Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

Artificial Intelligence Innovation by Financial Innovators: Evidence from US Patents

Jean Xiao Timmerman

2025-104

Please cite this paper as:
Timmerman, Jean Xiao (2025). "Artificial Intelligence Innovation by Financial Innovators: Evidence from US Patents," Finance and Economics Discussion Series 2025-104. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2025.104.

Artificial Intelligence Innovation by Financial Innovators: Evidence from US Patents

Jean Xiao Timmerman*

October 14, 2025

Abstract

This paper examines the evolution of artificial intelligence (AI) patent rates (i.e., the number of AI patents/number of firms of the same type) and concentration metrics (i.e., the Herfindahl-Hirschman Index (HHI) and Gini coefficient) among financial market participants from 2000 to 2020. It documents the historical trajectories of AI innovation for regulated banking entities and less-regulated firms, revealing that nonfinancial companies exhibit the highest baseline AI patent rate, while banks show the highest growth in AI patent rate over time. Banks have the highest HHI, and nonfinancial companies have the highest Gini coefficient, suggesting that a small number of banks dominate AI innovation and the distribution of AI innovation at nonfinancial firms – though higher in number – is highly skewed toward a subset of players. These findings indicate that the AI technological gap between small and large banks may be widening and the diversity of nonfinancial companies serving as third-party AI service providers may be limited.

I. Introduction

The rapid and widespread adoption of artificial intelligence (AI) has highlighted the need for a deeper understanding of how AI has affected different industries. In the realm of finance, this renewed focus on AI has amplified existing concerns and inquiries about AI's effects on financial institutions, market structures, and systemic stability. Financial market participants have been at the forefront of developing and adopting AI technologies for decades, employing classical machine learning algorithms for credit scoring, algorithmic trading, and fraud detection before newer technologies such as generative AI were invented (UST, 2024; Alan Turing Institute, 2019). Researchers (e.g., Kou & Lu, 2025; Eisfeldt & Schubert, 2024; Sheng et al., 2024; Weber et al., 2024; Zakaria et al., 2023; Babina et al.,

*The views expressed in this paper are solely those of the author and should not be interpreted as reflecting the views of the Board of Governors or the Federal Reserve System. The author would like to thank Jeff Allen, Jake Clark, Joseph Cox, Julia Gouny, Anne Hansen, Seung Lee, Art Lindo, Nitish Sinha, and Paul Soto of the Federal Reserve Board for valuable comments. The author would also like to thank Ryan Panley for helpful research assistance. This paper was written with generative AI assistance. All errors are the author's.

2023) and policymakers (e.g., Barr, 2025; Bowman, 2024; Cook, 2025; Hsu, 2024; Uyeda, 2025) are increasingly interested in understanding how AI technologies – especially newer forms of AI – are transforming the internal operations, product and service offerings, risk management, and profitability of firms participating in financial markets.

This paper empirically examines the historical trajectories of AI innovation, measured by AI patents, across different financial market participants from 2000 to 2020, revealing how various market segments have responded to and developed emerging technology. Despite the long-standing relationship between AI and finance, few studies have examined the historical patterns of AI innovation among banks, nonbank financial institutions (NBFIs), and nonfinancial companies – three interconnected types of firms. Both NBFIs and nonfinancial companies can exert competitive pressure, or serve as partners or vendors, to banks. By analyzing these historical trajectories, this study documents the evolution of AI innovation across regulated banking entities and less-regulated firms and sheds light on the potential concentration of AI capabilities in the financial sector.

First, in Section II, I briefly present relevant background information and discuss related literature. This section explores key factors driving AI innovation patterns, including firm heterogeneity, technological opportunities, and regulatory environments. It also provides context on the evolving banking regulatory perimeter and potential systemic risks associated with AI concentration in finance. Next, in Sections III and IV, I describe the data used and provide some descriptive figures of the data to paint a portrait of the historical landscape. In particular, I leverage AI patent data from the United States Patent and Trademark Office (USPTO) as a proxy for AI innovation to uncover trends over time across various types of financial innovators (i.e., holders of finance-related patents as identified by Lerner et al. (2024)).[1] This set of financial innovators includes banks, NBFIs, and nonfinancial companies, which include entities that could serve as technology vendors. In

[1]Lerner et al. (2024) use a sophisticated machine learning approach to identify finance-related patents and their corresponding owners. Their approach minimizes both false positives and false negatives and likely captures all key players in the realm of financial innovation in 2000-2018. Two examples of inventions that were patented are the automated teller machine (ATM) and blockchain.

Section V, I explain the empirical strategy for testing whether there are significant differences across different types of financial innovators over time in the AI patent rate (i.e., the number of AI patents/number of firms of the same type) and AI patent concentration (i.e., the Herfindahl-Hirschman Index (HHI) and Gini coefficient).

In Section VI, I report my regression results. The results reveal significant disparities in AI patent rate and concentration across different types of financial innovators from 2000 to 2020. Nonfinancial companies exhibit a 2.7 times higher baseline AI patent rate than that of banks. NBFIs, surprisingly, do not show a significantly higher baseline AI patent rate compared to that of banks. Banks show the highest growth in AI patent rate over time as compared to NBFIs and nonfinancial companies. NBFIs are slower by 6 percentage points, and nonfinancial companies are slower by 13 percentage points. Finance-related and planning and control AI patents (which capture business processes and operations) show higher baseline rates generally, with banks demonstrating focus in these areas. Additionally, the analysis of two complementary AI patent concentration measures reveals a consistently high level of concentration across different types of financial innovators. Banks show the highest HHI, with the HHIs of NBFIs and nonfinancial companies lower by at least 79 percent. Nonfinancial companies – though higher in number than banks and NBFIs – exhibit the highest Gini coefficient, almost 97 percent higher than that of banks. Importantly, the Gini coefficient is increasing for all firm types, indicating growing disparities in AI patent ownership across the board.

In Section VII, I discuss the implications of these findings. The results can be interpreted through the framework proposed by Di Lucido et al. (2023), who describe how the banking regulatory perimeter evolves in response to “outside-in” and “inside-out” pressures. The higher baseline AI patent rate of nonfinancial companies represents an outside-in force to the perimeter, while the rapid growth in banks’ AI patent rates signifies an inside-out response to this competitive pressure. Additionally, the analysis reveals high and increasing concentration of AI patents, particularly among large banks and nonfinancial companies.

This concentration suggests a potential widening technological gap between large and small banks, with AI patents potentially reinforcing the systemic importance of large banks. Furthermore, it indicates that the pool of third-party AI service providers that are nonfinancial firms may be limited, which could have implications for the broader financial ecosystem.

II. Background and Related Literature

A. Innovation

The economics and finance innovation literature is an extensive and multifaceted body of scholarly work spanning several decades. The theoretical and empirical examination of innovation processes have significant contributions emerging from industrial economics, which analyzes innovation through the lens of market structure, appropriability regimes, and firm behavior (see, e.g., Hall & Helmers, 2024; Cohen, 2010; Molyneux & Shamroukh, 1999). A specialized domain has emerged parallel to this broader literature, focusing on financial innovation and examining the unique dynamics of technological change and product development within financial markets and institutions (see, e.g., Molyneux & Shamroukh, 1999; Lerner et al., 2024; Frame & White, 2004, 2014; Frame et al., 2019; Litan, 2010; Kou & Lu, 2025).

This study most directly builds on the seminal work of Lerner et al. (2024), who examine the evolution of financial innovation in the United States from 2000 to 2018 using a novel dataset of over 24,000 finance-related patents. Their analysis reveals several key trends: a shift towards consumer-focused innovations, the increasing dominance of information technology (IT) and NBFI payments firms in financial innovation, and the geographic shift of innovation away from states with tighter financial regulation. This study adds a dimension to the literature by offering insights into the evolution of AI innovation (finance- and nonfinance-related) by different types of financial market participants over time.

Several key factors can drive different patterns of AI innovation across different types of financial innovators:

1. Firm Type Heterogeneity: Different types of firms operate under distinct business models and strategic objectives that shape their innovation priorities (Hall & Helmers, 2024). Banks, NBFIs, and nonfinancial companies allocate innovation resources differently based on their institutional characteristics and core competencies (Lerner et al., 2024).

2. Technological Opportunity: The evolving landscape of AI capabilities creates varying innovation incentives across applications and market segments (Hall & Helmers, 2024; Frame & White, 2004). Financial and nonfinancial companies differ in their capacity to identify and exploit these technological opportunities based on their existing assets and capabilities.

3. Regulatory Environment: Relative to nonfinancial companies and NBFIs, banks face regulatory constraints that influence their risk appetite for technological experimentation (Frame & White, 2004). These regulatory differentials shape what innovations firms pursue and where they locate their innovative activities, with evidence showing strategic shifts away from jurisdictions with more stringent regulation (Lerner et al., 2024).

4. Market Structure: Competitive dynamics and industry concentration significantly influence innovation incentives and the distribution of innovation returns (Hall & Helmers, 2024; Frame & White, 2004). Dominant firms in concentrated markets may innovate to maintain market power, while firms in competitive environments may innovate to differentiate their product offerings.

5. Product Market Demand Conditions: Financial institutions respond to market signals about consumer preferences and unmet needs when allocating innovation resources (Hall & Helmers, 2024; Frame & White, 2004). Different types of institutions may serve distinct market segments with varying demand characteristics, contributing to differences in their AI innovation portfolios.

6. Appropriability: The ability to capture returns from innovation shapes incentives and strategies, with financial institutions facing unique appropriability challenges (Hall & Helmers, 2024; Frame & White, 2004). Many financial innovators traditionally relied on trade secrets rather than patents. Patents became a much more viable form of intellectual property protection following the seminal State Street Bank & Trust Co. v. Signature Fin'l

Grp., 149 F.3d 1368 (Fed. Cir. 1998) case (see Lerner et al., 2024; La Belle & Schooner, 2014, 2020). In the twenty-first century, patents have become a reasonable measure of innovation in the academic literature (see Cohen, 2010), among other measures such as research and development (see, e.g., Soto, 2025).

7. Subject Matter of Invention: AI innovation focus varies across financial institutions based on their core competencies and strategic objectives (Hall & Helmers, 2024; Frame & White, 2004). For example, IT and payments firms might emphasize more consumer finance applications than banks do (Lerner et al., 2024).

8. Inventor Team Geography: The geographical locations of the different inventors of a patent is a representation of the spatial distribution of innovation activities, which affects outcomes through knowledge spillovers, talent access, and regional specialization (see Muro & Liu, 2021). For instance, different types of financial institutions exhibit varying geographic innovation strategies, influencing both the quantity and quality of their innovation (Lerner et al., 2024).

B. Banking Regulatory Perimeter

This study also contributes to the growing literature surrounding the banking regulatory perimeter, which refers to the legal framework that defines which entities and activities are subject to banking regulation and supervision. It essentially delineates the boundary between (1) regulated banking activities and organizations and (2) unregulated or less-regulated financial and commercial activities and organizations. Banks typically operate under stricter regulatory oversight than NBFIs and nonfinancial companies, which may influence their approach to innovation (Frame & White, 2004). Regulatory constraints can both impede innovation by imposing additional compliance burdens (Lerner et al., 2024; Acharya et al., 2024) and encourage certain types of innovation that address regulatory challenges (Silber, 1983).

Di Lucido et al. (2023) provide a framework for understanding how this perimeter evolves over time in response to two key pressures. "Outside-in" pressure occurs when firms operating outside the regulatory perimeter – such as technology companies and NBFIs – compete with regulated banks by offering financial services or products without facing the same regulatory constraints. "Inside-out" pressure refers to the strategic responses of banks to these competitive threats. Changes in the perimeter can be driven by technological advances. Recent papers in this literature have focused on how the innovation of stablecoins represents a significant challenge to the traditional banking regulatory perimeter (see, e.g., Awrey, 2022; Gordon and Zhang, 2023). Stablecoins allow non-bank entities to create monetary liabilities that functionally resemble bank deposits without being subject to conventional banking regulation.

As technological capabilities advance, the pressure on the regulatory perimeter intensifies. Nonfinancial companies, particularly large technology firms, and NBFIs can leverage their consumer data and technical expertise to develop financial services and products that compete with banks (Doerr et al., 2023; Feyen et al., 2021). Meanwhile, banks may respond by accelerating their own innovation efforts, venturing outside the perimeter where the boundaries are porous, or forming strategic partnerships with nonbanks (Jackson, 2020; Acharya et al., 2024; Omarova, 2013).

C. Concentration in AI and Systemic Risk

Finally, this study sits in the growing body of literature of AI in finance, which has traditionally focused on the applications, risks, and impact of AI technologies on financial activities, entities, and ecosystem. As financial institutions increasingly integrate AI into their operations, the potential systemic risks stemming from concentrated innovation patterns have attracted attention from researchers and policymakers alike (see, e.g., Lin, 2019; UST, 2024). International financial organizations have identified concentration risk as potentially amplifying existing financial vulnerabilities (OECD, 2023; FSB, 2024a).

One key mechanism through which AI concentration could generate systemic risk is third-party dependencies and service provider concentration. The AI supply chain is characterized by high market concentration in critical infrastructure components, including specialized hardware, cloud services, and foundation models (FSB, 2024a; Abbas et al., 2024; OECD, 2023). This creates a situation where numerous financial institutions may depend on the same small set of AI technology providers. This dependency creates operational vulnerabilities, as disruptions affecting these key providers could simultaneously impact multiple financial institutions.

A second important mechanism is correlated decision-making resulting from similar AI models and data sources, or potentially even collusion. When financial institutions rely on AI models trained on common data or using similar methodologies, they may reach similar conclusions about market conditions and adopt similar strategies (Danielsson et al., 2022). This technological homogeneity can lead to synchronized behaviors across market participants, particularly during periods of stress, leading to correlated trading or deposit withdrawal (OECD, 2023; Phillips, 2024). AI-driven market correlations could be exacerbated by increasing automation in financial markets, as algorithms may respond to market signals in similar ways (Abbas et al., 2024). In particular, the convergence of trading strategies creates the risk of feedback loops that can, in turn, trigger acute price moves and pro-cyclicality (OECD, 2023). Relatedly, AI can enable bad actors to intentionally manipulate financial markets through spreading deepfakes and misinformation (OECD, 2023).

III. Data

This study empirically examines how AI patent rate and AI patent concentration varies across firm types and time. AI patent rate is measured by the number of AI patents divided by the number of firms of the same type. AI patent concentration is measured by the HHI and Gini coefficient of AI patents, reflecting market structure. HHI indicates how AI patents are distributed across firms within each firm type, whereas the Gini coefficient measures unevenness in the distribution of patents among all firms within a firm type.[2]

[2]HHI and the Gini coefficient are both measures of concentration or distribution, but they capture different aspects. HHI reflects how concentrated AI patent ownership is among firms within each firm type, and the Gini coefficient measures inequality in the distribution of AI patents among all firms within a firm type. HHI is more sensitive to the number of firms and the

In order to conduct the analysis, I match three datasets for this paper: (1) the USPTO Artificial Intelligence Patent Dataset (AIPD); (2) the USPTO Patentsview data; and (3) the Lerner et al. (2024) financial innovator data. The USPTO AIPD, which identifies all AI patents from 1976 to 2023, is the source of AI patent data for this study (Pairolero et al., 2025).[3] The AIPD employs a machine learning approach to classify AI-related patents, utilizing Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018; Srebrovic & Yonamine, 2020) as its method. The training data for the BERT model comprises high quality data sources, including USPTO examiner-annotated patents. To generate the core seed set, they look for patents that are classified as relevant to eight AI component technologies by each of these four classification systems: the Cooperative Patent Classification (CPC) system, the International Patent Classification (IPC) system, the US Patent Classification (USPC) system, and Derwent's patent index. The eight AI component technologies are machine learning, evolutionary computation, natural language processing, vision, speech, knowledge processing, planning and control, and AI hardware (see definitions in Appendix Table A1). The AIPD provides three thresholds of AI patent prediction. For this study, I rely on a prediction threshold of 86 percent, which balances precision (reducing false positives) and recall (catching more true AI patents).

For patents granted by May 2025, I obtain patent identification numbers from Patentsview, where the USPTO makes patent attributes available (including patent filing date, grant date, CPC classification, and geographic location of any inventors).[4] These patent identification numbers correspond to financial innovators from Lerner et al. (2024). Lerner et al. (2024) employ a supervised machine learning approach to identify finance-related patents that were filed in 2000-2018 and granted by 2019; I consider the holders of these patents to be financial innovators.[5] Lerner et al. (2024) first utilize the USPTO CPC

market shares of the largest firms. HHI might not change much if patents are redistributed among mid-sized innovators, but would change a lot if the top innovator gains or loses patents. The Gini coefficient is more sensitive to changes in the middle of the distribution. The Gini coefficient would be more likely to reflect changes if, for example, a group of medium-sized firms started patenting more, even if the top firms' patent counts didn't change much.

[3]The AIPD also identifies AI patent applications, but this paper focuses on AI granted patents.

[4]The Patentsview data files are from their May 19, 2025, update and thus includes patents granted by May 2025.

[5]I obtain their data from Github. See Financial Patent Data Set, Github (last updated April 5, 2022), https://github.com/KPSS2017/Financial_Patent_Data_public.

codes to create an initial training set, focusing on G06Q 20 (data processing operations; generally covering payment architectures, schemes, and protocols) and G06Q 40 (finance, insurance, tax strategies, and corporate/income taxes). Their model incorporates natural language processing techniques applied to patent text and inventor characteristics, yielding 90 percent sensitivity and specificity, which suggests a robust identification process that minimizes both false positives and false negatives. This approach is then extended to patents with secondary classifications in the CPC groups, but primary classifications in nine other subclasses. Subsequently, Lerner et al. (2024) merge their patent data with financial data from Capital IQ by the first assignee of the patents, using the Global Corporate Patent Dataset (Bena et al., 2017) and name matching, given that by law, a corporate entity must be assigned the patent in order to hold it.[6] The Capital IQ data includes the Global Industry Classification Standard (GICS) code of the corporate patent holder.[7]

I use the Patentsview patent identification numbers to connect the AIPD data to patents held by financial innovators identified in Lerner et al. (2024). The most recent observation is used if multiple patent numbers are associated (which could be due to reissuance). Withdrawn patents are removed. The data is then restricted to patents that were filed during 2000-2020 for several reasons: First, post-2020, there is the greatest likelihood of incomplete data, as patents can take many years to be granted or assigned, and there is an observed decline in the number of patents filed after 2020. Second, there are relatively a small number of patents by financial innovators pre-2000 prior to the 1998 State Street Bank decision. Third, the identified financial innovators are from 2000-2018, so extending the data too many years beyond 2018 will likely miss new financial innovators and distort the results.

I construct the following variables of interest: (1) the AI patent rate (i.e., number

[6] By law, inventors must be natural persons. See 35 U.S.C. § 100(f). Currently, an AI system cannot be listed as the inventor on a patent. See Thaler v. Vidal, 43 F.4th 1207 (Fed. Cir. 2022). USPTO issued guidance in February 2024 that stated that an AI-assisted invention may be patented as long as at least one natural person has "significantly contributed" to the claimed invention (USPTO, 2024; Hickey & Zirpoli, 2024).

[7] The GICS categorizes firms based on their source of revenue, though earnings and market perception can also be considered. Each company is assigned a single GICS classification using a four-tiered structure from the broadest to the narrowest: sectors, industry groups, industries, and sub-industries.

of AI patents/number of firms of the same type), (2) the HHI of the AI patents, and (3) the Gini coefficient of the AI patents. Next, I create a firm-type variable that identifies the financial innovator as a bank, NBFI, or nonfinancial company by its GICS code. Banks are assignees with GICS codes for diversified banks and regional banks. NBFIs are assignees with GICS codes for thrifts and mortgage finance,[8] multi-sector holdings, property and casualty insurance, asset management and custody banks, investment banking and brokerage, financial exchanges and data, consumer finance, life and health insurance, specialized finance, diversified capital markets, insurance brokers, reinsurance, multi-line insurance, specialized real estate investment trusts (REITs), diversified REITs, and data processing and outsourced services. The remaining financial innovators are nonfinancial companies in various sectors. Further, I create an AI patent ratio variable that equals the number of AI patents divided by the number of total patents for all financial innovators.

As discussed in Section II, subject matter and inventor team geography can influence the supply of AI innovation. Accordingly, I construct a subject matter indicator that identifies if the patent has a finance-related CPC code (i.e., G06Q 20 and G06Q 40) as a primary or secondary CPC code. I create another subject matter indicator that identifies if the patent has the planning and control AI component technology, which reflects AI patents that contain methods to implement business goals (Giczy et al., 2022). For example, they can include inventions that make managing an organization, business processes, and operations, including workflow and forecasting, more efficient. Finally, I construct an inventor team geography variable to identify if the AI patent has a multi-region inventor team (i.e., if the inventor team is from multiple US regions – Northeast, Midwest, South, or West – or a US region and at least one foreign country).

[8]While in general some entities under thrifts and mortgage finance can be considered "banks," all of the entities in the merged data are nonbank mortgage companies. Thus, I put them under the NBFI category.

IV. Descriptive Observations

In this section, I present some descriptive figures of the data. As related to AI patenting activity, Figure 1 displays patterns across firm type and time. Panel A highlights the dominance of nonfinancial companies in AI patent counts from 2000 to 2020. Panel B shows that the number of entities that are nonfinancial companies are higher than the number of banks and the number of NBFIs. Panel C presents a more nuanced picture of the AI patent rate. While all firm types demonstrate an upward trend in AI patent rates, banks display the steepest growth, particularly in later years. This indicates that although fewer in number, banks are increasing their AI innovation efforts at a faster rate than other firm types. Finally, Panel D shows that there is a general upward trend in the AI patent ratio over time for all firm types. Banks consistently have the highest AI patent ratio across all periods, followed by NBFIs. Nonfinancial companies have the lowest AI patent ratios.

Appendix Figures A1 and A2 further shed light on Figure 1. Figure A1, Panel A, shows that the increase in bank AI patent rates is driven by diversified banks (large banks which offer a broad range of financial services) rather than smaller regional banks. The top two NBFI groups are data processing and outsourced services (which consist of payment firms) and property and casualty insurance. The top three nonfinancial sectors are IT (including technology hardware, software, and semiconductor companies), communication services (including telecom and media companies), and consumer discretionary (including automobile, retail, and consumer services companies). The graphs in Appendix Figure A2 suggest that the proportion of most impactful patents for banks are similar to those for NBFIs and nonfinancial companies, implying that banks are not simply following other entities' innovations to advance their technology.[9]

[9] Appendix Figure A2, Panel A depicts percentage of breakthrough patents over time by entity type. Breakthrough patents are defined by Kelly et al. (2021) as top 10 percent of patents with the highest ratios of forward similarity to backward similarity, indicating that they are dissimilar to prior patents but similar to future ones. The authors create the similarity measures based on word frequency vectors. While the analysis in their paper goes to 2010, they extend the breakthrough indicator calculations to 2016 in their Github: https://github.com/KPSS2017/Measuring-Technological-Innovation-Over-the-Long-Run-Extended-Data. Panel B depicts the percentage of patents that are in the top 25 percent of patents with the highest ratios of forward similarity to backward similarly, as defined by Arts et al. (2021). The authors use a cosine similarity measure that takes into account the combination of keywords and their frequencies. They define their measure for all patents granted by May 2018. Their data is available here: https://zenodo.org/record/3515985.

Figure 2 illustrates the concentration trends in AI patenting across different firm types over time. Panel A shows that the HHI for banks is higher than that of both nonfinancial companies and NBFIs. Panel B presents an increasing trend in the Gini coefficient over time, pointing to growing disparities in AI patent ownership within each firm type.

With respect to subject matter and inventor team geographical differences, Figure 3 shows the evolution of AI patent characteristics across different firm types over time. Panel A reveals a notable increase in the finance-related AI patent rate for both banks and NBFIs, suggesting that they focus on AI innovation related to their business functions. This trend contrasts with the slower growth observed for nonfinancial companies in this domain. Appendix Figure A3 shows that within the set of finance-related AI patents, the rate related to payment architectures, schemes, and protocols is the highest for all firm types. Figure 3, Panels B and C, focusing on planning and control AI patents and multi-region AI patents respectively, demonstrate a steeper increase in AI patent rate by banks than that of other firm types, particularly in the latter years of the study period. As shown in Appendix Figures A4 and A5, planning and control and multi-region AI patents are top contributors to patent rate for all firm types, especially for finance firms.

V. Empirical Strategy

I use the following baseline empirical model to analyze AI patent rate and AI patent concentration across firm types and time:

$$Y_{jtsr} = \alpha + \sum(\gamma_j FirmType_j) + \xi FilingYear_t + \sum(\pi_{jt}(FirmType_j \times FilingYear_t)) + \epsilon_{jtsr}$$

The dependent variable (Y_{jtsr}) is:

1. $\log(AI\_patent\_rate_{jtsr})$,

2. HHI_{jtsr}, or

3. $Ginicoefficient_{jtsr}$,

for firm type j, in filing year t, for subject matter s, and inventor team region r. All of the variables are aggregated by firm type, filing year, subject matter, and inventor team region (see below the variable definitions for subject matter and inventor team region). The linear regressions are estimated using a sample of 250 observations and robust standard errors.

In this baseline specification, the independent variables of interest are:

1. $FirmType_j$**:** A categorical variable denoting the type of entity (i.e., bank (reference category), NBFI, or nonfinancial company), capturing the firm type heterogeneity.

2. $FilingYear_t$**:** A continuous variable representing the filing year, centered at 2000 (e.g., 2000 = 0, 2001 = 1), allowing examination of changes in technological opportunities related to AI over time.

The interaction term ($FirmType_j \times FilingYear_t$) allows for testing differences in the rate of technological progress across firm types.

Given that subject matter and inventor team geography may be sources of heterogeneity influencing factors such as technological opportunity and product market demand conditions, this study also examines empirical models incorporating these elements:

$$
\begin{aligned}
Y_{jtsr} = \alpha &+ \sum(\gamma_j FirmType_j) + \xi FilingYear_t \\
&+ \sum(\delta_s SubjectMatter_s) \\
&+ \sum(\pi_{jt}(FirmType_j \times FilingYear_t)) \\
&+ \sum(\rho_{js}(FirmType_j \times SubjectMatter_s)) \\
&+ \sum(\tau_{ts}(FilingYear_t \times SubjectMatter_s)) \\
&+ \sum(\omega_{jts}(FirmType_j \times FilingYear_t \times SubjectMatter_s)) \\
&+ \epsilon_{jtsr}
\end{aligned}
$$

and

$$
\begin{aligned}
Y_{jtsr} = \alpha &+ \sum(\gamma_j FirmType_j) + \xi FilingYear_t \\
&+ \sum(\delta_r InventorRegion_r) \\
&+ \sum(\pi_{jt}(FirmType_j \times FilingYear_t)) \\
&+ \sum(\rho_{jr}(FirmType_j \times InventorRegion_r)) \\
&+ \sum(\tau_{tr}(FilingYear_t \times InventorRegion_r)) \\
&+ \sum(\omega_{jtr}(FirmType_j \times FilingYear_t \times InventorRegion_r)) \\
&+ \epsilon_{jtsr}
\end{aligned}
$$

These expanded models consider:

1. Subject matter of invention (s) – alternatively, (1) whether the dependent variable is associated with finance-related AI patents or not, or (2) whether the dependent variable is associated with planning and control AI patents or not; and

2. Inventor team region (r) – whether the dependent variable is associated with inventors from multiple geographic regions or not.

By analyzing the baseline and expanded models, this study aims to test whether variations in AI patent rate and concentration across firm types over time are significant, as well as by subject matter and inventor team geography.

VI. Results

A. AI Patent Rate

Table 1 presents the results of the AI patent rate regression analyses. The baseline model in Column 1 reveals significant differences in AI patent rate across firm types and over time. Notably, while NBFIs' baseline AI patent rate does not significantly differ from that of banks, nonfinancial companies exhibit a baseline rate that is 2.7 times higher.[10] A significant

[10] I derive 2.7 in the following way: (exp^(0.38 + 1.31) - exp^0.38) / exp^0.38.

positive trend in AI patent rates over time for all firm types is observed. However, this trend varies significantly across firm types. Both NBFIs and nonfinancial companies show slower rates of increase compared to that of banks. NBFIs are slower by 6 percentage points, and nonfinancial companies are slower by 13 percentage points.[11] These results demonstrate varying rates of technological progress across firm types, with banks showing the fastest growth in AI patent rates over the study period.

For finance-related AI patents, a higher baseline rate is observed compared to that of non-finance-related patents. However, this effect varies significantly by firm type. Both NBFIs and nonfinancial companies show lower rates for finance-related patents compared to that of banks. Over time, finance-related patents grow more slowly overall, but this slower growth is mitigated for NBFIs. Planning and control AI patents also show a higher baseline rate. Similar to finance-related patents, both NBFIs and nonfinancial companies display lower rates for planning-related patents compared to that of banks. Unlike finance-related patents, no significant differences in growth rates for planning-related patents over time across firm types are observed. Interestingly, no significant baseline difference is found for patents with inventors from multiple regions. Regarding time trends, there is evidence of a negative effect over time for NBFIs.

In summary, while nonfinancial companies have the highest AI patent rate, banks have the highest growth in AI patent rate over time. Banks are also more focused on both finance-related and planning and control AI patents. These results do not provide evidence for diverse inventor teams leading to a higher patent rate.

B. AI Patent Concentration

To analyze the concentration of AI patents among financial innovators, this study examines both HHI and the Gini coefficient. The HHI results reveal significant differences in AI patent concentration across firm types. NBFIs and nonfinancial companies exhibit

[11] I calculate the percentage difference in the following way: for NBFIs v. banks: (exp^(0.15 - 0.05) - 1) - (exp^0.15 - 1) -0.06 or -6 percentage points, and for nonfinancial companies v. banks: (exp^(0.15 - 0.12) - 1) - (exp^0.15 - 1) -0.13 or -13 percentage points.

significantly lower baseline HHIs compared to that of banks. NBFIs have a 79 percent lower HHI than banks, and nonfinancial companies have an 88 percent lower HHI than banks.[12] Over time, the concentration remains relatively stable for banks and nonfinancial companies, while NBFIs show a slight increase in concentration.

The Gini coefficient results paint a different, but complementary, picture of AI patent distribution. Nonfinancial companies show the highest baseline inequality, significantly higher than banks by about 97 percent.[13] Banks and NBFIs have similar levels of baseline inequality, as the difference between them is not statistically significant. Over time, unevenness in distribution is increasing for all firm types, but at a slower rate for nonfinancial companies compared to that of banks.

Examining finance-related AI patents reveals further nuances. The HHI model shows that NBFIs have even lower concentration for finance-related patents, with their concentration increasing over time. Similarly, the Gini model indicates that there is lower unevenness in distribution for finance-related patents for NBFIs and nonfinancial companies compared to that of banks. Interestingly, for such patents, inequality is increasing faster over time for NBFIs and nonfinancial companies compared to banks. Comparable patterns emerge for planning-related AI patents, with NBFIs showing lower HHI but increasing over time, and lower Gini coefficient for NBFIs and nonfinancial companies compared to that of banks. Finally, geographic diversity in inventor teams is associated with a higher HHI but a slightly lower Gini coefficient. This suggests that fewer players engage in multi-region collaboration, but AI patents may be more equally distributed among them.

In summary, these results demonstrate a concentrated AI patent landscape among financial innovators. The results suggest that AI patenting in the banking sector is dominated by a few major players (high HHI) and the distribution of patents among nonfinancial companies – though greater in number than banks – is highly skewed toward a subset of

[12] I derive these differences in the following way: for NBFIs v. banks: (exp^(8.26-1.57) - exp^8.26) / exp^8.26 = -0.79 or 79 percent, and for nonfinancial companies v. banks: (exp^(8.26-2.14) - exp^8.26) / exp^8.26 = -0.88 or 88 percent.

[13] I derive this in the following way: ((0.61 - 0.31) / 0.31 * 100) = 97 percent.

these firms (high Gini coefficient).

C. Additional Analysis

I conduct two robustness checks. First, I cluster standard errors at the firm type level. This approach accounts for potential correlation in the error terms within each firm type (banks, NBFIs, and nonfinancial companies). I find that all results remain significant. Second, I remove observations related to large firms that engage in a wide range of financial services that extend beyond traditional banking, potentially blurring the line between banks and NBFIs. I find that all results remain significant except the increasing HHI for NBFIs.

Next, I run regressions where the log of AI patent count (instead of log of AI patent rate) is the dependent variable and conduct marginal effects analysis on the annual growth rate. The results align, showing that banks have the highest annual growth rate.

Finally, I explore whether the AI patent ratio is significantly increasing over time. Appendix Table A3 is consistent with Figure 1, Panel D, and shows that the mean AI patent ratio is increasing over time for all firm types. Banks show significant increases in 2010-2014 and 2015-2020. Nonfinancial companies show a significant increase in 2005-2009.

VII. Discussion

A. AI Patent Rate

The analysis reveals a dynamic landscape of AI patent rates among financial innovators, with significant differences across firm types and over time. Nonfinancial companies – including IT firms – lead in AI patenting activity, demonstrating a substantially higher baseline AI patent rate compared to that of banks. However, the trajectory of AI patenting shows a shift over the study period. Banks exhibit the fastest growth in AI patent rate, outpacing both NBFIs and nonfinancial companies. Banks have a higher rate for finance-related and planning-related AI patents, as compared to those of other firm types.

The results of this paper can be understood through the lens of Di Lucido et al. (2023)'s outside-in/inside-out framework on the evolution of the regulatory perimeter. This study shows that the baseline AI patent rate of nonfinancial companies is substantially higher than banks, potentially creating outside-in pressure on banks. The rapid growth in the AI patent rate of banks can be interpreted as an inside-out response to this competitive pressure. Banks appear to be rapidly increasing their own AI innovation efforts to maintain their competitive position in an increasingly technology-driven financial landscape.

The findings of this study complement findings of finance-related innovation studies. Lerner et al. (2024) find that IT firms, along with other nonfinancial companies, have emerged as the dominant force in producing financial patents. Moreover, they provide evidence that banks increased their representation among "fintech" patents (i.e., communications, cryptocurrency, and security patents) and software patents at a faster rate than IT and NBFI payments firms. La Belle and Schooner (2020) and Awrey (2022) also describe increasing competition in the 2010s among IT companies, NBFIs, and banks in "fintech" patents like blockchain, mobile payments, cryptocurrencies, and other digital assets. Additionally, a study of worldwide AI patent data by the Center for Security and Emerging Technology shows that IT firms generally lead AI innovation (Thomas & Murdick, 2020).

Surprisingly, the results do not provide support for the baseline AI patent rate of NBFIs to be higher than banks. This could potentially be explained by the strategic decision of certain types of NBFIs, such as asset managers, to forgo patenting their AI innovations. Many large asset managers and hedge funds (e.g., BlackRock, Fidelity Investments, Bridgewater Associates, Renaissance Technologies, and Citadel) are not in this study's dataset. This explanation aligns with the framework proposed by Kumar and Turnbull (2008). They argue for certain types of financial innovations, particularly those that benefit from market liquidity and further development, non-patenting may be optimal. AI trading algorithms and processes often fall into this category. The value of these innovations often lies in their continuous refinement and adaptation to changing market conditions. Firms innovating in this space are likely opting to protect their innovations through trade secrets, which allows them to maintain their competitive edge without public disclosure.

Regarding subject matter, the growth of planning and control AI patents could be due to the enactment of the America Invents Act (AIA) in 2011, which lowered the cost of defending financial business methods patents.[14] The AIA created the Patent Trial and Appeal Board (PTAB) to oversee a new type of proceeding that allows the USPTO to review covered business methods (CBM) (La Belle & Schooner, 2020). In particular, CBM review allows the PTAB to deal quickly with invalid business-method patents related to financial services or products (La Belle & Schooner, 2014).[15] Since CBM review sunset in September 2020, some large banks have faced an uptick in patent lawsuits and have lobbied for renewal of CBM (Bultman, 2021). Additionally, some large banks have recently joined consortiums that encourage use of shared software licensing, agreements to not sue consortium members, and efforts to have patents owned by non-practicing entities invalidated (Crosman, 2022; Open Innovation Network, 2023).

B. AI Patent Concentration

The analysis of AI patent concentration among financial innovators, using both HHI and Gini coefficient measures, reveals a landscape characterized by high and increasing concentration. While the measures show different patterns across firm types, both indicate significant concentration in the AI patent space. The HHI results demonstrate that banks have the highest concentration of AI patents. Meanwhile, the Gini coefficient results further support the concentration narrative, showing high inequality in patent distribution, particularly for nonfinancial companies. Importantly, the Gini coefficient is increasing over time for all firm types, signaling a trend towards greater concentration across the board.

[14] Leahy-Smith America Invents Act, Pub. L. No. 112-29, 125 Stat. 284 (2011). Under the first-to-invent system, the first person to invent a patentable innovation could claim patent rights, even if they weren't the first to file a patent application. The AIA changed this so that patent rights are now generally awarded to the first inventor to file a patent application, regardless of the actual date of invention. This shift was intended to provide more certainty in the patent process, reduce legal disputes over invention dates, and harmonize the U.S. system with international practices.

[15] 35 U.S.C. § 321 note. The note applies CBM review to "covered business method patent" and defines this as "a patent that claims a method or corresponding apparatus for performing data processing or other operations used in the practice, administration, or management of a **financial product or service,** except that the term does not include patents for technological inventions" (emphasis added).

The concentration of AI patents among a few financial institutions indicates a substantial accumulation of data and advanced AI capabilities within these entities. In particular, the HHI and Gini coefficient results suggest that there may be a widening AI technological gap in the banking sector. Large banks appear to be at the forefront of AI innovation, developing increasingly sophisticated AI tools, products, and services (Chan, 2024; see diversified banks in Appendix Figure A1, Panel A). Notably, all five banks with the highest AI patent counts have asset sizes in the trillions and are identified as global systemically important banks (GSIBs) by the Financial Stability Board (FSB, 2024b).

AI patents can entrench the dominance and systemic importance of large financial institutions. Expanding the patent portfolio further helps large banks remain competitive by shielding them from patent infringement lawsuits. Large banks' patents can discourage other companies from suing by providing a credible threat of a counterclaim and serving as evidence to invalidate patents asserted against them (La Belle & Schooner, 2014, 2020). Developing and harnessing advanced AI capabilities provide large institutions with competitive advantages in areas such as market analysis, customer service, and operational efficiency. Disruptions at these large institutions could have far-reaching consequences for the whole financial system. Additionally, if large banks employ similar AI systems or methodologies, this could lead to correlated decision-making and synchronized market behaviors during periods of stress (Danielsson et al., 2022; Phillips, 2024).

Conversely, small banks – which do not appear as AI patent producers in the data – may lack access to comparable resources for research and development, data, and updating technological capacity and may find themselves at a disadvantage. They might struggle to compete effectively in terms of pricing, product offerings, or back-end operations. While large banks may be able to afford filing for patents and defending themselves from infringement suits, the costs are likely too high for small banks. Therefore, small banks may seek vendors to deploy patented AI technologies, potentially exacerbating third-party risk (Crosman, 2024). The high concentration observed among nonfinancial companies, as evidenced by their elevated Gini coefficient, suggests that AI service providers may be limited to a small group of entities. When numerous financial institutions depend on the same small set of AI vendors, operational disruptions affecting these key providers could simultaneously impact multiple small institutions.

VIII. Conclusion

This paper examines the AI patent rate and concentration metrics among financial innovators from 2000 to 2020, revealing significant heterogeneity across banks, NBFIs, and nonfinancial companies. First, I find evidence of different baseline AI patent rates across firm types. While nonfinancial companies have the highest baseline AI patent rate, banks demonstrate the fastest growth over time. Second, the results suggest that concentration is high and growing in the AI patent landscape. Banks exhibit the highest concentration as measured by HHI, while nonfinancial companies show the highest inequality in patent distribution as measured by the Gini coefficient. Further, the Gini coefficient is increasing for all firm types. These findings empirically support Di Lucido et al.'s (2023) theoretical framework on the changing regulatory perimeter, illustrating banks' response to outside-in pressure through increased AI innovation. Moreover, these results related to AI patents complement the work of Lerner et al. (2024) on financial patents.

Several avenues for future research emerge from this study. First, a deeper analysis of the factors driving the rapid growth in banks' AI patenting activity could provide valuable insights into the dynamics of innovation in regulated industries. Second, investigation into the strategies employed by NBFIs, particularly large asset managers and hedge funds, in AI innovation could shed light on alternative approaches to technological advancement in the financial sector. Finally, extending this analysis to other major financial markets (e.g., Europe) could reveal how these patterns vary across different international regulatory environments and market structures.

References

Abbas, N., Vitureira, G. E. C., Diaby, M., Dionis, G. F., Ferrante, A., Grolleman, D. J., Kramer, J., Lim, X., Mosk, B., Singh, P., & Stobo R. (2024). Advances in artificial intelligence: Implications for capital market activities. In Global Financial Stability Report (pp. 77-105). International Monetary Fund.

Acharya, V. V., Cetorelli, N., & Tuckman, B. (2024). Where do banks end and NBFIs begin? (Working Paper No. 32316). National Bureau of Economic Research.

Arts, S., Hou, J., & Gomez, J. C. (2021). Natural language processing to identify the creation and impact of new technologies in patent text: Code, data, and new measures. Research policy, 50(2), 104144.

Awrey, D. (2022). Unbundling banking, money, and payments. Georgetown Law Journal, 110(4), 715-784.

Babina, T., Fedyk, A., He, A. X., & Hodson, J. (2023). Artificial intelligence and firms' systematic risk. Social Science Research Network.

Barr, M. S. (2025). AI, fintechs, and banks. Federal Reserve. https://www.federalreserve.gov/newsevents/speech/barr20250404a.htm.

Bena, J., Ferreira, M. A., Matos, P., & Pires, P. (2017). Are foreign investors locusts? The long-term effects of foreign institutional ownership. Journal of Financial Economics, 126(1), 122-146.

Bowman, M. W. (2024). Artificial intelligence in the financial system. Federal Reserve. https://www.federalreserve.gov/newsevents/speech/bowman20241122a.htm.

Buchanan, B. G. (2019). Artificial intelligence in finance. The Alan Turing Institute.

Bultman, M. (2021, April 13). Banks face lawsuit 'frenzy' after business patent reviews end. Bloomberg Law.

Chan, B. (2024, March 4). Wall Street is always talking about AI. Here's how they are actually using it. Business Insider.

Cohen, W. M. (2010). Fifty years of empirical studies of innovative activity and performance. Handbook of the Economics of Innovation, 1, 129-213.

Cook, L. D. (2025). AI: A Fed Policymaker's View. Federal Reserve. https://www.federalreserve.gov/newsevents/speech/cook20250717a.htm.

Crosman, P. (2022, April 19). Truist, TD join group that pushes back on patent aggression. American Banker.

Crosman, P. (2024, December 10). How community bank 'mavericks' compete in AI space.

Danielsson, J., Macrae, R., & Uthemann, A. (2022). Artificial intelligence and systemic risk. Journal of Banking & Finance, 140.

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. ArXiv.

Di Lucido, K. E., Tabor, N. K., & Zhang, J. Y. (2023). Fenceposts without a fence. Vanderbilt Law Review, 76(4), 1215-1263.

Doerr, S., Frost, J., Gambacorta, L., & Shreeti, V. (2023). Big techs in finance. BIS Working Papers, No. WP1129.

Eisfeldt, A. L., & Schubert, G. (2024). AI and finance (Working Paper No. 33076). National Bureau of Economic Research.

Feyen, E., Frost, J., Gambacorta, L., Natarajan, H., & Saal, M. (2021). Fintech and the digital transformation of financial services: implications for market structure and public policy. BIS Papers, No. 117.

Financial Stability Board (FSB). (2024a). The financial stability implications of artificial intelligence.

Financial Stability Board (FSB). (2024b). 2024 List of Global Systemically Important Banks.

Frame, W. S., & White, L. J. (2004). Empirical studies of financial innovation: lots of talk, little action?. Journal of Economic Literature, 42(1), 116-144.

Frame, W. S., & White, L. J. (2014). Technological change, financial innovation, and diffusion in banking. The Oxford Handbook of Banking, 486-507.

Frame, W. S., Wall, L., & White, L. J. (2019). Technological change and financial innovation in banking: Some implications for fintech. The Oxford Handbook of Banking, 262-284.

Giczy, A. V., Pairolero, N. A., & Toole, A. A. (2022). Identifying artificial intelligence (AI) invention: A novel AI patent dataset. The Journal of Technology Transfer, 47(2), 476-505.

Gordon, G. B., & Zhang, J. Y., (2023). Taming wildcat stablecoins. The University of Chicago Law Review, 90(3), 909-972.

Hall, B. H., & Helmers, C. (2024). The economics of innovation and intellectual property. Oxford University Press.

Hickey, K. J., & Zirpoli, C. T. (2024). Artificial intelligence and patent law. Congressional Research Service.

Jackson, H. E. (2020). The nature of the fintech firm. Washington University Journal of Law & Policy, 61(1), 9-24.

Hsu, M. J. (2024). AI tools, weapons, and accountability: A financial stability perspective. Office of the Comptroller of the Currency. https://www.occ.gov/news-issuances/speeches/2024/pub-speech-2024-61.pdf.

Kelly, B., Papanikolaou, D., Seru, A., & Taddy, M. (2021). Measuring technological innovation over the long run. American Economic Review: Insights 3(3): 303-320.

Kou, G., & Lu, Y. (2025). FinTech: a literature review of emerging financial technologies and applications. Financial Innovation, 11.

Kumar, P., & Turnbull, S. M. (2008). Optimal patenting and licensing of financial innovations. Management Science, 54(12), 2012-2023.

La Belle, M. M., & Schooner, H. M. (2013). Big banks and business method patents. University of Pennsylvania Journal of Business Law, 16(2), 431-495.

La Belle, M. M., & Schooner, H. M. (2020). FinTech: New battle lines in the patent wars?. Cardozo Law Review, 42(1), 277-350.

Lerner, J., Seru, A., Short, N., & Sun, Y. (2024). Financial innovation in the twenty-first century: Evidence from US patents. Journal of Political Economy, 132(5), 1391-1449.

Lin, T. C. (2019). Artificial intelligence, finance, and the law. Fordham Law Review, 88(2), 531-551.

Litan, R. E. (2010). In defense of much, but not all, financial innovation. Brookings.

Molyneux, P. P., & Shamroukh, N. (1999). Financial innovation. John Wiley & Sons.

Muro, M., & Liu. S. (2021). The geography of AI. Brookings.

Omarova, S. T. (2013). The merchants of Wall Street: Banking, commerce, and commodities. Minnesota Law Review, 98(1), 265-355.

Organization for Economic Co-operation and Development (OECD). (2023). Generative artificial intelligence in finance.

Open Invention Network. (2023). Banks & financial institutions are turning away from patent suits & discovering the power of patent protection with OIN.

Pairolero, N. A., Giczy, A. V., Torres, G., Erana, T. I., Finlayson, M. A., & Toole, A. A. (2025). The artificial intelligence patent dataset (AIPD) 2023 update. The Journal of

Technology Transfer, 1-24.

Phillips, T. (2024). When Siri becomes a deposit broker. Social Science Research Network.

Sheng, J., Sun, Z., Yang, B., & Zhang, A. L. (2024). Generative AI and asset management. Social Science Research Network.

Silber, W. L. (1983). The process of financial innovation. The American Economic Review, 73(2), 89-95.

Soto, P. E. (2025). Research in commotion: measuring AI research and development through conference call transcripts. Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series, 2025-011.

Srebrovic, R., & Yonamine, J. (2020). Leveraging the BERT algorithm for patents with TensorFlow and BigQuery. Google White Paper.

Thomas, P., & Murdick, D. (2020). Patents and artificial intelligence: A primer. Center for Security and Emerging Technology.

Uyeda, M. T. (2025). Remarks at the SEC roundtable on artificial intelligence in the financial industry. Securities and Exchange Commission. https://www.sec.gov/newsroom/speeches-statements/uyeda-ai-roundtable-032725.

U.S. Department of Treasury (UST). (2024). Artificial intelligence in financial services.

U.S. Patent and Trademark Office (USPTO). (2024). Inventorship guidance for AI-assisted inventions, 89 Fed. Reg. 10043.

Varian, H. R. (2018). Artificial intelligence, economics, and industrial organization (Working Paper No. 24839). National Bureau of Economic Research.

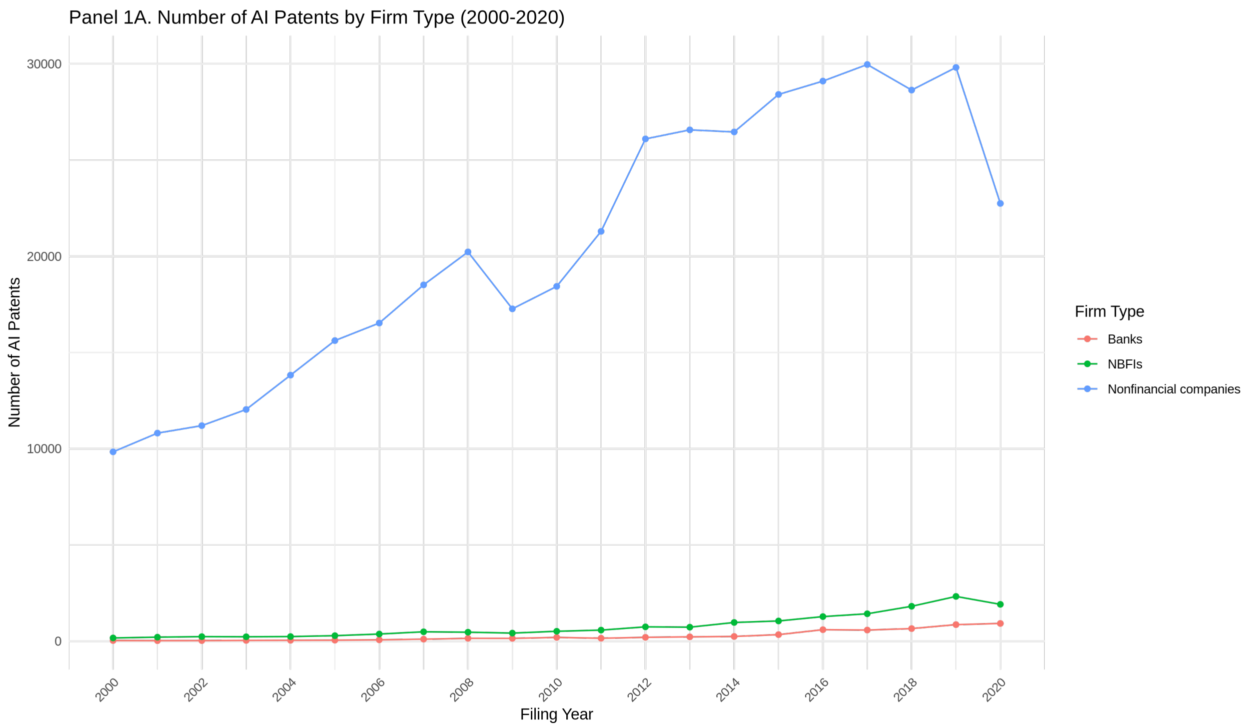
Weber, P., Carl, K. V., & Hinz, O. (2024). Applications of explainable artificial intelligence in finance—a systematic review of finance, information systems, and computer science literature.

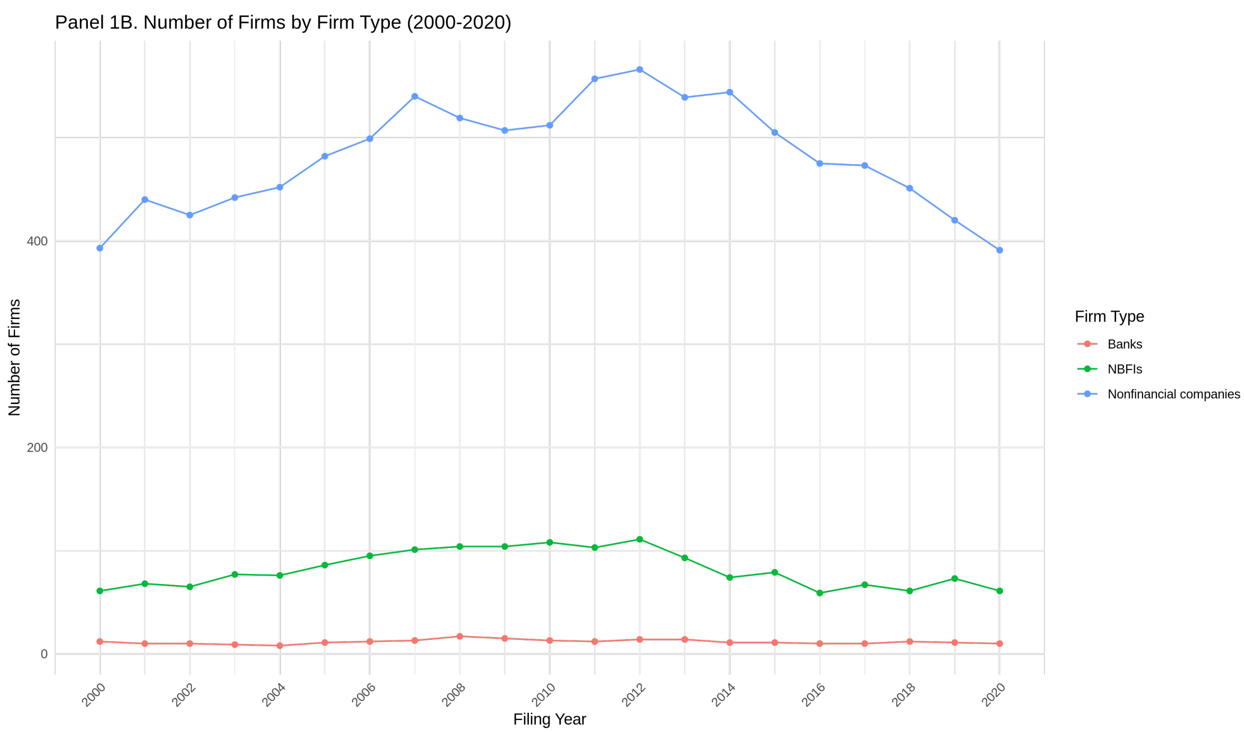
Management Review Quarterly, 74(2), 867-907.

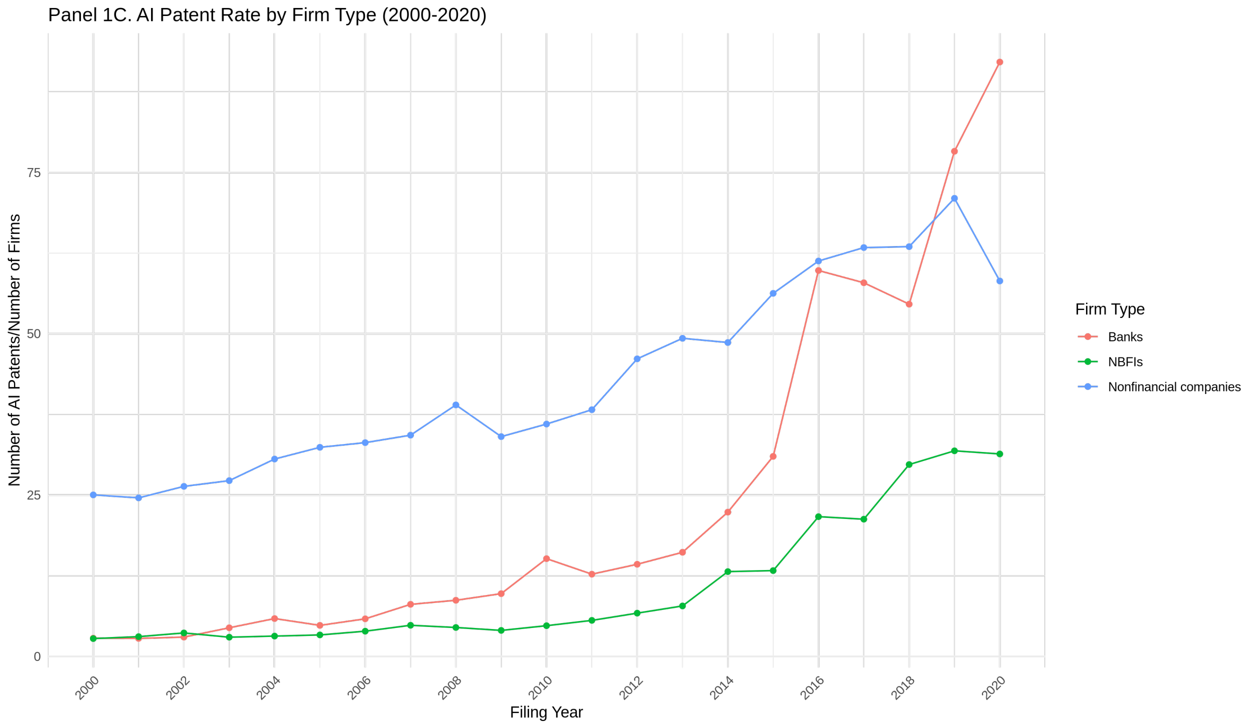
Zakaria, S., Manaf, S. M. A., Amron, M. T., & Suffian, M. T. M. (2023). Has the world of finance changed? A review of the influence of artificial intelligence on financial management studies. Information Management and Business Review, 15(4), 420-432.

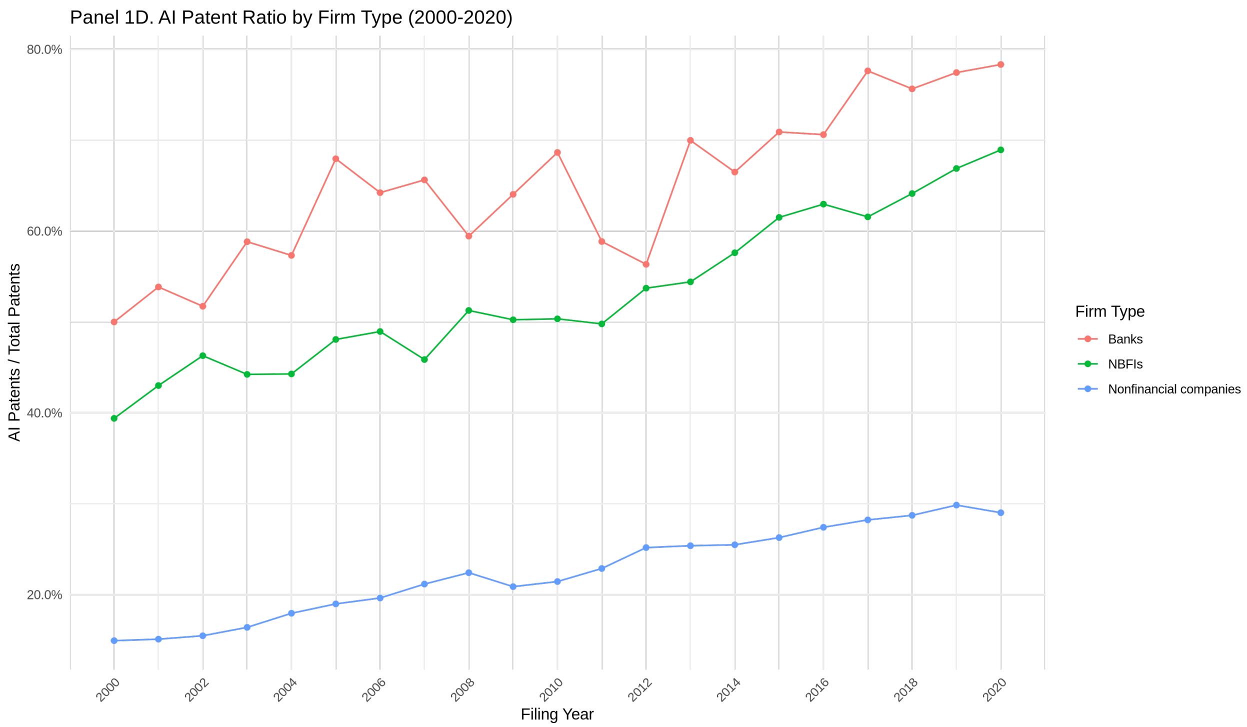
Figures and Tables

Figure 1. AI Patent Count, Number of Firms, AI Patent Rate, and AI Patent Ratio by Firm Type (2000-2020)



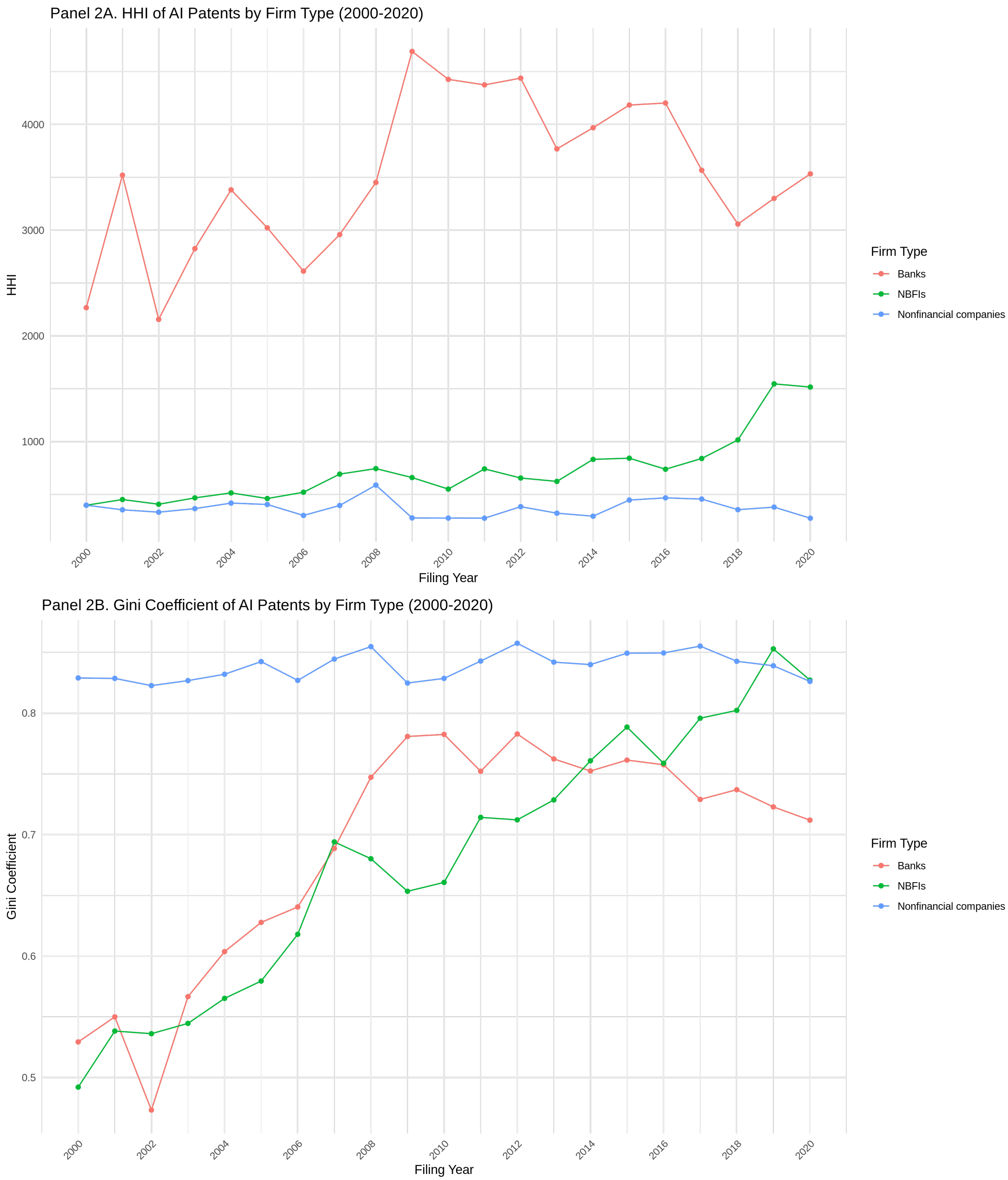






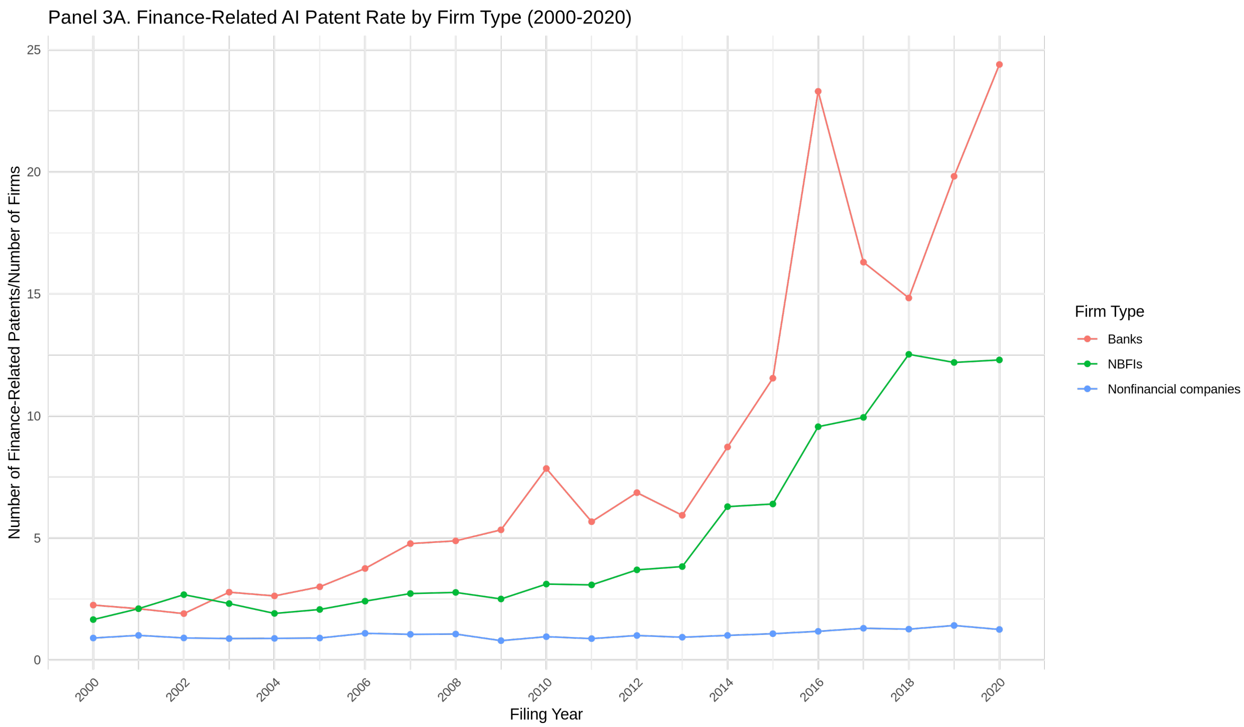
Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. For Panels A-C, the data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. For Panel D, the data consists of all patents (AI and non-AI) filed by financial innovators between 2000-2020 and granted by May 2025. Observations for these figures are at the level of firm type (bank, NBFI, nonfinancial company) and filing year. Panel A shows the number of AI patents. Panel B shows the number of firms. Panel C shows the AI patent rate, which is the number of AI patents divided by the number of firms. Panel D shows the AI patent ratio, which is the number of AI patents divided by total patents.

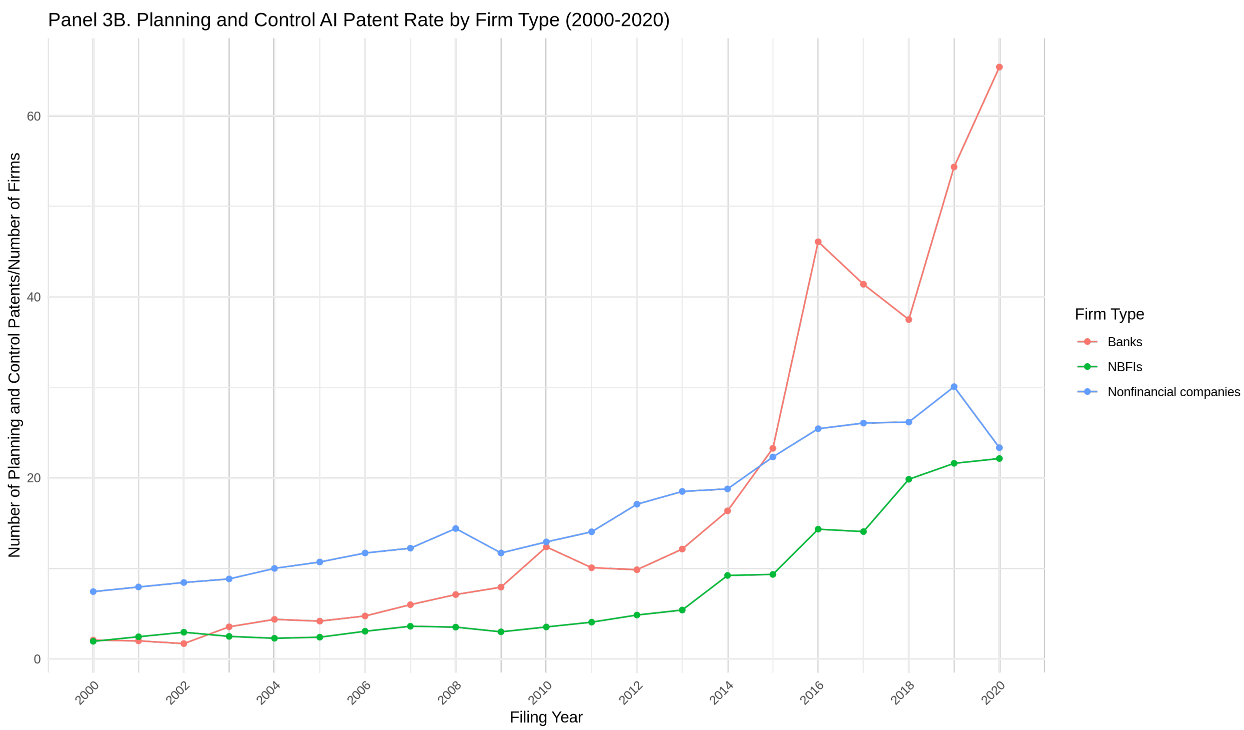
Figure 2. AI Patent Concentration Measures by Firm Type (2000-2020)

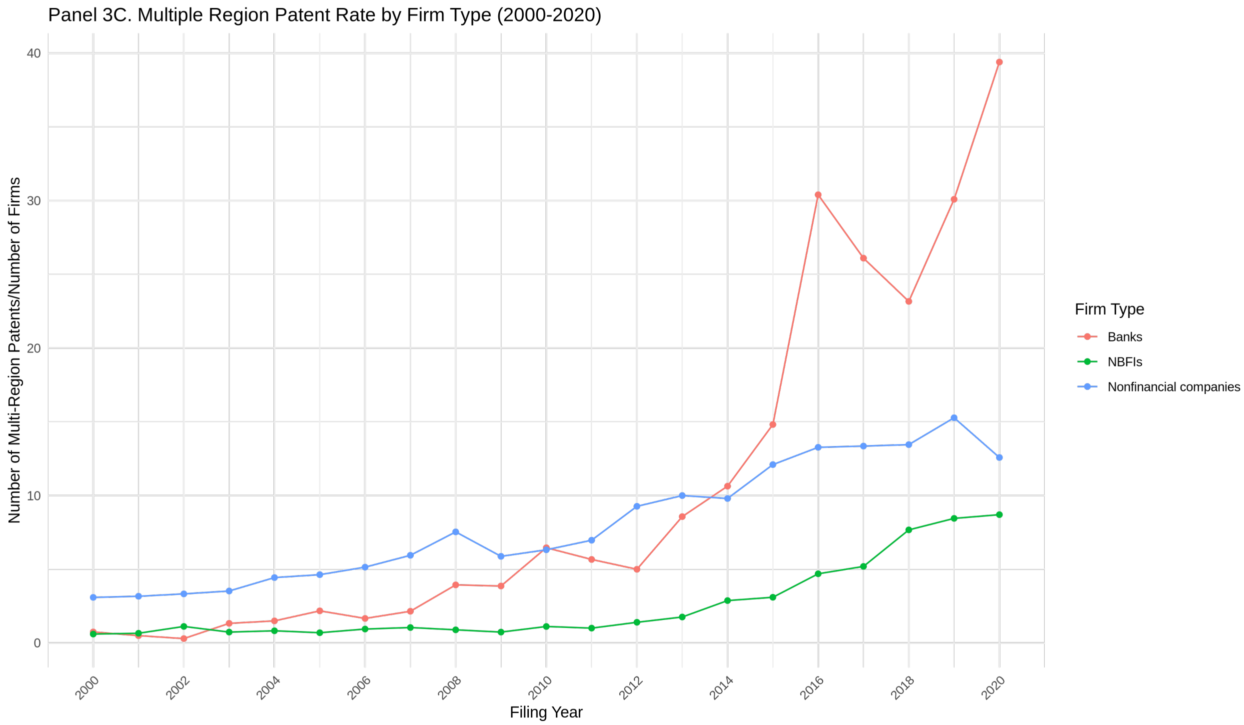


Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. Observations for these figures are at the level of firm type (bank, NBFI, nonfinancial company) and filing year. Panel A shows the Herfindahl-Hirschman Index (HHI) of AI patents. Panel B shows the Gini coefficient of AI patents.

Figure 3. AI Patent Rate – Subject Matter and Inventor Team Geographic Region (2000-2020)







Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. Observations for these figures are at the level of firm type (bank, NBFI, nonfinancial company) and filing year. Panel A shows the number of finance-related AI patents divided by the number of firms. Panel B shows the number of planning and control AI patents divided by the number of firms. Panel C shows the number of AI patents with an inventor team from different geographic regions divided by the number of firms (i.e., multiple region AI patent rate).

Table 1: AI Patent Rate Regressions

	(1) Baseline	(2) Subject Matter = Finance-related	(3) Subject Matter = Planning-related	(4) Geography = Multiple Regions
Intercept	0.38***	0.20*	0.04	0.49***
NBFIs	-0.02	0.25	0.18	0.03
Nonfinancial Companies	1.31***	2.41***	2.37***	1.53***
Filing Year	0.15***	0.19***	0.15***	0.14***
NBFIs * Filing Year	-0.05***	-0.08***	-0.05***	-0.02*
Nonfinancial Companies * Filing Year	-0.12***	-0.13***	-0.10***	-0.11***
Subject Matter	–	0.32**	0.48***	–
NBFIs * Subject Matter	–	-0.52**	-0.41*	–
Nonfinancial Companies * Subject Matter	–	-2.17***	-1.05***	–
Filing Year * Subject Matter	–	-0.08***	0.01	–
NBFIs * Filing Year * Subject Matter	–	0.07***	0.00	–
Nonfinancial Companies * Filing Year * Subject Matter	–	0.03	0.00	–
Multiple Regions	–	–	–	-0.26
NBFIs * Multiple Regions	–	–	–	-0.07
Nonfinancial Companies * Multiple Regions	–	–	–	-0.42
Filing Year * Multiple Regions	–	–	–	0.03
NBFIs * Filing Year * Multiple Regions	–	–	–	-0.05**
Nonfinancial Companies * Filing Year * Multiple Regions	–	–	–	-0.02
N	250	250	250	250
R-squared	0.43	0.89	0.84	0.48
Adj. R-squared	0.42	0.88	0.83	0.46

Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. The dependent variable for all columns is AI patent rate, which is the number of AI patents divided by the number of firms. Observations for these regressions are at the level of firm type (bank, NBFI, nonfinancial company), filing year, subject matter (either finance-related or not, or planning and control or not), and inventor team geography (multi-region or not). Significance: *p<0.1; **p<0.05; ***p<0.01.

Table 2: HHI Regressions

	(1) Baseline	(2) Subject Matter = Finance-related	(3) Subject Matter = Planning-related	(4) Geography = Multiple Regions
Intercept	8.26***	8.40***	8.38***	7.98***
NBFIs	-1.57***	-1.17***	-1.21***	-1.53***
Nonfinancial Companies	-2.14***	-2.12***	-2.18***	-2.23***
Filing Year	0.00	0.01	0.00	0.01
NBFIs * Filing Year	0.03**	0.00	0.00	0.02**
Nonfinancial Companies * Filing Year	0.00	-0.01	0.00	-0.02**
Subject Matter	–	-0.24	-0.18	–
NBFIs * Subject Matter	–	-0.82***	-0.71***	–
Nonfinancial Companies * Subject Matter	–	-0.06	0.40	–
Filing Year * Subject Matter	–	-0.02	0.00	–
NBFIs * Filing Year * Subject Matter	–	0.05***	0.04**	–
Nonfinancial Companies * Filing Year * Subject Matter	–	0.01	0.00	–
Multiple Regions	–	–	–	0.62***
NBFIs * Multiple Regions	–	–	–	-0.13
Nonfinancial Companies * Multiple Regions	–	–	–	0.13
Filing Year * Multiple Regions	–	–	–	-0.03**
NBFIs * Filing Year * Multiple Regions	–	–	–	0.01
Nonfinancial Companies * Filing Year * Multiple Regions	–	–	–	0.03**
N	250	250	250	250
R-squared	0.77	0.84	0.81	0.85
Adj. R-squared	0.77	0.83	0.80	0.84

Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. The dependent variable for all columns is the Herfindahl-Hirschman Index (HHI) of AI patents. Observations for these regressions are at the level of firm type (bank, NBFI, nonfinancial company), filing year, subject matter (either finance-related or not, or planning and control or not), and inventor team geography (multi-region or not). Significance: *p<0.1; **p<0.05; ***p<0.01.

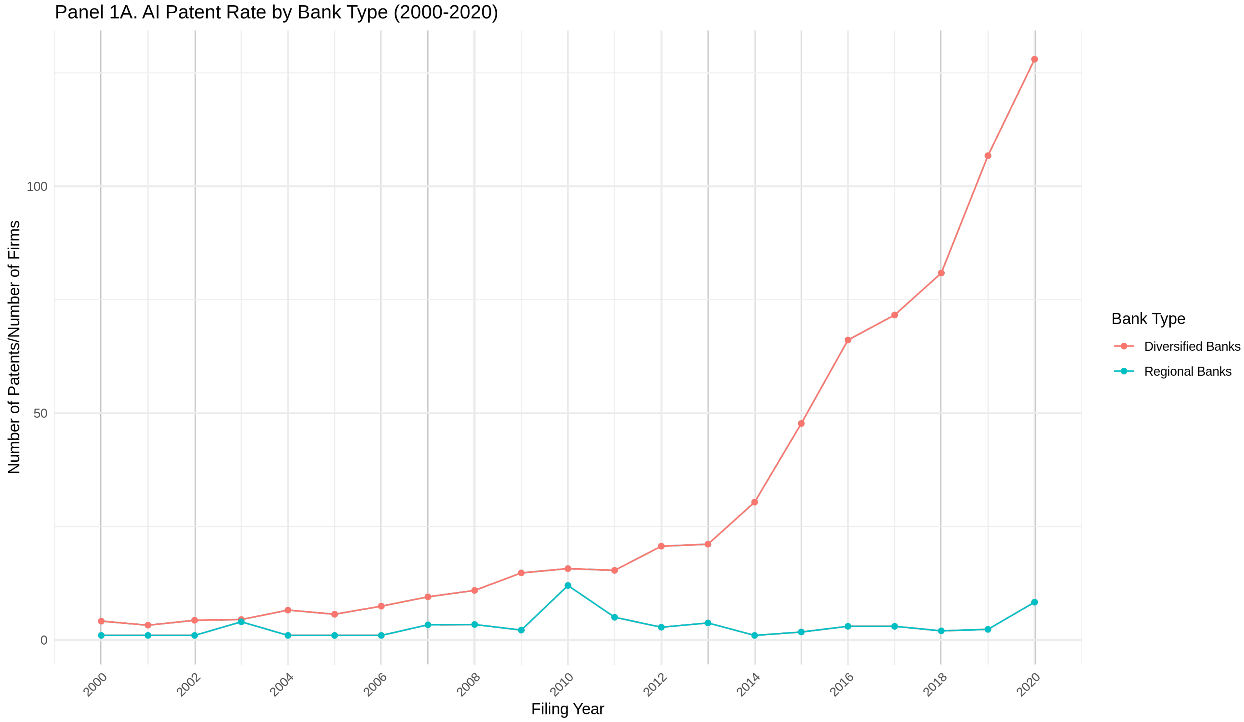
Table 3: Gini Coefficient Regressions

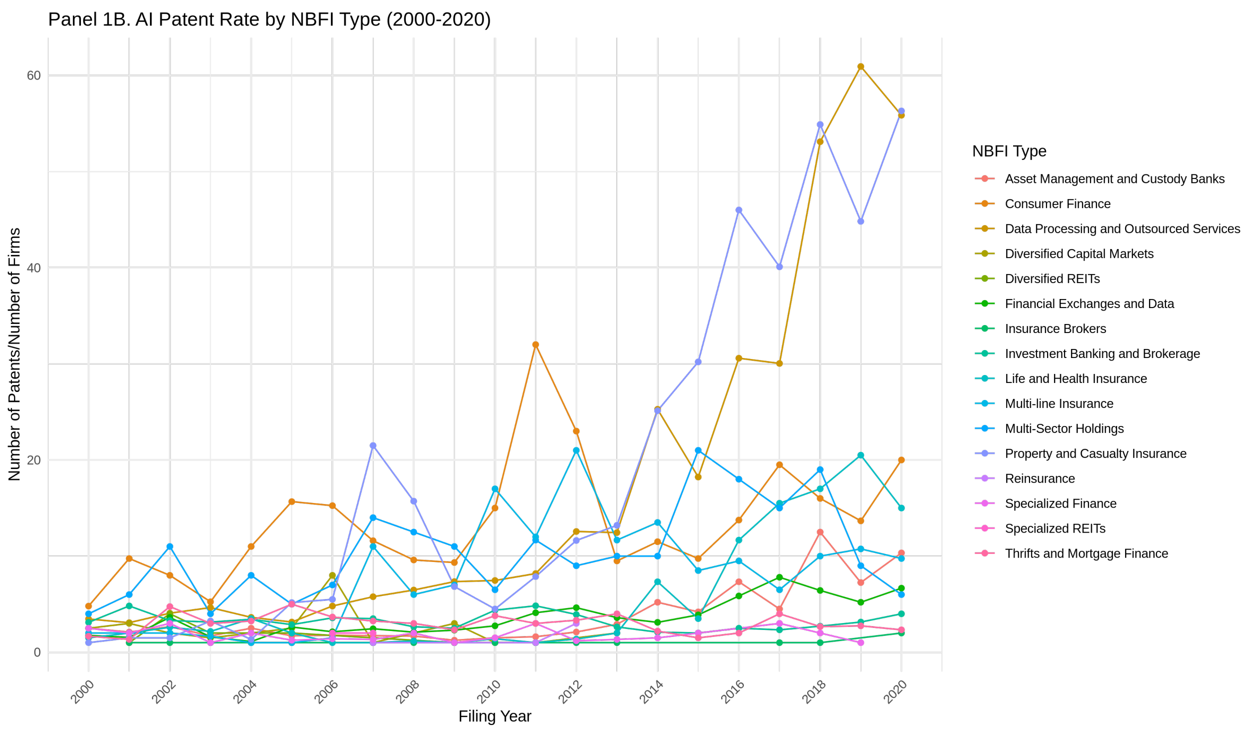
	(1) Baseline	(2) Subject Matter = Finance-related	(3) Subject Matter = Planning-related	(4) Geography = Multiple Regions
Intercept	0.31***	0.24***	0.13***	0.36***
NBFIs	0.02	0.11**	0.14**	0.05
Nonfinancial Companies	0.30***	0.53***	0.62***	0.29***
Filing Year	0.02***	0.02***	0.03***	0.02***
NBFIs * Filing Year	0.00	0.00	-0.01	0.00
Nonfinancial Companies * Filing Year	-0.01***	-0.02***	-0.02***	-0.01***
Subject Matter	–	0.13**	0.21***	–
NBFIs * Subject Matter	–	-0.16**	-0.13*	–
Nonfinancial Companies * Subject Matter	–	-0.45***	-0.25***	–
Filing Year * Subject Matter	–	-0.01***	-0.01	–
NBFIs * Filing Year * Subject Matter	–	0.01**	0.01	–
Nonfinancial Companies * Filing Year * Subject Matter	–	0.01***	0.01*	–
Multiple Regions	–	–	–	-0.10*
NBFIs * Multiple Regions	–	–	–	-0.06
Nonfinancial Companies * Multiple Regions	–	–	–	0.02
Filing Year * Multiple Regions	–	–	–	0.00
NBFIs * Filing Year * Multiple Regions	–	–	–	0.00
Nonfinancial Companies * Filing Year * Multiple Regions	–	–	–	0.00
N	250	250	250	250
R-squared	0.41	0.75	0.80	0.49
Adj. R-squared	0.40	0.74	0.79	0.47

Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. The dependent variable for all columns is the Gini coefficient of AI patents. Observations for these regressions are at the level of firm type (bank, NBFI, nonfinancial company), filing year, subject matter (either finance-related or not, or planning and control or not), and inventor team geography (multi-region or not). Significance: *p<0.1; **p<0.05; ***p<0.01.

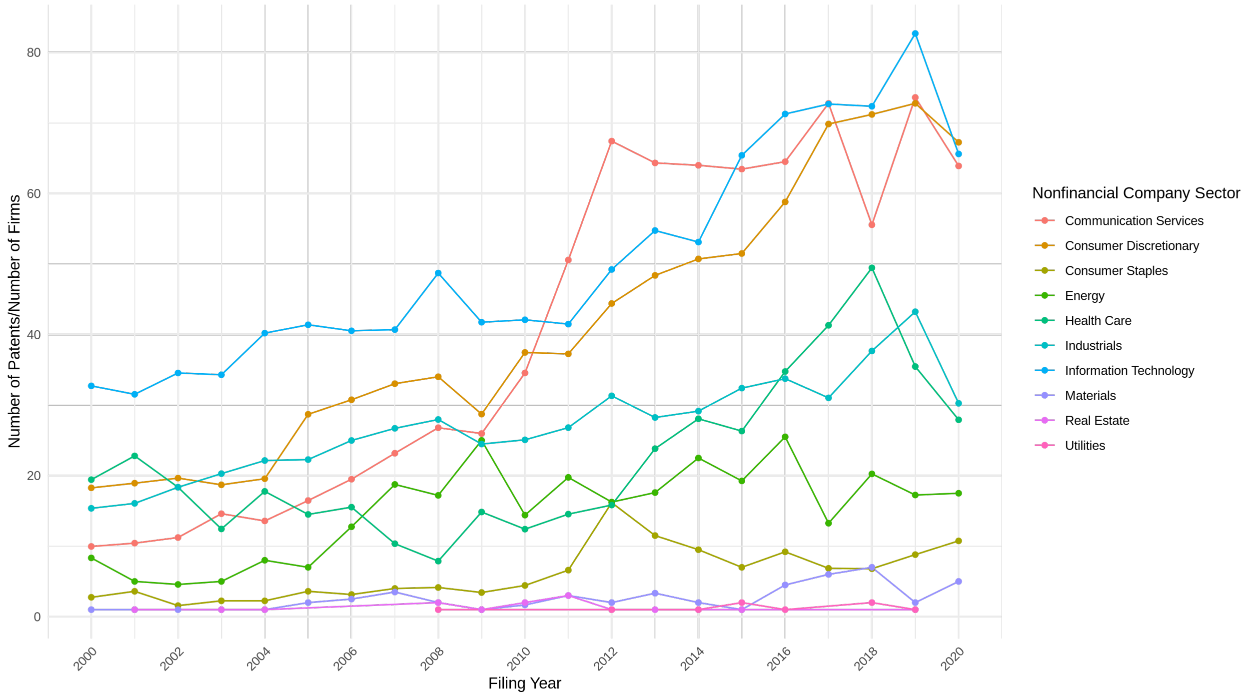
Appendix

Figure A1. AI Patent Rate within Firm Type (2000-2020)



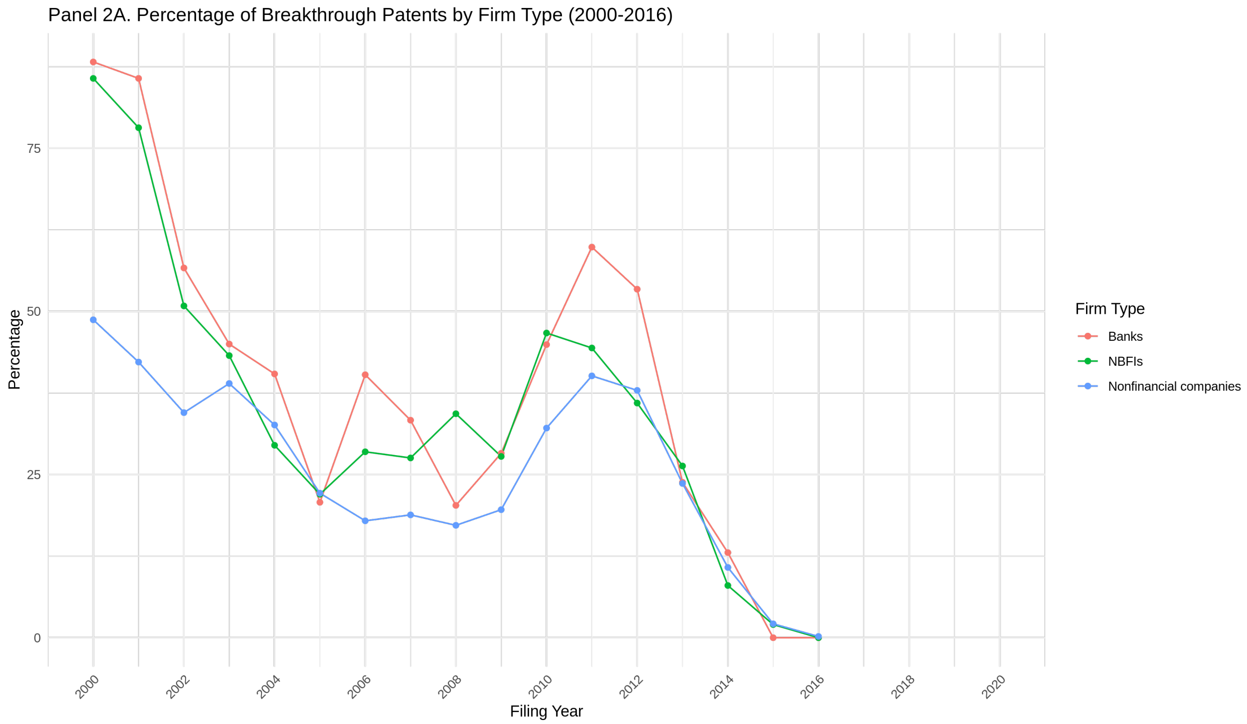


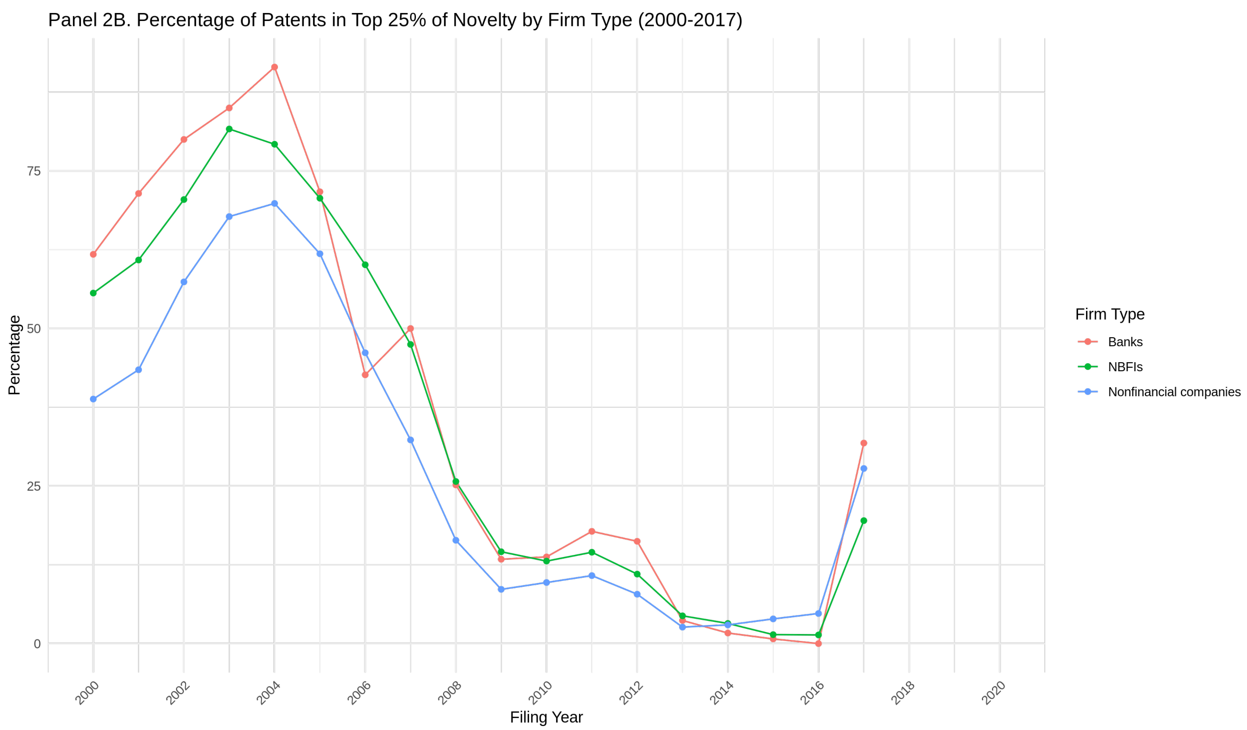
Panel 1C. AI Patent Rate by Nonfinancial Company Sector (2000-2020)



Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. Observations for these figures are at the level of firm sub-type and filing year. Panel A shows the number of AI patents divided by the number of firms by bank type (diversified banks, regional banks) and filing year. Panel B shows the number of AI patents divided by the number of firms by NBFI type (asset management and custody, consumer finance, data processing and outsourced services, diversified capital markets, diversified real estate investment trusts (REITs), financial exchanges and data, insurance brokers, investment banking and brokerage, life and health insurance, multi-line insurance, multi-sector holdings, property and casualty insurance, reinsurance, specialized finance, specialized REITs, and thrifts and mortgage finance) and filing year. Panel C shows the number of AI patents divided by the number of firms by nonfinancial company type (communication services, consumer discretionary, consumer staples, energy, health care, industries, information technology, materials, real estate, utilities) and filing year.

Figure A2. Percentage of Most Impactful AI Patents by Firm Type

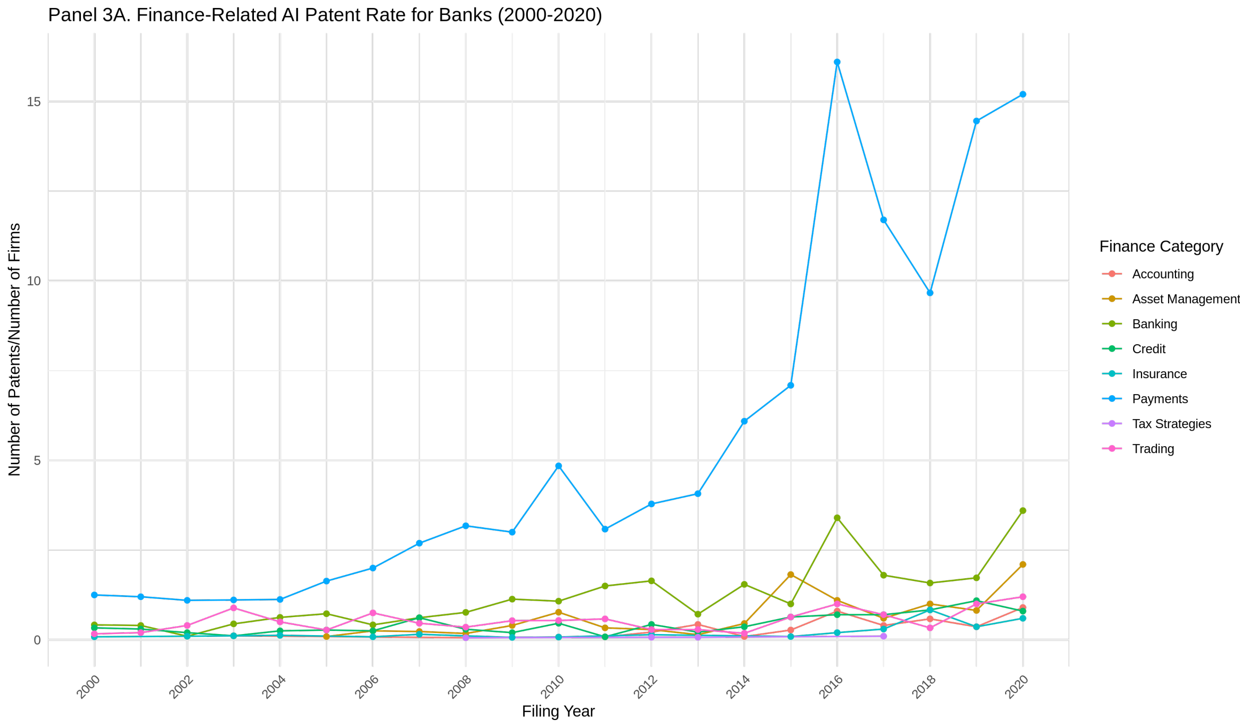


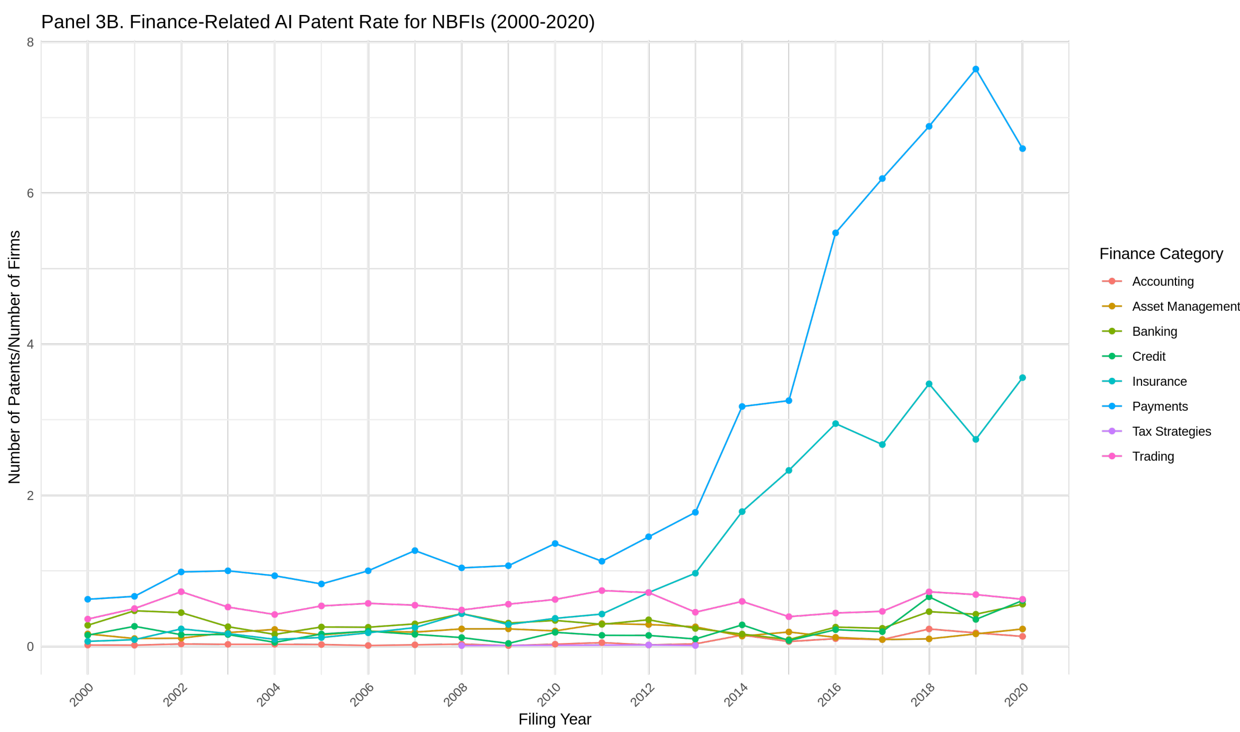


Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025 for which breakthrough patent or novelty patent data is available. Observations for these figures are at the level of firm type and filing year. Panel A shows the percentage of breakthrough AI patents. Breakthrough patents are defined by Kelly et al. (2021) as top 10 percent of patents with the highest ratios of forward similarity to backward similarity, indicating that they are dissimilar to prior patents but similar to future ones. The authors create the similarity measures based on word frequency vectors.

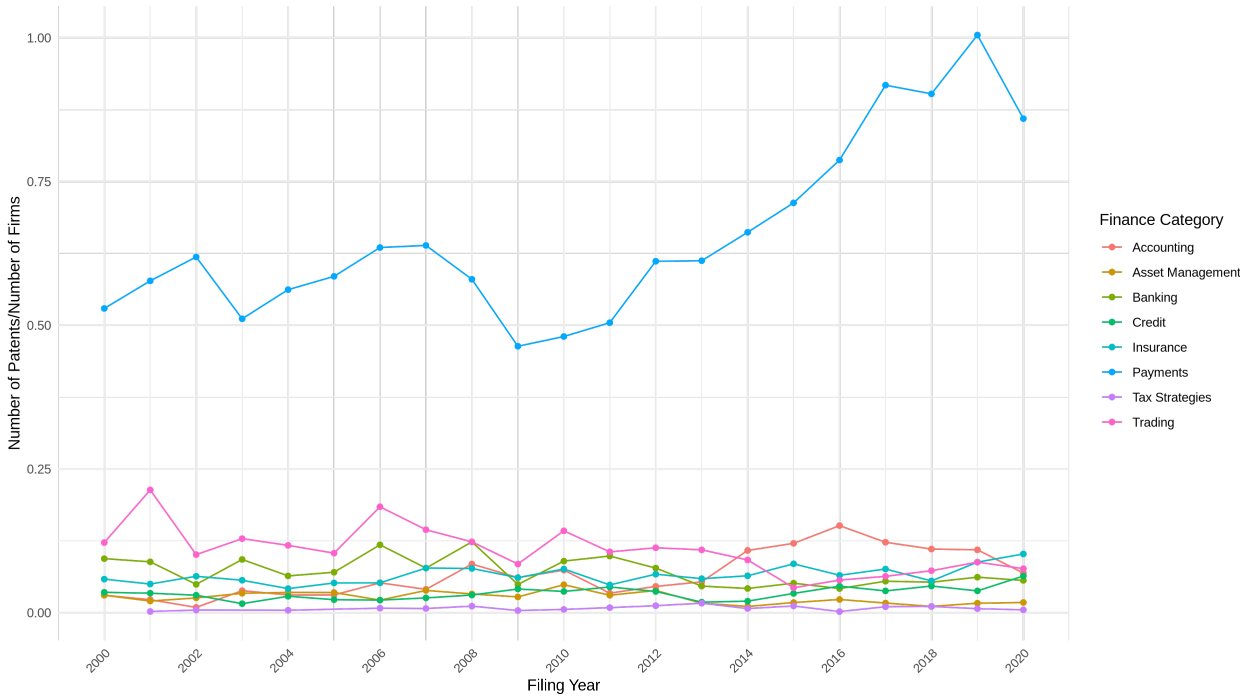
While the analysis in their paper goes to 2010, they extend the breakthrough indicator calculations to 2016 in their Github. Panel B depicts the percentage of patents that are in the top 25 percent of patents with the highest ratios of forward similarity to backward similarly, as defined by Arts et al. (2021). The authors use a cosine similarity measure that takes into account the combination of keywords and their frequencies. They define their measure for all patents granted by May 2018.

Figure A3. Finance-Related AI Patent Rate within Firm Type



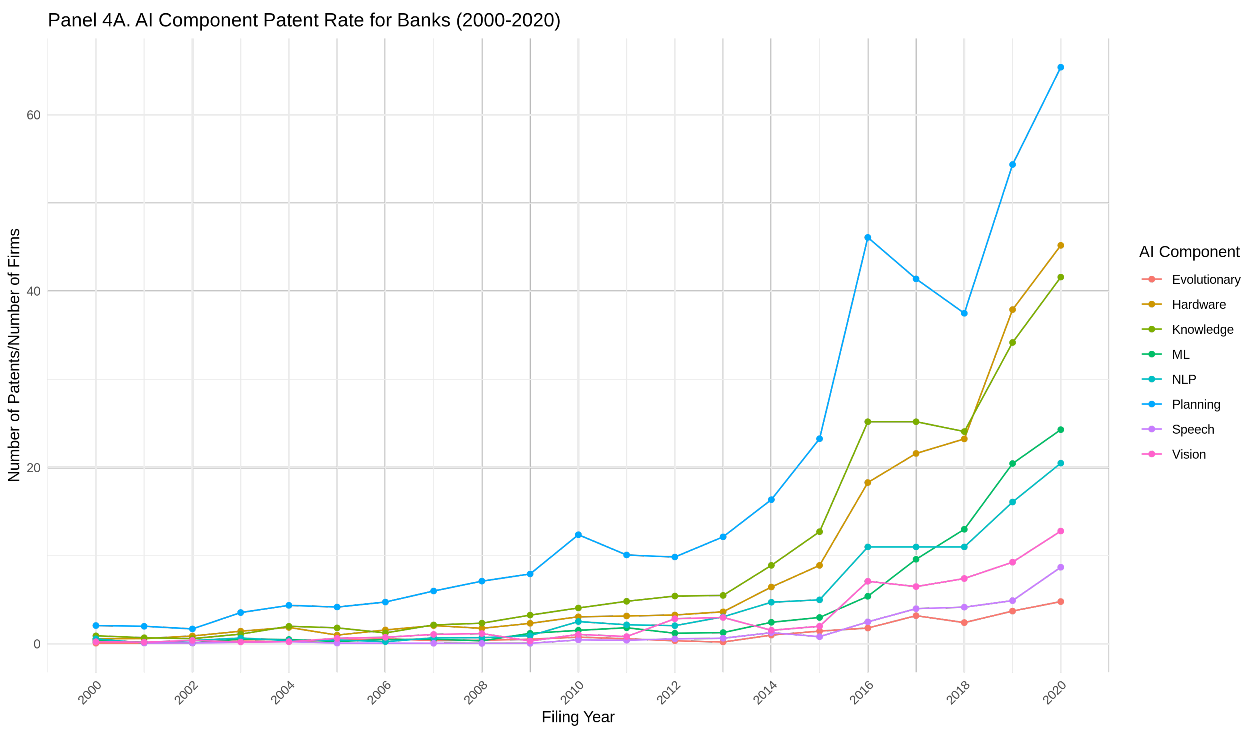


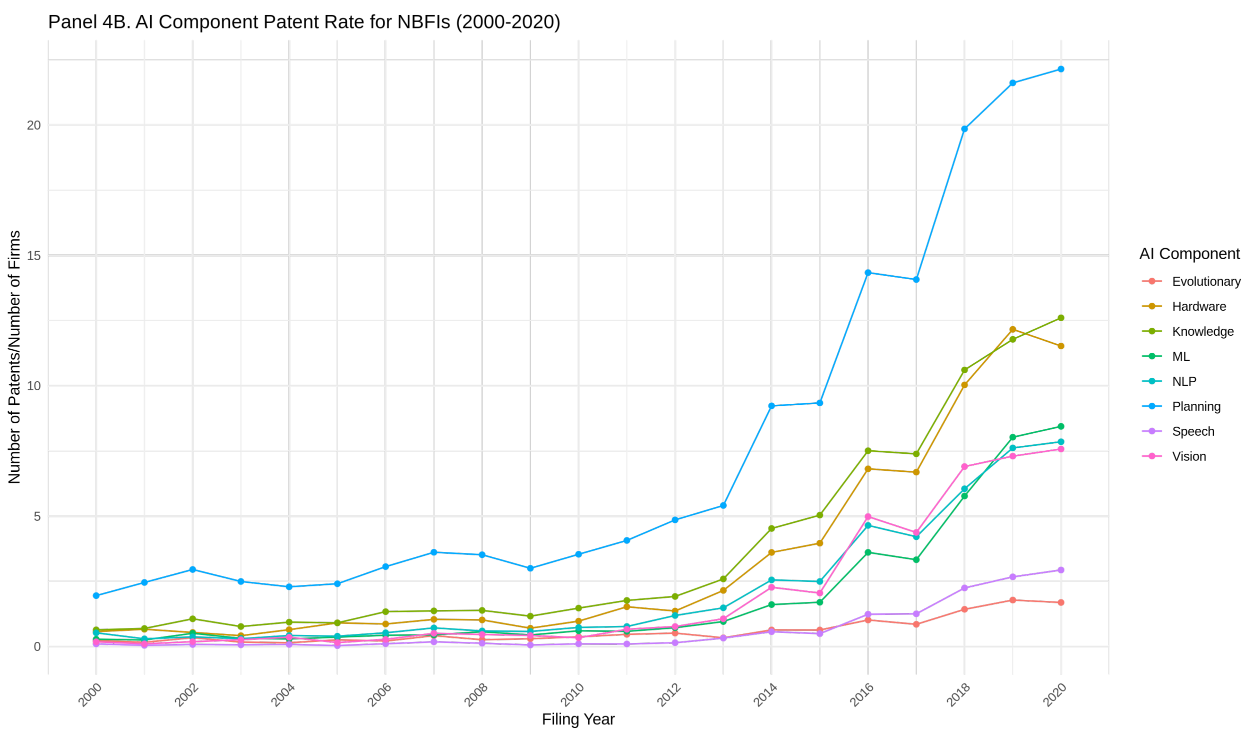
Panel 3C. Finance-Related AI Patent Rate for Nonfinancial Companies (2000-2020)



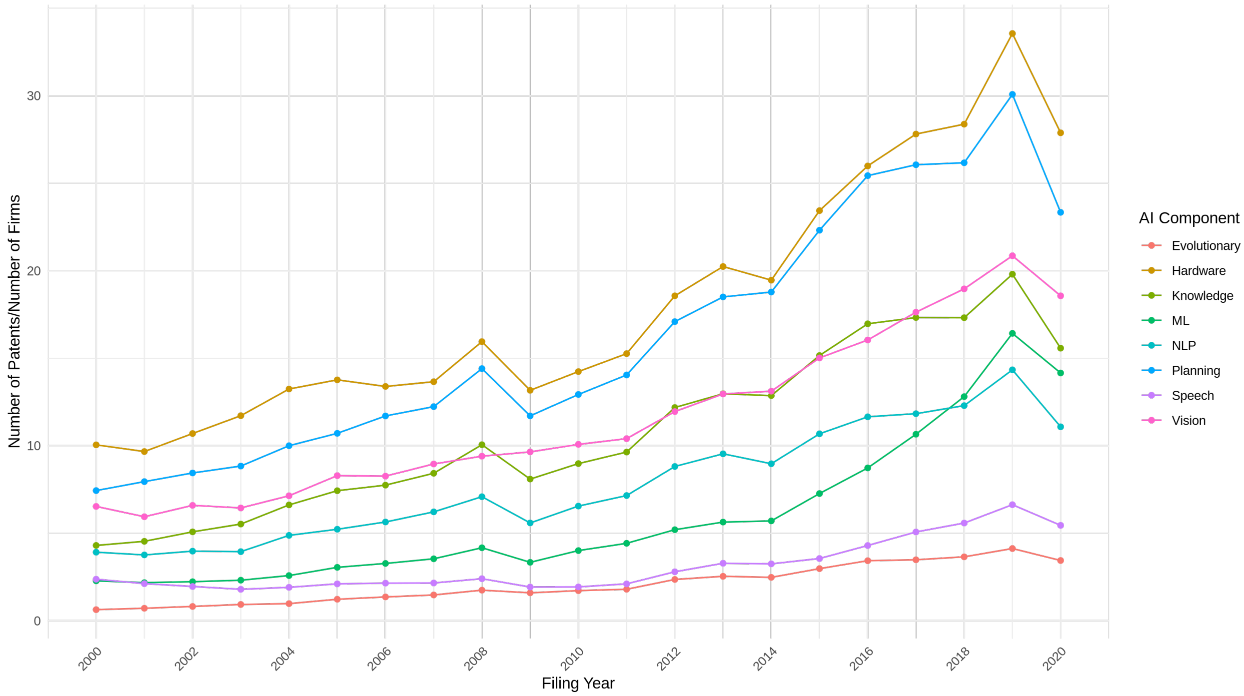
Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. Observations for these figures are at the level of finance category (accounting, asset management, banking, credit, insurance, payments, tax strategies, and trading) and filing year, restricted by firm type depending on the panel. Panel A shows the number of finance-related AI patents divided by the number of firms by finance category for banks. Panel B shows the number of finance-related AI patents divided by the number of firms by finance category for NBFIs. Panel C shows the number of finance-related AI patents divided by the number of firms by finance category for nonfinancial companies.

Figure A4. AI Component Patent Rate within Firm Type



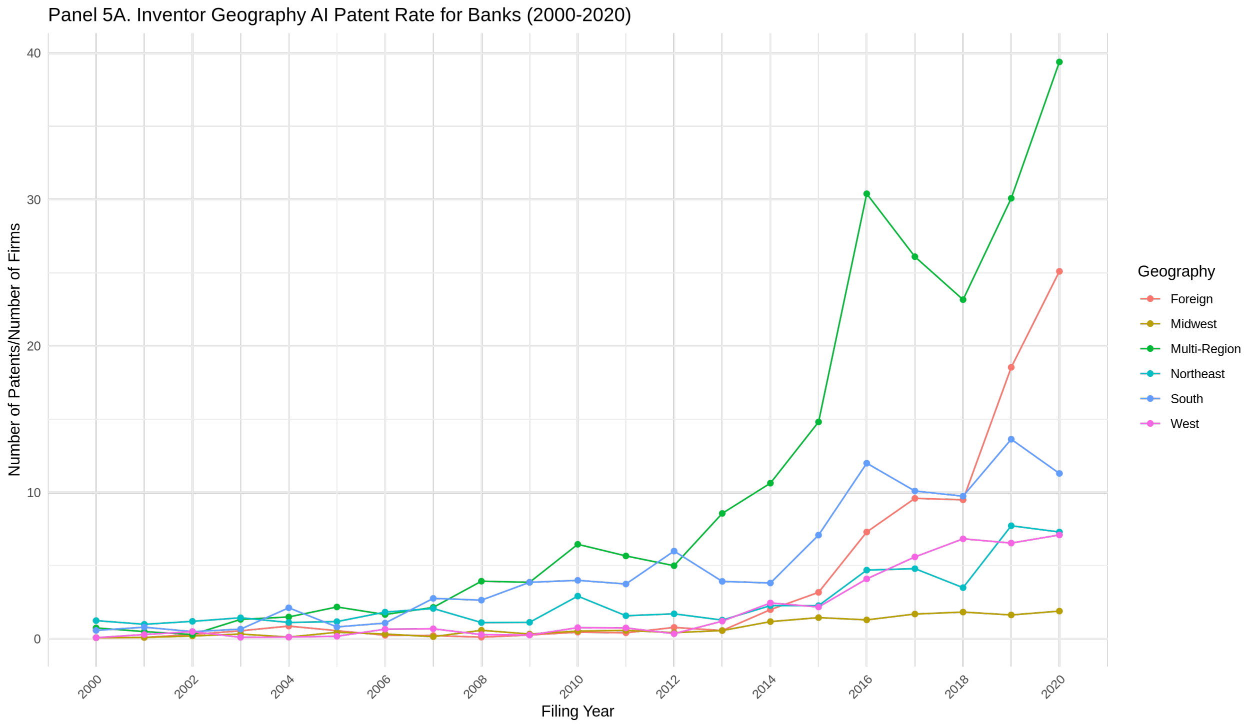


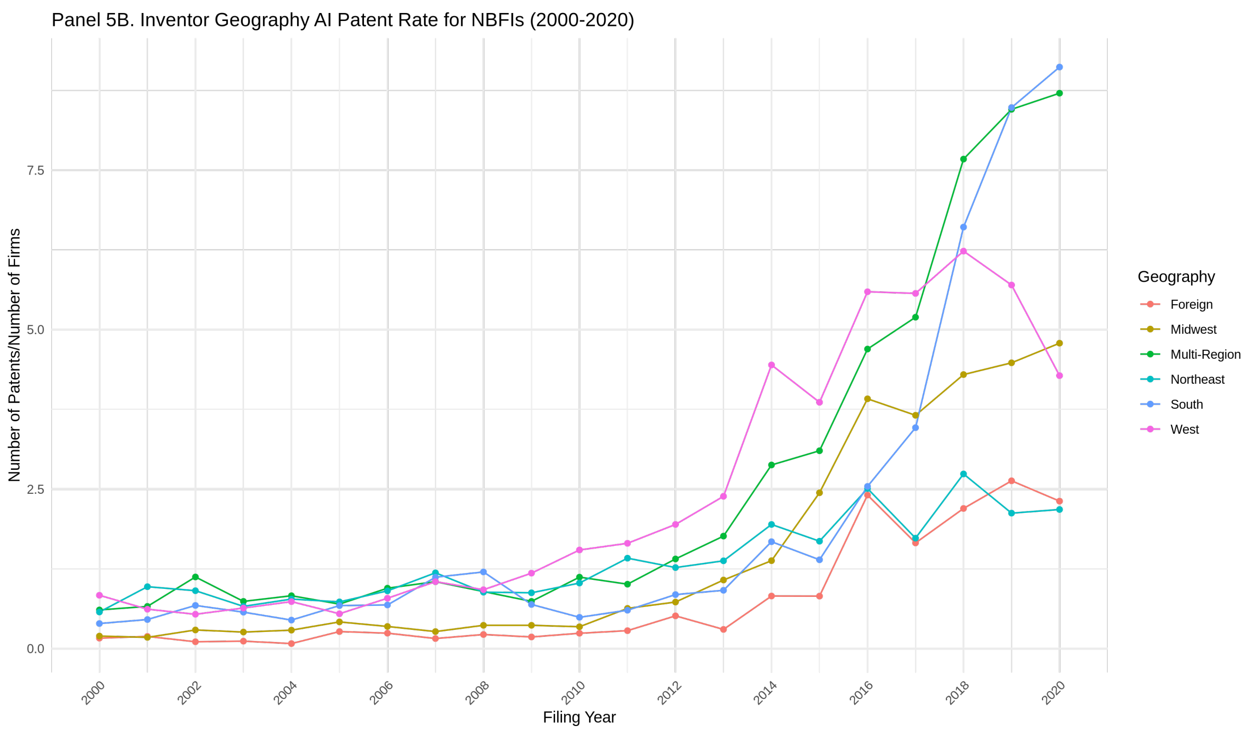
Panel 4C. AI Component Patent Rate for Nonfinancial Companies (2000-2020)



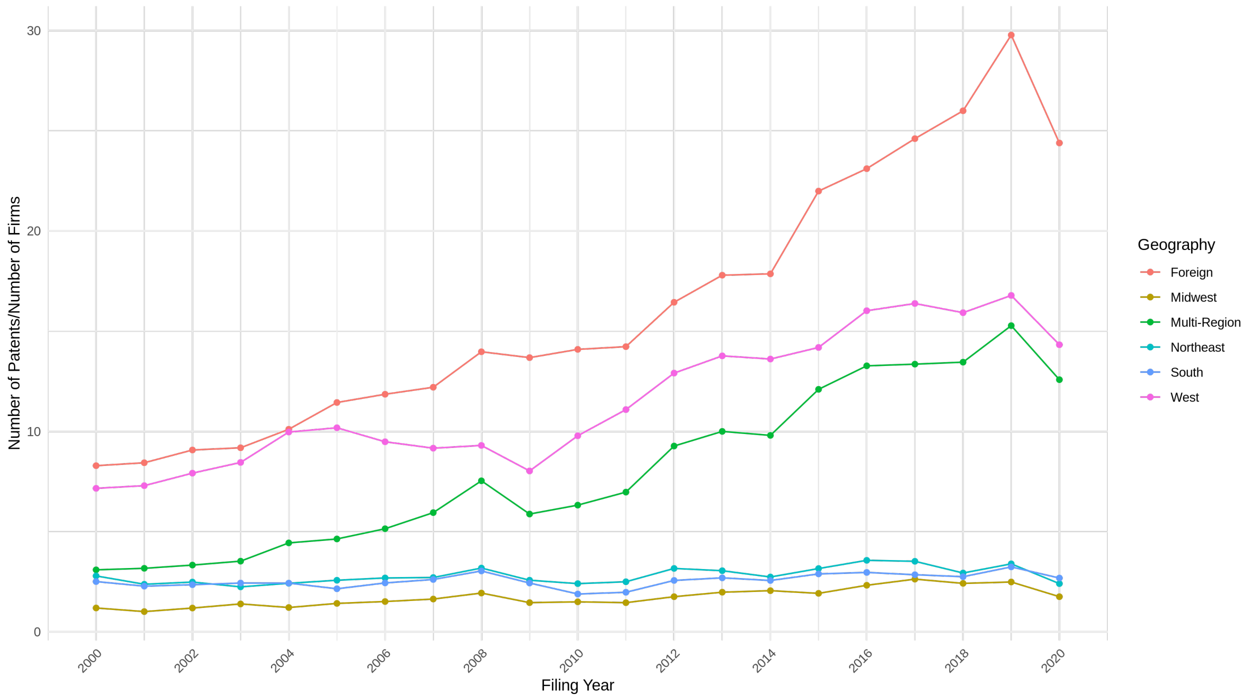
Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. Observations for these figures are at the level of AI component (evolutionary computation, AI hardware, knowledge processing, machine learning (ML), natural language processing (NLP), speech, and computer vision) and filing year. Panel A shows the number of AI patents divided by the number of firms by AI component category for banks. Panel B shows the number of AI patents divided by the number of firms by AI component category for NBFIs. Panel C shows the number of AI patents divided by the number of firms by AI component category for nonfinancial companies.

Figure A5. Inventor Geography AI Patent Rate within Firm Type





Panel 5C. Inventor Geography AI Patent Rate for Nonfinancial Companies (2000-2020)



Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. Observations for these figures are at the level of inventor team geography (all in west U.S., all in south U.S., all in midwest U.S., all in northeast U.S., all in foreign countries, or multi-region team) and filing year. Panel A shows the number of AI patents divided by the number of firms by inventor team geography for banks. Panel B shows the number of AI patents divided by the number of firms by inventor team geography for NBFIs. Panel C shows the number of AI patents divided by the number of firms by inventor team geography for nonfinancial companies.

Table A1: AI Component Definitions from Giczy et al. (2022)

AI Component	Definition
Knowledge processing	"The field of knowledge processing contains methods to represent facts about the world and to derive new facts (or knowledge) from a knowledge base. For example, expert systems generally contain a knowledge base and an inference method to obtain new facts from that knowledge base."
Speech	"Speech recognition includes methods to understand a sequence of words given an acoustic signal. For example, the noisy channel model is a statistical approach used to identify the most likely sequence of words given verbal input using Bayes' rule ...."
AI hardware	"The field of AI hardware includes physical hardware designed to implement artificial intelligence software. For example, Google designed the Tensor Processing Unit (TPU) to run neural network algorithms more efficiently. AI hardware may include logic circuitry, memory, video, processors, and solid-state technologies. It may also include embedded software that implements other AI component technologies, such as machine learning algorithms."
Evolutionary computation	"Evolutionary computation contains a set of computational methods utilizing aspects of nature and, specifically, evolution .... For example, genetic algorithms include methods for selecting algorithm variants through the selection of optimal random mutations by maximizing fitness."
Natural language processing	"Natural language processing contains methods for understanding and using data encoded in human natural language. For example, language models represent probability distributions of language expressions ...."
Machine learning	"The field of machine learning contains a broad class of computational learning models. For example, supervised learning classification models are algorithms that learn to classify observations based on pre-labeled training data. Machine learning includes, among other techniques, neural networks, fuzzy logic, adaptive systems, probabilistic networks, regression, and intelligent searching."
Computer vision	"The field of computer vision contains methods to extract and understand information from visual input, including images and videos. For example, edge detection identifies the boundaries and borders contained in an image. Additional areas of computer vision include object recognition, manipulation (e.g., transformation, enhancement, or restoration), color processing, and conversion."
Planning and control	"The field of planning and control contains methods to identify and execute plans to achieve specified goals. Key aspects of planning include representing actions and states of the world, reasoning about the effects of actions, and efficiently searching over potential plans. Modern control theory includes methods to maximize objectives over time .... For example, stochastic optimal control considers dynamic optimization in uncertain environments. Additionally, planning and control includes data systems for administration/ management (e.g., managing an organization and its employees, including inventory, workflow, forecasting, and time management), adaptive control systems, and models or simulators of systems."

Table A2: Full Data – Descriptive Statistics (2000-2020)

Statistic	*Banks*	*NBFIs*	*Other*
Total Number of Assignees	52	386	1291
Number of Patents			
Total Patent Count	5678	16464	433428
Mean Patent Count by Assignee	109.19	42.65	335.73
Median Patent Count by Assignee	3	3	9
Patent Subject Matter			
Percent Finance-Related	35.65	48.55	2.41
Percent Payments	22.77	24.34	1.52
Percent Banking	5.09	3.24	0.17
Percent Credit	1.85	2.03	0.08
Percent Trading	2.24	5.87	0.26
Percent Asset Management	2.11	2.02	0.06
Percent Insurance	0.65	10.47	0.15
Percent Tax Strategies	0.07	0.02	0.02
Percent Accounting	0.86	0.56	0.16
Percent Not Finance-Related	64.35	51.45	97.59
Percent Planning and Control	73.14	70.32	37.62
Percent Machine Learning	17.05	16.83	13.52
Percent Evolutionary Computation	4.47	5.61	4.85
Percent Speech	5.55	5.41	7.11
Percent Computer Vision	11.76	17.49	26.95
Percent AI Hardware	36.33	29.68	42.11
Percent Natural Language Processing	18.18	19.33	18.20
Percent Knowledge Processing	40.31	34.23	25.29
Patent Inventor Geography			
Percent Single US Region	42.18	69.14	43.53
Percent Northeast	10.58	13.63	6.57
Percent Midwest	3.17	13.31	4.05
Percent South	20.45	18.82	5.97
Percent West	7.98	23.38	26.94
Percent Only Foreign Countries	15.04	6.89	37.59
Percent Multiple Regions	42.76	23.96	18.85
Patent Concentration			
HHI	3387.41	591.91	332.19
Gini Coefficient	0.92	0.90	0.92

Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all artificial intelligence (AI) patents filed by financial innovators between 2000-2020 and granted by May 2025. Observations for this table are at the individual patent level.

Table A3: Mean AI Patent Ratio

	2000-2004	2005-2009	2010-2014	2015-2020
Banks	0.55	0.63	0.64*	0.76*
NBFIs	0.44	0.49	0.54	0.65
Nonfinancial companies	0.16	0.21**	0.24	0.28

Note: The data comes from Lerner et al. (2024), the U.S. Patent and Trademark Office (PTO) Artificial Intelligence Patent Dataset, and U.S. PTO Patentsview. The data consists of all patents filed by financial innovators between 2000-2020 and granted by May 2025. The table depicts the average ratio of artificial intelligence (AI) patents to total patents by firm type and filing year period. T-tests were conducted to determine if the average for the filing year period is significantly different from the average for the period prior. Significance: *p<0.1; **p<0.05; ***p<0.01.