights the behavioral biases that AI might later interact with.

Chapter 3 addresses the following research question: "In what ways can human experience enhance the performance of AI systems, and under what conditions is this contribution most valuable?" It investigates how human experience can be leveraged to improve AI performance. It compares human and AI earnings forecasts and reveals that while AI outperforms humans in predictive accuracy, human experience, especially general experience, significantly improves AI performance when incorporated into training data. This finding reframes experience as not just a personal asset but also an organizational input that can enhance the predictive capacity of AI systems.

Chapter 4 addresses the following research question: “How does AI adoption transform organizational predictive capabilities, and what role does human experience play in this transformation?” It explores how AI adoption reshapes the value of human experience in forecasting. Using data on organizational-level AI investment and analyst experience, the chapter finds that AI adoption improves organizational predictive capability. Importantly, this depends on the type of experience that human capital embedded within these organization possesses. General experience complements AI adoption and leads to better outcomes, while firm-specific experience appears less useful in harnessing the potential benefits derived from AI. This suggests that the rise of AI requires firms to rethink the composition of their human capital, placing greater emphasis on attracting individuals with broad, general experience that can complement and enhance AI-driven performance.

Table 5.1 provides the summary of key findings and implications of these chapters. Taken together, these chapters advance our understanding of the evolving role of human capital. Chapter 2 shows that human experience matters, as it helps to correct biases in complex decision-making. Chapter 3 explores how that experience can improve AI itself. Chapter 4 demonstrates how AI, in turn, reshapes the value of human experience. Thus, the dissertation offers a nuanced understanding of human-AI interplay, showing that human experience is not obsolete in the age of AI and can still drive value for organizations increasingly relying on this technology.

Table 5.1 – *Key Findings and Implications*

Chapter	Focus	Key Findings	Implications
2: Human Experience and Bias	How experience shapes bias in human forecasting	- Humans are initially biased - Experience reduces this bias	Experience has a "debiasing" function
3: Human Experience and AI	How experience affects both human and AI predictive accuracy	- Domain-specific experience lowers human accuracy, no effect on AI - General experience boosts AI, no effect on humans - Both types of experience improve accuracy under volatility, both for humans and AI	Human experience enhances AI performance, even if it does not improve human prediction directly
4: Human Experience and AI Adoption	How AI changes predictive capability and the value of experience	- AI adoption improves organizational predictive capability - Generalist experience amplifies this effect	AI shifts value toward generalist experience over specialization

Contributions

This dissertation makes several interconnected theoretical contributions across the domains of human capital and experience in knowledge work, cognitive biases, human–AI complementarities, and the organizational impact of AI.

It adds to the ongoing discussion on the impact of experience on exacerbation (Gaba et al., 2022) or mitigation (Christoffersen & Sarkissian, 2011; Gort et al., 2008) of cognitive biases. By revealing the nuanced interplay between experience accumulation and mitigation of biases, it further expands the boundary conditions under which experience can be a corrective force over cognitive biases (Kahneman & Klein, 2009). In addition, it also adds to our understanding of how the evaluations of external stakeholders (e.g. Bednar et al., 2015; Briscoe & Murphy, 2012; Mahoney & Mahoney, 1993) evolve in light of experience accumulation, and answers to the question of why do controversial practices proliferate despite supposed opposition from stakeholders. The findings of this dissertation also add to the ongoing discussion on analysts' biases (Hilary & Menzly, 2006) and the effect of experience accumulation on forecasting accuracy (Clement, 1999; Mikhail et al., 1997). Overall, when it comes to experience and biases, this dissertation highlights that while human capital is subject to bias, experience accumulation still provides a path to improved accuracy and mitigation of biases.

This dissertation also contributes to the literature on human-AI complementarity (Allen & Choudhury, 2022; Choudhury et al., 2020; Krakowski et al., 2022; Raisch & Krakowski, 2021) by showing that although human experience may not improve human forecast accuracy directly, it significantly improves AI accuracy when used as training input. This supports and extends research on organizational learning (Argote, 2012; Argote et al., 2021) and the repurposing of tacit knowledge for technological augmentation. The findings align with the logic of human-AI ensemble (Choudhary et al., 2023; Puranam, 2021), offering empirical evidence that general experience improves AI's capacity to generate accurate forecasts in volatile settings. In this way, the chapter reframes human experience as valuable not only for the direct forecasts or decisions it produces, but for how it enhances the performance of algorithmic systems. This highlights a new form of human–AI complementarity: whereas much of the existing research emphasizes how AI can augment human decision-making (Allen & Choudhury, 2022; Choudhury et al., 2020; Krakowski et al., 2022; Raisch & Krakowski, 2021), these findings suggest that the opposite is also possible and true - human expertise can improve AI-driven decisions and forecasts.

The dissertation also contributes to the emerging literature on the organizational-level implications of AI adoption (Babina et al., 2024) by demonstrating that the benefits of AI are not uniformly distributed, but rather contingent on the composition of human capital within firms. Through an analysis of how AI adoption affects organizational predictive capabilities, the chapter shows that generalist experience enhances the positive effects of AI, whereas narrow, domain-specific experience may lower them. These findings offer important nuance to existing research on labor substitution in the context of automation (Acemoglu et al., 2022; Autor, 2015; E. W. Felten et al., 2023), suggesting that human capital does not necessarily become obsolete in the face of AI. Instead, certain types of experience, particularly broad, generalist knowledge, can become even more valuable when paired with AI technologies.

Taken together, this dissertation points to a broader reconceptualization of human capital in the age of AI. Rather than viewing experience as becoming obsolete in the age of AI, this dissertation positions it as a critical asset. While experience continues to matter for human decision-making, particularly due to its potential to mitigate cognitive biases, its role is also transforming as AI becomes increasingly embedded within organizations. Human experience now plays a dual role: not only does it support better individual judgment, but it also enhances AI performance when it is used to inform, train, and guide algorithmic systems. Moreover, the breadth of experience becomes especially vital in the context of widespread AI adoption, as it enables organizations to fully harness the transformative potential of these technologies. As such, this dissertation highlights the evolving role of human experience in a world where AI increasingly takes on functions traditionally performed by humans.

Practical Implications

This dissertation also offers practical insights for firms to navigate forecasting and decision-making in AI-augmented environments. First, the findings of this dissertation suggest that experience plays a critical role in improving forecast accuracy, particularly in uncertain and novel contexts such as SPACs. This has important implications for how organizations structure human capital: experienced individuals should be strategically leveraged, as repeated exposure to the task or organizational settings enables them to learn, adapt, and reduce systematic biases over time. At the same time, the chapter offers a potential explanation for the persistence and spread of controversial practices like SPACs. If analysts and market participants have a systematic optimistic bias towards controversial practices in early periods due to lack of familiarity, these biases can inflate perceptions of legitimacy and facilitate further proliferation. This highlights a need for a greater awareness among investors, the public, and regulators about how cognitive biases shape financial markets, especially in the initial stages.

Second, the findings show that generalist experience, defined as broad exposure across industries or firms, plays a dual role in the age of AI. It not only improves the performance of AI systems when integrated into training data but also enhances the ability of humans to better leverage the potential benefits these tools. This suggests that firms should reconsider traditional definitions of "deep" expertise. While firm-specific knowledge remains valuable, general experience appears to be more transferable and more complementary to AI systems. In turn, human capital strategies may need to shift toward identifying, developing, and retaining employees with broad exposure and strategically leveraging the breadth of experience of human capital.

Finally, these insights have broader implications for how organizations conceptualize and build competitive advantage. While AI technologies are increasingly available and replicable across firms, the ability to effectively combine these tools with inimitable human capital may be more difficult to replicate (Krakowski et al., 2022). From the perspective of the Resource-Based View of the firm (Barney, 1991), AI alone may not constitute a source of sustained competitive advantage. However, AI coupled with the breadth of experience of human capital, particularly when embedded in organizational routines, may create unique capabilities that are hard to imitate. In this sense, experience does not lose its relevance in the age of AI - it becomes a strategic asset that enables firms to extract value from technological investments in ways that others cannot.

Limitations and Future Research

While this dissertation provides new insights into the evolving relationship between human experience and AI in forecasting, several limitations create opportunities for future research.

First, although the studies span different levels of analysis, from individual analysts to organizational-level forecasting, they are focused on the context of financial forecasting. Analysts operate in a relatively structured environment with well-defined performance measures, making it a suitable context for studying bias, learning, and AI interaction. In addition, this context is characterized with an abundance of codified historical data - an essential input to AI's performance. However, this type of data might not be available in other settings. Hence, these dynamics may differ from one setting to another. Future work could extend this to other knowledge-intensive professions where AI adoption is advancing, but where outcomes are harder to quantify.

Second, this dissertation emphasizes experience as a form of human capital, measured through observable characteristics such as firm coverage history or industry exposure. While these proxies are grounded in prior literature (Clement, 1999; Mikhail et al., 1997), they do not capture more tacit or interpersonal forms of expertise, such as intuition, peer learning, or access to private information. Future studies could build on this foundation by incorporating qualitative or experimental methods to investigate how different types of knowledge are transferred to and from AI systems.

Third, while the analyses in Chapters 3 and 4 focus on the implementation and effects of AI tools, the specific mechanisms through which analysts interact with these tools remain a black box. For example, it is unclear how much autonomy analysts have in choosing to follow algorithmic recommendations, do they develop algorithm-aversion or no, or how their decision-making changes after exposure to machine-generated forecasts. Future work could explore these mechanisms more directly, potentially using experiments or qualitative approaches, to better understand how human judgment and AI outputs are integrated in practice.

Finally, while the dissertation emphasizes the role of experience in shaping AI-related outcomes, it does not systematically examine how organizational structures or incentives mediate these effects. Firms may vary in how they integrate AI tools into workflows or how they train employees to use new technologies. A promising possibility for future research is to explore the organizational practices, such as team composition, training programs, and knowledge-sharing routines, that can amplify the value of human experience in AI-intensive environments.

In addition to possible research opportunities outlined above, the findings of this dissertation raise deeper questions about the long-term co-evolution of human capital and AI. If human experience is essential for improving AI performance, then organizations must ensure that such experience continues to develop. Yet, as AI systems increasingly automate tasks performed by humans, opportunities for humans to learn by doing may decline. This presents a potential paradox: AI may become more effective by learning from humans, even as humans become less experienced due to growing reliance on AI. However, this might result in a situation where human expertise increasingly fades away and is not capable of guiding AI anymore. Hence, following the insights derived from automation-augmentation paradox (Raisch & Krakowski, 2021), future research should explore how firms should design work environments that preserve opportunities for experiential learning, despite the increased reliance on AI.

Furthermore, the results point to a revaluation of experience types, suggesting a growing need for broad, cross-domain experience rather than narrow, firm or task-specific expertise. This raises important questions about how organizations should approach recruitment and talent development. In AI-enabled environments, might there be a growing preference for “T-shaped” individuals, those who combine deep knowledge in a specific area with the ability to collaborate across disciplines? Are firms more likely to prioritize building adaptable teams capable of evolving alongside emerging technologies? These considerations carry significant implications for career trajectories, workforce planning, and the broader strategies firms use to manage human capital in an increasingly digitized economy. Future research should investigate how firms are adapting their hiring practices, team structures, and training systems in response to these changes, and whether certain approaches are more effective in capturing the value of human-AI ensembles.

As artificial intelligence continues to reshape expert work, this dissertation underscores the enduring and evolving importance of human experience. Experience emerges not as a static asset but as a dynamic input: one that can reduce bias, enhance machine learning, and determine the success of AI implementation. Rather than making human capital obsolete, AI changes how it is leveraged, valued, and developed. Understanding these shifts is essential for organizations seeking to remain competitive in the digital economy. This dissertation sheds light on how experience shapes forecasting across different technological contexts, offering insights into how organizations can better structure work, manage talent, and foster learning in a world increasingly dominated by AI.

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Appendices

Appendix: Chapter 2

Table 2A.1 - *Likelihood of undervaluing SPACs relative to IPOs: Uncertainty split sample analysis*

	Negative error							
Variables	1	2	3	4	5	6	7	8
SPAC	-0.7617***	-0.7494***	-0.7601***	-0.7479***	-0.6416***	-0.5701***	-0.6628***	-0.6129***
	(0.0421)	(0.0423)	(0.0424)	(0.0426)	(0.0426)	(0.0431)	(0.0438)	(0.0441)
General experience			0.0378***	0.0418***			0.0322***	0.0342***
			(0.0053)	(0.0053)			(0.0054)	(0.0054)
Firm experience			0.0104*	0.0106*			0.0234***	0.0141**
			(0.0061)	(0.0062)			(0.0067)	(0.0069)
Number of companies covered			-0.0014	-0.0011			0.0000	0.0006
			(0.0020)	(0.0020)			(0.0026)	(0.0026)
Number of industries covered			0.0202**	0.0161*			0.0153	0.0159
			(0.0089)	(0.0090)			(0.0098)	(0.0098)
Top size bank			-0.0034	0.0097			0.0451	0.0422
			(0.0445)	(0.0447)			(0.0495)	(0.0497)
Forecast age		-0.0005*	-0.0006**	-0.0006**		0.0022***	0.0021***	0.0020***
		(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0003)	(0.0003)
Total assets		-0.0000*		-0.0000**		-0.0000***		-0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Total revenue		-0.0001***		-0.0001***		0.0001***		0.0001***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Net income		0.0007***		0.0007***		0.0015***		0.0015***
		(0.0000)		(0.0000)		(0.0001)		(0.0001)
Number of employees		0.0063***		0.0069***		-0.0010		-0.0003
		(0.0010)		(0.0010)		(0.0019)		(0.0019)
Constant	0.0000	-0.0469	-0.8647	-1.0164	-0.8650**	-1.0173**	-1.7662***	-1.8720***
	(1.4142)	(1.4152)	(1.4199)	(1.4191)	(0.4215)	(0.4224)	(0.4380)	(0.4394)
Observations	66,196	66,196	66,196	66,196	65,686	65,686	65,686	65,686
Uncertainty	High	High	High	High	Low	Low	Low	Low

Note: Robust standard errors in parentheses. All models include analyst fixed effects.

Table 2A.2 - *Effect of firm and SPAC experience on the likelihood of undervaluing SPACs: Uncertainty split sample analysis*

	Negative error									
Variables	1	2	3	4	5	6	7	8	9	10
SPAC	-0.7359***	-0.8217***	-0.7537***	-1.0901***	-1.0889***	-0.6128***	-0.7076***	-0.6914***	-0.8926***	-0.8768***
	(0.0423)	(0.0512)	(0.0438)	(0.1393)	(0.1398)	(0.0428)	(0.0497)	(0.0474)	(0.1195)	(0.1201)
Firm experience	0.0348***	0.0066			0.0066	0.0483***	0.0065			0.0066
	(0.0051)	(0.0063)			(0.0063)	(0.0057)	(0.0072)			(0.0072)
SPAC experience			-0.0281	-0.1570***	-0.1452***			0.1078**	-0.0300	-0.0024
			(0.0417)	(0.0444)	(0.0447)			(0.0447)	(0.0488)	(0.0492)
Firm experience X *SPAC*		0.0490***			0.0372*		0.0891***			0.0829***
		(0.0187)			(0.0190)		(0.0215)			(0.0220)
SPAC experience X *SPAC*				0.4048***	0.3476**				0.3052**	0.1929
				(0.1437)	(0.1461)				(0.1267)	(0.1297)
Total assets		0.0427***		0.0497***	0.0457***		0.0356***		0.0404***	0.0356***
		(0.0053)		(0.0046)	(0.0054)		(0.0054)		(0.0047)	(0.0055)
Total revenue		-0.0010		-0.0007	-0.0007		0.0011		0.0007	0.0011
		(0.0020)		(0.0020)	(0.0020)		(0.0026)		(0.0026)	(0.0026)
Net income		0.0157*		0.0175*	0.0173*		0.0139		0.0155	0.0138
		(0.0090)		(0.0090)	(0.0090)		(0.0099)		(0.0098)	(0.0099)
Number of employees		0.0095		0.0065	0.0061		0.0443		0.0435	0.0449
		(0.0447)		(0.0447)	(0.0447)		(0.0498)		(0.0497)	(0.0498)
Forecast age		-0.0006**		-0.0006**	-0.0007**		0.0020***		0.0020***	0.0020***
		(0.0003)		(0.0003)	(0.0003)		(0.0003)		(0.0003)	(0.0003)
General experience		-0.0000**		-0.0000**	-0.0000**		-0.0000***		-0.0000***	-0.0000***
		(0.0000)		(0.0000)	(0.0000)		(0.0000)		(0.0000)	(0.0000)
Number of companies covered		-0.0001***		-0.0001***	-0.0001***		0.0001***		0.0001***	0.0001***
		(0.0000)		(0.0000)	(0.0000)		(0.0000)		(0.0000)	(0.0000)
Number of industries covered		0.0007***		0.0007***	0.0007***		0.0015***		0.0015***	0.0015***
		(0.0000)		(0.0000)	(0.0000)		(0.0001)		(0.0001)	(0.0001)
Top size bank		0.0069***		0.0069***	0.0069***		0.0000		0.0001	-0.0000
		(0.0010)		(0.0010)	(0.0010)		(0.0019)		(0.0019)	(0.0019)
Constant	-0.0174	-1.0343	0.0000	-1.1986	-1.1124	-0.9065**	-1.8997***	-0.8650**	-2.0030***	-1.8967***
	(1.4143)	(1.4191)	(1.4142)	(1.4182)	(1.4194)	(0.4216)	(0.4394)	(0.4215)	(0.4357)	(0.4403)
Observations	66,196	66,196	66,196	66,196	66,196	65,686	65,686	65,686	65,686	65,686
Uncertainty	High	High	High	High	High	Low	Low	Low	Low	Low

Note: Robust standard errors in parentheses. All models include analyst fixed effects.

Table 2A.3 - *Likelihood of undervaluing SPACs relative to IPOs: Analyst accuracy split sample analysis*

	Negative error							
Variables	1	2	3	4	5	6	7	8
SPAC	-0.6141***	-0.5953***	-0.6063***	-0.5915***	-0.7526***	-0.7240***	-0.7720***	-0.7598***
	(0.0350)	(0.0352)	(0.0353)	(0.0354)	(0.0455)	(0.0457)	(0.0466)	(0.0468)
Firm experience			0.0185***	0.0211***			0.0337***	0.0378***
			(0.0046)	(0.0046)			(0.0060)	(0.0061)
SPAC experience			0.0169***	0.0185***			-0.0011	-0.0067
			(0.0054)	(0.0055)			(0.0071)	(0.0072)
Firm experience X *SPAC*			0.0007	0.0009			-0.0048*	-0.0045
			(0.0019)	(0.0019)			(0.0028)	(0.0028)
SPAC experience X *SPAC*			0.0025	0.0013			0.0186*	0.0138
			(0.0088)	(0.0088)			(0.0096)	(0.0096)
Total assets			0.0056	0.0055			0.0601	0.0779
			(0.0426)	(0.0427)			(0.0503)	(0.0505)
Total revenue		0.0008***	0.0007**	0.0007**		0.0014***	0.0013***	0.0013***
		(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0003)	(0.0003)
Net income		-0.0000		-0.0000		-0.0000***		-0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Number of employees		-0.0001***		-0.0001***		-0.0000***		-0.0001***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Forecast age		0.0009***		0.0009***		0.0007***		0.0007***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
General experience		0.0041***		0.0048***		0.0059***		0.0060***
		(0.0013)		(0.0013)		(0.0010)		(0.0010)
Number of companies covered	-1.7047**	-1.5978**	-2.0334***	-1.9489**	-0.7985**	-0.9213**	-1.5936***	-1.7244***
	(0.7687)	(0.7698)	(0.7731)	(0.7745)	(0.4014)	(0.4022)	(0.4230)	(0.4234)
Observations	67,657	67,657	67,657	67,657	66,695	66,695	66,695	66,695
Accuracy	High	High	High	High	Low	Low	Low	Low

Note: Robust standard errors in parentheses. All models include analyst fixed effects.

Table 2A.4 - *Effect of firm and SPAC experience on likelihood of undervaluing SPACs: Analyst accuracy split sample analysis*

	Negative error									
Variables	1	2	3	4	5	6	7	8	9	10
SPAC	-0.5973***	-0.6388***	-0.6312***	-0.7574***	-0.7365***	-0.7324***	-0.8496***	-0.7341***	-1.0985***	-1.1261***
	(0.0352)	(0.0431)	(0.0368)	(0.1237)	(0.1240)	(0.0457)	(0.0523)	(0.0498)	(0.1165)	(0.1175)
Firm experience	0.0284***	0.0158***			0.0159***	0.0239***	-0.0146**			-0.0145*
	(0.0047)	(0.0056)			(0.0056)	(0.0057)	(0.0074)			(0.0074)
SPAC experience			0.0588	-0.0190	-0.0043			-0.0423	-0.1710***	-0.1545***
			(0.0386)	(0.0411)	(0.0414)			(0.0461)	(0.0503)	(0.0507)
Firm experience X *SPAC*		0.0326*			0.0300*		0.0868***			0.0701***
		(0.0169)			(0.0172)		(0.0223)			(0.0227)
SPAC experience X *SPAC*				0.1692	0.1089				0.4706***	0.4010***
				(0.1280)	(0.1305)				(0.1254)	(0.1281)
Total assets		0.0215***		0.0287***	0.0216***		0.0404***		0.0374***	0.0432***
		(0.0047)		(0.0042)	(0.0047)		(0.0061)		(0.0050)	(0.0062)
Total revenue		0.0010		0.0010	0.0010		-0.0044		-0.0040	-0.0040
		(0.0019)		(0.0019)	(0.0019)		(0.0028)		(0.0028)	(0.0028)
Net income		0.0004		0.0011	0.0004		0.0137		0.0145	0.0142
		(0.0088)		(0.0088)	(0.0088)		(0.0096)		(0.0096)	(0.0096)
Number of employees		0.0055		0.0050	0.0056		0.0800		0.0711	0.0741
		(0.0427)		(0.0427)	(0.0427)		(0.0505)		(0.0505)	(0.0506)
Forecast age		0.0007**		0.0007**	0.0007**		0.0013***		0.0013***	0.0013***
		(0.0003)		(0.0003)	(0.0003)		(0.0003)		(0.0003)	(0.0003)
General experience		-0.0000		-0.0000	-0.0000		-0.0000***		-0.0000***	-0.0000***
		(0.0000)		(0.0000)	(0.0000)		(0.0000)		(0.0000)	(0.0000)
Number of companies covered		-0.0001***		-0.0001***	-0.0001***		-0.0001***		-0.0001***	-0.0001***
		(0.0000)		(0.0000)	(0.0000)		(0.0000)		(0.0000)	(0.0000)
Number of industries covered		0.0009***		0.0009***	0.0009***		0.0007***		0.0007***	0.0007***
		(0.0000)		(0.0000)	(0.0000)		(0.0000)		(0.0000)	(0.0000)
Top size bank		0.0048***		0.0049***	0.0048***		0.0062***		0.0060***	0.0062***
		(0.0013)		(0.0014)	(0.0013)		(0.0010)		(0.0010)	(0.0010)
Constant	-1.7311**	-1.9535**	-1.7047**	-2.0506***	-1.9547**	-0.8183**	-1.7792***	-0.7985**	-1.7296***	-1.8514***
	(0.7687)	(0.7745)	(0.7687)	(0.7740)	(0.7746)	(0.4014)	(0.4237)	(0.4014)	(0.4177)	(0.4245)
Observations	67,657	67,657	67,657	67,657	67,657	66,695	66,695	66,695	66,695	66,695
Accuracy	High	High	High	High	High	Low	Low	Low	Low	Low

Note: Robust standard errors in parentheses. All models include analyst fixed effects.

Table 2A.5 - *Likelihood of undervaluing SPACs relative to IPOs: Industry growth split sample analysis*

	Negative error							
Variables	1	2	3	4	5	6	7	8
SPAC	-0.4845***	-0.4745***	-0.4874***	-0.4871***	-0.8516***	-0.8335***	-0.8384***	-0.8249***
	(0.0405)	(0.0406)	(0.0411)	(0.0412)	(0.0424)	(0.0426)	(0.0428)	(0.0429)
Firm experience			0.0573***	0.0602***			-0.0191***	-0.0136***
			(0.0050)	(0.0051)			(0.0052)	(0.0053)
SPAC experience			0.0183***	0.0158**			-0.0048	-0.0021
			(0.0061)	(0.0062)			(0.0064)	(0.0064)
Firm experience X *SPAC*			0.0029	0.0031			-0.0043*	-0.0040*
			(0.0023)	(0.0023)			(0.0023)	(0.0023)
SPAC experience X *SPAC*			0.0067	0.0044			0.0107	0.0080
			(0.0094)	(0.0094)			(0.0093)	(0.0093)
Total assets			0.0374	0.0384			0.0343	0.0342
			(0.0483)	(0.0484)			(0.0451)	(0.0453)
Total revenue		0.0008***	0.0006*	0.0006*		0.0007**	0.0008**	0.0007**
		(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0003)	(0.0003)
Net income		-0.0000		-0.0000		-0.0000***		-0.0000***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Number of employees		-0.0000***		-0.0001***		-0.0001***		-0.0001***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Forecast age		0.0004***		0.0004***		0.0009***		0.0009***
		(0.0000)		(0.0000)		(0.0001)		(0.0001)
General experience		0.0040***		0.0053***		0.0085***		0.0084***
		(0.0011)		(0.0012)		(0.0012)		(0.0012)
Number of companies covered	-0.4055	-0.4928	-1.8006***	-1.9109***	-0.9555*	-1.0640**	-0.5108	-0.7111
	(0.6455)	(0.6462)	(0.6550)	(0.6553)	(0.5262)	(0.5273)	(0.5388)	(0.5401)
Observations	64,860	64,860	64,860	64,860	64,963	64,963	64,963	64,963
Growth	High	High	High	High	Low	Low	Low	Low

Note: Robust standard errors in parentheses. All models include analyst fixed effects.

Table 2A.6 - *Effect of firm and SPAC experience on likelihood of undervaluing SPACs: Industry growth split sample analysis*

	Negative error									
Variables	1	2	3	4	5	6	7	8	9	10
SPAC	-0.4416***	-0.5664***	-0.5226***	-0.6833***	-0.6668***	-0.8608***	-0.9633***	-0.8068***	-1.2748***	-1.2965***
	(0.0406)	(0.0484)	(0.0434)	(0.1244)	(0.1248)	(0.0425)	(0.0509)	(0.0452)	(0.1350)	(0.1356)
Firm experience	0.0541***	0.0111*			0.0111*	-0.0178***	-0.0112*			-0.0111*
	(0.0054)	(0.0064)			(0.0064)	(0.0054)	(0.0067)			(0.0067)
SPAC experience			0.1051**	-0.0737	-0.0558			-0.1222***	-0.1195***	-0.0925**
			(0.0431)	(0.0462)	(0.0465)			(0.0432)	(0.0464)	(0.0469)
Firm experience X *SPAC*		0.0672***			0.0614***		0.0982***			0.0847***
		(0.0216)			(0.0221)		(0.0189)			(0.0193)
SPAC experience X *SPAC*				0.2267*	0.1375				0.5327***	0.4141***
				(0.1310)	(0.1339)				(0.1408)	(0.1439)
Total assets		0.0609***		0.0675***	0.0620***		-0.0113**		-0.0126***	-0.0096*
		(0.0051)		(0.0046)	(0.0052)		(0.0053)		(0.0046)	(0.0054)
Total revenue		0.0032		0.0033	0.0034		-0.0035		-0.0037	-0.0034
		(0.0023)		(0.0023)	(0.0023)		(0.0023)		(0.0023)	(0.0023)
Net income		0.0036		0.0045	0.0040		0.0060		0.0090	0.0070
		(0.0094)		(0.0094)	(0.0094)		(0.0094)		(0.0094)	(0.0094)
Number of employees		0.0375		0.0380	0.0361		0.0374		0.0324	0.0359
		(0.0484)		(0.0484)	(0.0484)		(0.0453)		(0.0453)	(0.0453)
Forecast age		0.0006*		0.0006*	0.0006*		0.0007**		0.0007**	0.0007**
		(0.0003)		(0.0003)	(0.0003)		(0.0003)		(0.0003)	(0.0003)
General experience		-0.0000		-0.0000	-0.0000		-0.0000***		-0.0000***	-0.0000***
		(0.0000)		(0.0000)	(0.0000)		(0.0000)		(0.0000)	(0.0000)
Number of companies covered		-0.0001***		-0.0001***	-0.0001***		-0.0001***		-0.0001***	-0.0001***
		(0.0000)		(0.0000)	(0.0000)		(0.0000)		(0.0000)	(0.0000)
Number of industries covered		0.0004***		0.0004***	0.0004***		0.0009***		0.0009***	0.0009***
		(0.0000)		(0.0000)	(0.0000)		(0.0001)		(0.0001)	(0.0001)
Top size bank		0.0054***		0.0056***	0.0054***		0.0085***		0.0084***	0.0085***
		(0.0012)		(0.0012)	(0.0012)		(0.0012)		(0.0012)	(0.0012)
Constant	-0.4597	-1.9222***	-0.4055	-2.0660***	-1.9502***	-0.9417*	-0.7554	-0.9555*	-0.7443	-0.8002
	(0.6457)	(0.6553)	(0.6455)	(0.6540)	(0.6558)	(0.5263)	(0.5402)	(0.5262)	(0.5376)	(0.5407)
Observations	64,860	64,860	64,860	64,860	64,860	64,963	64,963	64,963	64,963	64,963
Growth	High	High	High	High	High	Low	Low	Low	Low	Low

Note: Robust standard errors in parentheses. All models include analyst fixed effects.

Appendix: Chapter 3

Appendix 3A - Random Forest Training

We trained the random forest models by adopting an approach similar to rolling windows regression. To ensure the availability of matched pairs of analyst and machine estimates, we trained the models on monthly basis. Hence, for each forecast period end date and firm, we trained 12 models, for each of the months preceding the publication of the actual values. These predictions are matched with the predictions of human analysts based on the time when they were made. For example, if an analyst makes an estimate on May 5, 1988, we will train a random forest using the data available as of May and will match its prediction with that estimate.

We use data from the preceding year as a training set for random forest models. In other words, we use the data from month t-12 to t-1 to train the random forest model and make the predictions at month t.

Furthermore, we train the random forest based on the data that was publicly available as of month t. Thus, we ensure that 1) data from future does not leak into the training set of the machines and that 2) humans and machines have comparable set of public signals based on which they can make the predictions. The random forest predictions model can be summarized as following:

$$EPS_{i,t+1} = RF[Ratios_{i,t}, Macro_t, AF_{i,t}]$$

Estimate of EPS for firm i at time t is a function of random forest (RF) based on financial ratios of firm i at time t $\left(Ratios_{i,t}\right)$, macroeconomic variables at time t $(Macro_t)$ and the analyst forecast at time t $\left(AF_{i,t}\right)$.

Firm-specific financial ratios. We obtain the financial ratios that measure various characteristics (e.g., valuation, liquidity, profitability) from Wharton Research Data Services. This data is available both at firm and industry level and it is provided on monthly basis. Again, similar to the approach with macroeconomic variable the algorithm can see only the most recent ratios as of the time when the matched analyst(s) were making estimates.

We drop PEG_1yrforward, PEG_ltgforward, pe_op_basic, pe_op_dil from our model since these variables have too many missing values. For all the remaining 68 ratios we replace the missing observations with the median values at the industry level. Table 3.A1 depicts the ratios used in the models.

Table 3A.1 - *Financial ratios used in Random Forest*

Variables	Description	Variables	Description
capei	Shillers Cyclically Adjusted P/E Ratio	debt_ebitda	Total Debt/EBITDA
bm	Book/Market	short_debt	Short-Term Debt/Total Debt
evm	Enterprise Value Multiple	curr_debt	Current Liabilities/Total Liabilities
pe_exi	P/E (Diluted, Excl. EI)	lt_debt	Long-term Debt/Total Liabilities
pe_inc	P/E (Diluted, Incl. EI)	profit_lct	Profit Before Depreciation/Current Liabilities
ps	Price/Sales	ocf_lct	Operating CF/Current Liabilities
pcf	Price/Cash flow	cash_debt	Cash Flow/Total Debt
dpr	Dividend Payout Ratio	fcf_ocf	Free Cash Flow/Operating Cash Flow
npm	Net Profit Margin	lt_ppent	Total Liabilities/Total Tangible Assets
opmbd	Operating Profit Margin Before Depreciation	dltt_be	Long-term Debt/Book Equity
opmad	Operating Profit Margin After Depreciation	debt_assets	Total Debt/Total Assets
gpm	Gross Profit Margin	debt_capital	Total Debt/Capital
ptpm	Pre-tax Profit Margin	de_ratio	Total Debt/Equity
cfm	Cash Flow Margin	intcov	After-tax Interest Coverage
roa	Return on Assets	intcov_ratio	Interest Coverage Ratio
roe	Return on Equity	cash_ratio	Cash Ratio
roce	Return on Capital Employed	quick_ratio	Quick Ratio (Acid Test)
efftax	Effective Tax Rate	curr_ratio	Current Ratio
aftret_eq	After-tax Return on Average Common Equity	cash_conversion	Cash Conversion Cycle (Days)
aftret_invcapx	After-tax Return on Invested Capital	inv_turn	Inventory Turnover
aftret_equity	After-tax Return on Total Stockholders' Equity	at_turn	Asset Turnover
pretret_noa	Pre-tax return on Net Operating Assets	rect_turn	Receivables Turnover
pretret_earnat	Pre-tax Return on Total Earning Assets	pay_turn	Payables Turnover
gprof	Gross Profit/Total Assets	sale_invcap	Sales/Invested Capital
equity_invcap	Common Equity/Invested Capital	sale_equity	Sales/Stockholders Equity
debt_invcap	Long-term Debt/Invested Capital	sale_nwc	Sales/Working Capital
totdebt_invcap	Total Debt/Invested Capital	rd_sale	Research and Development/Sales
capital_ratio	Capitalization Ratio	adv_sale	Advertising Expenses/Sales
int_debt	Interest/Average Long-term Debt	staff_sale	Labor Expenses/Sales
int_totdebt	Interest/Average Total Debt	accrual	Accruals/Average Assets
cash_lt	Cash Balance/Total Liabilities	ptb	Price/Book
invt_act	Inventory/Current Assets	peg_trailing	Trailing P/E to Growth (PEG) ratio
rect_act	Receivables/Current Assets	divyield	Dividend Yield
debt_at	Total Debt/Total Assets		

Appendix 3B – Robustness Checks

This section presents robustness checks to ensure the reliability and validity of the findings. Tables 3.B1 to 3.B4 compare analyst performance against the Random Forest (RF) model, providing insights into how well analysts' predictions align with or diverge from those generated by the RF model. These comparisons help assess whether analysts consistently outperform or underperform relative to the model. Meanwhile, Tables 3.B5 to 3.B9 focus on the RF model's performance across various settings, ensuring that the results are stable and not driven by specific conditions or anomalies. These robustness checks are crucial for confirming that the conclusions drawn from the analysis are robust and generalizable.

Table 3B.1 - *Additional controls: analyst performance relative to RF*

	Error difference			
VARIABLES	1	2	3	4
Analyst's firm-specific experience	4.60***	9.37***		
	(0.60)	(2.17)		
Analyst's general experience			2.99***	12.26***
			(0.74)	(1.83)
Volatility	339.72***	357.20***	339.31***	403.96***
	(14.87)	(16.12)	(14.84)	(19.26)
Analyst's firm experience X *Volatility*		-6.32**		
		(3.07)		
Analyst's general experience X *Volatility*				-11.82***
				(2.33)
Number of analysts following the firm	7.67***	7.67***	7.59***	7.69***
	(0.41)	(0.40)	(0.41)	(0.41)
Number of firms covered	0.28***	0.28***	0.26***	0.26***
	(0.07)	(0.07)	(0.07)	(0.07)
Number of industries covered	-1.26	-1.26	-1.27	-1.22
	(0.99)	(0.99)	(0.99)	(0.98)
Top size bank	7.11	7.40	5.35	5.75
	(7.48)	(7.49)	(7.75)	(7.72)
Forecast age	0.54***	0.54***	0.54***	0.54***
	(0.01)	(0.01)	(0.01)	(0.01)
Cumulative industry experience	0.02	0.01	0.04**	0.03*
	(0.02)	(0.02)	(0.02)	(0.02)
Average error by analyst, 5-year window	1,917.32***	1,914.51***	1,926.51***	1,917.00***
	(159.60)	(159.40)	(162.20)	(161.62)
Standard deviation of error by analyst, 5-year window	-212.89***	-212.64***	-214.34***	-213.67***
	(33.38)	(33.33)	(33.73)	(33.64)
Constant	-444.00***	-457.43***	-446.73***	-498.37***
	(15.23)	(15.59)	(15.58)	(18.10)
R-squared	0.37	0.37	0.37	0.37
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Notes. Number of observations is 660,379. Robust standard errors in parentheses.

Table 3B.2 - *Errors clustered at investment bank level: analyst performance relative to RF*

	Error difference			
VARIABLES	1	2	3	4
Analyst's firm-specific experience	2.69	8.96		
	(0.85)	(2.61)		
Analyst's general experience			-0.95	9.89
			(1.25)	(2.43)
Volatility	344.55	367.67	345.77	421.94
	(32.55)	(35.17)	(32.63)	(43.38)
Analyst's firm experience X *Volatility*		-8.36		
		(3.75)		
Analyst's general experience X *Volatility*				-13.93
				(3.33)
Number of analysts following the firm	7.72	7.72	7.49	7.60
	(1.14)	(1.14)	(1.14)	(1.13)
Number of firms covered	0.23	0.23	0.25	0.25
	(0.08)	(0.08)	(0.08)	(0.08)
Number of industries covered	-1.53	-1.52	-1.50	-1.43
	(1.08)	(1.07)	(1.07)	(1.07)
Top size bank	2.41	2.75	8.75	9.16
	(5.91)	(5.92)	(6.05)	(6.06)
Forecast age	0.54	0.54	0.55	0.55
	(0.03)	(0.03)	(0.03)	(0.03)
Constant	-377.87	-395.85	-368.78	-430.19
	(33.46)	(35.06)	(33.27)	(39.84)
R-squared	0.37	0.37	0.37	0.37
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Notes. Number of observations is 660,379. Robust standard errors in parentheses.

Table 3B.3 - *Errors clustered at firm level: analyst performance relative to RF*

	Error difference			
VARIABLES	1	2	3	4
Analyst's firm-specific experience	2.69***	8.96***		
	(0.85)	(2.61)		
Analyst's general experience			-0.95	9.89***
			(1.25)	(2.43)
Volatility	344.55***	367.67***	345.77***	421.94***
	(32.55)	(35.17)	(32.63)	(43.38)
Analyst's firm experience X *Volatility*		-8.36**		
		(3.75)		
Analyst's general experience X *Volatility*				-13.93***
				(3.33)
Number of analysts following the firm	7.72***	7.72***	7.49***	7.60***
	(1.14)	(1.14)	(1.14)	(1.13)
Number of firms covered	0.23***	0.23***	0.25***	0.25***
	(0.08)	(0.08)	(0.08)	(0.08)
Number of industries covered	-1.53	-1.52	-1.50	-1.43
	(1.08)	(1.07)	(1.07)	(1.07)
Top size bank	2.41	2.75	8.75	9.16
	(5.91)	(5.92)	(6.05)	(6.06)
Forecast age	0.54***	0.54***	0.55***	0.55***
	(0.03)	(0.03)	(0.03)	(0.03)
Constant	-377.87***	-395.85***	-368.78***	-430.19***
	(33.46)	(35.06)	(33.27)	(39.84)
R-squared	0.37	0.37	0.37	0.37
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Notes. Number of observations is 660,379. Robust standard errors in parentheses.

Table 3B.4 - *Volatility measure winsorized at 1% and 99%: analyst performance relative to RF*

	Error difference			
VARIABLES	1	2	3	4
Analyst's firm-specific experience	2.74***	10.46***		
	(0.64)	(1.84)		
Analyst's general experience			-0.93	11.65***
			(0.78)	(1.60)
Volatility	339.55***	368.70***	340.95***	432.63***
	(14.05)	(15.67)	(14.07)	(19.90)
Analyst's firm experience X *Volatility*		-10.31***		
		(2.80)		
Analyst's general experience X *Volatility*				-16.20***
				(2.20)
Number of analysts following the firm	7.68***	7.69***	7.45***	7.58***
	(0.40)	(0.40)	(0.41)	(0.41)
Number of firms covered	0.23***	0.23***	0.25***	0.25***
	(0.09)	(0.09)	(0.09)	(0.09)
Number of industries covered	-1.52	-1.50	-1.49	-1.41
	(1.09)	(1.09)	(1.10)	(1.09)
Top size bank	2.58	2.97	8.94	9.42
	(7.59)	(7.58)	(7.89)	(7.85)
Forecast age	0.54***	0.54***	0.55***	0.55***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	-372.80***	-395.40***	-363.81***	-437.28***
	(13.67)	(14.43)	(13.74)	(17.12)
R-squared	0.37	0.37	0.37	0.37
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Notes. Number of observations is 660,379. Robust standard errors in parentheses.

Table 3B.5 - Additional controls: RF performance

	RF error			
VARIABLES	1	2	3	4
Analyst's firm-specific experience	6.07***	51.64***		
	(1.56)	(18.54)		
Analyst's general experience			-2.58	50.98*
			(2.31)	(28.36)
Volatility	1,324.65***	1,491.73***	1,327.46***	1,700.92***
	(220.26)	(280.93)	(220.74)	(408.66)
Analyst's firm experience X *Volatility*		-60.40**		
		(24.31)		
Analyst's general experience X *Volatility*				-68.28*
				(37.21)
Number of analysts following the firm	-11.26***	-11.24***	-11.68***	-11.14***
	(1.26)	(1.26)	(1.30)	(1.25)
Number of firms covered	0.13	0.12	0.16	0.15
	(0.20)	(0.20)	(0.20)	(0.20)
Number of industries covered	-3.99	-3.93	-3.82	-3.50
	(2.61)	(2.59)	(2.60)	(2.51)
Top size bank	-12.98	-10.20	-1.43	0.86
	(13.53)	(13.38)	(13.59)	(13.52)
Forecast age	1.06***	1.06***	1.08***	1.07***
	(0.04)	(0.04)	(0.04)	(0.04)
Cumulative industry experience	-0.08	-0.11	0.02	-0.02
	(0.07)	(0.08)	(0.06)	(0.08)
Average error by analyst, 5-year window	3,321.96***	3,295.13***	3,263.23***	3,208.27***
	(655.50)	(656.16)	(666.10)	(667.46)
Standard deviation of error by analyst, 5-year window	67.43	69.83	79.15	83.00
	(137.71)	(137.84)	(139.60)	(139.59)
Constant	-909.79***	-1,038.12***	-891.71***	-1,190.03***
	(152.95)	(199.16)	(150.43)	(299.15)
R-squared	0.37	0.37	0.37	0.37
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Notes. Number of observations is 660,379. Robust standard errors in parentheses.

Table 3B.6 - *Errors clustered at investment bank level: RF performance*

	RF error			
VARIABLES	1	2	3	4
Analyst's firm-specific experience	1.45	50.34***		
	(1.31)	(17.94)		
Analyst's general experience			-10.24***	47.01*
			(2.04)	(27.36)
Volatility	1,330.55***	1,510.85***	1,336.26***	1,738.30***
	(225.15)	(284.68)	(225.63)	(412.79)
Analyst's firm experience X *Volatility*		-65.19***		
		(24.33)		
Analyst's general experience X *Volatility*				-73.52**
				(36.50)
Number of analysts following the firm	-11.19***	-11.16***	-11.91***	-11.32***
	(1.32)	(1.32)	(1.36)	(1.29)
Number of firms covered	0.16	0.15	0.27	0.26
	(0.23)	(0.23)	(0.23)	(0.23)
Number of industries covered	-3.35	-3.25	-3.14	-2.74
	(2.66)	(2.64)	(2.64)	(2.55)
Top size bank	-22.19	-19.55	6.14	8.32
	(17.35)	(17.39)	(17.34)	(17.65)
Forecast age	1.08***	1.08***	1.10***	1.10***
	(0.05)	(0.05)	(0.05)	(0.05)
Constant	-730.61***	-870.83***	-690.11***	-1,014.27***
	(156.37)	(202.51)	(153.33)	(303.77)
R-squared	0.37	0.37	0.37	0.37
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Notes. Number of observations is 660,379. Robust standard errors in parentheses.

Table 3B.7 - *Errors clustered at firm level: RF performance*

	RF error			
VARIABLES	1	2	3	4
Analyst's firm-specific experience	1.45	50.34***		
	(1.73)	(14.57)		
Analyst's general experience			-10.24***	47.01**
			(2.47)	(21.87)
Volatility	1,330.55***	1,510.85***	1,336.26***	1,738.30***
	(194.68)	(235.31)	(195.26)	(342.55)
Analyst's firm experience X *Volatility*		-65.19***		
		(20.11)		
Analyst's general experience X *Volatility*				-73.52**
				(29.48)
Number of analysts following the firm	-11.19***	-11.16***	-11.91***	-11.32***
	(2.02)	(2.01)	(2.06)	(2.02)
Number of firms covered	0.16	0.15	0.27	0.26
	(0.21)	(0.21)	(0.21)	(0.21)
Number of industries covered	-3.35	-3.25	-3.14	-2.74
	(2.39)	(2.37)	(2.38)	(2.31)
Top size bank	-22.19*	-19.55*	6.14	8.32
	(11.59)	(11.51)	(10.86)	(10.86)
Forecast age	1.08***	1.08***	1.10***	1.10***
	(0.06)	(0.06)	(0.06)	(0.06)
Constant			-10.24***	47.01**
			(2.47)	(21.87)
R-squared	0.37	0.37	0.37	0.37
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Notes. Number of observations is 660,379. Robust standard errors in parentheses.

Table 3B.8 - *Volatility measure winsorized at 1% and 99% level: RF performance*

	RF error			
VARIABLES	1	2	3	4
Analyst's firm-specific experience	2.44*	28.64***		
	(1.26)	(5.99)		
Analyst's general experience			-8.44***	21.31***
			(1.70)	(8.25)
Volatility	931.54***	1,030.42***	937.47***	1,154.31***
	(58.48)	(70.09)	(58.76)	(104.20)
Analyst's firm experience X *Volatility*		-34.97***		
		(8.51)		
Analyst's general experience X *Volatility*				-38.32***
				(11.47)
Number of analysts following the firm	-11.07***	-11.05***	-11.74***	-11.43***
	(1.25)	(1.25)	(1.29)	(1.27)
Number of firms covered	0.16	0.16	0.25	0.25
	(0.24)	(0.24)	(0.25)	(0.25)
Number of industries covered	-2.88	-2.83	-2.71	-2.52
	(2.57)	(2.56)	(2.57)	(2.55)
Top size bank	-19.05	-17.74	6.10	7.24
	(13.10)	(13.08)	(13.47)	(13.42)
Forecast age	1.09***	1.09***	1.11***	1.11***
	(0.04)	(0.04)	(0.04)	(0.04)
Constant			-8.44***	21.31***
			(1.70)	(8.25)
R-squared	0.36	0.36	0.36	0.36
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Notes. Number of observations is 660,379. Robust standard errors in parentheses.

Table 3B.9 - *Logged dependent variable - RF error*

	Log of RF error			
VARIABLES	1	2	3	4
Analyst's firm-specific experience	0.003271	0.014932***		
	(0.002577)	(0.004744)		
Analyst's general experience			-0.016432***	-0.002453
			(0.003527)	(0.004604)
Volatility	1.058426***	1.101428***	1.067662***	1.166046***
	(0.021335)	(0.024812)	(0.021033)	(0.029812)
Analyst's firm experience X *Volatility*		-0.015549***		
		(0.005488)		
Analyst's general experience X *Volatility*				-0.017985***
				(0.003879)
Number of analysts following the firm	0.001115***	0.001113***	0.001287***	0.001285***
	(0.000317)	(0.000317)	(0.000324)	(0.000324)
Number of firms covered	-0.015921***	-0.015897***	-0.015517***	-0.015426***
	(0.003609)	(0.003607)	(0.003600)	(0.003593)
Number of industries covered	0.001533	0.002163	0.048712*	0.049272**
	(0.024340)	(0.024281)	(0.024996)	(0.024920)
Top size bank	0.005879***	0.005879***	0.005912***	0.005912***
	(0.000038)	(0.000038)	(0.000037)	(0.000037)
Forecast age	1.443128***	1.409777***	1.493350***	1.416120***
	(0.031954)	(0.033020)	(0.034464)	(0.037999)
R-squared	0.545847	0.545865	0.546018	0.546064
Firm FE	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Notes. Number of observations is 660,379. Robust standard errors in parentheses.

Appendix: Chapter 4

This appendix provides details on the matching procedure between I/B/E/S and LinkedIn datasets.

Selection of investment banks from I/B/E/S

I filter the observations to include only firms based in the United States, using the 'usfirm' flag available in the I/B/E/S dataset. Since the majority of the I/B/E/S data comprises estimates for publicly listed companies in the U.S., excluding non-U.S. firms helps remove smaller investment banks or independent equity research organizations that could otherwise appear in the data.

Next, I limit the sample period to 2005–2016, aligning it with the availability of LinkedIn data, ensuring consistency and accurate matching between the two datasets.

Finally, I select the top 100 investment banks within this filtered dataset. The selection criterion combines the highest number of analysts and the highest number of estimates provided by each bank during this period.

Matching I/B/E/S with LinkedIn

In the subsequent step, I match the two datasets. However, this matching process involves several challenges. First, the I/B/E/S estimates dataset lacks explicit identification information for the investment banks and analysts, offering only anonymous IDs. Some identifying details are available in the separate I/B/E/S recommendations file. The primary difference between these datasets is that the estimates file includes earnings per share (EPS) forecasts for firms, whereas the recommendations file provides analyst stock recommendations (e.g., buy, hold, or sell). Given the inherent difficulty in objectively measuring the accuracy of stock recommendations, I focus exclusively on the estimates data, where I can objectively measure the accuracy of the forecasts.

Additionally, the identification details available in the recommendations dataset do not explicitly mention the names of investment banks. Instead, the dataset includes a variable named "estimid," but according to correspondence with WRDS support (the data source), there is no guarantee that these labels correspond precisely to the actual names of banks. For instance, an entry labeled "Goldman" may not necessarily represent "Goldman Sachs."

Another complication arises from the analyst identification information. The available data provides only analysts' last names and the initial letter of their first names, rather than full names. Previously, a separate dataset included the complete names of analysts and their corresponding banks, but this information is no longer made available for academic use.

To overcome these identification challenges, I implemented the following matching procedure:

- For each 'estimid' from the recommendations file, I manually verified at least ten analysts using LinkedIn. Specifically, I searched for individuals with professional titles such as "equity analyst," "research analyst," "financial analyst," or "securities analyst."
- I examined their LinkedIn profiles and cross-referenced their employment periods with the timing of forecasts in the I/B/E/S dataset to confirm matching employment dates.
- Through this process, I identified multiple possible investment bank names associated with each 'estimid,' which were manually extracted from the LinkedIn profiles.

Following these steps, I proceeded to match the I/B/E/S dataset with the LinkedIn data using this logic:

- Matching analysts based on their last names.
- Confirming matches using the first initial of their first names.

- Applying fuzzy matching techniques on either the 'estimid' or the alternative bank names manually derived from LinkedIn data.

As a result of this procedure, I compiled a pool of individuals who listed these investment banks as their employers on their LinkedIn profiles during the relevant time period. I then merge this data to I/B/E/S estimate data – the main data used in this analysis – by relying on the link between analyst ID in estimates data and analyst masked code (amaskcd) in I/B/E/S recommendations data.

Calculation of AI adoption measure

To calculate the AI adoption measure, I follow a modified version of the approach proposed by Baina et al. (2024). The original method involves identifying AI-related activity using a list of AI-specific keywords and checking their presence in Cognism data. Specifically, the authors examine whether these keywords appear in: (i) job roles, (ii) patent filings, or (iii) publications or awards.

However, since I do not have Cognism data, I had to rely on LinkedIn data, which presents certain limitations—primarily because it is self-reported. Users often omit patents or publications, and there is a risk of inaccurate or exaggerated claims on the platform, since user can report whatever they want. In addition, many users may use inconsistent job titles or informal terminology that complicates keyword searches. To address these limitations, I adopt a more conservative approach by focusing on job titles.

I match job titles in the filtered LinkedIn dataset with a standardized list of AI-related roles sourced from AIJobs.net. This platform has a comprehensive and up-to-date collection of real-world AI job titles based on industry hiring trends, job postings, and employer needs across various sectors. Examples include roles such as "Machine Learning Engineer", "Data Scientist", "AI Research Scientist" and "NLP Engineer."

Using AIJobs.net helps ensure that the roles identified truly reflect real-world, in-demand AI jobs. By basing the AI adoption measure on actual labor market trends and recognized job roles, this approach makes the measure both more accurate and easier to understand in terms of how organizations are building their AI capabilities.

I perform a fuzzy match between LinkedIn job titles and AI-related job titles derived from AIJobs.net. I then manually validate the matches to ensure accuracy. The matched titles are flagged as AI-related in my dataset, creating a dummy variable that indicates whether a given employee at an investment bank holds an AI-related role. At the investment bank-year level, I calculate the ratio of AI-related employees to the total workforce. This provides an estimate of the proportion of human capital involved in either the development or deployment of AI technologies within each firm.

I would like to thank the management team of AIJobs.net for generously sharing their data and supporting this study.