

Bank Culture Meets FinTech: Measuring Innovation with Large Language Models

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Luca Bellardini

Postdoctoral Research Fellow
University of Milano-Bicocca
E-mail: luca.bellardini@unimib.it

Na Dai^{*}

Esther Massry Professor of Finance
Massry School of Business
University of Albany
Email: ndai@albany.edu

Daniele Previtali

Associate Professor of Banking & Finance
University of Naples at Parthenope
Email: daniele.previtali@uniparthenope.it

Kinsun Tam

Associate Professor of Accounting
Massry School of Business
University of Albany
Email: ktam@albany.edu

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Abstract

This paper investigates how innovation culture influences banks' strategic responses to FinTech disruption. We develop a novel, data-driven measure of innovation culture using large language models (LLMs) applied to the Business Description, Risk Factors, and MD&A sections of 10-K filings for U.S. banks (2013–2023). This LLM-based textual analysis captures latent cultural signals and enables consistent, firm-year-level measurement across a large panel. We link this measure to banks' fintech engagement, risk-taking, capital adequacy, and stock performance. Results show that banks with stronger innovation cultures are significantly more likely to invest in FinTech startups and form partnerships with FinTech firms, maintain capital discipline and do not expose to excessive risk. Innovation culture also predicts stock returns as a key driver of strategic adaptability.

1. Introduction

The rapid rise of financial technology (FinTech) has profoundly reshaped the financial services landscape, posing both a competitive threat and an innovation catalyst for traditional banks. FinTech firms—leveraging cutting-edge digital technologies such as artificial intelligence (AI), blockchain, cloud computing, and big data analytics—have introduced user-centric business models that offer faster, more convenient, and lower-cost financial services. These innovations have disrupted core banking activities including payments, lending, wealth management, and insurance, thereby reducing customer dependence on traditional financial institutions (Thakor, 2020; Boot et al., 2021).

This wave of disruption has compelled incumbent banks to reevaluate their strategic positioning and adapt to a dynamic and increasingly digitized market environment. While some banks have responded with agility and foresight, embracing digital transformation and partnering with FinTech startups (Hornuf et al., 2021, Puri et al., 2024), others have been slower to act, hindered by legacy systems, bureaucratic inertia, and a conservative approach to technological change. Notably, large and diversified banks over the globe have taken proactive steps to innovate—launching digital banking platforms, investing in emerging technologies, and forming strategic alliances with FinTech firms (Bellardini et al., 2022). In contrast, laggard institutions have continued to rely on traditional business models, facing heightened risks of customer attrition, declining profitability, and regulatory pressure to modernize.

A critical, yet underexplored, factor that may explain this divergence in strategic responses is the innovation culture embedded within banks. Innovation culture refers to an organization's internal norms, values, knowledge and practices that foster openness to innovation, transformation,

and agility (Thakor, 2023). It shapes a bank's capacity to sense, interpret, and respond to external disruptions by supporting the execution of an innovative strategy. In fact, innovation in the banking sector is not merely hindered by technical or regulatory constraints, but fundamentally by the way innovation is perceived and prioritized within organizational and strategic agendas. A non-innovative culture manifests in constrained budgets, limited autonomy for innovation leaders, and internal rigidities that hamper the adoption of new technologies and operational models. In this context, the role of the top management is pivotal to spread innovation culture across the organization. When leadership is strategically oriented towards change and acknowledges the transformative potential of new technologies, the innovation process is more likely to receive consistent support, structure, and investment. In contrast, without executive commitment, innovation remains largely exploratory and disconnected from business operations. Hence, innovation in banking is fundamentally a matter of innovation culture rather than merely a technological challenge. It is the cultural orientation of an institution that determines whether innovation is viewed as core organizational enabler or a peripheral risk.

Banks with strong innovation cultures are more likely to encourage entrepreneurial thinking, break down hierarchical decision-making structures, and deploy digital solutions with agility reducing the time-to-market of innovation. This cultural foundation enhances the institution's capacity to respond to competitive pressures and customer expectations. In contrast, banks with rigid, risk-averse cultures may struggle to adapt. They may delay the adoption of emerging technologies, resist organizational change, and ultimately forgo opportunities to assert themselves in an increasingly digital and dynamic financial ecosystem. Thus, cultivating an innovation-oriented culture is not ancillary – it is the principal level through which banks can achieve adaptive capacity and long-term business sustainability.

Despite the growing recognition of the role of bank culture in influencing performance and risk propensity (Song & Thakor, 2019; Barth and Mansouri, 2021), empirical research examining the relationship between innovation culture and responses to FinTech disruption remains limited. One key barrier has been the difficulty of reliably measuring innovation culture at scale as it remains a nebulous concept (Thakor, 2023). Traditional approaches rely heavily on survey-based assessments, which are subject to self-reporting biases, limited comparability, and often capture only a static snapshot of culture (Naveed et al., 2022). Moreover, these methods are rarely feasible for large-scale, cross-institutional analyses in the banking sector.

To overcome these limitations, we develop a novel, data-driven measure of bank innovation culture by applying large language models (LLMs) to Business Description (Item 1), Risk factors (Item 1A) and MD&A (Item 7) in banks' 10-K filings. Our main results are based on LLaMA3 and we performed robustness checks using a variety of alternative LLMs, such as E5, MPNET, FinBERT, BGE, among others. This LLM-based textual analysis captures latent semantic signals in firm narratives and allows us to construct a continuous, firm-year-specific proxy for innovation orientation. Our methodology enables consistent, scalable, and temporally dynamic measurement of culture across a large panel of U.S. banks.

Using this measure, we investigate how banks' innovation cultures influence their strategic responses to FinTech disruption—specifically their likelihood of investing in and forming partnership with FinTech startups, and the downstream implications for risk-taking, capital adequacy, and financial performance. Our empirical analysis spans the period from 2013 to 2023 and integrates data from bank financial statements, Crunchbase FinTech investment records, manually collected bank-fintech partnership, and patent filings related to FinTech competition.

Our analysis reveals that innovation culture is a powerful and economically meaningful determinant of banks' strategic engagement with FinTech. Banks with stronger innovation-oriented cultures are significantly more likely to invest in or partner with FinTech firms, and these effects are large: moving from the 25th to the 75th percentile of innovation culture increases the likelihood of FinTech investment, partnership formation, or either activity by approximately 50–100 percent. Innovation culture matters most for *whether* banks engage with FinTech, and its effects are especially pronounced among small banks. While large banks are generally more active in FinTech overall, cultural orientation plays a much stronger role in driving FinTech adoption and early response among smaller institutions.

Despite this heightened engagement, innovation-oriented banks do not take on materially greater prudential risk. Across multiple risk measures—including RWA/TA, capital ratios, and forward-looking Z-scores—innovation culture does not consistently predict higher risk-taking or weaker capital positions. This suggests that banks can pursue digital transformation and technology partnerships without compromising financial stability. Finally, we find limited but directionally meaningful evidence that innovation culture and FinTech investment improve market-based performance. Innovation-oriented banks earn higher subsequent stock returns, and FinTech investments are similarly rewarded by the equity market, even as short-run accounting outcomes remain largely unchanged. These patterns point toward a dynamic in which investors recognize the strategic value of innovation and FinTech engagement before their operational benefits fully materialize.

This study contributes to the growing literature at the intersection of financial innovation, organizational culture, and banking strategy in several meaningful ways. First, it offers one of the first large-scale empirical examinations of how a bank's internal innovation culture shapes its

strategic response to FinTech disruption, particularly in terms of investment, external partnerships, risk-taking, and performance. While prior work has examined the drivers of bank innovation (Boot & Ratnovski, 2016; Navaretti et al., 2018) and the implications of FinTech partnerships (Frost et al., 2019; Hornuf et al., 2021; Collevocchio et al., 2023), few studies have systematically linked these strategic outcomes to an underlying cultural trait that differentiates banks' capacity to adapt to technological change.

Second, we advance the methodological frontier of corporate culture research by employing a large language model (LLM)-based textual analysis to construct a continuous and objective measure of bank innovation culture from 10-K filings. This approach addresses limitations associated with traditional survey-based measures, which suffer from biases and lack comparability across firms. Our technique complements recent developments in textual analysis of firm disclosures (Li, 2010; Hoberg & Phillips, 2016; Huang et al., 2018) and introduces a scalable framework for measuring cultural attributes with economic relevance.

Third, our findings add nuance to the literature on corporate innovation and risk by showing that innovation culture does not necessarily translate into excessive risk-taking. Contradicting the view that innovation correlates with financial fragility (Fiordelisi & Ricci, 2014, Song & Thakor, 2019), our evidence indicates that innovative banks uphold capital discipline, suggesting a more governed approach to experimentation. This supports theoretical perspectives from strategic management that describe innovation-oriented firms as more tolerant of uncertainty (March, 1991; Garud & Van de Ven, 1992), but not necessarily imprudent.

Understanding how banks respond to fintech disruption holds significant societal and economic implications. As fintech continues to reshape the financial services industry, the ability of traditional banks to innovate and adapt will play a critical role in maintaining financial stability,

ensuring competitive markets, and fostering financial inclusion. Banks that fail to embrace innovation risk being marginalized, which could lead to increased market concentration in the hands of a few dominant fintech and big tech players. By identifying the cultural factors that enable or hinder banks' adaptability, the research has the potential to guide policymakers in designing regulations that foster innovation while mitigating risks. Additionally, this work will enable bank top management to highlight how culture is a key determinant of innovation, without which it becomes difficult to adapt to constantly changing market conditions—especially due to the impact of technology on business and service models. Top management will thus be able to develop strategies and action plans to strengthen culture as a driver of growth and development, ultimately benefiting consumers through improved services, greater financial inclusion, and enhanced economic resilience.

The remainder of the paper is organized as follows. Section 2 provides a review of literature related to organizational culture, bank culture, and fintech disruptions. In section 3, we discuss how we create a measure of bank innovation culture using the LLM approach. Section 4 describes the data we use and provides summary statistics of our sample. In section 5, we perform empirical analysis and discuss various robustness checks. We conclude in section 6.

2. Literature Review

This study intersects several research streams in finance and management, including work on organizational culture, innovation in banking, strategic responses to technological disruption, and text-based measurement methods.

Organizational Culture, Innovation and Banking

A growing body of literature explores how corporate culture shapes financial decision-making, firm performance, and risk. Culture is typically conceptualized as a persistent and difficult-to-observe set of shared norms and values that influence risk tolerance, innovation propensity, and governance structures (Schein, 2010; Stock et al., 2013; Guiso et al., 2015). Martins & Terblanche (2003) argued that culture is a value driver determinant in the success of any organization as it lies at the core mechanism of organizational innovation (Tushman, 1997). Tian et al. (2018) review the evidence on how culture influences innovation.

In the context of banking, culture has been primarily defined and measured as *risk culture*, as it was identified as a key contributor to the 2007–2009 financial crisis. A poor risk culture can lead banks to excessive risk-taking and capital shortfalls, thereby increasing systemic risk (Song & Thakor, 2019). Using the *Competing Values Framework* (Cameron, 2006), Barth & Mansouri (2021) show that banks with a competition-oriented culture tend to compensate executives with a larger share of bonuses. Furthermore, a culture with an external focus is associated with higher returns, while a creative-oriented culture is linked to lower returns and a higher risk of bankruptcy, especially during periods of financial distress. Additionally, banks with a creative-dominant culture have been found to make greater use of discretionary loan loss provisions (LLPs) in response to increased competition, and are more likely to face formal regulatory enforcement actions (Luu et al., 2022). This aligns with the theoretical prediction of Thakor (2012), which suggests that financial innovation often entails greater bankruptcy risk and instability.

However, it is also important to note that a bank's creative culture could not be viewed solely through the lens of regulatory concerns around risk management. On the contrary, the key concepts underlying a creative culture—such as openness to innovation, proactive change, and visionary thinking—directly influence a bank's strategic positioning. A strong innovation

propensity can drive market share growth, differentiation in competitive ecosystems, and enhanced profitability over the medium to long term (Tian et al., 2018). These factors, in turn, constitute the primary safeguard for the preservation and growth of capital. In this context, relatively few studies have investigated how culture shapes strategic adaptation to technological change—particularly in heavily regulated industries such as banking. Our paper contributes to this emerging literature by investigating how a bank's innovation-oriented culture affects its ability to navigate FinTech-driven competition and sustain strategic advantage in a rapidly evolving financial landscape.

Bank Innovation, FinTech, and Strategic Adaptation

The literature on bank innovation has examined both its drivers and its consequences. Banks may innovate internally, through R&D and digital transformation, or externally, through partnerships and acquisitions (Thakor, 2020). While innovation can enhance competitive advantage, it may also increase opacity and risk (Delis, et al, 2020). Recent studies show that banks interact with FinTech startups via investment, acquisition, or partnership (Hornuf et al., 2021; Bellardini et al., 2022; Collevocchio et al., 2023; Puri et al., 2024), yet these interactions vary widely across institutions.

Empirical evidence shows that banks systematically invest in FinTech startups as a strategic approach to navigate innovation and competition. This is particularly the case for startups that complement their core business. However, investment in and acquisition of FinTech startups appear to have a negative impact on market returns (Carlini et al., 2021), as execution risks and valuation uncertainties can offset the potential benefits of innovation-driven strategies. In line with these findings, Hornuf et al. (2021) show that banks generally prefer product-based collaborations with FinTech firms over direct acquisitions, as acquisitions may represent a particularly complex

and risky method for internalizing financial innovation. This preference for collaborative models suggests that banks seek to balance innovation adoption with the need to manage organizational complexity and execution risks effectively.

A key question remains what drives the heterogeneity in Fintech strategies among banks. Most empirical work has focused on observable factors such as size, market power and competition, or capital constraints (Bellardini et al., 2022; Collevocchio et al., 2023 – among the others). In contrast, the role of internal, intangible factors—such bank’s cultural orientation toward innovation—has received comparatively little attention. Understanding how cultural attitudes influence the propensity to invest in, acquire, or collaborate with FinTech startups could provide important insights into the strategic behavior of banks and the long-term effectiveness of their innovation initiatives.

Strategic management research suggests that innovation-oriented cultures are more willing to experiment and invest in innovation contributing to product innovation and performance (March, 1991; Garud and Van de Ven, 1992; De Tienne & Mallette, 2012; Tian et al., 2018). Innovation culture, in particular, has been shown to interact positively with a firm’s ability to navigate technological change and competitive disruption. In the banking context, this may translate into earlier or more aggressive engagement with FinTech opportunities. However, existing empirical work on incumbent responses to FinTech innovation has largely overlooked the role of organizational culture. For example, Tang (2019) examines how peer-to-peer lending platforms compete with traditional banks, but does not explore differences in how banks’ internal cultures might shape strategic responses. Our study extends this literature by focusing on the cultural enablers of strategic FinTech engagement.

Textual Analysis and Measuring Intangibles in Finance

A parallel body of research in empirical finance has advanced the use of textual data to measure intangible firm attributes. This is because the amount of text and other forms of unstructured data have rapidly increased in the last decade. The rise in interest in human-generated data has led to the application of text mining for extracting information and finding patterns in texts. The growing academic interest in text mining within the financial sector is primarily driven by the exponential increase in available unstructured data. The volume of textual data generated from sources such as financial news, social media, corporate reports, and regulatory disclosures has expanded dramatically (Lewis and Young, 2019). This evolution has highlighted the need for automated tools capable of extracting relevant information, overcoming the limitations of manual analysis, which is slow and ineffective in handling large datasets (Fisher et al., 2016). Moreover, text-mining techniques such as sentiment analysis and natural language processing have proven essential for enhancing the capability of extracting new information from text in several finance contexts such as central banking, financial markets, risk management, corporate governance and disclosure (more recently: Carlini et al., 2020; Acheampong & Elshandidy, 2021; Bennani & Romelli, 2024; Tzomakas et al., 2023). The digitalization of financial services and the expansion of the FinTech sector have further encouraged the adoption of these methods, making text mining a key component in the innovation of financial decision-making processes (Zavolokina et al., 2016). Gupta et al. (2020) systematically review the text-mining application in finance. These studies often employ finance-specific dictionaries to capture sentiment or tone as in Loughran & McDonald (2011).

In this context, recent studies have increasingly applied text analysis techniques to the investigation of bank culture. Bank culture emerged as a critical topic following the Global

Financial Crisis, primarily to examine its role in influencing risk exposure (Fiordelisi & Ricci, 2014). Recently, Bianchi et al. (2021), analyzing a large sample of European banks, find that a sound risk culture significantly enhances bank performance. Similarly, Nguyen et al. (2024) employ machine learning techniques to identify risk culture as a key driver of improvements in capital adequacy and liquidity creation.

Over the past three years, particularly following the release of ChatGPT in November 2022, the literature has increasingly focused on exploring advanced text analysis methodologies, especially the application of Large Language Models (LLMs) in the financial domain. Unlike traditional bag-of-words approaches, which rely solely on word frequency without capturing contextual meaning, LLMs process language in a more sophisticated and nuanced manner, understanding syntax, semantics, and complex relationships within the text. Furthermore, compared to classical machine learning techniques, which often require extensive feature engineering and structured inputs, LLMs are capable of learning directly from raw textual data, offering superior performance in tasks such as sentiment analysis, event extraction, and predictive modeling. For instance, Huang et al. (2023) developed FinBERT, a large language model specifically trained on financial texts, aimed at enhancing information extraction tasks such as sentiment classification and ESG-related discussion identification. Their results demonstrate that FinBERT significantly outperforms traditional methods, such as the Loughran and McDonald (2011) dictionary and classical machine learning models. Similarly, Ardekani et al. (2024) introduced FinSentGPT, a fine-tuned version of ChatGPT, designed to predict financial sentiment from both structured and unstructured texts. Testing on U.S. financial news articles and European Central Bank statements reveals that FinSentGPT outperforms conventional machine learning approaches and demonstrates strong multilingual capabilities. These findings highlight the

potential of large language models to establish a universal, context-aware financial sentiment engine, overcoming many of the limitations associated with earlier sentiment analysis methodologies.

Our study builds on this literature by using large language models (LLMs) to construct a dynamic, firm-year-specific measure of bank innovation culture from the MD&A section of 10-K reports. This approach allows us to study how a largely unobservable trait—innovation culture—affects observable strategic and financial behavior in the banking sector.

3. Measure of Bank Innovation Culture: An LLM Approach

To quantify a bank's innovation culture, this study compares all texts from business description (Item 1), Risk factors (Item 1A) and MD&A (Item 7) in the annual 10-K filing of each sample bank to a reference document describing the practices of the most innovative banks using the large language model (LLM). We provide detailed explanations on our approach in this section.

3.1 LLM and Embeddings

To compare the meaning of texts in a computerized fashion, we need to first convert text data to numerical data in a way that systemically capture the meaning of text. LLM and embedding are useful tools in this regard. LLMs can reliably extract nuanced meanings from text. By employing LLMs in our study, we transform qualitative statements in the Form 10-K disclosures and the reference document on bank innovations into embeddings carrying quantitative data.

An LLM is a large neural network containing hundreds of millions to billions of parameters, which are initially randomized and then optimized during training. Each model is trained on vast text corpora that include content from web pages, books, Wikipedia, code repositories, and other sources. It is repeatedly trained on new sequences, refining its parameters to minimize errors. Through this training process, it learns patterns about co-occurring words, synonyms and analogies, verb-noun agreement, etc. which are then recorded in an internal map. For instance, it records learned patterns that (1) 'bank' near 'money' means finances, near 'river' means geography and (2) 'apple' near 'technology' means phone producer, near 'supermarket' means fruit.

An embedding is a high-dimensional numerical vector that encodes the semantic and linguistic features of a piece of text. Each dimension in the vector corresponds to some combination of learned features (e.g., finance, tech, emotion), and the numerical value represents the relevance of that dimension. Texts with similar meanings will have similar embeddings, placing their vectors close together in the embedding space.

Embeddings are gaining prominence in business text research. Li et al. (2021) apply machine learning and Mikolov et al. (2013)'s Word2vec model to produce embeddings that quantify and interpret the meaning of words and expressions in earnings call transcripts. We advance the methodology by deriving embeddings from a host of modern LLMs mostly released in 2024 (see Appendix C). These models are considerably more advanced than Word2Vec especially in gaining nuanced understanding of texts from contextual information.

When a trained LLM is asked to interpret a new document, it relies on its internal map to convert the document to embedding, in a process called embedding extraction. Suppose the new document mentions 'bank' near 'money' and 'apple' near 'technology'. The LLM will assign a high

numerical value to the dimensions about finance and phone producer. By repeating this process with other content and additional learned pattern, the LLM produces a final embedding capturing the meaning of the new document in a numerical vector. Using cosine similarity to compare the alignment of two embeddings enables us to quantify the semantic similarity between the corresponding texts.

3.2 Cosine Similarity

In natural language processing (NLP), cosine similarity is a measure of similarity between two documents represented as vectors. Cosine similarity measures the cosine of the angle between two vectors. Not dependent on the magnitudes of the vectors, but only on their angle, cosine similarity is scale-invariant. In NLP, the value of cosine similarity is bounded on the closed interval $[-1, 1]$.

The cosine between two vectors $\mathbf{A}$ and $\mathbf{B}$, as given by the Euclidean dot product formula, is

$$\cos \theta = \frac{\text{dot product of vectors } \mathbf{A} \text{ and } \mathbf{B}}{\text{magnitude of vector } \mathbf{A} * \text{magnitude of vector } \mathbf{B}} = \frac{\sum_{i=1}^n (A_i B_i)}{\sqrt{\sum_{i=1}^n (A_i^2)} * \sqrt{\sum_{i=1}^n (B_i^2)}}$$

where A_i and B_i are the weights of vectors $\mathbf{A}$'s and $\mathbf{B}$'s i -th dimension (i.e., i -th word).

Cosine similarity is a mathematical measure that assesses the alignment of two vectors (i.e. the embeddings) regardless of their magnitude. A higher cosine similarity score indicates a stronger alignment between the sample document and the reference document. Therefore, a strong alignment between a given bank's disclosures to the innovation reference document

suggests a strong focus on innovation in the given bank's disclosures. See Appendix D for simple examples about how cosine similarity is calculated.

3.3 Reference Document on Bank Innovation

We create bank innovation benchmark data from descriptions of practices of the most innovative banks each year by Qorus (<https://www.qorusglobal.com>) between 2013 and 2023.² Qorus is a global non-profit financial services association established in 1971 to promote financial services innovation and collaboration. Emphasizing a community-led approach, Qorus adopts a name that rhymes with "chorus", symbolizing a group united by common goals. Positioning as a neutral medium for members to build relationships that drive successful innovation, Qorus aims to be the catalyst for members to reinvent financial services.³ Stories of innovative transformations of Qorus-award winners have appeared in Harvard and INSEAD case studies.⁴

Qorus presents awards on bank innovation in multiple categories, including business model innovation, product service innovation, business banking innovation, operations and workforce transformation, customer experience innovation, and social, sustainable & responsible banking innovation. The award categories vary slightly over time to reflect the ever-changing banking ecosystem. For instance, a new award category on predictive, generative, and agentic AI innovation is added in 2025. Each category has a detailed description. There are usually three winners (gold, silver, and bronze, each with a separate description) in each category. We merge

² Qorus does not provide award information for 2020. To avoid a missing year, we combine 2019 and 2021 data to approximate 2020, resulting in 11 Qorus files in total: 2023, 2022, 2021, 2020, 2019, 2018, 2017, 2016, 2015, 2014, & 2013. Cosine similarity is scale-invariant, which means a longer 2020 file than the average year does not bias cosine similarity calculation.

³ <https://intlbn.com/2022/06/17/efma-rebrands-its-official-status-to-qorus/>

⁴ <https://fintechnews.sg/69368/digital-transformation/harvard-business-school-publishes-case-study-on-dbs-digital-transformation/>

all category descriptions and winner descriptions of a given year into a single reference document on bank innovation. For instance, for a specific year, assuming there were six categories of innovation awards, and three different banks were awarded in each category, our reference document will contain descriptions on how these 18 winners had been innovative in that specific year. In Appendix A, we provide an example of Qorus' 2023 Innovative Bank Award categories and winners' descriptions.

We analyze the Business (Item 1), Risk Factors (Item 1A), and MD&A (Item 7) sections of Form 10-K to assess innovation culture because these disclosures reveal how management narrates strategy, uncertainty, and execution around innovation. The Business section describes core products, R&D activities, competitive positioning, and explicit cultural themes such as collaboration or experimentation, linking innovation to the firm's business model. Risk Factors disclose how seriously the firm treats threats from technological change, failure to innovate, or loss of key talent, which offer informative insights on product innovation and human capital innovation. MD&A provides management's own account of strategic initiatives, technological investments, and forward-looking projects, which are tied to strategic, technological, and workforce innovations. Together, these disclosures are informative textual input for measuring a firm's innovation culture.

While these Form 10-K disclosures (i.e. Business, Risk Factors, and MD&A sections) contain innovation-related insights, innovation constitutes only a fraction of their overall coverage since they are primarily for communicating matters about operations, markets, strategy, competition, regulation, material risks, financial results, and future outlook. Directly measuring innovation characteristics from these sections is challenging because of their substantial non-innovation content.

To reduce the noise of non-innovation-culture related content in these disclosures, we ask ChatGPT to identify key terms from the Qorus reference document that are specifically related to the key dimensions of innovation culture based on the organizational behavior/innovation literature (e.g., openness/idea generation, tolerance of failure, collaboration/knowledge sharing, learning orientation/adaptability, empowerment/autonomy, leadership support/strategic emphasis). These key innovation culture terms are included in Appendix B. We developed a program to collect all sentences containing at least one of these key terms from these corporate disclosures. The program accommodates variations due to tense, comparative and superlative forms, and singular versus plural forms, and does not extract any sentence more than once. These sentences are then combined to form an input text file for each firm-year.

Sentiment and writing style of different banks' 10-K files are recognized as potential confounding factors in LLM-based textual analysis and similarity assessment. To mitigate these confounding factors, input texts are also neutralized to remove sentiments and writing style differences. The neutralizing program leverages meta-llama/Meta-Llama-3.1-8B-Instruct as LLM to remove tone words and simplify sentences to eliminate writing style variations. Meta-llama/Meta-Llama-3.1-8B-Instruct is well-known for its strength in following instructions, such as instructions on neutralizing input texts and removing emotional and stylistic markers. Cosine similarity is then computed between the embedding of the neutralized input file of a specific bank-year and that of the matching Qorus file.

We also considered alternative awards such as the Digital Banker's Global Retail Banking Innovation Awards and the Bank Administration Institute's BAI Global Innovation Awards. Because these award organizers provide little description of award categories and winner's achievements, this study focuses on Qorus awards.

4. Data and Sample

We start with the universe of public banks and bank holding companies (BHCs) in the U.S., matching the sets of (a) banking sector entities that submit a 10-K statement to the Securities and Exchange Commission (SEC), as issuers of securities admitted to trading on US regulated markets, and (b) those recorded by Moody’s BankFocus as listed credit institutions—either currently or in the past—excluding all entities with no recent financial data and those that can be regarded as public authorities, while including commercial, savings, cooperative, fintech, private, or investment banks, and BHCs. This first step yields 550 results based on (a) and 793 based on (b); the union of the two generates a comprehensive population of 1,059 entities. Then, we filter the sample by requiring they have available Form 10-K disclosure data and financial information (e.g., total assets, revenue growth, ROA, MB, stock return, Risk-Weighted Assets/Total Assets, Equity/Total Assets, Tier 1 Capital Ratio) during the period from 2013 to 2023 available. We obtain banks’ financial data from Moody’s BankFocus, cross-checked using Compustat and Bloomberg; stock price data are taken from the latter. This leaves us a sample of 276 public U.S. banks with a total of 1,715 bank-year observations.

Banks’ investments in fintech from 2013 to 2024 are obtained from Crunchbase. Crunchbase categorizes fintech startups into several key sectors, reflecting the diverse range of financial technologies and services.⁵ Bank-partnership data is manually collected by reviewing banks’ press releases, websites, and business news.

⁵ These sectors include:

- Payments and Transactions: Startups offering digital payment solutions, peer-to-peer transfers, and platforms facilitating seamless financial transactions.
- Lending and Credit: Companies providing alternative lending platforms, such as peer-to-peer lending, buy-now-pay-later (BNPL) services, and online personal or business loans.
- Investment and Wealth Management: Platforms offering robo-advisory services, online brokerage accounts, and tools for automated investment advice and portfolio management.

In Figure 2 we show the number of investments in fintech and the number of partnerships with fintech firms annually by banks in our sample. The pace of banks' fintech engagement picked up after 2017, and peaked in 2021.

[Insert Figure 2 about here]

As suggested by theories on disruptive innovations (Tang, 1988; Christensen, 1997; Christensen & Raynor, 2003), potential entrants can be harmful to the market share and performance of an industry's incumbents. We measure competition from fintech startups and big techs that entered financial markets using the count of financial technology related patents. Following Chen et al. (2019), we identify and classify fintech related patents using data on patent filings from 2013-2023. As shown in Figure 3, the number of fintech related patents increased at an exponential rate during the 2013-2019 period but slowed down afterward.

[Insert Figure 3 about here]

In Table 1, we provide summary statistics of our sample. As shown in Table 1, our final sample consists of 1,715 bank-year observations, though the number of observations varies across variables due to data availability constraints.

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- Insurtech: Startups innovating within the insurance industry, offering personalized policies, streamlined claims processes, and other technology-driven insurance solutions.
 - Blockchain and Cryptocurrency: Companies developing blockchain-based technologies, cryptocurrencies, and decentralized finance (DeFi) platforms.
 - Regtech (Regulatory Technology): Firms providing solutions for regulatory monitoring, compliance, and reporting, helping financial institutions adhere to regulatory requirements.
 - Financial Infrastructure: Startups offering core banking systems, financial data aggregation services, open banking APIs, and Banking-as-a-Service (BaaS) platforms.

[Insert Table 1 about here.]

The innovation culture variable (estimated using LLaMA3), which measures the extent to which banks exhibit characteristics aligned with innovative firms, has a mean and median value of 0.60. Banks in the sample vary widely in size, as indicated by the total assets (in millions of USD), with a mean of \$69.26 billion and a median of \$7.69 billion. This significant difference suggests a right-skewed distribution, where a small number of large banks dominate the sample.

Cost-to-Income ratio measures banks' operating efficiency. The mean Cost-Income ratio is 61.17%, with a median of 61%. Performance is assessed through Return on Assets (ROA), which has a mean of 1.41% and a median of 1.1%, reflecting the typical profitability of banks. The market-to-book (MB) ratio, a proxy for valuation, has a mean of 1.37 and a median of 1.25, suggesting that, on average, banks' market valuation modestly exceeds their book value. Additionally, revenue growth exhibits a mean of 11.26% and a median of 7.45%, indicating heterogeneity in growth rates across institutions. Stock return performance over the sample period is captured through the mean stock return of 12.85% and a median of 7.24%, showing a generally positive but widely dispersed return distribution.

Table 1 also includes four key indicators of bank risk and capitalization. Risk-weighted assets to total assets (RWA/TA), a measure of risk exposure, has a mean of 75.90% and a median of 76.79%. Equity to total assets (Equity/TA), a measure of capital adequacy, has a mean of 13.25% and a median of 11.23%. The Tier 1 Capital Ratio, a regulatory measure of core capital strength, stands at a mean of 12.85% and a median of 12.32%, suggesting that banks maintain regulatory

capital levels well above minimum requirements. Finally, the Z-score, a forward-looking indicator of insolvency risk, has a mean of 196.15 and a median of 65.82.

The last part of Table 1 measures the banks' engagement with fintech via investments or partnership. About 16% of banks have at least one investment in a FinTech firm, and 13% of the banks formed some kind of partnership with fintech firms, though the median value of both is 0, indicating that the majority of banks do not invest in fintech startups or have partnerships with fintech firms.

In Table 2, we categorize banks into four quartiles based on their innovation culture every year, with Q1 representing the least innovative banks and Q4 representing the most innovative banks. We compare these quartiles across a range of financial metrics as shown in Table 1. Median total assets are presented, and Wilcoxon rank-sum tests are conducted to assess differences in medians. All other variables are reported as means. Statistical significance is assessed through a comparison of Q4 (least innovative banks) and Q1 (most innovative banks), with p-values denoting significance levels at *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

[Insert Table 2 about here]

Banks with stronger innovation cultures differ systematically from their less innovative peers in size, capital structure, and their approach to FinTech engagement. Median total assets decline sharply from \$9.3 billion among the most innovative banks (Q1) to \$5.9 billion among the least innovative banks (Q4), and the difference is highly significant ($p = 0.000$). Tier 1 capital ratios also vary across quartiles: innovative banks exhibit somewhat lower regulatory capital (Q1 = 12.54%) than less innovative banks (Q4 = 13.03%), with the Q4–Q1 difference statistically significant at the 5% level ($p = 0.010$). Other balance sheet and risk indicators—including ROA ,

market-to-book ratios, revenue growth, stock returns, RWA/TA, equity ratios, cost-to-income ratios, and Z-scores—do not display statistically significant differences between the two groups.

The most pronounced contrasts emerge in banks' external FinTech activities. Highly innovative banks (Q1) are substantially more likely to invest in FinTech firms (3.55% vs. 1.16%, $p = 0.021$) and form partnerships with FinTechs (19.15% vs. 9.28%, $p = 0.000$). These results suggest that banks with stronger innovation cultures are larger, more externally engaged with FinTechs, and more active in using outside collaborations to complement their internal innovative capabilities, whereas less innovative banks engage less extensively with the FinTech ecosystem.

5. Empirical Analysis

5.1 Innovation Culture and Bank FinTech Engagement

5.1.1 Are Innovative Banks More Likely to Engage FinTechs?

This section investigates whether banks with a stronger innovation culture are more likely to invest in or partner with FinTech firms. Because bank innovation culture represents a relatively persistent organizational attribute with limited within-bank variation over time (as demonstrated in Table 4), our analysis focuses on how *cross-sectional differences* in cultural orientation relate to banks' strategic engagement with FinTech.

We estimate probit models for three binary outcomes: (i) whether a bank made a FinTech investment in a given year (Model 1), (ii) whether it formed a FinTech partnership (Model 2), and (iii) whether it engaged in either activity (Model 3). The key independent variable, Innovation Culture, is measured using an LLM-based dictionary approach with tone and narrative adjustment. Control variables include lagged bank size, market valuation (MB ratio), sales growth, profitability

(ROA), stock returns, and competitive pressure from FinTech and BigTech firms (log number of FinTech-related patents filed by FinTech and Big Tech firms). All regressions include year fixed effects and standard errors clustered at the bank level. Table 3 reports the full results.

[Insert Table 3 about here]

Across all three models, innovation culture emerges as a strong and economically meaningful predictor of banks' FinTech engagement. The marginal effects underscore that even moderate differences in innovation orientation across banks translate into sizable differences in strategic technology adoption.

In the FinTech investment model (Column 1), moving from the 25th to the 75th percentile of innovation culture raises the predicted probability of making a FinTech investment from 1.37% to 2.62%, a 1.29 percentage-point increase, or an approximate 95% rise relative to the baseline rate. Given the low unconditional frequency of FinTech investments, this magnitude is substantial and suggests that internal cultural orientation materially influences banks' willingness to allocate capital toward emerging technologies. The effect is even stronger for FinTech partnerships (Column 2). The predicted probability of forming a partnership increases from 10.1% at the 25th percentile of innovation culture to 16.0% at the 75th percentile, a 5.0 percentage-point difference, representing a 50% increase relative to the baseline partnership probability. The combined specification (Column 3) reinforces this pattern. Moving across the interquartile range of innovation culture increases the likelihood that a bank either invests in or partners with a FinTech firm from 11.4% to 17.6%, a 6.2 percentage-point increase, or roughly a 55% rise relative to the baseline probability.

Taken together, these results show that innovation culture is not merely symbolic or cosmetic. The implied probability shifts are large enough to meaningfully alter a bank's

technological posture. Innovation-oriented banks are consistently more active across both equity-based and collaboration-based channels of FinTech engagement, underscoring innovation culture as a core institutional driver of strategic technological adaptation.

Bank size is consistently positive and statistically significant across all columns, implying that larger banks have greater capacity or incentives to undertake FinTech investment and partnership activities. Profitability (ROA) enters positively and marginally significantly only in the investment model, suggesting that better-performing banks are selectively more likely to commit capital to FinTech ventures. Stock returns also predict higher FinTech activity, with significant effects across all specifications, consistent with the view that market-recognized banks leverage periods of strong valuation to expand strategic technology initiatives. Sales growth shows a small negative effect on investment likelihood but is otherwise insignificant, while market-to-book ratios do not meaningfully explain FinTech engagement.

In summary, the results show that banks with stronger innovation cultures are consistently more likely to engage with FinTech—whether through investment, partnership, or either channel. The effects are economically meaningful across all specifications, indicating that innovation culture plays a central role in shaping banks’ overall strategic orientation toward technological innovation.

5.1.2 Reverse Causality Test: Does FinTech Engagement Shape Innovation Culture?

A potential concern in interpreting the earlier results is reverse causality: banks with higher FinTech investment or more partnerships may become more innovative *because* digital engagement induces organizational learning, technology adoption, or cultural shifts. To assess this possibility, we estimate a series of bank fixed-effects regressions in which innovation culture is

the dependent variable and lagged FinTech investments and partnerships serve as key predictors. The specification includes bank fixed effects to absorb time-invariant cultural traits and year fixed effects to capture common shocks:

$$\text{InnovationCulture}_{i,t} = \alpha_i + \delta_t + \beta_1 \text{FinTechInvestment}_{i,t-1} + \beta_2 \text{Partnership}_{i,t-1} + X'_{i,t-1} \Gamma + \varepsilon_{i,t}.$$

Controls include bank size, market-to-book ratio, sales growth, ROA, stock returns, and nonbank FinTech patent counts, all lagged to maintain temporal ordering. Standard errors are clustered at the bank level.

[Insert Table 4 about here.]

Table 4 reports the estimates. Across both specifications—with and without the lag of innovation culture as a regressor—the coefficients on FinTech investment and partnership activity are small in magnitude and statistically insignificant. Additional joint significance tests confirm that FinTech variables do not predict subsequent increases in innovation culture ($F \approx 0.84\text{--}0.85$; $p \approx 0.43$). By contrast, innovation culture exhibits strong persistence over time (lag coefficient ≈ 0.073 , $p = 0.022$), and bank fixed effects explain more than half of the variance ($\rho \approx 0.55\text{--}0.58$), consistent with innovation culture being a relatively stable internal attribute rather than a short-term adjustment margin (Li et al, 2026). The only robust predictor is nonbank FinTech patenting—which loads positively—suggesting that external technological pressure correlates with gradual increases in innovation emphasis.

The evidence strongly rejects the concern that FinTech investments or partnerships *cause* observable increases in a bank’s innovation culture over the short horizon examined. Instead, innovation culture appears to be a predetermined, slow-moving organizational characteristic. Banks do not become more innovative simply because they increase FinTech investments or form

new partnerships. The absence of feedback effects supports treating innovation culture as an exogenous driver—rather than an outcome—of banks’ strategic FinTech responses. Thus, reverse causality does not appear to explain earlier findings: the direction of influence runs from innovation culture to digital engagement, not the other way around.

5.1.3 Robustness Checks: Innovation Culture Using Different LLMs

To provide evidence that our research conclusions are not narrowly tailored to a single model type but instead hold across diverse LLM paradigms, we adopt a multitude of LLMs that differ considerably in architecture, training data, and application focus (see Appendix C). All of these LLMs are freely accessible, which enhances the reproducibility of our findings and encourages future research.

As discussed earlier, our main results are based on LLaMA3, a large-scale model with strong reasoning capabilities, and can effectively process extended inputs. E5 is based on Bert and optimized for text embedding tasks due to its large embedding size. Mpnet excels in capturing semantic information with high-quality sentence embeddings and determining sentence similarity. Mistral7b is known for its speed, accuracy, and efficiency in handling various NLP tasks and its ability to process long sequences as in Qorus reports and Form 10-Ks. Bert, a popular choice for various NLP tasks and widely known for its bidirectional context understanding, performs well in general NLP tasks and excels in tasks requiring deep semantic comprehension (Liu et al. 2021; Siano 2025; Huang et al. 2023). Finbert, built by further training BERT on a large financial corpus, is optimized for financial sentiment analysis. Finbert-UST is pretrained on financial texts and optimized for financial NLP. E5Inst, JinaInst, and Bgeinst are fine-tuned to accept user-provided instructions to guide embedding creation. These models

usually perform better when instructions are provided but crafting a suitable instruction needs experimentation.

Since our primary task is analyzing banks' 10-K Forms and comparing them to Qorrus reports of most innovative banks to compute a similarity score, LLMs that excel in semantic similarity/documenting embedding, handling long financial texts, and capturing domain-specific nuances (finance, innovation-related language) would be preferable. LLaMA3, E5, BGE, FinBERT stand out in these specific tasks according to ChatGPT.

We document that E5 (both without and with instructions), mistral7b, finBert, and BGE with instructions generate positive and significant results, consistent with Table 3 which is based on LLaMA3.

5.1.4 Innovation Culture and Banks' Speed of Responding to FinTech Competition

In this section, we examine whether banks with stronger innovation cultures adopt FinTech strategies earlier in response to competitive pressure. Using annual bank-level data from 2013–2023, we estimate a discrete-time hazard model in which the event of interest is a bank's first FinTech adoption—defined as the first year in which a bank either makes an investment in a FinTech firm or forms a FinTech partnership. For each bank, observations begin in 2013 and continue until the first adoption event occurs; observations after adoption are dropped because the bank is no longer at risk of “first adoption.”

We model the discrete-time hazard using a generalized linear model with a binomial distribution and a complementary log–log (cloglog) link, which provides a discrete approximation to a continuous-time proportional hazards framework. The estimated hazard represents the

conditional probability that a bank adopts a FinTech strategy in year t , given that it has not adopted before t . Innovation Culture (measured using our LLM-based narrative-adjusted dictionary approach) is the key independent variable of interest. Control variables include lagged bank size, market valuation (MB ratio), sales growth, ROA, stock returns, and FinTech/BigTech patent-based competition. All specifications include year fixed effects and cluster standard errors at the bank level to account for common time shocks and within-bank correlation. Table 5 presents the results.

[Insert Table 5 about here.]

Across all three hazard specifications, the coefficient on Innovation Culture is positive but statistically insignificant. This pattern indicates that, although more innovative banks are more likely to engage in FinTech activities overall (as shown in earlier sections), they do not appear to systematically adopt FinTech strategies earlier than their less innovative peers when conditioning on being at risk of adopting for the first time. In other words, innovation culture strongly predicts *whether* banks enter the FinTech space, but it does not have a clear effect on *when* they choose to do so.

The control variables show consistent patterns. Bank size is a significant and positive predictor of early adoption across all models ($p < 0.01$), suggesting that larger banks possess the scale, resources, or organizational capacity needed to act more quickly in response to FinTech competition. Stock returns also positively predict early adoption (significant in all specifications), implying that banks experiencing stronger market performance may have more strategic flexibility or investor support to initiate FinTech activities sooner. ROA is marginally significant only in the investment hazard model, while sales growth shows a small negative association with early adoption in that same specification. Competition from FinTech and BigTech firms does not significantly explain early adoption timing.

Taken together, the hazard model results suggest that innovation culture is a strong predictor of the propensity to engage with FinTech—but not necessarily of the speed with which banks adopt FinTech strategies once exposed to competitive pressures.

5.1.5 Does Innovation Culture Play a Different Role in Big Banks vs. Small Banks?

In this section, we examine whether the influence of innovation culture on banks' FinTech engagement differs systematically between small and large institutions. We estimate Probit models for FinTech investment and partnership outcomes and discrete-time hazard models for early adoption, interacting Innovation Culture with an indicator for whether a bank's size is above the sample median. This design allows us to assess whether the effect of innovation culture varies with scale, holding constant other bank characteristics and year effects. Table 6 presents the results.

[Insert Table 6 about here.]

Across all specifications, the coefficients reveal a clear and consistent pattern: innovation culture strongly predicts FinTech engagement among small banks, but its effect is significantly weaker among large banks. In all three models, the coefficient on Innovation Culture is positive and statistically significant, indicating that among *small banks*, stronger innovation culture substantially increases the likelihood of FinTech investment, partnership formation, and early adoption. However, the interaction term between innovation culture and the above-median size indicator is negative and statistically significant in each specification. This implies that for *large banks*, the marginal effect of innovation culture is markedly reduced.

The economic interpretation is straightforward. The main effect captures the role of innovation culture for small banks, while the interaction term measures how much of that effect

is offset in large banks. In the FinTech investment model, for instance, the coefficient on Innovation Culture is 14.74 ($p < 0.05$), but the interaction term is -13.25 ($p < 0.05$), implying that the effect of innovation culture for large banks is close to zero. A similar pattern holds for FinTech partnerships: innovation culture has a strong positive effect for small banks (5.64; $p < 0.01$), but the interaction effect of -3.32 ($p < 0.05$) substantially diminishes the impact for large banks. The early-adoption hazard model likewise shows that innovation-oriented small banks respond faster to FinTech competition, while this acceleration effect is significantly muted for large banks.

These findings suggest that organizational culture plays a more decisive role in shaping FinTech engagement for small banks, which may rely more heavily on internal cultural orientation to overcome resource constraints and adopt new technologies. In contrast, relying instead on scale, formal innovation processes, or dedicated innovation units, which could attenuate the influence of cultural variation. The positive and significant coefficients on the BankSizeAboveMedian indicator across models further support this interpretation: large banks are generally more active FinTech participants, but their engagement appears to be driven by scale and institutional capacity rather than cultural orientation.

For small banks, cultural orientation functions as a critical catalyst for FinTech adoption, whereas for large banks, culture likely plays a secondary role relative to organizational scale and capacity.

5.2 Innovation Culture, FinTech Engagement, and Bank Risk Taking

While the previous section established that banks with a strong innovation culture are more likely to invest in FinTech firms, it remains an open question whether such strategic investments

influence banks' risk exposure and capital adequacy. Understanding these dynamics is essential because regulators must balance the benefits of technological innovation with the imperative of preserving financial stability (Vives, 2019; Boot et al., 2021). If innovation-oriented banks expand into FinTech without proportionately strengthening their capital buffers, they could amplify systemic vulnerabilities during downturns. Conversely, if FinTech engagement occurs within established risk-management frameworks, such activities may enhance efficiency and competitiveness without undermining prudential objectives. This section therefore examines how innovation culture, FinTech investments, and FinTech partnerships relate to multiple dimensions of banks' risk-taking, shedding light on whether innovation-driven banks assume riskier balance sheet positions or maintain conservative capital structures.

There are several theoretical channels through which a strong innovation culture could shape a bank's risk-taking behavior. First, the risk-taking channel suggests that innovation-oriented organizations may exhibit greater tolerance for experimentation, uncertainty, and technological adoption, which could translate into riskier lending, investment, or trading strategies. Innovative banks may also reallocate resources toward emerging digital activities whose risk profiles are less well understood. Second, the strategic competition channel posits that banks facing competitive pressure from FinTech and BigTech entrants may accelerate innovation to defend market share, potentially relaxing lending standards or pursuing riskier growth strategies in the process. Third, the governance channel emphasizes that innovation culture is often associated with flexible organizational structures, decentralized decision-making, and empowered technical teams. While these traits support creativity, they may weaken internal controls or create misalignment between innovation goals and risk-management functions. Taken together, these channels motivate the

empirical question of whether innovation-oriented banks ultimately take more balance sheet risk—or whether they innovate in ways consistent with prudential discipline.

To capture the multidimensional nature of bank risk-taking, we employ four complementary indicators widely used by regulators (Federal Reserve, FDIC, Basel Committee) and the banking literature to evaluate prudential risk profiles. These measures reflect distinct channels through which innovation culture may influence banks' willingness or ability to take risk: portfolio risk, capital structure, regulatory capital adequacy, and overall distance to insolvency.

- Risk-Weighted Assets to Total Assets (RWA/TA) – This ratio captures the risk intensity of a bank's asset composition. A higher value indicates that a greater share of assets carries elevated regulatory risk weights, implying more aggressive lending or trading strategies.
- Equity-to-Total Assets (Equity/TA) – A core measure of leverage and financial stability. Banks with higher equity ratios rely less on debt funding and are better positioned to absorb losses (Admati et al., 2013).
- Tier 1 Capital Ratio – A central regulatory metric reflecting a bank's ability to absorb losses. A decline in this ratio can signal weaker financial health and may trigger supervisory scrutiny.
- Log Z-score – A forward-looking indicator of insolvency risk calculated as

$$Z\text{-score} = \frac{ROAA + (Equity/Assets)}{\sigma(ROAA)_{3\text{-year}}},$$

which we transform using the natural logarithm to reduce skewness. Higher z-scores indicate lower default risk, capturing the combined effects of profitability, capitalization, and earnings volatility.

Together, these measures allow us to assess whether innovation-oriented banks alter risk profiles through asset allocation, capital structure, capital adequacy, or solvency buffers—a multidimensional perspective needed because banks may adjust different components of their balance sheets in response to innovation incentives, regulatory pressure, or managerial preferences.

OLS and standard panel regressions assume strict exogeneity of regressors. However, risk-taking, leverage, capital ratios, and Z-scores are highly persistent over time and are influenced by past performance and unobserved managerial traits. Moreover, innovation culture and fintech responses are likely endogenous. For instance, larger banks may self-select into innovation strategies, making OLS estimates biased and inconsistent. To address these concerns, we employ two step System GMM (Blundell and Bond, 1998) which incorporates lagged dependent variables to model persistence in risk and capital decisions, uses internal instruments (lags of endogenous variables) to correct for simultaneity bias, and controls for unobserved heterogeneity and measurement error using differencing and level equations. Specifically, our GMM panel regressions model is as follows:

$$Y_{i,t} = \alpha + \beta_1 \times Y_{i,t-1} + \beta_2 \times Innovation\ Culture_{i,t-1} + \beta_3 \times FinTech\ Engagement_{i,t-1} + X'_{i,t-1}\Gamma + \delta_t + \varepsilon_{i,t}$$

Where:

- $Y_{i,t}$ represents risk-taking, leverage, Tier 1 capital ratio, and the natural logarithm of Z-score in year t,
- $Y_{i,t-1}$ (Lagged Dependent Variable) captures persistence,
- Innovation Culture is measured using the continuous tone-adjusted embedding similarity score and a top-quartile indicator,

- FinTech Engagement indicate whether the bank made investment in fintech firms or formed partnership with fintech firms in year $t-1$,
- $X'_{i,t-1}\Gamma$ represents a vector of control variables including bank-specific controls such as bank size, market valuation (MB), return on assets (ROA), sales growth, and stock return, and industry-level fintech activity measured by the number of non-bank fintech patents filed, capturing the competition banks were facing from fintech and bigtech firms,
- Year fixed effects control for macroeconomic shocks,
- Diagnostic tests (AR(1), AR(2), Hansen J) are used to assess serial correlation and instrument validity.

[Insert Table 7 about here]

The results in Table 7 provide limited evidence that innovative banks take on more risk. In the RWA/TA specification (Column 1), Innovation Culture enters positively and significantly at the 5% level, suggesting that more innovative banks exhibit slightly higher risk-weighted assets relative to total assets after controlling for dynamics and other balance sheet characteristics. The magnitude, however, is modest and must be interpreted in the context of strong persistence in risk exposure, as reflected in the highly significant coefficient on lagged RWA/TA (0.61; $p < 0.01$).

Across the remaining specifications, the coefficients on Innovation Culture are statistically insignificant. In the Equity/TA and Tier 1 capital regressions, the point estimates are negative but imprecisely estimated, offering no robust indication that innovation-oriented banks systematically adjust their capital buffers downward. Likewise, the coefficient in the log Z-score regression is positive and insignificant, implying no detectable relationship between innovation culture and future insolvency risk.

Taken together, these results suggest that innovative banks do not appear to take on materially greater risk when measured through multiple complementary channels of regulatory capital ratios and forward-looking solvency metrics. Although the positive effect on RWA/TA indicates a mild increase in asset-side risk exposure, this effect does not translate into weaker capital positions or heightened insolvency risk.

The control variables behave as expected in a dynamic risk-setting. Lagged dependent variables are large and highly significant, confirming strong inertia in bank risk and capital decisions. Bank size is negatively associated with RWA/TA and unrelated to capital adequacy or Z-scores, consistent with larger banks' ability to maintain stable risk profiles despite complexity. Other bank fundamentals—including market valuation, profitability, sales growth, and stock performance—do not show systematic relationships with risk outcomes in the system GMM framework. Diagnostic tests (AR1, AR2, and Hansen J) support the validity of the GMM instruments and the absence of second-order serial correlation.

Overall, Table 7 indicates that innovation culture shapes banks' technological strategies and FinTech engagement, but does not meaningfully alter their risk-taking behavior. Innovative banks may pursue FinTech-related transformation without compromising their prudential risk profile.

From a supervisory perspective, these findings are reassuring. The evidence does not support concerns that banks with stronger innovation cultures—or those more active in FinTech investments and partnerships—engage in materially higher risk-taking. Traditional drivers of bank safety, including capital adequacy and the composition of risk-weighted assets, continue to dominate risk outcomes. Within the sample and horizon examined, FinTech engagement appears

largely orthogonal to solvency risk, suggesting that regulators need not view innovation-oriented strategies as inherently destabilizing.

For bank managers, the results indicate that fostering an innovation-oriented culture does not, by itself, compromise financial resilience. Banks can pursue digital transformation, technological partnerships, and innovation-driven growth without materially increasing balance-sheet risk, provided that capital buffers and portfolio quality are maintained. Innovation culture thus shapes how banks compete and adapt—rather than the level of prudential risk they assume.

5.4 Innovation Culture, FinTech Engagement, and Bank Performance

While the previous sections examined whether innovation culture affects banks' strategic responses to FinTech disruption and their prudential risk-taking, it is equally important to assess whether innovative banks translate their cultural orientation into superior operating or financial outcomes. From a theoretical standpoint, innovation culture may influence performance through several channels. First, an efficiency channel suggests that innovation-oriented banks may streamline processes, adopt automation, or redesign service delivery, potentially lowering operating costs or improving net interest margins. Second, a capability-enhancement channel implies that innovative banks may better integrate digital tools into underwriting, marketing, or customer engagement, which could raise profitability or noninterest revenues. Third, a strategic competition channel predicts that banks emphasizing innovation may reposition their business models, altering revenue mixes or risk-adjusted returns relative to less innovative peers. Finally, a learning and adaptability channel suggests that innovative cultures could help banks respond more effectively to technological, competitive, or macroeconomic shocks.

To empirically assess these mechanisms, we examine whether innovation culture—together with FinTech investment and partnership activity—predicts cross-sectional or intertemporal variation in banks’ operating and financial outcomes. Specifically, we examine five dependent variables capturing distinct dimensions of bank performance: cost-to-income ratio (efficiency), sales growth (top-line expansion), ROA (profitability), MB ratio (market valuation), and stock return (market performance). All explanatory variables—including Innovation Culture, FinTech investment, and FinTech partnership indicators—enter with a one-year lag to reduce simultaneity bias and to reflect the timing required for strategic initiatives to affect measurable outcomes. The specification includes year fixed effects to absorb macroeconomic and industry-wide shocks and clusters standard errors at the bank level to account for serial correlation and within-bank dependence. This setup allows us to isolate how pre-existing cultural orientation and technology-related strategic actions shape subsequent operational, financial, and market-based performance.

[Insert Table 8 about here.]

The results suggest limited but directionally consistent evidence that innovation-oriented banks exhibit stronger market performance. The coefficient on Innovation Culture is positive and statistically significant only for stock returns (Column 5), where a one-unit increase in innovation culture predicts a sizable increase in next-year stock performance (31.15%; $p < 0.05$). This finding indicates that equity markets may reward banks with more innovation-oriented cultures—either because investors expect future growth or because such banks signal greater strategic adaptability. For other performance metrics—efficiency, profitability, growth, and valuation—innovation culture coefficients are positive but statistically insignificant, providing no consistent evidence of near-term accounting or operational gains.

FinTech engagement yields a similar pattern. FinTech investment is positively associated with future stock returns (9.90; $p < 0.05$), consistent with capital market recognition of technology-led strategic initiatives. However, the negative coefficient on sales growth (-5.88 ; $p < 0.10$) suggests that investments in FinTech may involve short-run costs or resource reallocation that temporarily dampen revenue expansion. Partnership activity shows limited performance implications, with the only statistically significant coefficient appearing in the MB regression (-0.048 ; $p < 0.10$), indicating a modest reduction in valuation multiples—possibly reflecting higher perceived uncertainty around partnership payoffs.

Across control variables, several patterns emerge. Larger banks exhibit lower sales growth and stock returns but higher valuation multiples (negative coefficient on MB), consistent with the lower-growth, lower-risk profile of large institutions. As expected, MB strongly predicts future valuation and ROA is highly persistent. Competition from FinTech and BigTech firms is associated with lower MB ratios and lower stock returns, suggesting that markets penalize banks exposed to stronger technological disruption pressures.

Taken together, the results indicate that innovation culture and FinTech investment are associated with stronger market-based measures of performance, while their effects on accounting-based outcomes are modest and statistically weak. It is important to interpret the findings in light of potential differences between short-run and long-run effects. The performance regressions capture one-year-ahead outcomes, a horizon that may be too short for innovation culture or FinTech strategies to manifest fully in accounting-based performance metrics. Digital transformation, technology adoption, and FinTech collaborations often involve upfront investment, adjustments to internal processes, and learning curves that may temporarily depress sales growth or profitability before longer-term benefits emerge. In contrast, stock

returns—being forward-looking—may incorporate expectations about these longer-term gains well before they materialize in financial statements. The positive and significant market-based effects, coupled with muted short-run accounting outcomes, are therefore consistent with a dynamic in which markets recognize the strategic potential of innovation-oriented banks even as the operational payoffs unfold gradually. Future work with a longer post-adoption horizon or cumulative performance measures may shed further light on the long-run trajectory of these effects.

6. Conclusions

This study investigates how banks' innovation culture shapes their strategic and financial responses to FinTech disruption. Using a novel LLM-based measure of innovation culture constructed from banks' 10-K disclosures, and a comprehensive panel of U.S. banks from 2013 to 2023, we document three central findings. First, banks with stronger innovation cultures are significantly more likely to invest in FinTech startups and make more of such investments, consistent with a proactive and adaptive strategic orientation. Second, neither innovation culture nor FinTech investment is associated with heightened risk-taking or weaker capital adequacy, suggesting that innovation is pursued within a framework of capital discipline. Third, innovation culture has a significant positive effect on future stock returns, while FinTech investment does not lead to immediate profitability gains, underscoring the long-term strategic nature of innovation investments.

Our findings have important implications. For bank managers, fostering an innovation-oriented culture is associated not only with greater strategic investment in FinTech but also with stronger market valuation, without incurring excessive risk. For regulators, the evidence offers

reassurance that technological innovation in banking—when driven by internal innovative culture—does not compromise prudential soundness. For researchers, the study demonstrates the value of applying natural language processing and LLM tools to extract economically meaningful insights from textual disclosures, particularly in the context of intangible firm attributes such as culture.

Future research could extend this work in several directions. First, a longer-term horizon may reveal delayed effects of FinTech investment on operating performance and risk-taking behavior. Second, examining how innovation culture interacts with internal governance (e.g., board composition, compensation incentives) could illuminate the mechanisms through which strategic flexibility is achieved. Third, comparative cross-country analyses could assess how institutional environments—such as regulatory stringency or competitive intensity—moderate the relationship between culture, innovation, and performance. As financial institutions continue to adapt to rapid technological change, understanding the organizational foundations of innovation will remain critical for both academic inquiry and policy design.

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Appendix A: Qorus 2023 Innovative Bank Award Categories and Winners

In the table below, we provide the description of the three winners of the Beyond Core Banking Offerings category of Qorus 2023 Innovative Bank Award. The details of other categories and winner descriptions can be found in

<https://www.qorusglobal.com/awards/banking/winners/2023#qorus-banking-innovation-awards-2023-beyond-core-banking-offerings>

Categories and descriptions	Winners and descriptions
BEYOND CORE BANKING OFFERINGS [Creative new products that change the bank's business model and expand or redefine its role. These novel offerings may be developed and distributed by the bank alone or with ecosystem partners in other industries. They may either be stand-alone banking products or be incorporated into broader, more diverse non-financial offerings. #Ecosystems #Marketplaces #Superapps #NewProducts #OpenBanking #API #EmbeddedFinance #NewBusinessModels]	Gold: BNP Paribas [Many people dream of having their own place, but buying property is becoming increasingly out of reach. This is where HappyNest, the rental and purchase solution from BNP Paribas Fortis and Matexi comes in. HappyNest allows the dream of home ownership come true step by step for those without enough savings to buy right away. HappyNest makes sustainable living accessible to more people by allowing prospective buyers to rent an energy-efficient new-build home until they are able to purchase the property. The rents are then partly deducted from the purchase price. <u>Innovation presentation</u> As leading bank and major credit issuer, BNP Paribas Fortis has the responsibility to build a strong sustainability strategy to reduce the carbon footprint of our residential real estate portfolio and support our clients in the transition to green. Driving an energy transition in our residential real estate market should be realized with limited exclusion, focusing on both environmental and social angles whilst keeping bottom line profitability for BNPPF intact. The road toward Net Zero requires a joint effort from all income classes. HappyNest fits in this vision as it only offers newly build, energy efficient units, with the best practices in energy and resource efficiency. HappyNest offers a rent-to-own formula, in which customers will first rent the real-estate, before buying it. At the moment of purchase half of the rent (of the last 4 years) is refunded in the form of a discount on the purchase price. This formula makes green residential real estate more accessible to a wider audience. With this cross-industry platform we bring innovation in the real-estate market by introducing a new product. The bank (BNP Paribas Fortis) brings the financial acumen of financial leasing whereas the construction company (Matexi) delivers real-estate expertise and product offer. HappyNest offers a 'Phygital' user experience in which we cover most of the customer journey on our digital channels, whereas physical visits are done with our local sales agents. The full sales funnel is managed through a CRM system from qualified lead up until contract signature.] Silver: Standard Chartered [Introducing Standard Chartered nexus – your bridge to banking innovation. We enable digital ecosystems to become their own

	‘banks’ without needing to go through the heavy lifting of becoming one, by leveraging Standard Chartered’s banking licenses to integrate financial services into their offerings.] Bronze: Ecobank [Ellevate by Ecobank: gender financing initiative with a unique offering of financial and non-financial support to positively impact women-owned, led or focused businesses.]
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Appendix B: Terms related to Innovation Culture

customer centric, customer experience, personalization, next best product, contextual data, customer dialogue, customer base coverage, proactive actions, reactive actions, cross/up-selling, customer satisfaction, loyalty, engagement, transparency, open access, feedback, early financial education, financial literacy, empowerment, accessibility, disruptive innovation, pilot test, sandbox, gamification, fail fast, bold, proactive, experimentation, innovative features, prototypes, 30-second loan, mash-up innovation, first of its kind, industry-first, revolutionary, cutting edge, state of the art, transformative, partnership, co-managed effort, alliance model, joint ventures, strategic collaboration, co-creation, consortium, ecosystem, incubator, accelerator, network, community, co-develop, cross-functional team, collaboration functionalities, learning, continuous fine tuning, improvement, adaptive, lessons learned, training, educate, financial education, simulation, tutorials, retrospective, analytics, predictive model, insights, knowledge, business intelligence, data-driven, big data, feedback mechanisms, empower, ownership, initiative, intrapreneurship, autonomy, grassroots, inclusive, accessibility, financial inclusion, self-service, instant access, customer choice, DIY onboarding, bottom-up, decentralized, innovation strategy, leadership commitment, strategic investment, resource allocation, innovation agenda, visionary, champion innovation, management reporting system, top management, executive support, strategic cooperation

Appendix C: An Example to Illustrate Cosine Similarity

Here is an example to illustrate cosine similarity in NLP. To make the illustration concise and intuitive, the document vectors given below are 5-dimensional vectors of word frequencies. Computing cosine similarity between two LLM embeddings follows the same formula although there a lot more (i.e. from 768 to 4096) dimensions, each corresponding to a learned feature rather than a word.

		D1	D2	D3	D4
1	innovation	348	348	0	348
2	culture	160	160	160	160
3	bank	36	36	36	36
4	research	25	25	25	25
5	cat	0	0	0	1
	Cosine similarity with D1		1.000000	0.430315	0.999997

D1 to D4 represent four document vectors in a simplified five-word vocabulary. Because D2 shares an identical distribution of words with D1, cosine similarity $(D1, D2) = 1$. With the word "innovation" missing from D3, the corresponding cosine similarity value shrinks substantially because the high frequency of "innovation" in D1 makes it a heavily weighted dimension. D4 contains the extra word "cat", which represents an infrequent random error. Because of the low frequency of the random error, cosine similarity $(D1, D4)$ is affected only

minimally and remains close to 1. Notably, weighting each word (i.e. dimension) by its frequency, cosine similarity duly recognizes high-frequency words and handles random errors.

$$\text{Cosine similarity (D1,D3)} = \frac{348*0+160*160+36*36+25*25+0*0}{\sqrt{348*348+160*160+36*36+25*25+0*0}*\sqrt{0*0+160*160+36*36+25*25+0*0}}$$

$$= 27521 / (385.519131 \times 165.894545) = 0.430315 .$$

$$\text{Cosine similarity (D1,D4)} = \frac{348*348+160*160+36*36+25*25+0*1}{\sqrt{348*348+160*160+36*36+25*25+0*0}*\sqrt{348*348+160*160+36*36+25*25+1*1}}$$

$$= 148625 / (385.519131 \times 385.520427) = 0.999997 .$$

Appendix D: LLMs Used for Measuring Banks' Innovation Culture

Abbreviation	Creator/Full model name	Release Date	Pretraining Corpus	Primary Applications
LLaMa3	meta-llama/Meta-Llama-3-70B	2024-04-18	15T+ tokens (web, code, academic, etc.)	General-purpose LLM (chatbots, summarization, reasoning)
E5	intfloat/e5-mistral-7b-instruct	2024-05-28	Natural Questions, MS MARCO, BEIR, etc.	Text embedding, semantic search, retrieval-based QA
Mpnet	sentence-transformers/all-mpnet-base-v2	2024-05-27	BooksCorpus, Wikipedia, and other public text corpora	Sentence embeddings, semantic similarity, ranking
Mistral7b	mistralai/Mistral-7B-v0.3	2024-05-22	Public internet (web docs, code, math, etc.)	General-purpose (strong in summarization, Q&A, reasoning)
Bert	google/bert-base-uncased	2018-10-11	BooksCorpus + English Wikipedia	NLU tasks (NER, QA, classification, embeddings)
Finbert	prosusAI/finbert	2024-05-28	SEC filings (10-K, earnings calls, etc.)	Financial sentiment analysis, classification
Finbert-UST	yiyanghkust/finbert-pretrain	2020-06-16	UST finance texts, sentence pairs for similarity	Sentence similarity, embeddings in financial context
JinaInst	jinaai/jina-embeddings-v3 with instruction	2024-09-18	Varies (often uses general + task-specific datasets)	Neural search, ranking, multimodal retrieval
BgeInst	BAAI/bge-m3 with instruction	2024-08-07	Mixture of general text + supervised contrastive data (Q&A, STS)	Semantic search, embeddings for reranking, retrieval tasks

Appendix E: Definition of Variables

Variables	Definitions
Innovation Culture	Cosine similarity estimated using LLM by comparing the bank's MD&A of a given year to the reference document on innovative banks of that year
Bank Size	the natural logarithm of total assets plus 1
ROA (%)	return on assets during the fiscal year
MB	the ratio of market capitalization to book value of equity
Revenue Growth (%)	year-by-year growth rate of the bank's revenue
Stock Return (%)	buy-and-hold return at the fiscal year end; obtained from Bloomberg
RWA/TA (%)	the percentage of risk weighted assets out of total assets
Equity/TA (%)	the percentage of equity capital out of total assets
Tier 1 Capital Ratio (%)	the percentage of Tier 1 capital out of risk weighted assets
Cost to Income Ratio	The ratio of operating expenses to operating income
Zscore	A forward-looking indicator of insolvency risk calculated as $Z\text{-score} = \frac{ROAA + (Equity/Assets)}{\sigma(ROAA)_{3\text{-year}}}$
Investment in FinTech	a dummy variable that is set to 1 if the bank invested in at least one fintech startup in a specific year, 0 otherwise
Partnership with FinTech	a dummy variable that is set to 1 if the bank had at least one partnership with fintech firm in a specific year, 0 otherwise
Competition from FinTech & Big Tech	the natural logarithm of total nonbank fintech patents plus 1

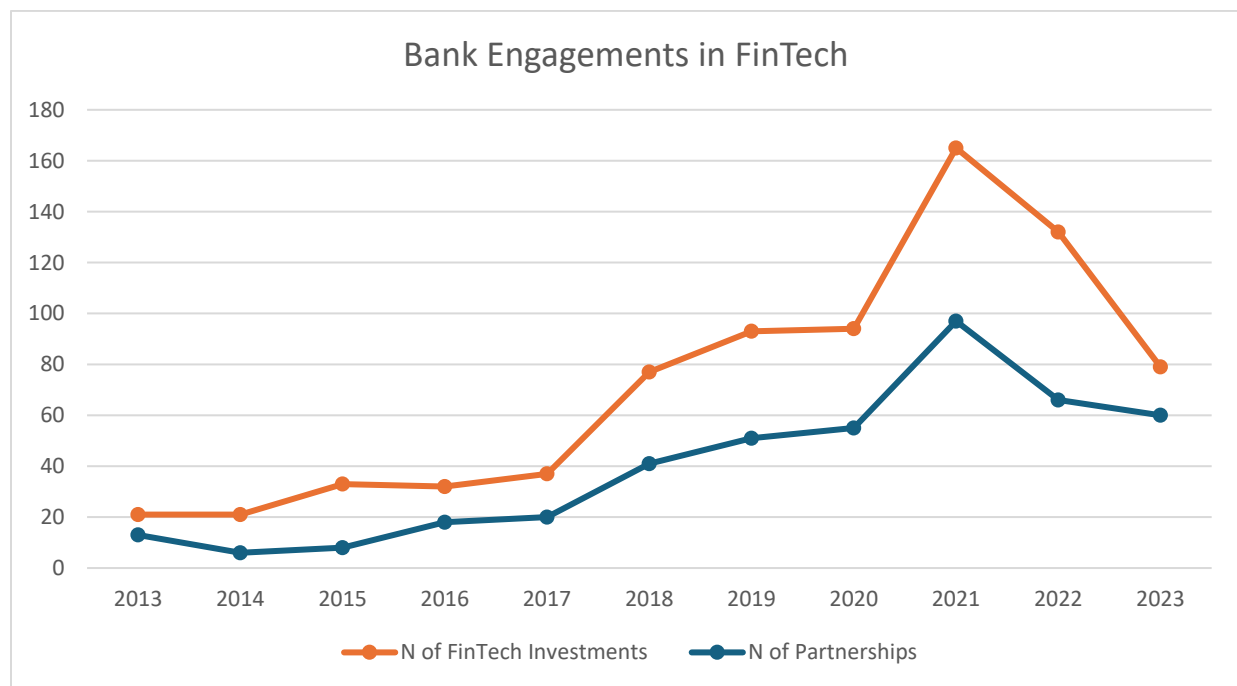


Fig 1. Bank Engagements in FinTech, 2013-2023

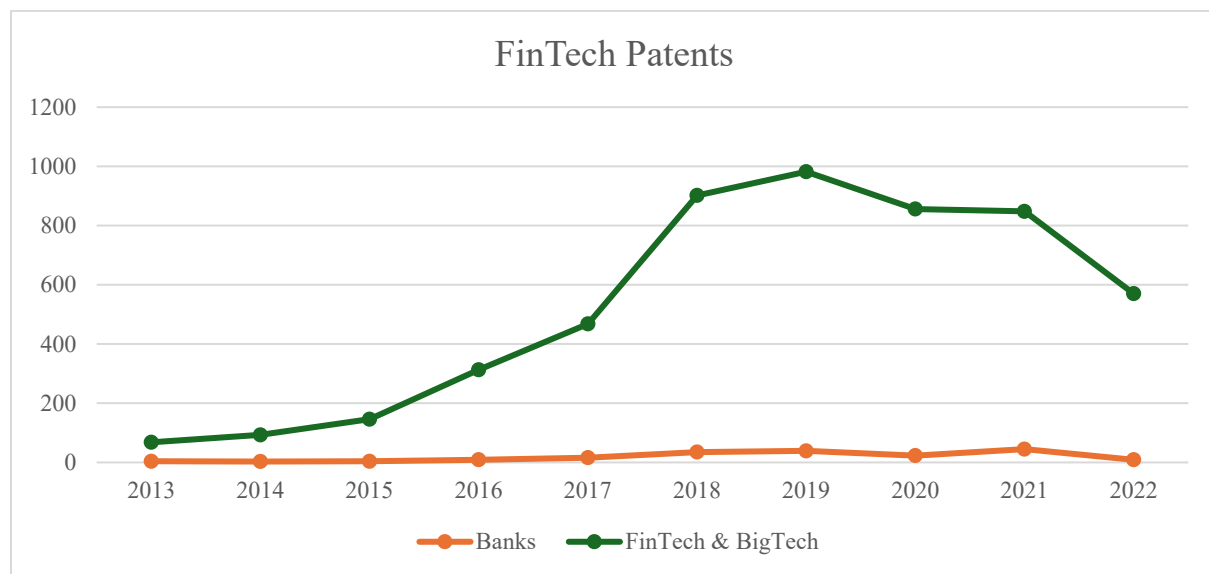


Fig 2. Number of FinTech Patents: FinTech & BigTech v.s. Banks

Table 1 Summary Statistics

This table provides summary statistics of the key variables. Please refer to Appendix B for definitions of these variables.

Bank Characteristics	N of Observation (Bank-Year)	Mean	Median
Innovation Culture	1705	0.60	0.60
Total Asset (\$M)	1683	69264.03	7694.75
Cost-to-Income Ratio (%)	1530	61.17	61.00
ROA(%)	1644	1.41	1.1
MB	1597	1.37	1.25
Revenue Growth (%)	1601	11.26	7.45
Stock Return	1708	12.85	7.24
RWA/TA (%)	1330	75.9	76.79
Equity/TA (%)	1644	13.25	11.23
Tier 1 Capital Ratio (%)	1353	12.85	12.32
Z-score	1515	196.15	65.82
With Investment in FinTechs (%)	1708	15.9	0
Partnerships with FinTechs (%)	1706	13.2	0

Table 2 Innovation Culture and Bank Characteristics

We sort banks based on their innovation culture into quartiles every year from 2013-2023. Summary statistics are provided for banks in each quartile. Median total assets are presented, and Wilcoxon rank-sum tests are conducted to assess differences in medians. All other variables are reported as means. The p-values of the differences are provided in the last column. ***, **, and * denote statistical significance at 99%, 95%, and 90% confidence level, respectively.

Innovation Culture	Q1 (Most Innovative)	Q2	Q3	Q4 (Least Innovative)	Diff. (Q4 v.s. Q1)
Total Asset (\$M)	9328.72	7828.26	7780.63	5888.53	0.000***
ROA(%)	1.49	1.57	1.28	1.29	0.190
MB	1.32	1.42	1.37	1.36	0.295
Revenue Growth (%)	11.56	13.72	10.19	9.67	0.671
Stock Return (%)	15.66	11.11	14.28	10.96	0.109
RWA/TA (%)	76.31	76.58	75.35	75.52	0.262
Equity/TA (%)	13.50	13.00	12.79	13.78	0.712
Tier 1 Capital Ratio (%)	12.54	12.77	13.04	13.03	0.010**
Z-score	380.36	126.95	151.15	115.66	0.299
Cost-to-Income Ratio (%)	60.87	62.65	61.64	59.49	0.406
With Investment in FinTechs (%)	3.55	1.41	2.12	1.16	0.021**
With Partnerships with FinTechs	19.15	14.29	10.14	9.28	0.000***

Table 3 Do Innovation Culture Affect Banks' FinTech Engagement?

In this table, we investigate whether more innovative banks are more likely to invest in fintech investments or fintech partnerships using probit regressions with year fixed effect with standard errors clustered by banks. The dependent variable of the first specification is FinTech Investment. The dependent variable of the second specification is FinTech Partnership. The dependent variable of specification (3) is FinTech Investment or FinTech Partnership. All the independent variables are lagged by 1 year. The definitions of all variables are available in Appendix B. All regressions include year fixed effect. Robust standard errors clustered by banks are estimated and reported in parentheses. ***, **, and * denote statistical significance at 99%, 95%, and 90% confidence level, respectively.

	(1)	(2)	(3)
	FinTech Investment	FinTech Partnership	FinTech Investment or FinTech Partnership
Innovation Culture [t-1]	3.4009* (2.0149)	3.2537*** (1.0905)	3.2760*** (1.0682)
Bank Size [t-1]	0.3036*** (0.0807)	0.2032*** (0.0362)	0.2554*** (0.0353)
MB[t-1]	-0.2959 (0.2437)	0.0424 (0.1101)	-0.0139 (0.1093)
ROA[t-1]	0.0565* (0.0301)	-0.0203 (0.0204)	-0.0053 (0.0154)
Sales Growth[t-1]	-0.0024** (0.0010)	0.0007 (0.0007)	0.0002 (0.0007)
Stock Return[t-1]	0.0098*** (0.0034)	0.0040** (0.0020)	0.0057*** (0.0020)
Competition from FinTech & BigTech	-0.8351 (0.9729)	0.5865 (0.5225)	0.3645 (0.5223)
Constant	-1.5403 (6.9288)	-8.7532** (3.7913)	-7.7062** (3.7604)
Year Fixed Effect	Yes	Yes	Yes
Standard Error Clustered by Bank	Yes	Yes	Yes
N of Observations	1,244	1,389	1,389
Pseudo R-squared	0.229	0.140	0.169

Table 4 Reverse Causality Test: Does FinTech Engagement Shape Innovation Culture?

In this table, we investigate whether fintech engagement shape banks' innovation culture. In both specifications, the dependent variable is the innovation culture. All the independent variables are lagged by 1 year. The definitions of all variables are available in Appendix B. In specification (2), we further include the lagged innovation culture measure. Both regressions include year fixed effect and bank fixed effect. Robust standard errors clustered by banks are estimated and reported in parentheses. ***, **, and * denote statistical significance at 99%, 95%, and 90% confidence level, respectively.

VARIABLES	(1) Innovation Culture	(2) Innovation Culture
Innovation Culture [t-1]		0.0731** (0.0316)
FinTech Investment[t-1]	0.0137 (0.0113)	0.0133 (0.0115)
FinTech Partnership[t-1]	-0.0011 (0.0032)	-0.0015 (0.0032)
Bank Size [t-1]	-0.0147** (0.0065)	-0.0141** (0.0061)
MB[t-1]	-0.0048 (0.0047)	-0.0043 (0.0046)
ROA[t-1]	0.0000 (0.0000)	0.0000 (0.0000)
Sales Growth[t-1]	0.0004 (0.0007)	0.0003 (0.0007)
Stock Return[t-1]	-0.0001 (0.0000)	-0.0001 (0.0000)
Competition from FinTech & BigTech[t-1]	0.0259*** (0.0034)	0.0220*** (0.0037)
Constant	0.6729*** (0.0526)	0.6417*** (0.0502)
Year Fixed Effect	Yes	Yes
Bank Fixed Effect	Yes	Yes
Standard Errors Clustered by Banks	Yes	Yes
Observations	1,338	1,337
R-squared	0.7234	0.7251
Number of banks	191	191

Table 5 Do Innovative Banks Respond to FinTech Competition Faster?

In this table, we investigate whether more innovative banks respond to fintech competition faster either by investing in fintech firms or forming partnerships with fintech firms. All regressions are GLM Hazard regressions. The dependent variable in specification (1) is FinTech Investment dummy. The dependent variable of specification (2) is the Partnership dummy. The dependent variable specification (3) is the FinTech Investment or Partnership dummy. All the independent variables are lagged by 1 year. The definitions of all variables are available in Appendix B. All regressions include year fixed effect. Robust standard errors clustered by banks are estimated and reported in parentheses. ***, **, and * denote statistical significance at 99%, 95%, and 90% confidence level, respectively.

	(1)	(2)	(3)
	Early Adopter: FinTech Investment	Early Adopter: Partnership	Early Adopter: FinTech Investment or Partnership
Innovation Culture [t-1]	0.9948 (5.2828)	2.3426 (2.1465)	0.9669 (2.1169)
Bank Size [t-1]	0.4393*** (0.1272)	0.2410*** (0.0562)	0.2546*** (0.0545)
MB[t-1]	-0.1345 (0.4669)	-0.0422 (0.1619)	-0.1039 (0.1538)
ROA[t-1]	0.0878* (0.0514)	-0.0014 (0.0314)	0.0263 (0.0197)
Sales Growth[t-1]	-0.0041** (0.0019)	0.0001 (0.0013)	-0.0006 (0.0011)
Stock Return[t-1]	0.0180*** (0.0067)	0.0092** (0.0038)	0.0110*** (0.0034)
Competition from FinTech & BigTech[t-1]	-3.8234 (3.3226)	0.8992 (1.2919)	0.1306 (1.2236)
Constant	15.7289 (22.4558)	-12.0266 (9.1458)	-6.0917 (8.6869)
Year Fixed Effect	Yes	Yes	Yes
Standard Error Clustered by Bank	Yes	Yes	Yes
Observations	1,243	1,173	1,173
Pseudo R-squared	0.2033	0.2356	0.2383

Table 6 Does Innovation Culture Impact Big Banks and Small Banks Differently?

In this table, we investigate whether innovation culture plays a different role in small banks vs big banks. The first two regressions are Probit regressions whether the dependent variable is the With FinTech Investment dummy. Regressions (3) and (4) are Probit regressions where the dependent variable is the Partnership with FinTech dummy. The last two regressions are GLM Hazard regressions on the early responses to fintech threat. Our key variable of interest is the interaction terms between innovation culture and the BankSizeAboveMedian dummy. The innovation culture used here is estimated using LLAMA3 with dictionary guidance and tone/narrative adjustment. All the independent variables are lagged by 1 year. The definitions of all variables are available in Appendix B. All regressions include year fixed effect. Robust standard errors clustered by banks are estimated and reported in parentheses. ***, **, and * denote statistical significance at 99%, 95%, and 90% confidence level, respectively.

	FinTech Investment	FinTech Partnership	Early Adopter
Innovation Culture [t-1]	14.7403** (5.9597)	5.6360*** (1.2485)	5.6204** (2.7239)
X BankSizeAboveMedian	-13.2454** (5.9646)	-3.3170** (1.5024)	-6.5384** (2.8927)
BankSizeAboveMedian	9.3300** (4.0459)	2.3114** (0.9187)	4.4766** (1.7578)
MB[t-1]	-0.4881 (0.3219)	-0.0311 (0.1169)	-0.1959 (0.1617)
ROA[t-1]	0.0650* (0.0375)	-0.0159 (0.0194)	0.0327* (0.0195)
Sales Growth[t-1]	-0.0052*** (0.0017)	0.0004 (0.0008)	-0.0010 (0.0014)
Stock Return[t-1]	0.0118*** (0.0041)	0.0043** (0.0020)	0.0110*** (0.0034)
Competition from FinTech & BigTech[t-1]	-0.7236 (1.0355)	0.6728 (0.4937)	0.3802 (1.2129)
Constant	-6.9174 (7.9520)	-8.8815** (3.5027)	-8.2798 (8.8428)
Year Fixed Effect	Yes	Yes	Yes
Standard Error Clustered by Bank	Yes	Yes	Yes
Observations	1,243	1,389	1,173
Pseudo R2	0.177	0.117	0.2374

Table 7 Do Innovative Banks Take on More Risk?

In this table, we investigate whether innovative banks take on more risks using system GMM framework. All specifications include lagged dependent variable to model persistence in risk and capital decisions; use internal instruments (lags of endogenous variables) to correct for simultaneity bias, and control for unobserved heterogeneity and measurement error using differencing and level equations. The dependent variables of specification (1) is the ratio of RWA/TA, which measures banks' overall risk exposure. The dependent variable of specifications (2) is the ratio of Equity/TA. The dependent variable of specifications (3) is Tier 1 Capital Ratio. These two ratios measure the bank's capital adequacy. The dependent variable of specifications (4) is the natural logarithm of Z-score which is a forward-looking indicator of insolvency risk. All the independent variables are lagged by 1 year. The definitions of all variables are available in Appendix B. All regressions include year fixed effect. Robust standard errors clustered by banks are estimated and reported in parentheses. ***, **, and * denote statistical significance at 99%, 95%, and 90% confidence level, respectively.

VARIABLES	(1) RWA/TA	(2) Equity/TA	(3) Tier 1 Capital Ratio	(4) log Z-score
Innovation Culture[t-1]	35.3759** (1.9929)	-13.0322 (-1.0283)	-8.6596 (-1.6048)	1.9465 (0.3793)
FinTech Investment[t-1]	-4.0441 (-0.6999)	-0.8655 (-0.3815)	0.8167 (1.5841)	0.6326 (0.8613)
Partnership[t-1]	0.7574 (0.4810)	-0.7616 (-0.4880)	0.1006 (0.1973)	0.7283 (1.4348)
BankSize[t-1]	-0.7282** (-2.5289)	0.0338 (0.2780)	0.0618 (1.1986)	0.0035 (0.1003)
MB[t-1]	-1.0222 (-1.4804)	0.1621 (0.7049)	0.3639 (1.6356)	0.0684 (0.8515)
ROA[t-1]	0.2632 (0.3698)	0.0516 (0.1776)	0.0563 (0.3194)	-0.0014 (-0.0569)
Sales Growth[t-1]	-0.0103 (-0.9477)	0.0008 (0.3477)	0.0007 (0.1729)	-0.0002 (-0.3799)
Stock Return[t-1]	0.0029 (0.2422)	0.0035 (0.6391)	-0.0009 (-0.3338)	-0.0017 (-0.7266)
Competition from FinTech & BigTech[t-1]	0.4707 (1.6365)	-7.1645 (-0.7766)		

RWA/TA [t-1]	0.6109***			
	(4.9258)			
Equity / TA [t-1]		0.9491***		
		(12.8628)		
Tier 1 ratio [t-1]			0.6765***	
			(4.1557)	
log Z-score [t-1]				0.3429**
				(2.4013)
Constant	15.2982	56.2256	7.8696*	1.0992
	(1.0964)	(0.8808)	(1.7915)	(0.4082)
Observations	1,071	1,344	1,087	1,172
Number of Banks	173	191	175	179
AR(1) p-value	4.68e-05	0.00184	5.63e-05	0.000165
AR(2) p-value	0.0597	0.0948	0.0732	0.536
Hansen J p-value	0.382	0.341	0.777	0.510

Table 8 Innovation Culture, FinTech Engagement, and Bank Performance

In this table, we investigate whether innovation culture and fintech engagement have implications for bank performance. The dependent variables include cost to income ratio, ROA, sales growth, MB, and stock return. All the independent variables are lagged by 1 year. The definitions of all variables are available in Appendix B. All regressions include year fixed effect. Robust standard errors clustered by banks are estimated and reported in parentheses. ***, **, and * denote statistical significance at 99%, 95%, and 90% confidence level, respectively.

VARIABLES	(1) Cost_to_Income Ratio	(2) Sales Growth	(3) ROA	(4) MB	(5) Stock Return
Innovation Culture[t-1]	-15.7194 (14.5159)	20.8099 (41.1573)	0.4743 (0.4301)	0.1888 (0.1608)	31.1532** (12.3043)
FinTech Investment[t-1]	-15.7409 (15.6246)	-5.8833* (3.5348)	-0.3268 (0.2358)	0.1360 (0.0961)	9.8999** (4.4739)
Partnership[t-1]	-0.2028 (1.9066)	0.7433 (2.0706)	-0.1240 (0.0915)	-0.0479* (0.0252)	1.6411 (1.9674)
BankSize[t-1]	-1.1254 (0.8374)	-1.8357** (0.7420)	0.0118 (0.0174)	-0.0126** (0.0056)	-1.2116*** (0.4630)
MB[t-1]	1.9593 (2.3723)	1.5013 (2.5759)	0.4108** (0.2079)	0.8282*** (0.0390)	-3.0882* (1.6561)
ROA[t-1]	-0.0092 (0.0077)	-0.1153*** (0.0315)	-0.0040 (0.0040)	-0.0003 (0.0003)	0.0209* (0.0124)
Sales Growth[t-1]	0.1757 (0.2910)	-0.3499 (0.5497)	0.7295*** (0.1305)	0.0074 (0.0056)	0.0015 (0.2835)
Stock Return[t-1]	-0.0114 (0.0301)	0.0620 (0.0418)	-0.0019 (0.0024)	-0.0009 (0.0007)	-0.0880*** (0.0306)
Competition from FinTech & BigTech[t-1]	-0.6488 (1.8850)	5.7441 (6.0760)	-0.2184 (0.2287)	-0.1528*** (0.0362)	-12.0884*** (1.6445)
Constant	84.7088*** (18.6465)	-22.8867 (17.0594)	0.7726 (1.3304)	1.0492*** (0.1593)	78.8728*** (9.2050)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Standard Error Clustered by Bank	Yes	Yes	Yes	Yes	Yes
Observations	1,202	1,319	1,320	1,319	1,338
R-squared	0.0317	0.0250	0.6379	0.7055	0.4365