Financial Innovation in the 21st Century: Evidence from U.S. Patents[1]

Josh Lerner Amit Seru Nicholas Short Yuan Sun

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We develop a dataset of U.S. finance patents using machine learning techniques. We find that financial innovation is substantial and important. The subject matter of financial patents has changed, consistent with the financial services industry's shift towards household investors and borrowers. The surge in financial patenting was driven by information technology firms and others outside of finance. While academic knowledge remains associated with more valuable patents, citations in finance patents to academic papers, especially by banks, fell sharply. The location of innovation has shifted, with banks moving from regions with tight financial regulation to more permissive ones. High-tech regions have attracted financial innovation by payments, IT, and other non-financial firms.

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[1] jlerner@hbs.edu; aseru@stanford.edu; nshort@g.harvard.edu; ysun@hbs.edu. All authors are affiliated with Harvard University except for Seru, who is at Stanford University and the Hoover Institution. Lerner and Seru are affiliates of the National Bureau of Economic Research. Harvard Business School's Division of Research and Doctoral Programs provided financial support for this project. We thank Robin Greenwood, Howell Jackson, Adam Jaffe, Danielle Li (discussant), Andrei Shleifer, John Squires, Andy Toole, and participants at seminars at the Bank of Italy, Harvard Business School, Stanford Law School, the University of Michigan, and the 2020 Finance, Organizations and Markets conference for helpful comments. Rick Townsend kindly allowed us to use the patent-venture capital mapping. Patrick Clapp, Amin Gulamali, Stephen Moon, Mahlon Reihman, Kathleen Ryan, Rhys Sevier, James Zeitler, and especially Zunda Xu provided excellent research assistance. Lerner has received compensation for consulting with financial institutions. All errors and omissions are our own. *First Version: September 2020*

1. Introduction

Despite the intense interest in financial innovations and their consequences,[2] we know remarkably little about where or by whom these new products and services are developed. This paper seeks to address this gap using finance patents. While not all financial innovations receive patents, and the legal treatment of these awards has shifted over time, patents provide a valuable window into the nature of financial innovation.

To do so, we develop a dataset of over 24 thousand financial U.S .patents applied for between 2000 and 2018, and awarded by February 2019. We employ machine learning techniques to identify the many financial patents that are assigned to patent classes other than those in those devoted exclusively to financial innovations, and extensively audit the results to ensure their reasonableness. We exploit both the "front page" data from the awards, as well as the patent text, to better understand their characteristics.

Five broad conclusions emerge for the analysis. First, financial innovation is substantial and important. As Figure 1 depicts, the volume of financial patent awards (the red line) and applications (the blue line) in the U.S. surged in the late 1990s and early 2000s, from a nearly infinitesimal share to between 0.4% and 1.1% of all grants. While this level was still modest compared to the finance and insurance's share of GDP (7.6% in 2019[3]), financial patents were disproportionately important ones. Figure 2 plots the logarithm of the mean of two commonly used measures of patent value, that of Kogan et al. (2017) and the citation count, by year of award. Financial patents since the global financial crisis (GFC) have had an average Kogan value considerably greater than any other broad class. Using the count of citations, finance patents are second only to "Human Necessities," which includes pharmaceuticals. These patterns also hold when examining the top 5th percentile of awards (Appendix Figure A-1).

Second, the subject matter of financial patents has changed sharply, consistent with the shift in the financial services industry towards household investors and borrowers documented by Greenwood and Scharfstein (2013) and Philippon (2019). An increasing fraction of patented innovation has focused on consumer rather than business applications. As Panel A of Figure 3 depicts, the bulk of the awards were not in areas related to security design or investment banking. Rather, they were dominated by payments and various supporting back-office technologies. Figure 4—which illustrates the patents in the sample with the greatest number of citations and the highest Kogan et al. (2017) and Kelly et al. (2020) weights—underscores this point. While the most-cited patent is geared toward professional traders, the other two are oriented towards meeting the needs of retail investors (fraud protection in banking and tax planning).

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[2] Recent theoretical papers include Biais, Rochet, and Woolley (2015), Caballero and Simsek (2013), Gennaioli, Shleifer, and Vishny (2012), Rajan (2006), and Thakor (2012). Recent empirical papers examining financial innovation in the run-up to the GFC include Chernenko and Sunderam (2014), Fostel and Geanakoplos (2012), Keys et al. (2010), and Simsek (2013). Another set of papers look at fintech innovation specifically, such as the special issue summarized by Goldstein, Jiang, and Karolyi (2019). Chen, Wu, and Yang (2019) in that volume use patent data to look at fintech firms. The older literature is reviewed in Frame and White (2004) and Lerner and Tufano (2011).

[3] https://fred.stlouisfed.org/series/VAPGDPFI.

Third, the surge in financial patenting was driven by U.S. information technology firms and those in other industries outside of finance. As Panel B of Figure 3 suggests, banks and other financial institutions represented a modest share of the awards, with information technology (IT) companies dominating. Banks and payments firms have increasingly focused on their core areas, while IT firms and other financial firms have continued to patent widely in finance. IT, payments, and other firms are more likely to be issued process patents, as well as consumer finance ones.

Fourth, the relationship between financial innovators and the academic knowledge base has changed. Over the sample period, academic citations in finance patents were associated with more impactful patents, an effect that held for such citations in general, as well as those to articles in business, economics, and finance journals specifically. The relationship between academic citations and patent value has become stronger over time, particularly in the 2015-18 period.

Over time, however, the number of citations in finance patents to academic papers fell. This shift has been most dramatic for banks, which experienced by far the most precipitous decline, and for citations to business, economics, and finance journals. Citations have been to increasingly older academic articles. Three explanations can be offered for these patterns. First, as the focus of financial patents has shifted to consumers, there may be less relevant academic work to cite. Second, commercially relevant academic discoveries in finance may be harder to come by, consistent with the "fishing out" hypothesis advanced in Eaton and Kortum (2002) and Bloom et al. (2020). Finally, financial organizations, especially banks, may have less ability to absorb these insights.

We finally highlight changes in the geography of financial innovation in the U.S. In particular, we document dramatic shifts across the metropolitan areas in the amount of financial innovations, with the rise of the greater San Francisco region (and the Pacific more generally) and the decline of the New York area.

Consistent with evidence that innovation responds to shifting demand and regulatory conditions (Acemoglu and Linn, 2004; Finkelstein, 2007), we show that financial regulatory actions seem to have adversely affected innovation by financial firms. In the years after the GFC, financial innovation by banks shifted from locations with tight financial regulation to more permissive places. These results suggest that the seeming failure of banks and other financial institutions to expand their innovative scope documented above may have (at least partially) been due to pressures from financial regulators, consistent with the observations of Miller (1986) and Kane (1986) about the importance of regulation as a driver of financial innovation. By way of contrast, regions with the highest technology innovation in general attracted financial innovation by payments firms, IT firms, and other non-financial firms.

In the final section, we argue that these findings suggest two broad conclusions. First, financial innovation is a far more complex and richer phenomenon than has been depicted in the academic literature to date, which has largely focused on either the design of novel securities or fintech, especially blockchain. The extent to which finance patenting has been increasingly dominated by firms outside the finance industry is striking. So is the importance of payments technologies, as well as back-office functions such as security and communications.

Second, the results pose a puzzle regarding the failure of traditional financial institutions to maintain pace in consumer-focused innovation. The results hint at factors that may have exacerbated the declining share of financial innovation by banks: the seeming decrease in relevant contemporaneous academic discoveries (or the ability to identify and absorb them), as well as regulatory pressures after the GFC (Buchak et al., 2018). These patterns were consistent with the arguments of Philippon (2019) regarding the impediments to innovation by incumbent banks, and the potential for breakthroughs by new entrants. They are also in line with the changing distribution of value added in credit intermediation away from traditional banking, as documented by Greenwood and Scharfstein (2013). While these analyses cannot ultimately address questions regarding the social welfare of financial innovations, they suggest that the nature of financial innovation has evolved with broader trends in the financial sector that has not been appreciated in the literature. In the final section, we also discuss some of the opportunities for future research.

2. Patents as Indicators of Financial Innovation

2.1 A Historical Perspective

The financial services industry has historically differed from the bulk of manufacturing industries with regard to the ability of innovators to appropriate their discoveries. There has long been ambiguity about the patentability of financial discoveries in the United States. At least since a 1908 court decision established a "business methods exception" to patentability,[4] many judges and lawyers have presumed that business methods were not patentable subject matter. While the USPTO issued patents on financial and other business methods during the twentieth century, many observers questioned their enforceability. Another concern limiting patenting was that it was very difficult for firms to detect infringement of their valuation- and trading-related patents. (Of course, the same considerations also affected the decision to file process patents in many other industries.)

Consequently, awardees were reluctant to incur the time and expense to file for awards. Instead, new product ideas diffused rapidly across competitors (Tufano, 1989). But a theoretical analysis by Herrera and Schroth (2011) argued that even when inventions could not be patented, investment banks had considerable incentives to develop new products.

As a result, patents traditionally only provided a limited guide to innovative activity in finance, in contrast to other fields (Griliches, 1990). This disparity was highlighted in Lerner (2002), who documented that between 1971 and 2000, only 445 financial patents were issued by the USPTO. These represented less than 0.02% of all awards during this period. A disproportionate share of these awards were made to individual inventors. Academic research, while highly relevant to many of these patents, was rarely cited or identified by the patent examiners.

At the same time, other metrics of innovative activity in financial services are also problematic. Finance has had extremely low levels of reported R&D. For instance, in 2016, the U.S. finance and insurance sector spent 0.17% of total revenue on R&D, as opposed to 13.5% for pharmaceuticals, 10.7% for computers and electronic products, and 3.4% for manufacturing as whole (based on calculations by Kung (2020)). At least in part, this reflects measurement challenges: innovation in

[4] *Hotel Security Checking Co. v. Lorraine Co.*, 160 F. 467 (2d Cir. 1908).

a financial services firm is often widely dispersed across the organization, rather than concentrated in a centralized research facility. Moreover, the historical ambiguities about whether R&D tax credit covered such expenditures reduced the incentives for financial firms to track this spending (National Research Council, 2005). Baily and Zitzewitz (2001) highlighted how government productivity measurement in financial services can be distorted by new goods and inappropriate output measures.[5]

Attitudes toward business method patents changed with the July 1998 appellate decision in *State Street Bank and Trust v. Signature Financial Group*. This case originated with a software program used to determine the value of mutual funds, on which Signature had obtained a patent in 1993. State Street Bank sued to have the patent invalidated on grounds that it covered a business method. While State Street's argument prevailed in the district court, the Court of Appeals for the Federal Circuit (the central appellate court for patent cases, also known as the CAFC) reversed the finding. The court affirmed the patentability of financial software that valued mutual funds since it produced a "useful, concrete, and tangible result."[6] The Supreme Court declined to hear State Street's appeal in January 1999.

State Street thus established that business methods were statutory subject matter on an equal playing field with more traditional technologies. Numerous trade press articles interpreted the case as unambiguously establishing the patentability of business methods. While this decision was refined in important subsequent rulings such as *Bilski v. Kappos* and *Alice Corp. v. CLS Bank* (discussed in Appendix A), it nonetheless represented a sharp discontinuity.

Conversations with practitioners actively involved in prosecuting finance patents suggested that the historical differential between patenting in finance and in other technological domains narrowed considerably in recent decades. In addition to the greater (though not iron-clad) confidence in the enforceability of finance patents, two factors have contributed to this change in practice. One reason is that greater regulatory disclosures and more public scrutiny has made it hard to keep discoveries secret. In these settings, the disclosure associated with patent awards may be less problematic. A second reason has the emergence of fintech firms that are not vertically integrated. Since these new firms cannot capture the returns from their inventions directly, they regularly file financial patents. These filings in turn spurred many incumbents who did not traditionally patent to protect their innovations as well.

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[5] The OECD (2020) reported the U.S. gross value added per person employed (constant prices) has declined at an -0.19% annual rate for "finance and insurance services" between 2010 and 2018 (the last available year), as opposed to rising at a 0.94% rate for the entire economy, with similar patterns seen in the United Kingdom. See also Philippon (2015).

[6] In particular, the court held "... that the transformation of data, representing discrete dollar amounts, by a machine through a series of mathematical calculations into a final share price, constitutes a practical application of a mathematical algorithm, formula, or calculation, because it produces 'a useful, concrete and tangible result'–a final share price momentarily fixed for recording and reporting purposes and even accepted and relied upon by regulatory authorities and in subsequent trades." See *State Street Bank and Trust v. Signature Financial Group*, 149 F.3d 1368 (Fed. Cir. 1998).

2.2. *Empirical Evidence on Financial Patent Quality*

The qualitative discussion above suggested that the mapping between financial innovations and patenting has become closer. These arguments were borne out in three preliminary empirical analyses.

The first analysis looked at the extent to which patent awards were scrutinized by USPTO. As noted above, Lerner (2002) suggested that the pre-*State Street* awards were subject to ineffective reviews. To examine the quality of review in the 21st century, we created a sample of U.S. utility[7] patents filed between 2000 and 2018, awarded by February 2019, and whose original applications were published by the USPTO. We compared the crucial independent claims in the applications and awards, and determine the extent to which the number and length of these claims were modified during the review process, following the methodology of Marco, Sarnoff, and deGrazia (2019).[8]

Panels A and B of Figure A-2 presents a comparison of 2.6 million non-finance patents and almost 16 thousand finance ones. Finance patents were more likely to have the number of independent claims reduced than non-finance patents (by one-half, rather than one-third, of an independent claim) and to have the shortest independent claim lengthened (by 84 words, as opposed to 49).[9] Both of these results were consistent with more intensive scrutiny of finance patents during the past two decades. This greater scrutiny appears to have been consistent since the mid-2000s. Table A-1 in the Appendix presents a more detailed tabulation and statistical comparison, and finds consistent results.

The second analysis looks at the relative impact of patent awards. Table 1 examines all finance and non-finance patents filed between 2000 and 2018, and awarded by February 2019, using three leading measures of patent impact. These three measures, while positively correlated (Kelly et al., 2020), differ in both their methodologies and points of focus, and thus identify different patents and firms as the most impactful:

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[7] 6% of U.S. patent applications between 2000 and 2018 were in classes other than utility (https://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm). These are primarily for design and plant patents that have little relevance to finance. Following the literature, we do not consider non-utility patents throughout this paper.

[8] An independent claim "is a standalone claim that contains all the limitations necessary to define an invention" (https://www.uspto.gov/sites/default/files/documents/Website%20PDF%20-%20Invention%20Con%202017%20Claim%20Drafting%20Workshop%20-%20OPLA.pdf) and as such, are the most important such rights granted. Not all patents have published applications: for instance, those applications only filed in the U.S. are often not published (https://www.uspto.gov/web/offices/pac/mpep/s1122.html#d0e120159). We determined the count and the length of independent claims in issued patents using the Patentsview database. Due to the difficulty in obtaining the claim text in application publications, we only used the applications analyzed by Marco, Sarnoff, and deGrazia (2019) and archived at https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-claims-research-dataset.

[9] In patent claims, patentees generally strive to have the broadest claims, i.e., those with the fewest limitations. An increase in claim length is thus often associated with a narrowing of claim breadth.

- The first of these was the subsequent patent citations (through October 2019) that the patent garnered. Because the propensity to cite patents varied across technologies and over time, we normalized the citations by the mean number received by other patents in that four-digit Combined Patent Classification (CPC) class and awarded in the same quarter.
- The second impact measure was the Kogan et al. (2007) estimate of patent value, based on market reactions to the award grants. This measure could only be calculated for publically traded firms. Unlike the other two measures, this metric only captured private, rather than private and social, returns.
- The final measure was the metric of patent novelty developed by Kelly et al. (2000), based on the relative novelty of the patent language compared to prior and subsequent patents. Because this measure required a substantial corpus of subsequent patents, it was only calculated for patents awarded through the end of 2015.

Using the citation measure, the mean finance patent was on average 25% more impactful than the typical award. Using Kogan et al. (2017) average market values, the finance patents were four-and-a-half times more valuable. The differential in mean Kelly et al. (2020) weights is about 6%. These differences in means, as well as those in medians, were statistically significant. We also expressed these as differences in the percentile of the distribution of the finance and non-finance patents, and generally found substantial disparities. The results were inconsistent with the awards being trivial discoveries devoid of economic value.

Finally, we looked at whom was filing the finance patents. We examined the identity of the assignees of all utility patents applied for between 2000 and 2018 and awarded by February 2019. We used the classification of assignees provided by the USPTO, and assume that all unassigned patents were awarded to individuals.

Table 2 shows that 8.6% of finance patents since 2000 were assigned to individuals, similar to non-finance patents (7.8%). This share differs sharply from the 25% share in the pre-*State Street* sample of finance patents collected by Lerner (2002), as reported in Table A-2 in the Appendix, which compares the older patents and this sample.[10] Since many of the most problematic patents in the earlier era were those of individual inventors, this result was again consistent with the suggestion that patent awards filed in recent decades may provide a valuable window into changing trends in financial innovation more broadly.

2.3. *Patents as a Measure of Financial Innovation*

Another natural concern is that patents did not correspond well to financial innovations, not because patents were not legitimate awards, but because firms chose to protect many inventions through trade secrecy. Patents may thus give a distorted view of financial innovation.

[10]Another way to assess the importance of individual patentees is to look at the difference in the share of awards were made to individuals between finance and all other patents. While this gap was less than 1% in patents filed in 2000 and later, it was 10% in the earlier period.

Trade secrets are of course virtually impossible to observe on a systematic basis. We cannot thus definitively put this concern to rest, which affects many other fields as well, even ones where patenting has been long-established.[11] To address this concern, however, we examined another way in which incumbent firms invest in new technologies: through corporate venture capital programs. In these instances, the companies typically designate a group of professionals to make investments in entrepreneurial firms. They will usually purchase minority stakes in entrepreneurial firms, in transactions undertaken alongside other venture capitalists, with the hope that these expenditures will lead to more informed decisions about acquisitions, internal investments, or licensing arrangements (Ma, 2020).

We totaled the dollar volume of closed corporate venture investments in U.S.-based finance firms reported by Capital IQ between January 2000 and December 2019, broken down by the industry of the investor. The patterns are summarized in Figure 5. (The methodology we employ is detailed in Appendix C.)

The tabulation of alternative manner of pursuing innovation was consistent with that of patenting in several significant respects:

- The level of innovative activity increased over time.
- There was modest share of activity associated with banks, which fell over time as a share of all such investments, while the IT/other and (to a lesser extent) payments categories grew.
- The share of total corporate venturing activity in the financial sector was roughly similar to the shares in patenting seen in Figure 1. For instance, the share of total corporate venture activity devoted to financial services between 2000 and 2016 was 1.5% of total investment amount over that period (as computed in Akcigit et al., 2020).

3. Construction of a Financial Patent Dataset

3.1 Identification of Financial Patents

The first step in the construction of our dataset was to develop an approach for identifying a "financial patent." Social scientists have generally relied on three types of information when classifying patents: the patent's technological classification code, the firm to which it was initially assigned (usually the inventor's employer), and/or keywords from some subset of the patent text, such as the title or abstract.

Each approach had advantages and disadvantages. Classification codes, for example, were created to help patent examiners identify prior art and often evolved in a somewhat piecemeal fashion. As a result, the codes do not necessarily map into broad technological categories like "finance." For example, while most finance patents were classified under the current system within G06Q 40 (Finance; Insurance; Tax strategies; Processing of corporate or income taxes), a substantial number of blockchain and cryptocurrency patents were classified within H04L 09 (Cryptographic mechanisms or cryptographic arrangements for secret or secure communications).

[11] For an example from the pharmaceutical industry, see https://www.justice.gov/usao-edpa/pr/former-glaxosmithkline-scientist-pleads-guilty-stealing-trade-secrets-benefit-chinese.

Another problem with identifying financial patents by classification code is that the U.S. changed from the U.S. Patent Classification (USPC) to Combined Patent Classification scheme in January 2013, during our period under study. The USPTO offers a concordance between CPC and USPC codes. However, this crosswalk is based on an unpublished statistical association between the old and new codes. As a result, CPC codes for patents issued before January 2013 are essentially imputed and may contain inaccuracies. Moreover, the USPTO stopped using USPC codes in 2015, so the use of those codes would limit our study and exclude recent technologies like blockchain.

Alternatively, we can identify financial firms using published lists of fintech firms, such as the Forbes 100, the KPMG 50, or the CB Insights Fintech 250, and assume that the patents held by these firms are all financial patents. For firms in the start-up phase, this assumption may be reasonable. But as firms grow larger and potentially expand into multiple lines of business, it no longer makes sense to assume that all of their issued patents are in finance. For example, a subsidiary of the payments firm Square, Weebly, held several patents. But Weebly was a website builder, rather than a financial company, and thus the bulk of their awards were associated with web site design and manipulation. Thus, it would be incorrect to assume that patents held by Square and its subsidiaries are financial patents. A similar issue surfaces when considering patents owned by established financial institutions. Thus, this approach might bias the sample of financial patents in unpredictable ways.

Finally, we can use Google BigQuery to execute SQL queries for certain keywords across the corpus of all published U.S. patent documents, using the IFI Claims patent data. We thus can generate a suitable set of keywords predictive of “financial” status—for example, some form of the word “finance”—and search for those keywords across all patents. The main challenge here was to identify a suitable set of keywords without arbitrarily picking words that might bias the sample towards specific examples of financial innovation (like cryptocurrency) known to the researcher. Another challenge was to identify words that have high specificity and would not pick up too much noise (e.g., patents that use some form of the word “finance” but are not financial patents).

Of course, we could also use any combination of the sets of financial patents produced from each of these three techniques, like $(A \cup B) \cap C$ (Hall and MacGarvie, 2010). However, without extensive auditing, we could not easily identify the best combination of techniques, nor evaluate how well these various combinations eliminate or reduce inherent bias in the merged dataset.

We broke with prior literature by employing supervised machine learning (ML) techniques to develop an algorithm for appropriately classifying patents as “financial” (treatment) or “not financial” (control), based on each patent’s features. As with any standard supervised machine learning, we had to first choose a way to label the training set of patents. Based on our survey of existing classification techniques above, we elected to use CPC codes, under the belief that the codes would allow us to label a large sample of financial patents with relatively high accuracy. We chose CPC over USPC codes to enable future work and comparisons (as patents today and in the future are only classified using the CPC scheme). We experimented with various feature sets—the patent text, inventors, assignees, and the CPC codes of backward citations—before settling on the patent text and inventor names as the two feature sets which produced, in combination, the highest and most balanced levels of accuracy.

To determine which CPC codes might allow us to label a set of financial patents, we first looked at the USPTO's concordance file for the financial patent classes analyzed in Lerner (2002) (former USPC class 705, subclasses 35-38). We determined that CPC groups G06Q 20 and G06Q 40 broadly captured what we considered to be financial patents. Patents in G06Q 20 involved significant data processing operations and generally related to payment architectures, schemes, or protocols, while those in G06Q 40 generally covered finance, insurance, tax strategies, and the processing of corporate or income taxes. Patents with a primary CPC code (note the USPTO typically places patents into one primary and multiple secondary categories) in these two groups constituted our treatment set (set A).

Within subclass G06Q, we excluded groups 10 and 30, as those groups covered data processing systems or methods specially adapted to administrative or managerial purposes (group 10) and electronic commerce (group 30), categories that are not financial in our view. We also excluded group 50 and all subsequent groups, as they either did not involve significant data processing steps or cover technologies specially adapted for certain non-financial industries or technologies outside of our view of finance (e.g., business processing using cryptography). Patents with a primary CPC subclass in G06Q but not in groups 20 or 40 constituted our control set (set B).

Next, we merged our treatment set and control set, then bifurcated the data into a training set with 70% of the data and a testing set with 30% of data. Then we applied natural language processing techniques to each patent's text and the inventor names. When we first experimented with this approach, we used patent titles and abstracts for the patent text, but neither of these textual sources produced models with suitable accuracy.[12] Our initial model runs produced high sensitivity (also called the true positive rate, the proportion of actual positives correctly identified as such) of about 98 percent. But the specificity (the true negative rate, the proportion of actual negatives that are correctly identified as such) was very poor: about 30 percent. We therefore elected to use each patent's entire written description, as the much richer set of language features obtained from the written descriptions produced much better results. With the entire written description as features, we obtained 91 percent sensitivity and 85 percent specificity.

Figure A-3 in the Appendix depicts how we applied the standard supervised machine learning process to predict financial patents.

We then repeated a similar natural language processing procedure for other features of interest, in addition to the written text. We also generated feature sets of the prior art cited in each patent, the names of the firms to which the patent was initially assigned, and the names of the inventors. When we applied each model to the test data, we found that the text model was the most accurate, followed by the inventor model. The prior art and assignee models could not improve accuracy beyond what could be achieved with the text and inventor models. Compared to the text-only model, the text-inventor model slightly decreased sensitivity from 91.3 to 89.9 percent (a drop of 1.4 percentage

[12] Intermediate steps included the removal of extra blank spaces, the converting of accented characters to ASCII characters, the removal of non-English characters, the removal of stop words, the stemming of each word, and the lowercasing of the text. (Stop words are very common words such as "we" or "are," which do not provide necessary differentiable information for machine learning classifiers.)

points), but significantly improved specificity from 85.3 to 90.0 percent (an increase of 4.7 percentage points). As a result, our new model generated false positives and false negatives at about a similar rate. This low rate (10 percent) was a tremendous improvement compared to our initial model.[13] The structure of our model is presented in Figure A-4.

We then deployed the model to capture financial patents outside G06Q by applying it to other "supplemental" classifications where some financial patents might reside. After analyzing all patents that had "any" (but not a "primary") classification in G06Q groups 20 or 40, we found that nearly 80% of those patents had a "primary" subclass in nine other categories that we had not considered (G06F, G06K, G07C, G07F, G07G, H04L, H04M, H04N, and H04W). There were 12,010 such patents. Our next step was therefore to generate text and inventor feature sets for these patents, and apply our text-inventor model to that data to predict which could be financial. This process identified 6,777 of those patents as financial. The final data set of financial patents thus consisted of 17,511 patents with a primary CPC group in G06Q 20 or 40 plus an additional 6,777 patents in the nine subclasses listed above that were predicted by the model to be financial, for a total of 24,288 patents.

To verify the quality of the ML model, we audited the results. Appendix B describes the auditing process.

3.2 *Joining with Other Data Sets*

After generating a list of financial patents and auditing the results of our ML models, we then obtained additional information about the financial patents and the firms to which our financial patents were assigned, as well as the matching process.

The first step in our process was to obtain additional patent-level data on financial patents from Derwent. Such information included the publication date, inventor names, assignee names, and abstract. We noticed one discrepancy in the assignee field when comparing the Derwent data and the IFI Claims patent data (accessed through Google BigQuery), but determined that the discrepancy could be readily addressed after auditing (see Appendix B).

We also obtained from Patentsview the patent assignee type (corporation, government, or individual, divided by domestic or foreign),[14] the number of forward citations, and the geographical location of

[13] Our initial strategy was to adopt a stacking technique, an ensemble learning method that has the potential to improve further the classification accuracy but requires the combination of multiple classification models via a meta-classifier. After experimenting with different types of stacking architecture, we settled on the use of a Naive Bayes model for the patent description text, and a Logistic Regression model for the inventor names (Jurafsky and Martin, 2019, chapters 4-5). A concise "sum up" text-inventor model was adopted, in which a patent was predicted to be financial if either the text model or the inventor model made such a prediction.

[14] Between 7% and 8% of the patents in the financial patent and overall samples had no assignee type in Patentsview. We audited 2% of the financial patents with a missing assignee type, and discovered that 99% of these were assigned to individuals (also known as inventor-assignees). In the analyses below, we treated all patents with a missing assignee type as assigned to an individual.

the first-named inventor. We included all patents applied for between January 2000 and December 2018 and issued by February 2019, and citations through October 8, 2019.[15]

We then matched the firms listed as the first assignee of the financial patents to Capital IQ firms, in order to access more detailed information about the firms. First, we used the Global Corporate Patent Dataset (GCPD) developed by researchers at the University of Virginia (Bena et al., 2017). This database allowed us to match 12,351 patents to a Compustat GVKEY, which can be easily linked to the associated Capital IQ identifier because both Compustat and CapitalIQ are Standard & Poor's databases. Then, after removing inventor-assignees, we used a Levenshtein distance-based fuzzy name matching technique to match the remainder of the first assignee names with 12 million firm names in the Capital IQ database.[16]

After examining the data, we determined that a matching score of 0.95 or higher was sufficiently accurate that the match could be accepted without further scrutiny. This yielded an additional 6,237 patents matched to Capital IQ firms. Similarly, we found that matches with scores below 0.8 were so poor that they should be rejected outright. For the 1,940 potential matches with scores between 0.80 and 0.95, we had a research assistant examine the potential matches, ultimately identifying an additional 818 patents with good assignee matches. This yielded Capital IQ identifiers for 19,406 patents, or 80% of the sample (nearly 88% of the patents not awarded to individuals). We used the Capital IQ identifier to join to our financial patent database a host of detailed financial information about each firm in the year of the patent application, as well as its industry, employment, and whether it was publicly traded at the time. We used the Refintiv VentureXpert database to determine whether the firms were actively venture-backed at the time of the patent filing, following the methodology in Akcigit et al. (2020).

The industry groups that we focused on, and the associated GICS codes, were as follows:

- Banks covered large and geographically diverse institutions, as well as regional and local ones, with significant business activity in retail banking, underwriting, and corporate lending. This category also included thrifts and mortgage finance firms providing mortgage and mortgage related services, and diversified financial services firms (GICS 401010, 401020, and 402010).
- Other finance included providers of consumer services like personal credit and lease financing (GICS 402020), capital markets including asset management, and financial exchanges for securities, commodities, and derivatives (GICS 402030), and insurance (GICS 403010).
- Payments firms were classified under Data Processing and Outsourced Services (GICS 45102020).
- Information technology firms covered a wide variety of computer hardware and software developers, as well as technology consulting firms (GICS 45 outside of payments).

[15] We also used Patentsview data to assign payments to primary CPC classes in some ambiguous cases where patents had more than one "primary" CPC code in the IFI data.

[16] We divided the Capital IQ database into three subsets, with four million company names in each subset, to execute the fuzzy name-matching algorithm in parallel and save computing time, and to get multiple optimum matches within each subset.

- All other.

We thus constructed a database containing, for each financial patent in our list, Derwent patent data, Patentsview patent data, and financial data from Capital IQ (for each assignee that could be matched). Figure A-5 depicts the process we used in this step. We then used similar techniques to match assignee names with the names of Systematically Important Financial Institutions (SIFIs).[17]

We matched all patents to the database of citations to academic articles compiled by Marx and Fuegi (2019). This database contained all academic citations contained within patent documents (whether on the front page or in the text), as well as information about the subject matter of the articles and the name and impact factor of the journals in which the articles appeared. We downloaded these data for all U.S. patents applied for between 2000 and 2018, and awarded by February 2019.

As a last step, we associated financial patents with particular functions in financial services, which we refer to as patent type or subject matter. The patent classification scheme was insufficient here, as many categories did not map readily to particular subject matters. Instead, we created a set of keywords (listed in Table A-3 in the Appendix) associated with accounting, commercial banking, communications, cryptocurrency, currency, insurance, investment banking, payments, real estate, retail banking and wealth management. We based these keywords on a review of the patent abstracts, finance glossaries, and industry knowledge. Some keywords were associated with a single patent type; others with multiple ones. Accordingly, for each patent that fell into more than one category, we assigned it a fractional share to all of the associated types.

We adopted four progressively wider searches to identify these keywords. First, we just examined the patent abstracts. For the patents with no matches, we examined the first 100 words of the background section of the patent. For firms with no matches, we examined the entirety of the background section. For the remaining firms without matches, we examined the entirety of the patent text. Tables A-4 and A-5 summarize the matching process. For the 345 patents without a match, we read the patents. For the 33 patents that could not be classified even after manual examination, we excluded them from our dataset. Hence the final dataset contains 24,255 (24,288-33) patents. For the purposes of the analyses below, we consolidated the patent types into banking (encompassing commercial, investment, and retail), payments, and all others.

Panel A of Table 3 summarizes the ten most frequent assignees in the finance patent sample. There was heavy representation of banks, computer hardware and software firms, and other finance firms. One possibility was that the impact of small firms may be collectively significant, even if they did not show up in this tabulation. To explore this possibility, Panel B presents the share of applications between 2000 and 2004 and between 2015 and 2018 applied for by small firms, using three thresholds based on employment in the application year. (These totals excluded patents awarded to individuals, which as shown below, have been falling sharply.) In each case, despite the media attention paid to fintech start-ups, the share of patents going small businesses were quite modest and falling over time. Panel C looks at the substantial financial patentees with the most influential

[17] Data on SIFIs was taken from https://www.fsb.org/work-of-the-fsb/policy-development/addressing-sifis/global-systemically-important-financial-institutions-g-sifis/. We focused on the initial SFIs designated in November 2011.

patents. The compilations here were limited to the firms with 200 or more financial patents. The table reports the firms whose financial patents had the highest average citation, Kogan et al. (2000), and Kelly et al. (2020) weights. The heavy representations of payments, banking, and computer firms was apparent.

Figure A-6 presents an overview of the financial dataset construction procedure.

4. Shifts in Financial Patenting

This section examines the changes in financial patenting since 2000 in a decomposition analysis. While there was a dramatic increase in financial patenting of all types, these years also saw a substantial shift in the nature of the innovators. In particular, awards to U.S. information technology and other non-financial assignees surged. We have also seen a shift in patent subject matter away from banking.

Before we turn to this analysis, we can illustrate the churn qualitatively. While the ranks of top patenting firms overall have remained largely constant over the 21st century (with companies like IBM, Canon, Hitachi, and Samsung dominating the compilations year after year), there has been considerable volatility in the financial patentees.

Panels D and E of Table 3 show the largest changes in patent assignees during the period between 2000 and 2004 on the one hand and 2015 and 2018 on the other. The table indicates that the share of innovation fell most sharply for unassigned patents (typically filed by individual inventors), computer hardware firms (Diebold Nixdorf, Fujitsu, Hitachi, HP, and IBM), legacy software firms (e.g., First Data and Oracle), and investment banks (Goldman Sachs and JP Morgan). Meanwhile, the most rapid growth was from commercial banks (Bank of America and Wells Fargo), insurers (State Farm, Allstate, The Hartford, and USAA), and payments firms, whether incumbents or entrants (Capital One, PayPal, Square, and Visa).

We then undertook a decomposition of patenting trends. To do so, we create 456 cells, one for each award year, for each of the three broad patent types (banking, payments, and other), for each broad assignee industry (banking, other finance, payments, and IT plus all others), and for U.S. and foreign inventors. We estimated ordinary least squares (OLS) regressions of the form:

$$\textit{Patent Count}_{ilpt} = \beta_0 + \beta_1 (\textit{Patent Type}_p \times \textit{Award Year}_t) + \beta_2 (\textit{Assignee Industry}_i \times \textit{Award Year}_t) + \beta_3 (\textit{Inventor Location}_l \times \textit{Award Year}_t) + \mu_i + \eta_l + \varphi_p + \gamma_t + \epsilon_{ilpt} \quad (1)$$

The dependent variable was the number of patents in a given cell for each award year t, patent type p, assignee industry i, and inventor location l. $\textit{Patent Type}_p \times \textit{Award Year}_t$ represented the vector of dummy variables denoting where the cell is an observation of award year t and patent type p. (This variable took the value of 1 in each case for eight observations, one for each assignee industry-inventor location pair). The other interacted dummy variables were defined similarly. This analysis can help us better understand what is behind the surge of patenting, though it cannot explain what factors led to the boost in a specific category.

All the sets of explanatory variables jointly had significant explanatory power. The joint significance tests are presented in Table A-6. Figure 7 present the year interaction effects, in each case with 2001 normalized as zero. Panel A shows the sharp increase in the number of patents per year across all cells. To calibrate the rise in the year fixed effects from 0 to about 200 patents per cell, the mean cell had 53.2 patent awards. Panel B shows the steady decline in the share of patenting in banking relative to payments and all other subject matters.

Additional patterns are shown in Figure A-7. Panel A displays the sharp decline in patenting by banks and other financial institutions relative to IT and other firms, a decline that started at the beginning of the sample, accelerated after the GFC, and only began recovering in the mid-2010s. Payments firms, after mirroring the decline of banks, experienced a somewhat more rapid recovery of the 2010s. Panel B shows the strong trend towards increasing patenting by domestic assignees, at least up until the mid-2010s. This pattern was consistent with the strong domestic bias in finance patents shown in Table 2.

This analysis also lent itself to a classic difference-in-differences analysis, which we focused around the Global Financial Crisis of 2008-09. To examine the changes in this manner, we substituted for the year dummies an indicator variable for whether the observation was from 2009 or after, or

$$Patent\ Count_{ilpt} = \beta_0 + \beta_1\,(Patent\ Type_p \times Post\text{-}Crisis_t) + \beta_2\,(Assignee\ Industry_i \times Post\text{-}Crisis_t) + \beta_3\,(Inventor\ Location_l \times Post\text{-}Crisis_t) + \mu_i + \eta_l + \varphi_p + \gamma_t + \epsilon_{ilpt} \quad (2)$$

The dependent variable was again the number of patents in a given cell: before 2009 or after, patent type p, assignee industry i, and inventor location l. $Patent\,Type_p \times Post\text{-}Crisis_t$ represented the vector of dummy variables denoting whether the cell was an observation before or after the financial crisis and of patent type p.

The interaction between the indicator for an assignee in the banking industry and a post-GFC observation was significantly negative (coefficient of -125.4, with a p-value of 0.000), as was that for an assignee in another finance industry and a post-GFC observation (-104.7 and 0.000) and similarly for payments firms (-116.7 and 0.000). The interaction between patents with a subject matter in payments and the post-GFC dummy was insignificant, but that between banking-type awards and the post-GFC indicator was significantly negative at the 5% level (-25.2 and 0.031). The interaction between domestic patentees and the post-GFC indicator was significantly positive (79.2 and 0.000).

While the above analysis suggested that the years after the GFC saw more patenting by firms outside of finance, and outside of the banking subject matter, it did not explore the interactions between assignee industry and patent type. To explore this phenomenon at a deeper level, we repeated the analysis, now with the addition of an interaction between the award year, assignee industry, and dummies denoting whether the patent by a bank patenting an invention in banking or a payments firm patenting in payments. (In addition, we added controls for the interactions between assignee industry and patent type.)

Figure 7 graphically depicts the interactions. Both banks and payments firms became progressively more likely (relative to other firms) to patent in their core areas over time. Thus, banks actually *increased* their share of patenting in banking, controlling for the overall decline for patenting activity by this type of firm and in this subject matter. The null hypothesis that the three-way interaction terms were equal to zero was rejected at the 1% confidence level. In short, innovation became more specialized over time: banks did not responded to the apparent decline in innovative potential in banking by moving their innovative efforts into other areas.

We also looked at the nature of the patent awards. Table 4 describes two distinct dimensions, gleaned from the language in patent claims:

- The first column examines whether the patent is a *process* one, as opposed to a product-focused award. Based on our classification of patent types, we assumed that all communications and security patents are unambiguously process-related ones. For the remaining patents, we divide them into process and product ones following the methodology of Banholzer et al (2019), which focused on the presence of process patent-related keywords in independent claims. We took the most conservative of their measures, which measured the share of independent claims that are process-related based on the initial two keywords.
- The second approach determined whether the patent had a *consumer finance* application. We scrutinized the website for the Consumer Financial Protection Bureau and the titles of working papers of the Household Finance Working Group for keywords or bigrams (two-word phrases) that related to consumer products. (These are listed in Table A-7.) We totaled the number of these keywords or bigrams in the first 100 words of the field labelled "description" or "background" field, the section where these phrases most frequently appeared.

Panel A of Table 4 relates these two metrics to a number of features of financial patents in the sample. We see that the share of process and consumer finance patents increased over the sample period. The category of IT, payments, and other firms were more likely to be issued process patents, as well as consumer finance ones.[18] The final two lines in the panel suggested that, in regard to process and consumer finance awards, patents assigned to IT, payments and other firms became less

[18] We also looked at whether the awards encompassed *software* technologies. We followed the methodology employed by Chattergoon and Kerr (2020), which in turn is based on Bessen and Hunt (2007), and again draws primarily on key words in the description field. Table A-8 reveals that a very large share of the finance patents are classified as "software," which may reflect judicial tests that linked the patentability of financial topics to their embodiment in software. For instance, in *State Street*, the relevant test in determining patentability "requires an examination of the contested claims to see if the claimed subject matter as a whole is a disembodied mathematical concept representing nothing more than a 'law of nature' or an 'abstract idea,' or if the mathematical concept has been reduced to some practical application rendering it 'useful.'" *Ibid.* at 1544, 31 U.S.P.Q.2D (BNA) at 1557. This test was a restatement of a rule first articulated in *In re Alappat*, 33 F.3d 1526, 31 USPQ2d 1545 (Fed.Cir.1994). Puzzlingly, IT firms were less likely to be issued patents classified as software. Practitioners that we discussed the results with hypothesized that financial firms may have faced greater skepticism than IT companies about whether their applications satisfied the *Alappat* test, and thus erred on the side of explicitly using software-related terminology.

differentiated over time. Put another way, the gap in the probability that these firms' patents were differentially process or consumer ones narrowed over time.

Panel B of Table 4 examines these relationships in regression analyses. We used each finance patent with available data as an observation. We estimate:

$Consumer/Process\ Patent?_i = \beta_0 + \beta_1(IT\ Other_i) + \beta_2(IT\ Other_i \times Early\ Award_t) + \beta_3(IT\ Other_i \times Late\ Award_t) + \eta_l + \gamma_t + C'\mathbf{B} + \epsilon_{ilpt}$ (3)

Consumer Patent?$_i$ and *Process Patent?*$_i$ represented dummy variables indicating whether a given patent *i* was consumer finance or process in focus, defined as above. The key independent variables were *IT Other*$_i$—that is, whether the patent was assigned to an information technology, payments, and other non-finance firm—and dummies for the time period of the application. In the second and fourth regression, we add interactions between two time dummies (*Early Award*$_i$, for 2000-04 application, and *Late Award*$_i$, for applications in 2015 and after), an inventor location fixed effect, and *C'***B**, a set of control variables. (These unreported controls were the age of the firm at the time of the application, its revenue, and its status as an academic institution, other non-corporate entity, publicly traded firm, and/or SIFI.)

Taken together, the analysis suggested that the financial institutions' share of financial innovation fell sharply over time, in part due to their failure to expand their range of innovative activities. The increased focus on banking patents by banks may have reflected the fact that they, perhaps more than IT and other companies, had existing businesses that faced intense competitive challenges and required great managerial focus. Another possibility is that these firms aspired to expand into other areas of financial innovation, but found it difficult to do so. Two possible constraints may have been regulatory pressures or their lack of ability to innovate in these new technologies.

5. Trends in Academic Ties

This section examines the changing utilization of academic knowledge. Using citations in patents to academic prior art, we show that there was a strong—and indeed growing—association between academic citations and financial patent impact. But in recent years, the rate of citation to academic research fell, particularly among banks.

Table A-9 presents a first look at the journals most frequently cited in finance patents. Aside from one anomalous case (discussed in the note to the table), the journals were well known ones that fell into three categories: journals devoted to computer technologies, academic finance journals, and practitioner-oriented finance publications.

We first looked at the probability that academic citations were included in finance patents. As Panel A of Table 5 illustrates, the correlation coefficients revealed a negative relationship between the number of academic citations in the finance patents and the award date. This pattern held for publications in all and business/economics/finance–related publications, as well as those in "Top 3" finance journals.[19] When we decompose the patents, the effect was far stronger and more consistent for patents assigned to banks than for other assignee industries. Meanwhile, the average age of the citations (the years between the article publication and the patent grant) increased. Either less relevant academic knowledge existed, or firms were putting less effort into accessing these insights.

One concern was that the number of citations to academic work may have fallen more generally. Such shifts may reflect, for instance, a changing overall propensity to cite academic work, or longer examination periods for patent applications with many academic citations. Thus, we looked at the changes in these citations relative the academic citations per patent in non-finance patents.[20] In particular, we normalized the ratio of the average number of academic citations in finance patents to the mean number of academic citations in other patents be 100 in 2000, and looked how this ratio changed over application years. We looked separately at citations to articles in business, economics, and finance journals, those in IT publications, and other periodicals. Panel A of Figure A-8 shows a precipitous drop relative to other patents, particularly for citations to business, economics, and finance journals. Panel B looks at academic citations (all and business, economics, and finance publications) in finance patents, comparing patents assigned to banks to all other awards. The figure demonstrates a sharp decline in such relative citations since the GFC.

Thus, it appears that financial institutions, especially banks, accessed academic work less than they did in the past. Whether this reflected the shifts in the supply of relevant academic knowledge or in the ability of firms to absorb this knowledge (Cohen and Levinthal, 1990) was not obvious from this analysis, but below we find some clues to this question.

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[19] We identify the "Top 3" finance journals (the *Journal of Finance, Journal of Financial Economics*, and *Review of Financial Studies*), from numerous efforts to rate journals in the literature, such as Chan, Chang, and Chang (2013).

[20] Table A-10 compares the finance patents to two broader populations: the entire population of patents applied for and awarded over the same period, and those in "academic-heavy" patent classes. To determine the academic-heavy classes, we first identified patents assigned to academic institutions. (We compiled all patents with an assignees containing the word "university," as well as those on the various annual lists of the most active academic patentees compiled by the Association of University Technology Managers (which allowed us to capture entities as the Massachusetts Institute of Technology and the Wisconsin Alumni Research Foundation).) We then extracted the four-digit CPC subclasses in which these patents most frequently had a primary assignment. We designated the 53 top classes (all those with 500 or more patent awards by academic institutions in the sample period) as academic heavy. In general, finance patents cited less academic work than other patents. The disparity between the finance and the academic-heavy awards was particularly striking. When we looked at the citations to articles in business, economics, and finance, and even more so top finance and top practitioner finance journals, a very different picture emerges: the financial patents made significantly more such citations. Moreover, the finance patents cited significantly fresher prior art: that is, the mean lag between the article publication and patent application was nearly a year shorter for finance patents. Table A-11 examines these patterns in regression analyses, and highlights how many of these patterns were driven by the patenting practices of U.S. corporations, the most frequently represented assignees.

It is natural to wonder how consequential these shifts in academic citations are. While academic citations have been shown to be linked to patent impact in other fields (Watzinger and Schnitzer, 2019; Poege et al., 2019), to what extent is this knowledge relevant for financial patents?

Panel B of Table 5 takes a first look. We compared the impact of finance patents with and without academic citations. As in Table 2, we used three metrics of patent value: citation weights, Kogan et al. (2017) patent values, and Kelly et al. (2020) weights. A striking association between more academic citations and greater patent impact appeared. Using citation weights, there was a statistically significant relationship for all academic cites, high-impact academic citations, business/economic/finance citations, and high-impact business/economic/finance citations. The only exception was citations to Top 3 journals, where the results were directionally similar, but insignificant. The results using Kogan et al. (2017) and Kelly et al. (2020) values were similar directionally, and consistently statistically significant. Moreover, the results were large in economic magnitude: for instance, a financial patent without an academic citation was subsequently 8% more cited than a typical patent in its subclass; for ones with such citations, they were 52% more cited.

In Panel C of Table 5, we used two metrics of patent value as the explanatory variable in OLS regressions. Again, we used each patent with sufficient data as an observation. The specification was:

$$Patent\ Value_i = \beta_0 + \beta_i (Academic\ Citations_i \times Time\ Period_t) + \mu_i + \gamma_t + C'\mathbf{B} + \epsilon_{ilpt} \quad (4)$$

The dependent variable, $Patent\ Value_i$, was the normalized citations and the Kogan et al. (2017) value. The key independent variable was the number of academic citations interacted with the time period of the patent application (again, in four five-year blocks). We also included controls for the time period, inventor location, and assignee characteristics (again, the age of the firm, its revenue, and its status as an academic institution, other non-corporate entity, publicly traded firm, and/or SIFI).

The repression highlighted that the relationship between the number of academic citations and two metrics of patent value, citations and Kogan et al. (2017) value, increased sharply over time. In particular, the relationship was much stronger for patents applied for between 2015 and 2018 than in other periods. (It did not seem relevant to use Kelly et al. weights in this analysis, as these were not calculated for patent awards made after 2015.)

Overall, the analysis suggested a substantial change. Academic knowledge appeared to be an important driver of financial patent impact, and this relationship strengthened over time. But citations to academic research have fallen, particularly for the banking industry. Moreover, financial patents in general were citing increasingly older academic knowledge. These patterns may be due to the shifting focus of patenting away from areas where there is relevant academic knowledge, a reduction in the creation of relevant academic knowledge, or a decreased ability by firms, especially banks, to absorb this knowledge.

6. The Changing Geography of Innovation

This section focuses on the changing geography of financial innovation. Focusing on the United States (which as shown above, was the primary and increasingly important locus of financial innovation), we document two distinct effects. First, the locus of innovation dramatically shifted to the San Jose-San Francisco metropolitan area, largely at the expense of the New York-Newark one. While part of this change was due to the entry and exit of firms, it was primarily driven by the shifts in the locus of innovation within incumbent firms. These shifts appeared to reflect both regulatory pressures and technological opportunities.

6.1. Summarizing the Shifts

In order to undertake both analyses, we needed to map each patent to a combined statistical area (CSA). To do this, we used the state and county Federal Information Processing Standard (FIPS) code of the first-named inventor, also provided by Patentsview, and a crosswalk, compiled by the U.S. Bureau of the Census, between county-level FIPS codes and CSA codes as of mid-2013.[21]

Table 6 shows the share of patenting by CSA for the ten CSAs with the highest financial patent counts. The table tabulates for four periods these patents as a share of all finance patents, using simple patent counts, citation weights, and Kogan et al. (2017) weights.

The table shows that financial patenting concentrated over time, with the share of applications from the ten largest CSAs rising from 40.5% in 2000-04 to 45.5% in 2015-18. The rise of patenting in the San Jose-San Francisco CSA drove much of the increase in concentration. The decline in the importance of New York and the rise of Charlotte (which passed New York using Kogan-weighted patents by the 2015-18 period) were also evident.

The change in the location of non-finance patents mirrored these changes, but in much less dramatic form. For instance, the share of non-finance patents awarded to a first investor in the San Francisco-San Jose CSA rose from 18.5% for awards applied for between 2000 and 2004 to 22.8% for awards applied for between 2015 and 2018 (and awarded by February 2019). The share of New York CSA awards fell over the same two periods from 8.2% to 7.9%.

In Panels A through C in Table A-12, we assembled a variety of patenting measures for these three CSAs. The "tale of three cities" painted a sharp set of contrasts:

- San Jose-San Francisco-Oakland saw dramatic growth, whether measured using raw or weighted patenting. This was driven by mid-sized firms (i.e., those where the firm's revenue in the application year was more than $100 million but less than $10 billion), rather than by small and large ones. The patenting activity was driven by firms in the IT and other category, but especially by payments firms.

[21] https://www.nber.org/cbsa-csa-fips-county-crosswalk/List1.xls. Our use of the first-named inventor reflects the consensus for our conversations with legal practitioners. To quote one practitioner guide, "there is always significance to the order [of inventors]. On a patent, the person who is named first is usually considered the primary contributor" (https://www.upcounsel.com/patent-inventor-name-order).

- New York-Newark, by way of contrast, saw a sharp decline in patenting. This was driven by a decline in patenting by large firms, especially SIFIs. Meanwhile, innovation by small firms increased sharply, reflecting the rise of fintech companies there. Firms in the IT and other category saw the fastest growth.
- Charlotte-Concord saw rapid growth, particularly when using Kogan weighting. This growth was driven by patenting by large firms and SIFIs in banking. A closer look at the data shows that this change was largely driven by Bank of America, which not only consolidated its patenting activity in Charlotte (in the 2000-04 period, the largest CSA for patent applications by the bank was New York, with 26% of the total; in 2015-18, Charlotte-Concord represented 66% of its awards), but also greatly accelerated its innovative activities.

Figure 8 provides another view of the overall patterns, focusing on activity across U.S. Census regions over time. We constructed the analysis sample at the application year – U.S. census region level, for a total of 171 observations (19 years x 9 census regions). We estimated the following specification to examine the pattern of financial patenting in U.S. census regions over time:

$$Patent\ Count_{rt} = \beta_0 + \beta_1 (Region_r \times Time\ Period_t) + \mu_r + \gamma_t + \epsilon_{rt} \quad (5)$$

The dependent variable was the number of finance patents applied for in census region r in year t. As before, we divided the application years into four periods. The key independent variables were application period indicators $Time\ Period_t$ interacted with the US census region dummies $Region_r$, with the Middle Atlantic region and the 2000-2004 period as baseline. We also included census region fixed effects μ_r and year fixed effects γ_t as controls in our regression.

The figure presents the coefficients of the above regression for two specific regions: the Pacific and South Atlantic (which includes Charlotte) regions. Financial patenting in these two regions increased sharply over time relative to the Middle Atlantic region, suggesting that the locations of financial patenting gradually shifted from the east coast to the west and south. These results were consistent with the rise of patenting in the San Jose-San Francisco and the Charlotte-Concord CSAs and the decline in the importance of New York reported from Table 6. Table A-13 further presents the detailed share of patenting by region for the nine U.S. Census regions between 2000 and 2018. More details on the construction of the CSA data set are in Appendix D.

6.2. Geographic Changes

We undertook two sets of analyses of the drivers of these geographic change. These sought to understand the importance of two possible sets of explanations: the push of regulatory pressures and the pull of technological opportunity.

A first possibility was that these effects may have been driven by regulation. To explore the impact of regulation, we used the data from Buchak et al. (2018), which developed three measures of county-level regulatory burdens between 2008 and 2015, with a higher number in each representing greater regulatory pressure: (1) the changes in bank capital ratios; (2) mortgage servicing rights (MSR) percentage of Tier 1 capital; and (3) the share of loan originations in 2008 that were within the purview of the Office of Thrift Supervision. Using the same U.S. Bureau of the Census crosswalk, we converted the county-level measures to CSA-level data. We used all 121 CSAs with at least one first inventor in a finance patent during 2000 and 2015. We interacted this geographic measure with assignee industry and patent type, for a total of 1452 observations.

With this merged regulatory activities and finance patent CSA-level dataset, we examined the impact of regulatory burdens on financial patenting in a given geographic location. To do so, we estimated the following specification:

$$Patent\ Count_{ipc} = \beta_0 + \beta_1 (Reg_c \times Assignee\ Industry_i) + \beta_2 (Reg_c \times Patent\ Type_p) + \varphi_p + \chi_c + \mu_i + \epsilon_{ipc} \quad (6)$$

The dependent variable was the number of p type finance patents applied for by assignee industry i between 2008 and 2015 in CSA c. Reg_c was one of the aforementioned measures of CSA-level regulation. The key independent variables were the regulatory measure Reg_c interacted with the assignee industry type $Assignee\ Industry_i$ (with the interaction with IT/Other firms being the baseline), as well as the Reg_c interacted with the patent type $Patent\ Type_p$ (with the interaction with payment type being the baseline). We also included patent type (φ_p), assignee industry (μ_i), and CSA (χ_c) fixed effects in our regression. The results in Table 7 show that the impact of regulatory burdens was far more negative for the three finance industries—banking, other finance, and payments—than it was for the IT/Other category, using all three measures. Meanwhile, we also found a consistent and strong negative effect of regulatory pressure on banking-type patents (relative to payment types).

To further examine the effects of regulation on financial patenting overtime, we undertook a similar analysis, using an alternative measure of regulatory actions regarding banks. Following Lucca et al. (2014), we collected formal enforcement actions data from four banking regulatory institutions: the Federal Reserve Banks (Fed), the Federal Depository Insurance Corporation (FDIC), the Office of Comptroller and Currency (OCC), and the Office of Thrift Supervision (OTS). We then constructed state-level panel data using the intensity of these enforcement orders by all regulators as an indicator of regulatory strictness. We used state-application year-assignee industry-patent type interactions, for a total of 11,400 observations. Using the merged state-level panel data, we estimated the following specification, similar to equation (6);

$$Patent\_Count_{ipst} = \beta_0 + \beta_1 (Reg_{st} \times Assignee\ Industry_i) + \beta_2 (Reg_{st} \times Patent\ Type_p) + \chi_s + \varphi_p + \mu_i + \gamma_t + \epsilon_{ipst} \quad (7)$$

The dependent variable was the number of p type finance patents applied for by assignee industry i in state s at year t. The key independent variables were the measure of enforcement actions in that specific state in a given year Reg_{st} interacted with (a) the assignee industry type $Assignee\ Industry_i$ (with the interaction with IT/Other firms being the baseline) and (b) the patent type $Patent\ Type_p$ (with the interaction with payment type being the baseline). We also included time fixed effects γ_t, state fixed effects χ_s, patent type fixed effects φ_p, and assignee industry effects μ_i in our regressions. We examined the impact of enforcement actions on patenting in the year of the action, and in the two years thereafter. Again, as shown in Panel A of Table A-14, the impact of enforcement actions was far more negative for the three finance industries (relative to IT/Other) and for the banking-type patents (relative to payment type). Taken together, these results suggested that part of the rise of patenting by non-finance firms and the drop of banking-type patenting may have been driven by increased pressure on banks due to financial regulation, particularly in the years after the GFC.

Table A-15 takes another look at these patterns. The specifications were as elaborated in equations (6) and (7), but now with an interaction between observations of banks and payments firms on the one hand and the type of patenting on the other as additional independent variables. Banks were particularly less likely to patent in their respective core areas in the face of regulatory pressure. This finding was again consistent with financial regulation having a particularly depressing effect on established financial incumbents.

To explore the influence of technological opportunity, we used the State Technology and Science Index (STSI) data provided by Milken Institute to measure the state-level technology.[22] The STSI data included an overall technology index assessing states' overall technology development and capabilities, as well as five sub-indexes that measure different aspects of a state's technology level. These were termed Technological Concentration and Dynamism (which measures industrial activity in technology-related sectors), R&D Input, Risk Capital and Entrepreneurial Infrastructure, Technology and Science Workforce, and Human Capital Investment (which measured of educational achievement and throughput, with a particular emphasis on science and technology). These measures, released on a biannual basis since 2008, were based primarily on statistics from the U.S. Bureau of Labor Statistics, U.S. National Science Foundation, as well as private sector sources such as Moody's and PitchBook.

We used as observations states interacted with the patent application year (focusing on the period from 2008 to 2018, due to the coverage of the index), assignee industry, and patent type. Thus, we had a total of 6600 observations. After merging those observations with the STSI data, we examined the impact of technological opportunity on financial patenting in a given state over time using a specification very similar to equation (7) above:

$$Patent\ Count_{ipst} = \beta_0 + \beta_1 (Tech_{st} \times Assignee\ Industry_i) + \beta_2 (Tech_{st} \times Patent\ Type_p) + \chi_s + \varphi_p + \mu_i + \gamma_t + \epsilon_{ipst} \quad (8)$$

As before, the dependent variable was the number of patents in a given cell. $Tech_{st}$ was one of the STSI's technology indexes of state s in year t. The key independent variables were the technology index $Tech_{st}$ interacted with the patent assignee industry and with the patent type. The baseline assignee industry was banks and the baseline patent type banking type. We also employed fixed effects for time, state, patent type, and assignee industry in our regressions. Table 8 (with some index measures) and Table A-16 (with the other index measures) show that there was a much stronger association between state-level technology development and financial patenting of the IT/Other firms and payments firms (relative to the banks). We also found a strong positive association of state-level technological progress on the number of payment and other types of patents applied (relative to the banking type).

Using the specifications equivalent to those used above, we also examined the potential association of regulatory pressure and technological development on finance patents' quality. More specifically,

[22] http://statetechandscience.org/.

using the same datasets as in Tables 7 and 8 and Panel A of Table A-14, we employed a measure of the patent quality, as captured by average citations per patent in a given cell. Using the patent quality measure as the new dependent variable in those specifications, we tested the association between regulatory burden and technological progress on financial patenting quality but found no clear evidence (see Panel B of Table A-14 in the Appendix).

6.3 The Impact of Switchers

We then sought to understand these changes in more detail. In particular, we explored what drove these shifts in patenting location. The results highlight the importance of the shifts in innovative activities by existing firms.

Table A-17 undertakes an initial decomposition of firms. Panel A divides them into three categories:

- Exiting innovators, who filed an (ultimately successful) financial patent in 2000-04, but not in 2015-18;
- Entrant innovators, who filed an (ultimately successful) financial patent in 2015-18, but not in 2000-04, and;
- Continuing innovators, who filed an (ultimately successful) financial patent in 2000-04 and in 2015-18.

(Note we did not include firms that did not patent in 2000-04 and 2015-18, but just in intermediate years.)

For the third category, we also broke out firms that shifted their modal CSA for patenting between these two periods. Location-switching continuers are relatively few in number (26 firms), but very significant when patents are tabulated: these firms represent 55% of the awards by continuing innovators, and 41% of the awards across all three categories.

Panel B looks at the 26 location-switching continuers in more depth. Nine of the firms (representing 9293 patents in total) moved their modal location from New York-Newark; no other CSA is close in losses. Meanwhile, San Jose-San Francisco was the destination of choice for four of the switchers, representing 5562 patents. These results suggested the importance of location-switching continuers in the location analyses.

We also explored the impact of switchers in supplemental analyses. Table A-18 presents another way to dramatize the impact of shifts in innovative location by continuers. The table presents counterfactual calculations of patenting shares in 2015-18, under two assumptions; (a) that the 26 continuing financial innovators that shifted their modal location retained the same geographic distribution of patenting that they had in 2000-04, and (b) that all 130 continuers retained the same geographic distribution of patenting that they had in 2000-04. Focusing again on the three cities highlighted above, had all continuers maintained the innovative locations they had in 2000-04, the decline in patenting in New York and the rise in San Francisco each would have been half as large.

The dramatic growth in Charlotte would not have happened at all, because (as discussed above) it was largely driven by a single switcher.[23]

One possibility is that banks were more likely to switch to escape regulatory pressures. To examine this hypothesis, we used a sample consists of continuing financial innovators (here we required that innovators have filed successful patents before 2008 and after 2014). We defined a switcher as an organization which shifted the modal location of its innovative activities between 2000 and 2007 on the one hand and 2008 and 2015 on the other (i.e., before and after the GFC). We tested whether banks were more likely to switch their location of innovation when the regulatory pressure in their original modal CSA increased rapidly after the GFC, using the following probit model:

$$\mathbf{Pr}\ (\textit{Firm is Switcher}_i = 1) = \mathbf{\Phi}(\beta_0 + \beta_1(\textit{Reg}_{origincsa} \times \textit{Firm Industry}_i) + \mu_i + C_i'\mathbf{B} + \epsilon_i)\ (10)$$

Pr (·) denoted probability and **Φ** was the cumulative distribution function of the standard normal distribution. $\textit{Firm is Switcher}_i$ was an indicator for whether a firm shifted its innovation modal location before and after the GFC. For the regulatory pressure in firm's original modal CSA $\textit{Reg}_{origincsa}$, we used the same three measures of CSA-level regulatory burdens from Buchak et al. (2018), as in Table 7. The key variables of interest were the measure of the extent of regulatory scrutiny interacted with the industry dummies, especially the interaction with the dummy for banks. We also included firm industry dummies and a vector of firm controls C_i, such as whether the firm was publicly traded or venture backed, in our probit analysis.

As the results are shown in Panel A of Table 9. Regardless of which regulatory measure were employed, banks were more likely to switch their innovation location when their original modal CSA faced greater regulatory pressure. Moreover, they were likely to switch to a CSA with less regulatory pressure. The existence of those "switchers" may have been an important factor in the decrease of the financial patents by the banking industry in their original modal CSA.

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[23] Table A-19 looks at which continuing financial innovators were switchers in a probit analysis. We use all 130 continuing innovators as observations. We estimated:

$$\mathbf{Pr}\ (\textit{Firm is Switcher}_i = 1) = \mathbf{\Phi}(\beta_0 + \beta_1(\textit{Modal 2000-04 Location}_i) + \beta_2(\textit{2000 Finance VC in Modal 2000-04 Location}_i) + \mu_i + C_i'\mathbf{B} + \epsilon_i)\ (9)$$

Pr (·) denoted probability and **Φ** was the cumulative distribution function of the standard normal distribution. $\textit{Firm is Switcher}_i$ was an indicator for whether a firm shifted its modal location for innovation changes from 2000-04 to 2015-18. $\textit{Modal 2000-04 Location}_i$ were dummy variables indicting whether the firm's modal patent applied for between 2000 and 2004 was in the New York or the San Jose/San Francisco CSAs. $\textit{2000 Finance VC in Modal 2000-04 Location}_i$ was the dollar volume of venture financing of finance firms in 2000 in the modal location for the firm's patenting in 2000-04. We also included firm industry dummies and a vector of firm controls C_i, such as whether the firm was publicly traded or venture backed. The results suggested that banks and payments firms were consistently more likely to switch than IT and other firms. Firms with the modal early patenting location in the greater San Francisco area, as well as those that were publicly traded, were less likely to switch.

Meanwhile, payments firms have switched their location to pursue the advantages associated with innovation by other entities in some regions. Panel B of Table 9 looks specifically at the payments firms that switched their locus of innovative activities. As in Table 8, we again used the STSI index data to measure state-level technological progress. Since the STSI index was updated only every two years, we split our data sample between 2008 and 2016 into four time periods. We only considered the continuing financial innovators (in this case, the firms that had financial patents applied before 2008, in all four periods between 2008 and 2016, and after 2016). We defined a "switch event" as one where the firm changed its modal location for innovation across successive periods. Again, we tested whether payments firms were more likely to switch when the technological capabilities in their original modal state were less developed, using the following probit model equivalent to equation (10):

$$\mathbf{Pr}\,(\textit{Firm is Switcher}_i = 1) = \mathbf{\Phi}(\beta_0 + \beta_1\,(\textit{Tech}_{origins} \times \textit{Firm Industry}_i) + \mu_i + \gamma_t + C_i'\mathbf{B} + \epsilon_i)\ (11)$$

As before, the key variables of interest were the industry dummies interacted with the technology index $Tech_{origins}$. We were particularly interested in the interaction term including the dummy for payments firms. We also included firm industry and time fixed effects and C_i, a vector of controls for firm characteristics.

The results suggested that payments firms were more likely to switch their innovation location from a state with weaker technology capability and slower technology development to a state with a more advanced technology environment. As before, the existence of those "switchers" were an important factor that increased the financial patents by the payments industry in those high-tech states.

These results were consistent with the finding of Moretti (2019) of the importance of location to innovative efficiency. It appeared that finance firms actively shifted their location, whether to pursue innovative advantages or to escape regulatory pressures. These shifts had important impacts on the location of financial innovation.

7. Conclusion

In this paper, we explored the evolution of financial innovation by examining U.S. patents applied for between 2000 and 2018. We highlighted five key conclusions:

- *The surge in the volume of financial patenting in the U.S. since the late 1990s*. Moreover, financial patents were disproportionately important ones.
- *The sharp change in the subject matter of financial patents, consistent with the broader shift in the financial services industry towards household investors and borrowers*. An increasing fraction of patented innovation focused on consumer and process innovations rather than business applications.
- *The entry of U.S. IT and payments firms, and the associated reduction in innovation by banks and other financial institutions*. Banks did not respond by the decline of innovation in their core area by shifting their innovative focus: in fact, they have become more focused on banking innovations. IT, payments, and other firms were more likely to be issued process patents, as well as consumer finance ones.

- *The reduction in the incorporation of academic knowledge in financial patents, despite the continuing (and indeed growing) association of such insights with patent value*. This trend affected banks most adversely, as seen in the steep decline in their academic citations over time.
- *The reshaping of the geography of financial innovation*. This shift reflected both regulatory pressures and the changing location of technological opportunities. These shifts were largely driven by continuing innovators moving their locus of innovative activity, rather than the entry or exit of financial innovators. IT firms and payments firms, as well as banks facing intense regulatory scrutiny, were behind many of these changes.

We conclude with two observations. The first is the difference between the focus of academic studies of the financial innovation discussed in the introduction and the patterns documented here. The literature on financial innovations has largely highlighted new financial instruments created by banks and capital market firms, as well as cryptocurrencies. While these areas are doubtless important, the extent to which innovation is occurring in areas like payments, and has been driven by firms outside the traditional definition of financial institutions, has received little attention in the literature.

A second observation relates to the pressure that financial institutions have felt in regard to innovation. The declining share of banks in financial innovation and their continuing focus on banking technologies may reflects (at least in part) optimization decisions based on existing product lines. But other shifts may be beyond their control, such as the decreased availability of relevant academic research and the increased regulatory pressures on banks.

Of course, there are many areas for future exploration. Foremost of these is the assessment the social impact of these discoveries. As Lerner and Tufano (2011) highlight, the evaluation of the social impact of financial innovations is particularly subtle: unlike a new chemotherapy or solar panel, these discoveries can have dramatically different impacts over time as they diffuse and the behavior of consumers and financial institutions changes. Some of the conceptual approaches highlighted in papers such as Budish, Roin, and Williams (2016) may represent a way forward.

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Figure 1. Financial patents and applications as a share of total U.S. patenting. The red line shows the ratio of the number of financial utility patents granted annually to the total number of utility patents granted. The blue line shows the number of financial utility patents applied for annually divided by the total number of utility patents applied for. The chart is drawn from two samples: the sample in this paper, namely patents applied from January 2000 to December 2018 and issued by February 2019, and the sample in Lerner (2002) (for applications before 2000 and awards before 2001). The definition of financial patents differs modestly across the two samples. Certain patents applied for before 2000 and awarded in March 2000 and after are not included in the numerator or denominator of any year. The number of applications in years before 1976 may be understated by the USPTO.

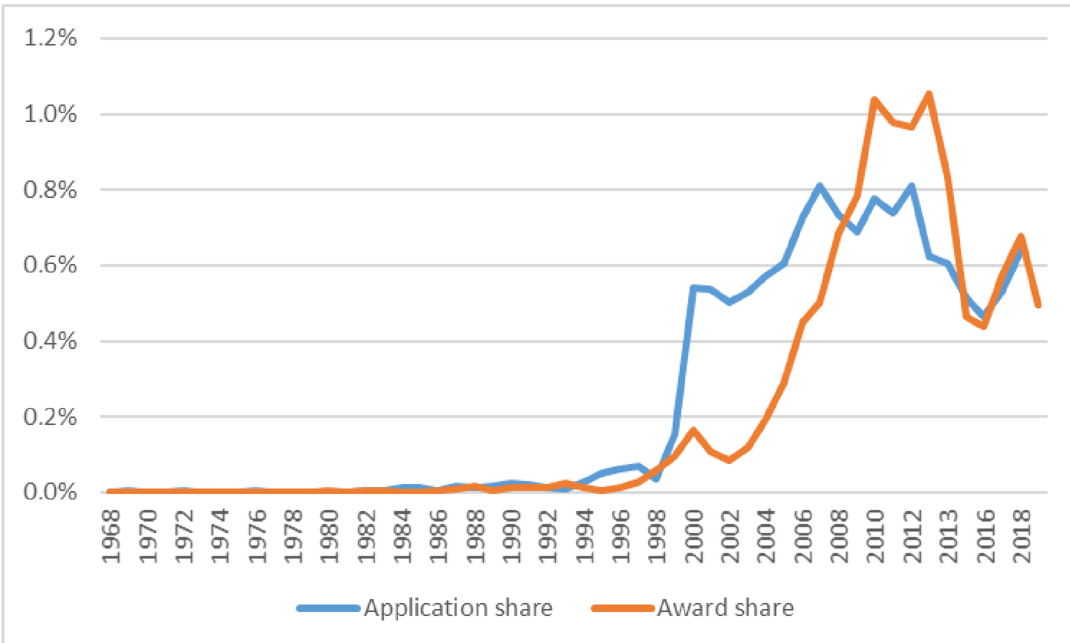
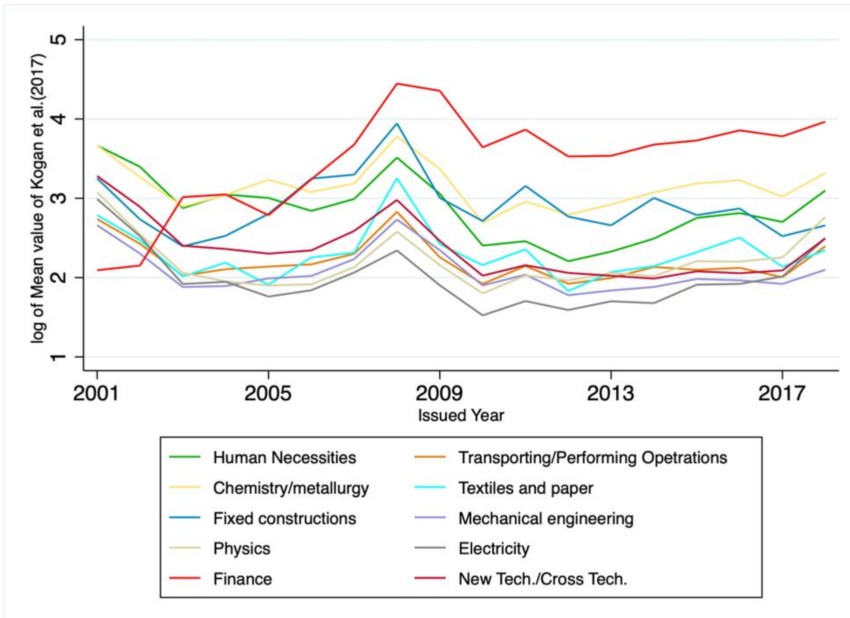


Figure 2. Trends in Kogan et al. (2017) value and patent citations by cooperative patent classification (CPC) category and award year. We use all patents applied for between 2000 and 2018 and awarded by February 2019. There are nine main categories under the CPC scheme. We separate all of our finance patents and classify them into a new category. Panel A depicts the log of the mean Kogan et al. (2017) value by CPC category over time, and Panel B depicts the log of the mean patent citations (through October 2019) by CPC category over time.

Panel A: Mean of Kogan et al. (2017) value over time, by patent's CPC category.



Panel B: Mean of patent citations over time, by patent's CPC category.

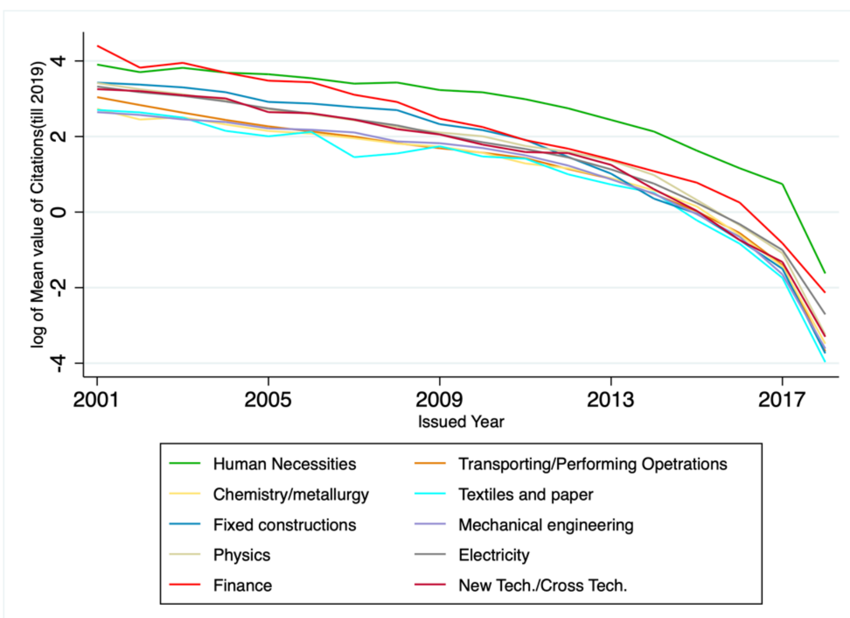
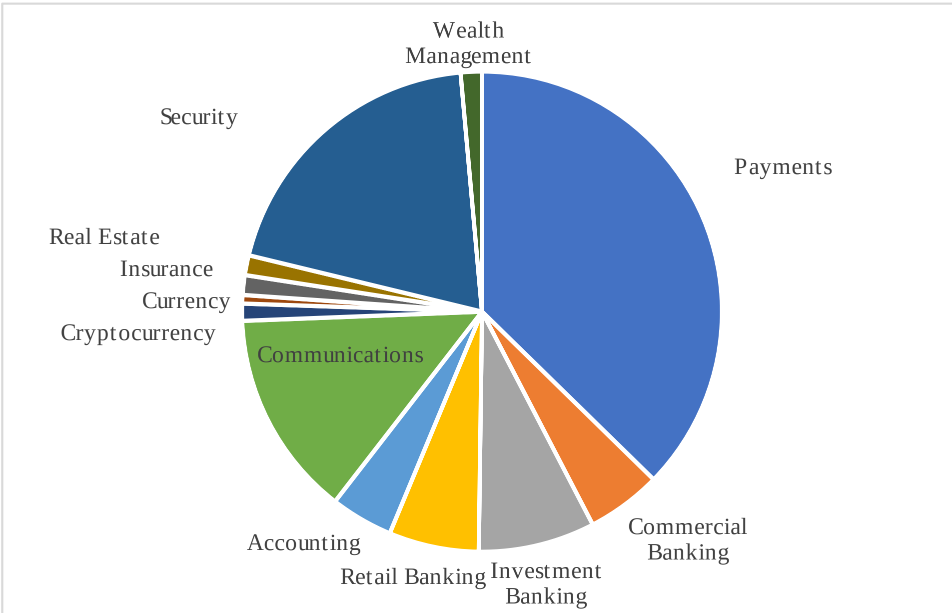


Figure 3. Composition of financial patents. The figures present the breakdown of patent type (Panel A) and assignee industry (Panel B) for patents applied for between 2000 and 2018 and awarded by February 2019. The tabulation in Panel B excludes patents assigned to governments, universities, or individuals, as well as those where the industry cannot be determined.

Panel A: Financial patenting by patent type.



Panel B: Financial patenting by assignee industry.

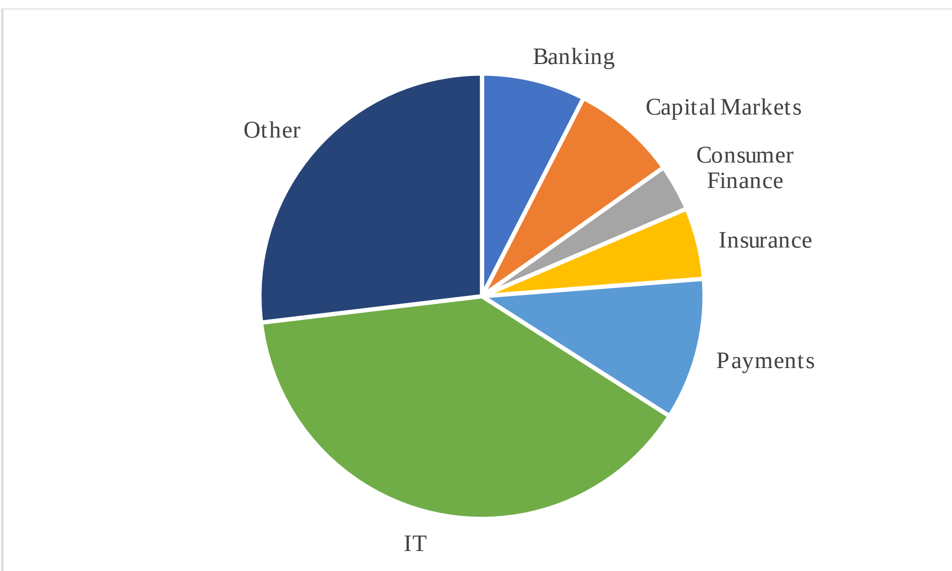


Figure 4. The front pages of the three most influential patents in the sample, as measured by cumulative numbers of citations, Kogan et al. (2017) weight, and Kelly et al. (2020) weight.

Panel A: Patent in the sample with the most citations.

US006772132B1

(12) **United States Patent**
Kemp, II et al.

(10) **Patent No.: US 6,772,132 B1**
(45) **Date of Patent: Aug. 3, 2004**

(54) **CLICK BASED TRADING WITH INTUITIVE GRID DISPLAY OF MARKET DEPTH**

(75) Inventors: **Gary Allan Kemp, II**, Winnetka, IL (US); **Jens-Uwe Schluetter**, Evanston, IL (US); **Harris Brumfield**, Chicago, IL (US)

(73) Assignee: **Trading Technologies International, Inc.**, Chicago, IL (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 245 days.

(21) Appl. No.: **09/590,692**

(22) Filed: **Jun. 9, 2000**

Related U.S. Application Data

(60) Provisional application No. 60/186,322, filed on Mar. 2, 2000.

(51) **Int. Cl.**[7] **G06F 17/60**

(52) **U.S. Cl.** **705/37**; 705/35; 705/36; 705/37; 705/10; 705/14; 345/814

(58) **Field of Search** 705/35, 36, 37, 705/10, 14; 345/814

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WO	WO 01/16852		3/2001
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Kharouf, A trading room with a view, Fututes, 27,11, Nov. 1998.*

USPTO Presentation, NASDAQ, Nov. 8, 2001, enclosed pp. 1–13.

Primary Examiner—Richard Weisberger
(74) *Attorney, Agent, or Firm*—Foley & Lardner

(57) **ABSTRACT**

A method and system for reducing the time it takes for a trader to place a trade when electronically trading on an exchange, thus increasing the likelihood that the trader will have orders filled at desirable prices and quantities. The "Mercury" display and trading method of the present invention ensure fast and accurate execution of trades by displaying market depth on a vertical or horizontal plane, which fluctuates logically up or down, left or right across the plane as the market prices fluctuates. This allows the trader to trade quickly and efficiently.

56 Claims, 6 Drawing Sheets

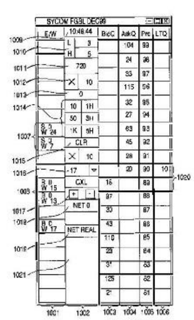

Figure 4 (continued).

Panel B: Patent in the sample with the highest Kogan et al. (2017) weight.

US007575157B2

(12) **United States Patent**
Barnhardt et al.

(10) **Patent No.: US 7,575,157 B2**
(45) **Date of Patent: Aug. 18, 2009**

(54) **FRAUD PROTECTION**

(75) Inventors: **David Wayne Barnhardt**, Huntersville, NC (US); **Charles F. Pigg**, Plano, TX (US)

(73) Assignee: **Bank of America Corporation**, Charlotte, NC (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 71 days.

(21) Appl. No.: **11/752,224**

(22) Filed: **May 22, 2007**

(65) **Prior Publication Data**

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(51) **Int. Cl.**
G06Q 40/00 (2006.01)

(52) **U.S. Cl.** **235/379**; 235/380; 705/42; 705/43; 705/44; 705/379

(58) **Field of Classification Search** 235/380; 705/42–44; 380/51
See application file for complete search history.

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Primary Examiner—Allyson N Trail
(74) *Attorney, Agent, or Firm*—Banner & Witcoff, Ltd.; Michael A. Springs

(57) **ABSTRACT**

Systems and methods are illustrated for providing enhanced fraud protection. Aspects of the fraud protection system may be implemented by a filter that may be configured to detect fraud in a transaction between a financial institution and a customer. An input device may receive data that corresponds to a transaction between a financial institution and a customer, such as a transfer of money. A data store may store information relating to the transaction that includes the serial number and dollar amount of the transfer of money. When the filter detects fraud, an output device may output an alert resulting in zero false positives. The filter may also include a module that is configured to compare the data that is received by an input device to data that is stored in the data store. Oftentimes, the data in the data store may be information relating to past fraud protection.

28 Claims, 3 Drawing Sheets

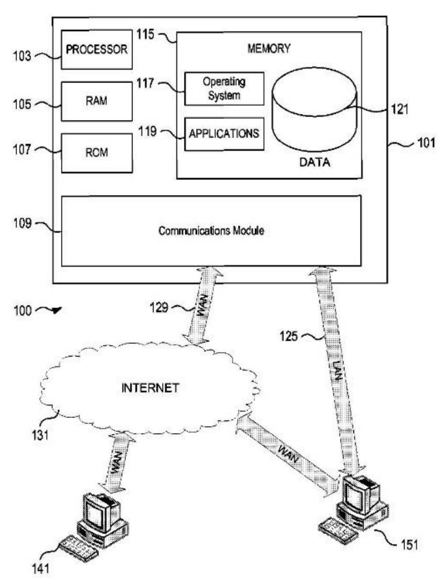

Figure 4 (continued).

Panel C: Patent in the sample with the highest Kelly et al. (2020) weight.

US007461021B2

(12) **United States Patent**
Bergmann et al.

(10) **Patent No.: US 7,461,021 B2**
(45) **Date of Patent: Dec. 2, 2008**

(54) **METHOD OF ASCERTAINING AN EFFICIENT FRONTIER FOR TAX-SENSITIVE INVESTORS**

(75) Inventors: **Michael D. Bergmann**, Bow Mar, CO (US); **Daniel Yoo**, Aurora, CO (US)

(73) Assignee: **AMG National Trust Bank**, Englewood, CO (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 1228 days.

(21) Appl. No.: **09/995,178**

(22) Filed: **Nov. 27, 2001**

(65) **Prior Publication Data**

US 2002/0143682 A1 Oct. 3, 2002

Related U.S. Application Data

(60) Provisional application No. 60/253,918, filed on Nov. 29, 2000.

(51) **Int. Cl.**
G06Q 40/00 (2006.01)

(52) **U.S. Cl.** **705/36**; 705/400; 705/35

(58) **Field of Classification Search** .... 705/36 R, 705/36 T, 400, 35
See application file for complete search history.

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Primary Examiner—Harish T. Dass
(74) *Attorney, Agent, or Firm*—Gregory W. O'Connor

(57) **ABSTRACT**

There are computerized processes for financial planning for individuals and groups whose financial portfolio would be subject to tax on certain events. But these processes do not take into account these taxes when optimizing investment decisions, since taxes levied on investment outcomes, typically on income and realized capital gains, may have an important impact on net portfolio results. This invention is a method for transforming the usual pretax information for calculation of an efficient frontier, unique to an investor's portfolio, in such a manner that any portfolio on the calculated frontier is efficient after incorporating the effect of taxes on the risk and expected return of each asset class permitted in the investor's portfolio. This invention addresses how this may be done and how certain facets of the process may be incorporated into a computer program or system so as to provide convenience to the potential user.

8 Claims, 3 Drawing Sheets

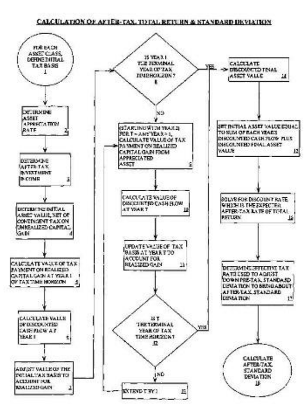


Figure 5. The volume of corporate venture investment in U.S. finance firms, by industry of the investor. The figure presents the breakdown of the volume (in millions of U.S. dollars) of corporate venture investments over four five-year periods, with the investors divided into those that fall into the banking, other finance, payments, and IT and other industries. See Appendix C for details about the construction of the data set.

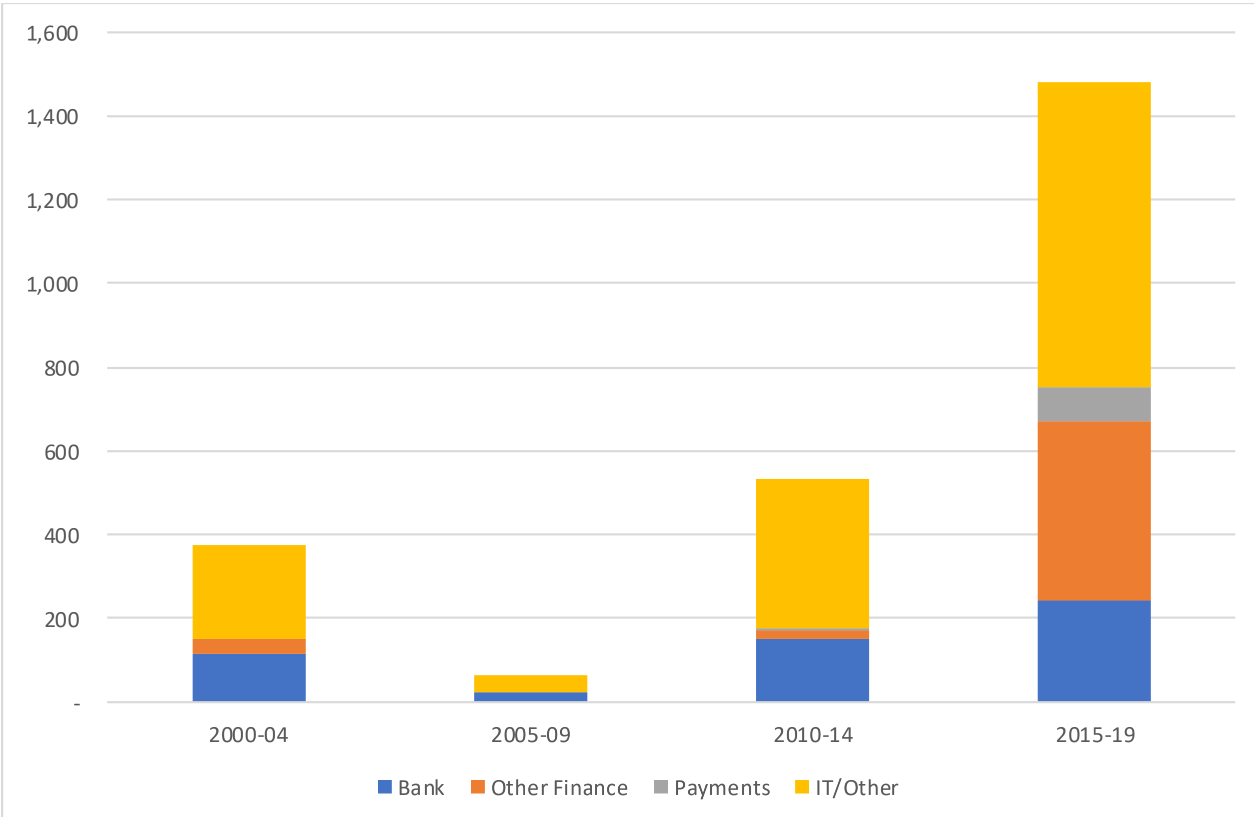
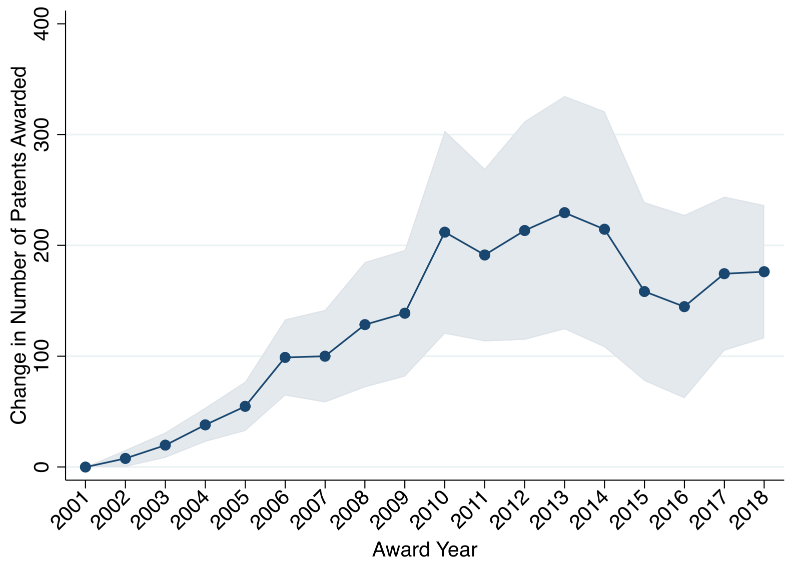


Figure 6. Decomposition of the rise of financial patenting. The charts depict the results of an OLS regression analysis of the rise of patenting, where the dependent variable is the number of financial patents awarded by each award year-assignee firm industry-patent type-inventor location cell. The charts depict the annual fixed effects with 95% confidence limits (Panel A) and the interactions between year and patent type fixed effects (Panel B, relative to "Other Types").

Panel A: Financial patenting by award year



Panel B: Financial patenting by patent type

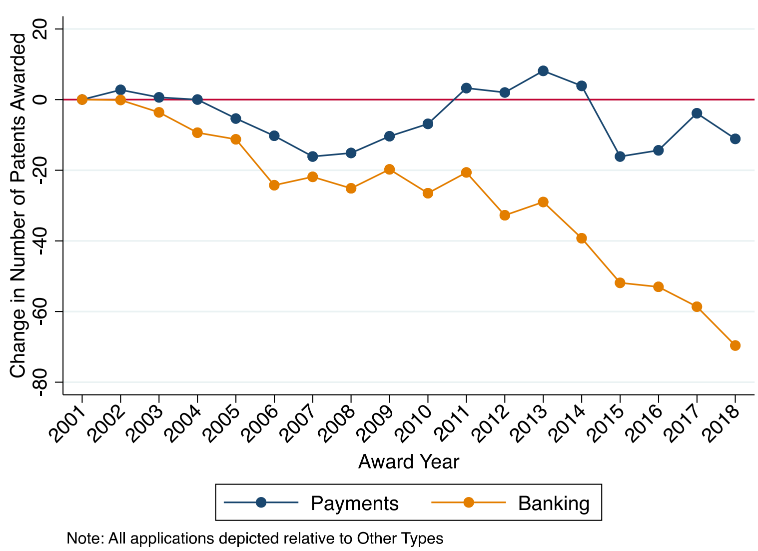


Figure 7. Decomposition of the rise of financial patenting. The charts depict the results of an OLS regression analysis of the rise of patenting, where the dependent variable is the number of financial patents awarded by each award year-assignee industry-patent type-inventor location cell. The chart depicts the coefficients of the interactions between award year, assignee industry, and patent type fixed effects (relative to the year 2001, “IT and Other Industries,” “Other Types”).

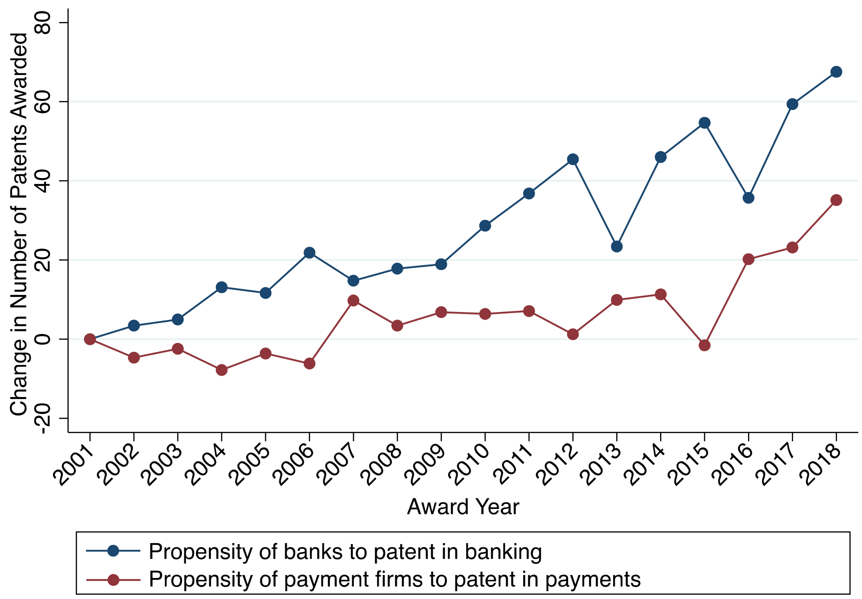


Figure 8. Financial patenting in U.S. census regions over time. The chart depicts the results of an OLS regression analysis of financial patenting across U.S. census regions over time. Using observations at the application time period-census region level, the dependent variable is the number of financial patents in a given cell. The chart presents coefficients on the interactions of the application time period fixed effects with fixed effects for two specific census regions: Pacific and South Atlantic regions. The Middle Atlantic region is the baseline region**.** Robust standard errors (95% level) are denoted with shadowed areas.

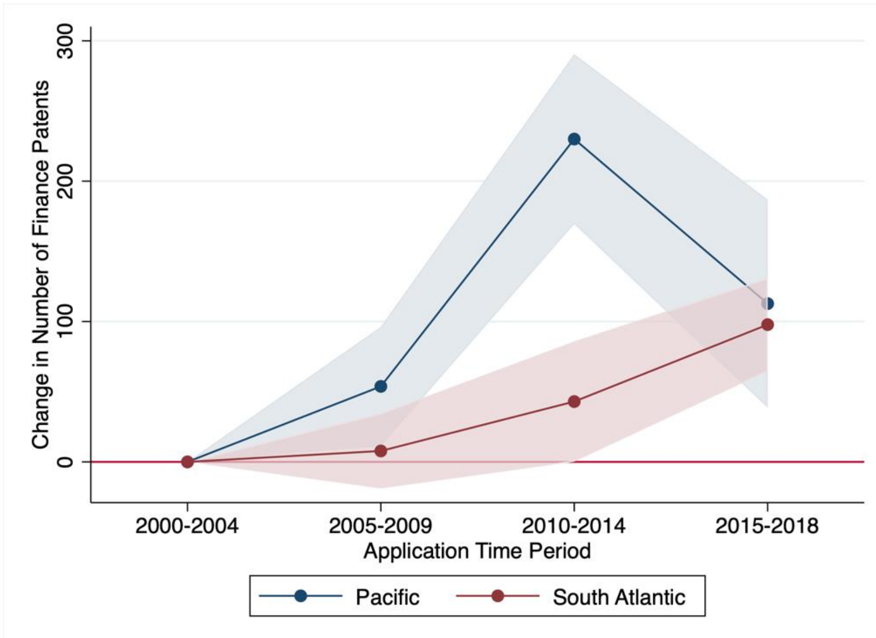


Table 1. The impact of finance patents and all patents, by assignee type. The table presents the citation weights, the Kogan et al. (2017) weights, and the Kelly et al. (2020) weights for finance patents and all other patents applied for between 2000 and 2018 and awarded by February 2019. The table presents as well results of a t-tests and nonparametric k-sample tests of the equality of medians. The table also presents the differences in the percentile ranks of the means and medians of the finance and non-finance patents using the distribution of all patents in the sample.

	Citation weights		Kogan et al. weights		Kelly et al. weights		# of patents
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	
Finance Patents	1.25	0.28	53.61	17.50	0.86	0.99	24,255
All Other Patents	1.00	0.26	11.81	4.04	0.81	0.89	3,781.439
p Value, equality test	0.000	0.034	0.000	0.000	0.000	0.000	
Difference percentile	+4	+0	+20	+34	+6	+14	

Table 2. The assignee types of financial and non-financial patents. The sample consists of finance and non-finance patents applied for between 2000 and 2018 and awarded by February 2019. We compare the distribution of assignees of finance and non-finance patents in t-tests. * denotes rejection of the null hypothesis of no difference in the means at the 10% level; ** at the 5% level; and *** at the 1% level.

	Finance patents	*Non-finance patents*
Assignee Type:		
U.S. corporation	81.29%	46.50%***
Foreign corporation	17.40%	50.21%***
Individual	8.65%	7.79%***
U.S. government	0.08%	0.36%***
Foreign government	0.01%	0.09%***
U.S. university	0.21%	1.45%***
Foreign university	0.07%	0.75%***
Share active VC backed	4.02%	2.22%***
Share VC backed, U.S. inventors only	4.99%	4.43%***

Table 3. The assignees of financial patents. Panel A presents the most frequent assignees of finance patents applied for between 2000 and 2018 and awarded by February 2019. Panel B presents the share of applications with assignees below various employment size thresholds in the application year, as a share of all corporate applications with employment data in that period. Panel C presents the assignees with at least 200 finance patents in the sample and with the most influential patents. Panels D and E present the most sharply declining (growing) financial patent assignees. These are identified by comparing the share of financial patents in the sample applied for between 2000 and 2004 and between 2015 and 2018.

Panel A: Most frequent assignees.

	Number of patents
Bank of America Corporation	652
Trading Technologies International	645
Visa Inc.	608
Diebold Nixdorf, Inc.	597
International Business Machines Corporation	589
Mastercard Inc.	418
JPMorgan Chase & Co.	407
American Express Company	404
United Services Automobile Association	351
Intuit	310

Panel B: Representation of small businesses.

Employment threshold	*2000-04 patent applications*	*2015-18 applications*
<250	2.4%	1.7%
<500	5.8%	2.1%
<1000	7.8%	3.2%

Panel C: Assignees with most influential patents (with at least 200 finance patents): Means using various weighting schemes.

Citation weights		*Kogan et al. (2017) weights*		*Kelly et al. (2020) weights*	
Square, Inc.	3.50	JP Morgan Chase & Co.	266.30	NCR Corporation	1.09
United Services Automobile Association	3.00	Bank of America Corporation	108.28	First Data Corporation	1.09
Visa Inc.	1.81	Visa Inc.	107.98	Microsoft	1.05

Table 3 (continued).

Panel D: Most rapidly declining finance patent assignees.

	Change in share
Unassigned	-6.1%
First Data Corporation	-2.4%
Goldman Sachs Group, Inc.	-1.5%
JPMorgan Chase & Co.	-1.4%
Fujitsu Limited	-1.3%
Hitachi, Ltd.	-1.3%
HP Inc.	-1.2%
International Business Machines Corporation	-1.2%
Oracle Corporation	-1.0%
Sony Corporation	-1.0%
Diebold Nixdorf, Inc.	-1.0%

Panel E: Most rapidly growing finance patentee assignees.

	Change in share
Bank of America Corporation	+6.1%
Square, Inc.	+4.3%
State Farm Mutual Automobile Insurance Company	+3.8%
Mastercard Inc.	+3.3%
PayPal Holdings, Inc.	+3.1%
Visa Inc.	+2.7%
Capital One Services, LLC	+2.2%
The Allstate Corporation	+1.5%
The Hartford Financial Services Group, Inc.	+1.1%
Wells Fargo & Company	+0.9%
United Services Automobile Association	+0.8%

Table 4. Consumer finance and process patents. The sample consists of all finance patents applied for between 2000 and 2018 and awarded by February 2019. Panel A reports correlations between (a) whether a patent involved consumer finance or was a process award and (b) patent characteristics. The construction of the consumer finance and process variables are described in the text. The rows look at their relationship with the application and award date, the assignee industry, and the interactions between these measures. Panel B presents OLS regression analyses. The dependent variables are the dummy variables denoting if the patents are consumer finance and process. The key independent variables are dummies for whether the patent was assigned to an information technology, payments, and other non-finance firm and for the time period of the application. In the second and fourth regression, we add interactions between two time dummies and whether the patent is assigned to an information technology, payments, and other non-finance firm. We also include unreported controls for firm characteristics (see text for details). Robust standard errors in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

A. Correlations.

	Consumer Finance	*Process*
Mean	24.2%	46.6%
Correlation coefficient between patent type and…		
Application date	0.021***	0.016**
Award date	0.017***	0.032***
Assignee in banking industry	0.004	-0.088***
Assignee in capital markets	-0.021***	-0.090***
Assignee in IT, payments, or other	0.016**	0.131***
Correlation of IT/payment/other assignee and date for patents of a given type		
Application date	-0.033**	-0.046***
Award date	-0.040**	-0.048***

B. Regression analyses.

	Consumer finance patent?				Process patent?		
	(1)		*(2)*		*(3)*		*(4)*
Assignee in IT, payments, or other	0.024***		0.141***		0.121***		0.116***
	[0.008]		[0.015]		[0.006]		[0.011]
IT/payment/other * Early application			-0.009				-0.021
			[0.027]				[0.020]
IT/payment/other * Late application			0.0001				-0.133***
			[0.033]				[0.044]
Observations	24,355		13,259		20,613		11.073
R-squared	0.001		0.016		0.038		0.050
Time FEs	Yes		Yes		Yes		Yes
Location FE	No		Yes		No		Yes
Assignee characteristics controls	No		Yes		No		Yes

Table 5. The relationship between academic citations and grant date. The sample consists of finance patents applied for between 2000 and 2018 and awarded by February 2019. Panel A presents the correlation coefficient between the grant date and the number of academic citations in these patents, the number of citations to business, economics, and finance journals, the number to Top 3 finance journals, and the mean age of the citations in each patent (years between the article publication and patent application date), in aggregate and divided by patent assignee industry. Panel B reports the mean citation weight, the Kogan et al. (2017) weight, and the Kelly et al. (2020) weight for patents that do and do not cite any academic output, cite publications with an above-median impact factor, and cite publications of various types (all business, economics, and finance journals, all business, economics, and finance journals with an above-median impact factor, and "Top 3" finance journals). Panel C reports OLS regression analyses of financial patent value and academic citations over time. The dependent variables are the citation weight and the Kogan et al. (2007) weight for each patent, and the key independent variables are the interaction between the number of academic citations and the patent application time period. The regressions control for time and location, as well as for assignee characteristics (see text for details). Robust standard errors are in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

	Academic citations	*Bus/econ/fin citations*	*Top 3 citations*	*Citation age*
All finance patents	-0.007	-0.016**	-0.027***	0.144**
By assignee industry				
Banking	-0.216***	-0.286***	-0.152***	0.156***
Other finance	0.010	-0.075***	-0.067***	0.178***
Payments	-0.060***	-0.009	-0.025	0.098**
IT/other	0.008	-0.005	-0.008	0.149***

Panel B: Patent value and the presence of academic citations

	Mean, weighted citations		Mean, Kogan et al. value		Mean Kelly et al. value	
	Yes	*No*	*Yes*	*No*	*Yes*	*No*
Academic Citation(s)?	1.52	1.08***	59.4	50.1***	0.88	0.84***
Citation(s) to High-Impact Factor Journals?	1.74	1.23***	67.1	53.0***	0.78	0.86***
Citation(s) to Business/Economics/Finance Journals?	1.38	1.22***	85.3	48.0***	0.90	0.85***
Citation(s) to High-Impact Bus/Econ/Fin Journals?	1.52	1.27**	96.6	52.2***	0.91	0.85**
Citation(s) to Top 3 Finance Journals?	1.30	1.25	184.2	52.1***	0.93	0.86***

Table 5 (continued).

Panel C: Academic article citations and patent value over time.

	Weighted citations		*Kogan et al. value*
Academic Citations x 2000-2004 Application Period	0.016***		1.270**
	[0.004]		[0.507]
Academic Citations x 2005-2009 Application Period	0.025***		0.843***
	[0.006]		[0.281]
Academic Citations x 2010-2014 Application Period	0.091***		0.413***
	[0.017]		[0.137]
Academic Citations x 2015-2018 Application Period	0.590***		2.071**
	[0.166]		[1.018]
Observations	13,256		9,173
R-squared	0.103		0.302
Time FEs	Yes		Yes
Location FE	Yes		Yes
Assignee characteristics controls	Yes		Yes

Table 6. Financing patenting by U.S. urban area over time. The table presents the share of patenting by CSA for the ten CSAs with the most financial patents overall. The analysis uses patents applied for between 2000 and 2018 and awarded by February 2019. The table presents patents from the given CSA as a share of all financial patents, computed using patent counts, citation weights, and Kogan et al. (2017) weights. We assign patents based on the location of the first inventor.

	Patent Count				Citation Weighted				Kogan et al. Weighted			
	2000-04	*2005-09*	*2010-14*	*2015-18*	*2000-04*	*2005-09*	*2010-14*	*2015-18*	*2000-04*	*2005-09*	*2010-14*	*2015-18*
San Jose-San Francisco-Oakland	8.5%	10.7%	15.7%	18.3%	11.5%	16.2%	21.3%	21.5%	8.4%	14.8%	25.0%	25.6%
New York-Newark	13.4%	11.6%	9.5%	5.7%	14.6%	7.8%	6.4%	5.7%	34.6%	19.8%	14.4%	5.7%
Chicago-Naperville	3.4%	6.2%	7.5%	3.9%	5.6%	5.8%	7.3%	3.0%	2.9%	4.5%	4.4%	4.4%
Washington-Baltimore-Arlington	4.0%	3.4%	3.2%	4.0%	4.7%	6.0%	3.3%	2.2%	3.1%	2.6%	1.4%	4.1%
Los Angeles-Long Beach	2.4%	2.1%	2.8%	1.8%	3.1%	2.8%	5.0%	3.7%	0.3%	0.9%	0.7%	0.9%
Cleveland-Akron-Canton	2.4%	2.8%	2.7%	1.7%	1.3%	1.8%	2.3%	0.7%	0.6%	0.5%	0.3%	0.3%
Atlanta-Athens-Clarke County	2.0%	2.6%	2.0%	2.8%	2.5%	3.7%	1.8%	1.3%	0.7%	1.4%	1.1%	2.1%
Seattle-Tacoma	1.9%	2.5%	2.3%	1.8%	2.0%	2.5%	2.5%	1.7%	1.8%	1.7%	2.4%	2.8%
Charlotte-Concord	0.3%	1.7%	2.3%	4.2%	0.4%	1.5%	3.2%	1.6%	0.4%	11.0%	8.7%	13.7%
Denver-Aurora	2.2%	2.0%	2.1%	1.3%	1.9%	1.4%	1.2%	0.5%	2.7%	1.2%	1.3%	0.6%

Table 7. OLS regression analyses of the impact of regulatory actions on financial patenting. The table uses observations at the CSA (121 CSAs with any financial patents applied between 2000 and 2015)-assignee industry (banks, other finance, payments, and IT/other)-patent type (banking, payments, and other) level, for a total of 1452 observations. The dependent variables are the number of patents in a given cell. The key independent variables are the measure of CSA-level regulatory activities from Buchak et al. (2018) interacted with assignee industry as well as patent type. All regressions include CSA fixed effects and controls for patent type and assignee industry. Clustered standard errors (at the CSA level) are in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

	Patent count		
	(1)	*(2)*	*(3)*
Δ Capital Ratio x Bank Firms	-6.974**		
	[3.033]		
Δ Capital Ratio x Other Finance Firms	-6.227**		
	[2.933]		
Δ Capital Ratio x Payments Firms	-5.394**		
	[2.814]		
Δ Capital Ratio x Banking Type	-1.963**		
	[0.799]		
% MSR x Bank Firms		-7.643**	
		[3.317]	
% MSR x Other Finance Firms		-7.748**	
		[3.070]	
% MSR x Payments Firms		-7.846**	
		[3.186]	
% MSR x Banking Type		-2.283**	
		[0.890]	
% OTS x Bank Firms			-14.880***
			[4.650]
% OTS x Other Finance Firms			-14.038***
			[4.535]
% OTS x Payments Firms			-12.179***
			[4.376]
% OTS x Banking Type			-3.682**
			[0.012]
Observations	1,452	1,452	1,452
R-squared	0.468	0.472	0.479
CSA FEs	Yes	Yes	Yes
Patent type FEs	Yes	Yes	Yes
Assignee industry FEs	Yes	Yes	Yes
Data sample period	2008-2015	2008-2015	2008-2015
Test Equality of Coefficients (F Statistic Reported)			
Interaction with Bank vs. IT/Other	5.29**	5.31**	10.24***
Interaction with Other Finance vs. IT/Other	4.51**	6.37**	9.58***
Interaction with Payments vs.IT/Other	3.67*	6.06**	7.75***
Interaction with Banking vs. Payment Type	4.51**	6.58**	6.31**

Table 8. OLS regression analyses of the impact of technology progress on financial patenting. The table uses observations at the state-assignee industry (banks, other finance, payments, and IT/other)-patent type (banking, payments, and other)-application year (2008-18) level, for a total of 6,600 observations. The dependent variable is the number of patents in a given cell. The key independent variables are interactions between two different STSI technology indexes in a given state in year t and assignee industry i. All regressions include fixed effects for time, state, patent type, and assignee industry. Clustered standard errors (at the state-year level) are in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

	Patent count		
	(1)		(2)
State Technology & Science Index x Payments Firms	0.048***		
	[0.017]		
State Technology & Science Index x IT/Other Firms	0.216***		
	[0.041]		
State Technology & Science Index x Payment Type	0.063***		
	[0.014]		
State Technology & Science Index x Other Type	0.065***		
	[0.014]		
Research & Development Inputs x Payments Firms			0.033***
			[0.011]
Research & Development Inputs x IT/Other Firms			0.129***
			[0.028]
Research & Development Inputs x Payment Type			0.040***
			[0.010]
Research & Development Inputs x Other Type			0.042***
			[0.009]
Observations	6,600		6,600
R-squared	0.392		0.377
Time FEs	Yes		Yes
State FEs	Yes		Yes
Patent type FEs	Yes		Yes
Assignee industry FEs	Yes		Yes
Data sample period	2008-18		2008-18
Test, Equality of Coefficients (F Statistic Reported)			
Interaction with Payments vs. Bank	8.13***		17.35***
Interaction with IT/Other vs. Bank	27.97***		8.37***
Interaction with Payment vs. Banking Type	20.22***		17.38***
Interaction with Other vs. Banking Type	22.21***		20.15***

Table 9. Probit regression analyses of the shifting innovative location of banks and payment firms. Panel A analyzes the shifting innovative location of banks and regulatory pressure. The sample consists of continuing financial innovators (the firms with financial innovation activities before 2008 and after 2015). The dependent variable takes on a value of one if its modal location for innovation changes from 2000-2007 and 2008-2015, and zero otherwise. The independent variables in Panel A consist of dummies for the industry of the firm and controls for assignee characteristics (see text), as well as interactions between each industry dummy and three measures of the intensity of regulatory scrutiny in the original CSA where the firm was based using the data from Buchak et al. (2018). Panel B analyzes the shifting innovative location of payments firms and technological progress. The sample consists of continuing financial innovators, defined as above. The dependent variable takes on a value of one if its modal state for innovation changes between two successive periods, and zero otherwise. The independent variables consist of dummies for the industry of the firm and time period and controls for assignee characteristics (see text), as well as interactions between each industry dummy and two technology indexes in the original state where the firm was based using the STSI data. The tables report the marginal effects of interaction terms. Robust standard errors are in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Panel A: Regulatory pressure and the shifting innovative location of banks.

	Did firm switch CSAs after 2008?				
	(1)		*(2)*		*(3)*
Original Δ Capital Ratio x Bank Firms	1.682***				
	[0.244]				
Original % MSR x Bank Firms			2.061***		
			[0.159]		
Original % OTS x Bank Firms					1.929***
					[0.541]
Weighted Observations	3,007		3,007		3,007
Pseudo R-squared	0.149		0.359		0.195
Assignee industry FEs	Yes		Yes		Yes
Assignee characteristics controls	Yes		Yes		Yes
Chi-squared	422.6		591.9		539.6
p-value	0.000		0.000		0.000
Test Equality of Marginal Effects (Chi-square Reported)					
Interaction with Other Finance vs. Bank	83.91***		125.26***		8.51***
Interaction with Payments vs. Bank	47.45***		168.32***		12.71***
Interaction with IT/Other vs. Bank	35.54***		61.79***		11.40***

Table 9 (continued).

Panel B: Technological progress and the shifting innovative location of payment firms.

	Did firms switch modal state?		
	(1)		*(2)*
State Technology & Science Index x Payments Firms	-0.307***		
	[0.006]		
Research & Development Inputs x Payments Firms			-0.234***
			[0.006]
Weighted Observations	18,421		18,421
Pseudo R-squared	0.257		0.206
Time FEs	Yes		Yes
Assignee industry FEs	Yes		Yes
Assignee characteristics controls	Yes		Yes
Chi-squared	3783.5		3466.4
p-value	0.000		0.000
Test Equality of Marginal Effects (Chi-square Reported)			
Interaction with Other Finance vs. Payments	526***		368***
Interaction with Bank vs. Payments	2410***		1500***
Interaction with IT/Other vs. Payments	2410***		1500***

Appendix A: Major Judicial Decisions and Policy Changes Post-*State Street* that Affected Financial Patenting

Two important Supreme Court decisions revisited the validity of business method patents during the period studied in this paper (2000-2019). First, in *Bilski v. Kappos*, the Supreme Court affirmed a CAFC decision rejecting the patentability of a method for hedging against price risk in commodities trading but also rejected a *per se* exclusion against patenting business methods.[24] The decision also rejected the judicial standard by which the CAFC had assessed the patentability of business method patents, which injected uncertainty into questions about the validity of such patents.[25]

Next, in June 2014, the Supreme Court ruled in *Alice Corp. v. CLS Bank* that Alice's patent for a computerized trading program that mitigated settlement risk and facilitated the exchange of financial obligations was invalid. The Court found the patent to be merely an abstract idea and thus ineligible for patent protection.[26] At the same time, the Court again made no categorical rejection of business methods or software, *Alice* amplified concerns over the extent of financial-related software patentability.

Patent law changes in 2011 also affected financial patenting. Specifically, the Leahy-Smith America Invents Act (P.L. 112-29) added a new method of post-grant review for "covered business methods" (CBMs), a provision which took was in effect between 2012 and 2020. This legislation was motivated by critics of the financial patents, summarized in Hunter (2004, Table 1), who questioned (a) the capabilities of the USPTO to process applications, (b) the validity of such patents in terms of obviousness and novelty, and (c) its overall impact on innovation and competition.

In this context, a CBM is essentially a financial patent.[27] The provision was meant to stifle litigation over questionable patents by enabling alleged infringers being sued in district court to challenge patent validity in a less expensive forum with a faster timeline, before a board perceived as being harsher on questions of patentability. Practitioners suggest that while current attitudes

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[24] "Section 101 similarly precludes a reading of the term 'process' that would categorically exclude business methods." See *Bilski v. Kappos*, 561 U.S. 593 (2010).

[25] The *en banc* CAFC rejected its prior test for determining whether a claimed invention was a patentable "process" under Patent Act, 35 U. S. C. §101—i.e., whether the invention produced a "useful, concrete, and tangible result," as delineated in *State Street*—holding instead that a claimed process is patent eligible "if: (1) it is tied to a particular machine or apparatus, or (2) it transforms a particular article into a different state or thing." See *In re Bilski*, 545 F.3d 943, 88 U.S.P.Q.2d 1385 (Fed. Cir. 2008).

[26] In particular, the Supreme Court held that "an instruction to apply the abstract idea of intermediated settlement using some unspecified, generic computer is not 'enough' to transform the abstract idea into a patent-eligible invention." See *Alice Corp. v. CLS Bank Int'l* 573 U.S. 208 (2014).

[27] A covered business method patent is defined 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...." 37 *C.F.R.* 42.301(a).

towards granting finance patents are quite permissive within the USPTO, the Federal Circuit is taking a harder line on the validity of finance patents in their rulings.

The ambiguities associated with finance patents in the U.S. have also manifested elsewhere. European patent law explicitly excludes methods of doing business and finance from patent protection. But given the complexity of the definitions, some finance patents appear to have made it past these categorical exclusions. Meanwhile, Japan has shifted from one of the most skeptical patent offices regarding business methods to a much more permissive one: its rejection rate for these patents, of which finance constitutes a considerable number, fell from 92% in 2000 to 34% in 2012 through 2014 (Japanese Patent Office, 2019).

Appendix B: Financial Database Validation Analyses

Auditing the Sorting between Finance and Non-Finance Patents

Within our initial sample, there were 66,534 patents assigned to CPC subclasses G06Q. Of these, 17,511 were assigned to CPC groups G06Q 20 or 40, and the remaining 47,023 to other groups. These patents were divided with random assignment, with 70% (45,174) of the patents as the training data, and 30% (19,360) patents as the testing data.

As is routine with machine learning models, after we estimated the model with the training data, we tested its accuracy using the testing data: that is, we used the testing data to quantify the extent to which the model successfully distinguished between patents that were actually in CPC groups G06Q 20 and 40 and those that were not. Our chosen model operated with about 90 percent sensitivity and specificity: that is, the true positive and true negative rates were both quite high.

Even so, the test set contained 1,426 patents (out of 14,106) that were not actually in CPC groups G06Q 20 and 40 that were predicted to be financial (false positives), and 526 patents in CPC groups G06Q 20 and 40 (out of 5,253) that were predicted to be non-financial (false negatives). (See the schematic below.) To determine whether these inaccuracies represented the performance limits of our model or suggested some noise in the primary CPC codes we used to classify patents, we had a research assistant audit a 10% random sample from each group of misclassifications (false positives and false negatives). He read the title and abstract (and more text if needed) and determined whether the patent is financial or not based on these descriptions.

		Predicted		
		Negative	Positive	Total
Actual	Negative	True Negative (12,680)	False Positive (1,426)	Actual Negative (14,106)
	Positive	False Negative (526)	True Positive (4,727)	Actual Positive (5,253)

The research assistant found that 61 out of 143 (43 percent) allegedly false positives were actually financial patents, and that 39 out of 53 (74 percent) allegedly false negatives were actually not financial patents. In other words, of the patents not included in CPC groups G06Q 20 and 40 but predicted to be financial, 43% percent turned out to actually be financial upon an examination of the patent text itself. Similarly, of the patents included in CPC groups G06Q 20 and 40 but predicted to be not financial, 74% turned out to be not financial. These results broadly suggest some error in the labelling for "marginal" patents—–those patents for which a judgment call is difficult.

These results raised the concern that the initial labelling of patents in the training and test sets based on CPC codes could be erroneous. To satisfy ourselves that this was not the case, and that the large inaccuracies only affected approximately 10 percent of the data (the "marginal" patents), we had the same research assistant do a similar audit for the "true positives" and "true negatives": those patents that the model correctly predicted were or were note in CPC groups 20 and 40. He found that 231 out of 254 (91%) true positives (patents with CPC codes in G06Q 20 or 40 and predicted to be financial by the model) were actually financial patents. He also found that only 4 out of 95 (96%) true negatives (patents not in G06Q 20 or 40 and predicted to be "not fintech" by the model) are financial in nature. These accuracy levels were much higher than the 43 and 74 percent accuracies found in samples of false positives and negatives, and suggested that the low levels of accuracy in those samples stemmed from the difficulty of determining whether the patent is financial or not, rather than from any major flaw in the CPC classifications.

We then used the model to identify financial patents with a primary subclass or group outside of G06Q, where we believed (after analyzing other common CPC codes for known financial patents) finance patents could be located. We did not generate a "test set" to evaluate the performance of our model when deployed to patents with a primary CPC subclass outside of G06Q. Instead, we had a research assistant audit small samples of patents that were predicted to be financial or not financial when we deployed the model on these "supplemental" subclasses. He found that 23 out of 67 (34%) patents identified as financial were actually financial, and that 51 out of 53 (96%) identified as not financial were actually not financial. For these patents, our model appeared to have high sensitivity but relatively poor specificity, a common problem.

This was expected because we did not include any financial patents with a primary CPC subclass outside of G06Q in the treatment group when we built and tested the machine learning model. Hence just like many other in many tests and applications, it is easier to precisely eliminate negative cases than identify positive ones. As a result, our list of financial patents should be considered a broad and perhaps over-inclusive sample of true financial patents.

Assessing an Alternative Assignment Method

We also explored whether an alternative approach using patents assigned to fintech firms would have generated better results. Using the lists mentioned above, we had a research assistant manually search Google patents to identify the standardized assignee names of known fintech firms in the underlying IFI Claims patent data. Through these searches, and additional web searches and examinations of patent filings, our assistant was able to identify common spellings of each firm and some of its publicly known subsidiaries.

Using this list of standardized firm names, we identified 1,065 patents assigned to known fintech firms. We found that only 32 percent of these patents ended up on our final list of financial patents using the methodology described above. Another research assistant audited a random sample of 101 of the patents assigned to known fintech firms that did not end up on our list. He found that only six of these patents were indeed financial. These results confirmed our belief that using firm names to label financial patents would not be appropriate in this context.

Issues with Proper Assignee Names

After pulling over patent-level data from Derwent, we noticed that Derwent often carried the inventor or applicant over into the assignee field in many instances in which it was not appropriate to do so (i.e., when the inventors were not assignees in the raw USPTO data from IFI). We therefore audited a two percent sample of the financial patents with multiple assignees (a sample of 150 patents) by having research assistants categorize the nature of the discrepancies between Derwent data and raw patent data. We found that in most instances (136 out of 150), the data either agreed (and contained only inventors or corporate entities as assignees) or the data disagreed but Derwent simply appended the inventor names onto a list of true corporate assignees. In some instances (13 out of 150), the raw data contained no assignee but the Derwent data listed all the inventors, a result which is consistent with the pre-2012 rule vesting ownership in inventors in the absence of a written assignment (see MPEP Section 301, 37 C.F.R. 3.1(I)).

Reflecting these findings, we purged all inventor names from the assignee field except when the only assignees were the inventors. In one instance (0.7 percent of the sample), in actuality the patent listed both the inventor and corporate entities as assignees. In this instance, our process caused a discrepancy by purging the individual inventor from the list of assignees. These incorrect corrections affected only a very small portion of the data set.

Capital IQ Identifier Issues

We were concerned that the Capital IQ identifiers used in our financial patent dataset might be associated with subsidiaries rather than the parent companies, despite our efforts to ensure matching to the ultimate parent company. By looking at the list of 2011 Systemically Important Financial Institutions (listed at the last page of https://www.fsb.org/wp-content/uploads/Policy-Measures-to-Address-Systemically-Important-Financial-Institutions.pdf), we identified 1,611 patents with a first assignee among the SIFI list. After auditing this list, we found that 1,563 out of 1,611 SIFI patents (97 percent accuracy) were assigned to the correct parent companies. And if we only looked at the SIFIs who were awarded more than 20 patents (their granted patents covered 95% of all SIFI patents), the accuracy rate was further increased to 98.7% (1511 out of 1531 patents were correctly assigned).

We identified two reasons for the erroneous matching with subsidiaries instead of parent companies. First, the UVA dataset on which we heavily relied has some errors. For instance, the UVA dataset assigns separate identifiers for "Morgan Stanley Capital International Inc." and "Morgan Stanley," though all patents associated with these companies should be assigned to a single parent company identifier. Second, our fuzzy name matching efforts also had some errors. For example, we matched some patents to the subsidiary "Credit Suisse Securities (USA) LLC" instead of its parent "Credit Suisse."

In total, 5 SIFI patents were not assigned to any identifiers by either UVA dataset or fuzzy name matching method, and 43 SIFI patents were wrongly assigned to the subsidiaries rather than their corporate parents. We did not see any time distribution differences among those problematic patents. In sum, though our analysis of the SIFI patents suggests that there are some errors in our dataset when it comes to matching patents with parent companies, they errors seem to affect only a small percentage of the data and should not affect the analysis materially.

Appendix C: Corporate Venture Capital Database Construction

We totaled the number and dollar volume of closed corporate venture investments in the United Statas, regardless of the nation of original of the investor, as reported by Capital IQ, focusing on the period between January 2000 and December 2019. We did not require that the companies in the corporate venture fund portfolios have (or ultimately be granted) financial patents, as many went bankrupt or were acquired before any patents issued.

Capital IQ's classifications scheme allowed us to identify corporate venture investors. In particular, we included investments that Capital IQ declared as being by groups that Capital IQ classified as "corporate investments arms" and "financial institution investment arms." We then did extensive reviews using a wide variety sources[28] of the investment groups that had undertaken two or more investments in finance portfolio companies,[29] to eliminate investors that we did not consider to be true corporate venture investors that were nonetheless in these categories.

In particular, we eliminated investments by:

- Traditional private equity and venture capital funds without a corporate sponsor,
- Publicly traded entities that operated largely as traditional investment funds (for example, Softbank),
- Family offices,
- Government- or non-profit affiliated bodies (e.g., International Finance Corporation, European Bank for Reconstruction and Development),
- Subsidiaries of financial institutions that primarily invested funds for third parties, rather than internally (for instance, Norwest Capital, Goldman Sachs Principal Investment Arm), and
- Groups investing internal capital but with explicitly stated financial (as opposed to strategic) objectives (e.g., GE Capital).

Some smaller investment and merchant banks doing primarily financial investments (whether proprietary or for third third-party clients) doubtless "slipped through" these screens, potentially overstating the investment amounts. Groups that occasionally made strategic investments "off the balance sheet" without a formal program may have been undercounted.

Capital IQ, like most venture capital databases, did not provide a break-down of the amount of financing provided by each investor in each round, so we divided the total financing amount in each round by the number of investors, assuming each investor provided an equal amount of capital. We eliminated the largest 2% of investments, which appear to be co-investments in buyouts that

[28]Sources used include lists of CVCs compiled by Global Corporate Venturing, CB Insights, and Crunchbase. We also manually checked Capital IQ database entries, web sites, media reports, and filings with the U.S. Securities and Exchange Commission

[29] We defined finance portfolio companies as those with a primary assignment (using the Capital IQ industry classification scheme) in financial services (including banks, insurers, exchanges, etc.) and payments, or providing internet services, IT consulting services, and software primarily for the financial services and payments industries.

appear to have been accidentally included in the database. The industry assignments for the investors are based on the Capital IQ industry classifications and the authors' own research.

The computation of the share of total corporate venture capital investment is based on the data compiled above, the share of U.S. venture capital investment that was corporate venture capital computed by Akcigit et al. (2020) for the period between 2000 and 2016, and the estimates of total venture capital invested in the U.S. in those years by the National Venture Capital Association (https://nvca.org/research/nvca-yearbook/, which are based on PitchBook and Refinitiv VentureXpert data).

Appendix D: CSA Database Construction

The U.S. Bureau of the Census has used varying definitions for urban areas over time and has periodically redrawn the boundaries of these regions. We attempted to be as consistent as possible in defining geographic regions, subject to the limitations of data availability.

First, we associated each patent to a local geography using the county FIPS of the first inventor, provided by Patentsview. We then matched county FIPS to 2013 CSA regions using Census/NBER crosswalk discussed in the text of the paper. We then aggregated simple and weighted patent counts to the CSA-year level using this mapping. Patents associated with counties outside of the 166 CSAs (we excluded the three CSAs in Puerto Rico) were collectively associated with an aggregate "Not a CSA Region." The 2013 CSAs include all major finance patenting hubs with the exception of Austin, Texas: the Census Bureau recognized the Austin-Round Rock-Marble Falls, TX CSA in the late 2000s and early 2010s, but then eliminated it after the criteria for selecting CSAs changed.

We similarly obtained from VentureXpert county-by-county data (and the associated FIPS code) on venture capital financing (both for all transactions and for finance transactions) between 2000 and 2018. We computed the number of deals and transaction volume using the 2013 mapping from counties to CSAs.

We then collected additional annual data about each CSA that existed in 2013, including: (1) total population, (2) total number of households, (3) median household income, (4) total adult (aged 25 or older) population, (5) total adult population with an education level of a bachelor's degree or higher, (6) the number of non-employer establishments in finance or insurance (NAICS 52), and (7) the number of employees in finance or insurance.

For census year 2000, data was collected at the county level and aggregated to the CSA-level using the Census/NBER crosswalk. For variables (1)-(2) and (4)-(7), the data were aggregated with simple summations. For median household income, the CSA-level value is a weighted mean of the county median incomes using county households as weights.

For non-decennial census years, these data were not available for the county level in most cases. Variables (1) through (5) above were reported annually for each CSA, however, in the American Community Survey. These data at the CSA level, however, had three limitations:

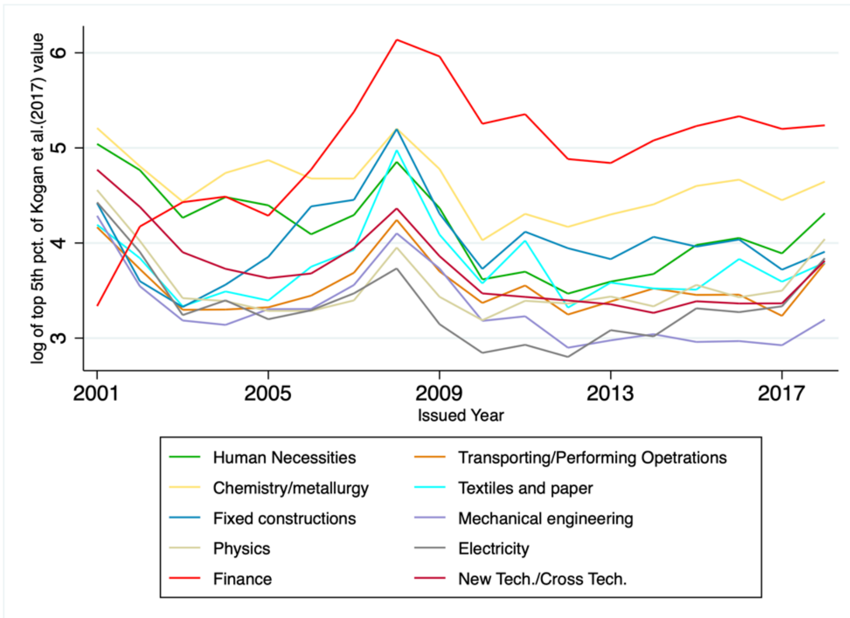
- The ACS data for 2001-04 (as well as 2000, which we did not use) was removed by the Census Bureau from its online servers due to reliability concerns.
- As noted above, the Census Bureau adds and sometimes removes urban areas from its list of CSAs. The ACS data were reported only for CSAs that were on the Census Bureau list at the time.
- The boundaries of CSAs may change over time.

As a result, for variables (1)-(5), we generally imputed missing values using a simple linear regression based on non-missing data in instances where the variable had two or more observations. If only one observation of a variable within a CSA was available, we attributed that value to all years in which the variable is missing, making the variable constant over time.

Variables (6)-(7) were taken from the quinquennial economic census from years 2002, 2007, 2012, and 2017. We generally imputed 2000 and 2001 observations in a CSA using the 2002 observation, and the 2018 observation using the 2017 observation. For years 2003-06, 2008-11, and 2013-16, we generally imputed missing values by fitting a linear regression using data from 2002, 2007, 2012, and 2017.

Figure A-1. Trends in Kogan et al. (2017) value and patent citations by cooperative patent classification (CPC) category and award year. We use all patents applied for between 2000 and 2018 and awarded by February 2019. There are nine main categories under the CPC scheme. We separate all of our finance patents and classify them into a new category. Panel A depicts the log of the top 5th percentile of Kogan et al. (2017) value by CPC category over time, and Panel B depicts the log of the top 5th percentile of patent citations (through October 2019) by CPC category over time.

Panel A: Top 5th percentile of Kogan et al. (2017) value over time, by patent's CPC category.



Panel B: Top 5th percentile of patent citations over time, by patent's CPC category.

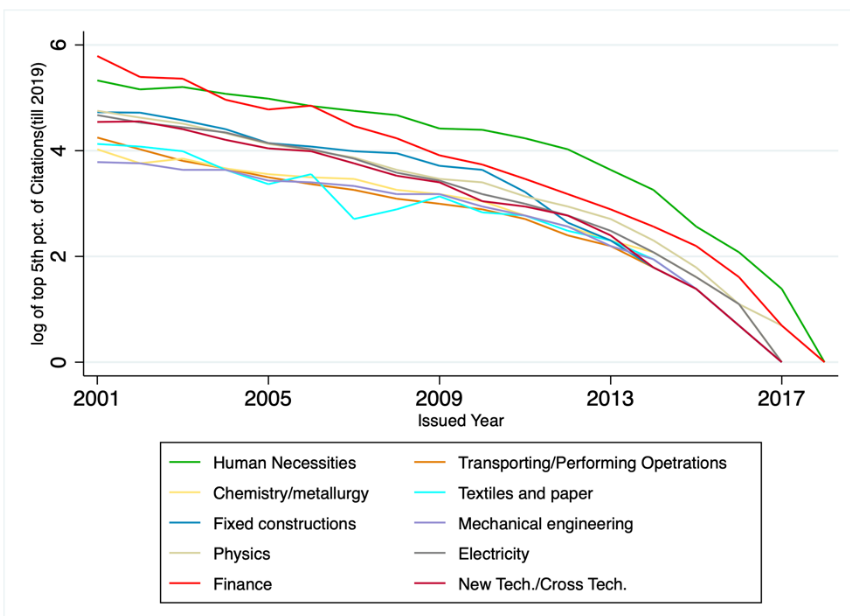
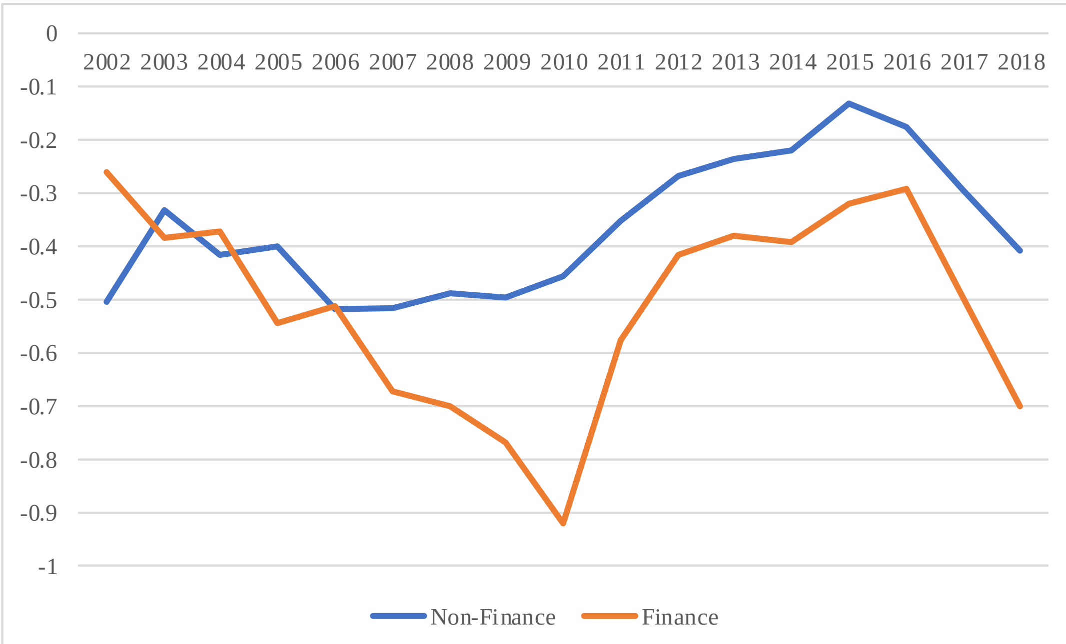


Figure A-2. The extent of patent change between application publication and award, over time. Panel A reports the change in the number of independent claims at the time of application publication and award, for finance and other patents. Panel B reports the change in the length of the shortest independent claim at these two points, for finance and other patents. The mean values are presented by year of award.

Panel A. Change in independent claim count.



Panel B. Change in independent claim length.

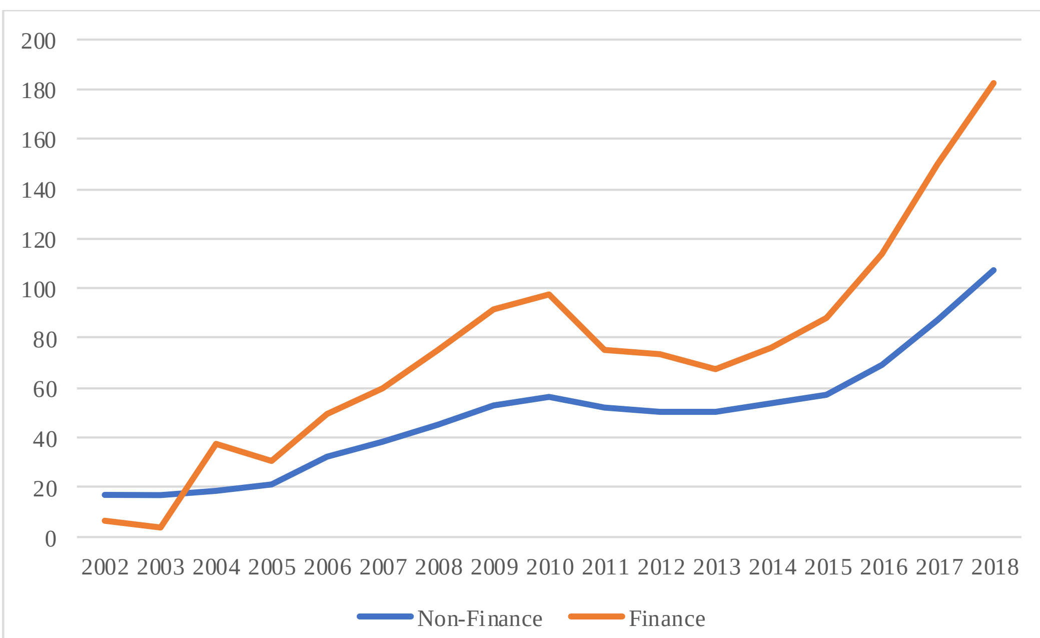


Figure A-3. Financial Patents Supervised Machine Learning Flow Chart. The figure presents how we predict financial patents using supervised machine learning. First, the labeled patents (financial data and non-financial data) are divided into training data (70%) and test data (30%). Then the machine is trained using the training data. Then different ML models are compared and the best model is selected as our prediction model. Finally, the unlabeled supplemental patents are used as the input of the prediction model, and the predicted labels of these patents are obtained.

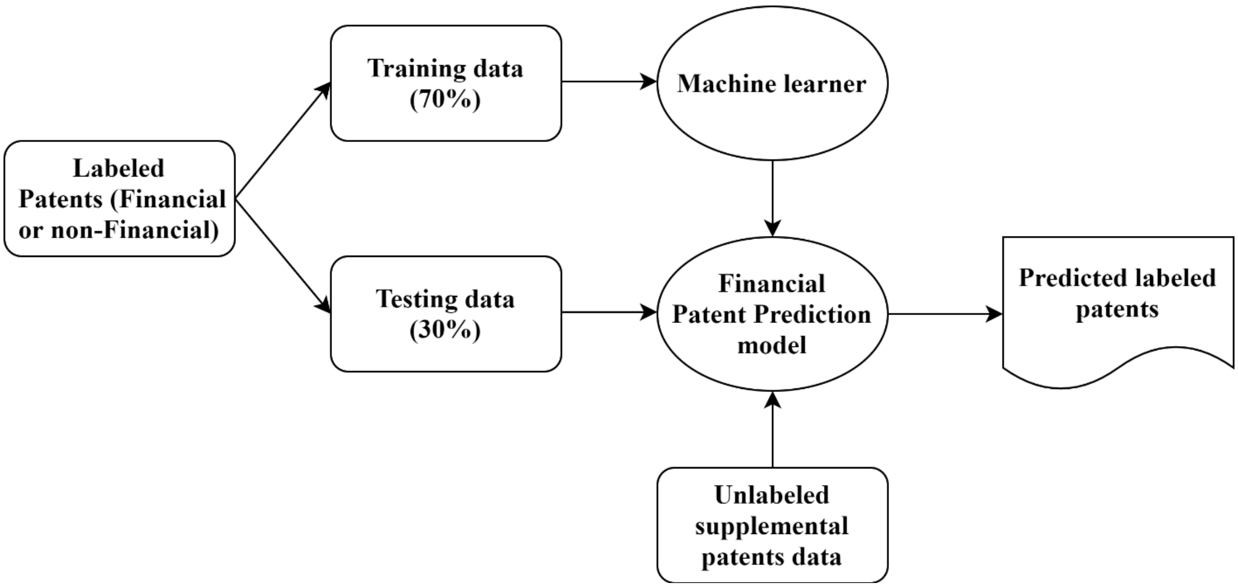


Figure A-4. Financial Patents Machine Learning Model Architecture. The figure presents the structure of our final machine-learning model. Compared to the text-only model, the text-inventor model slightly decreases sensitivity from 91.3 to 89.9 percent (a drop of 1.4 percentage points), but significantly improves specificity from 85.3 to 90.0 percent (an increase of 4.7 percentage points). With about 90 percent sensitivity and specificity, respectively, we consider this model to be reliable and scalable for predictions.

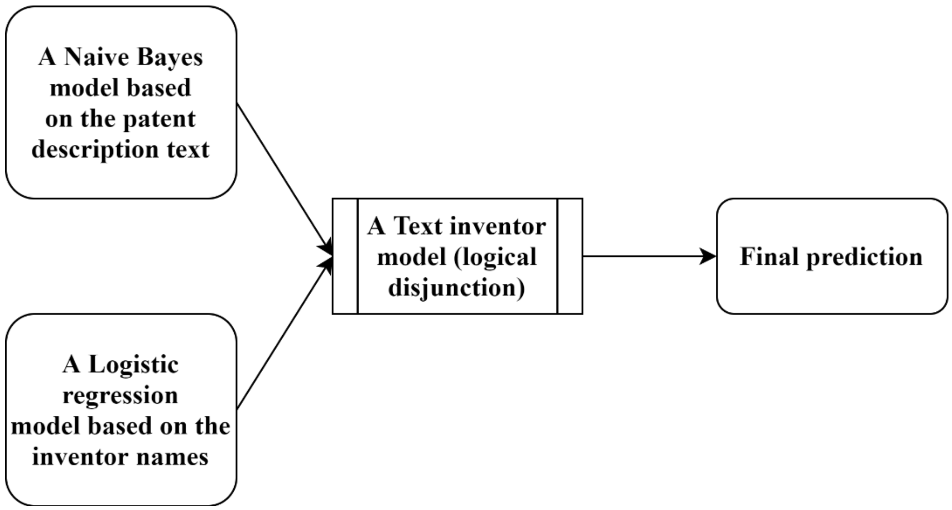


Figure A-5. Fuzzy Name Matching between Assignee Names and Capital IQ Names. This figure presents how we use a Levenshtein distance-based fuzzy name matching techniques to match the remainder of assignee names with 12 million firm names in the Capital IQ database. The Capital IQ database was divided into three3 subsets, with four million company names in each subset. After examining the data, we determine that matches in which the matching score is 0.95 or higher were so accurate that they could be adopted without further scrutiny. Similarly, matches with scores below 0.8 were so poor that they could be rejected outright. For matches with scores between 0.8 and 0.95, the results were inspected to determine which is appropriate. In the last step, the high confidence results are merged.

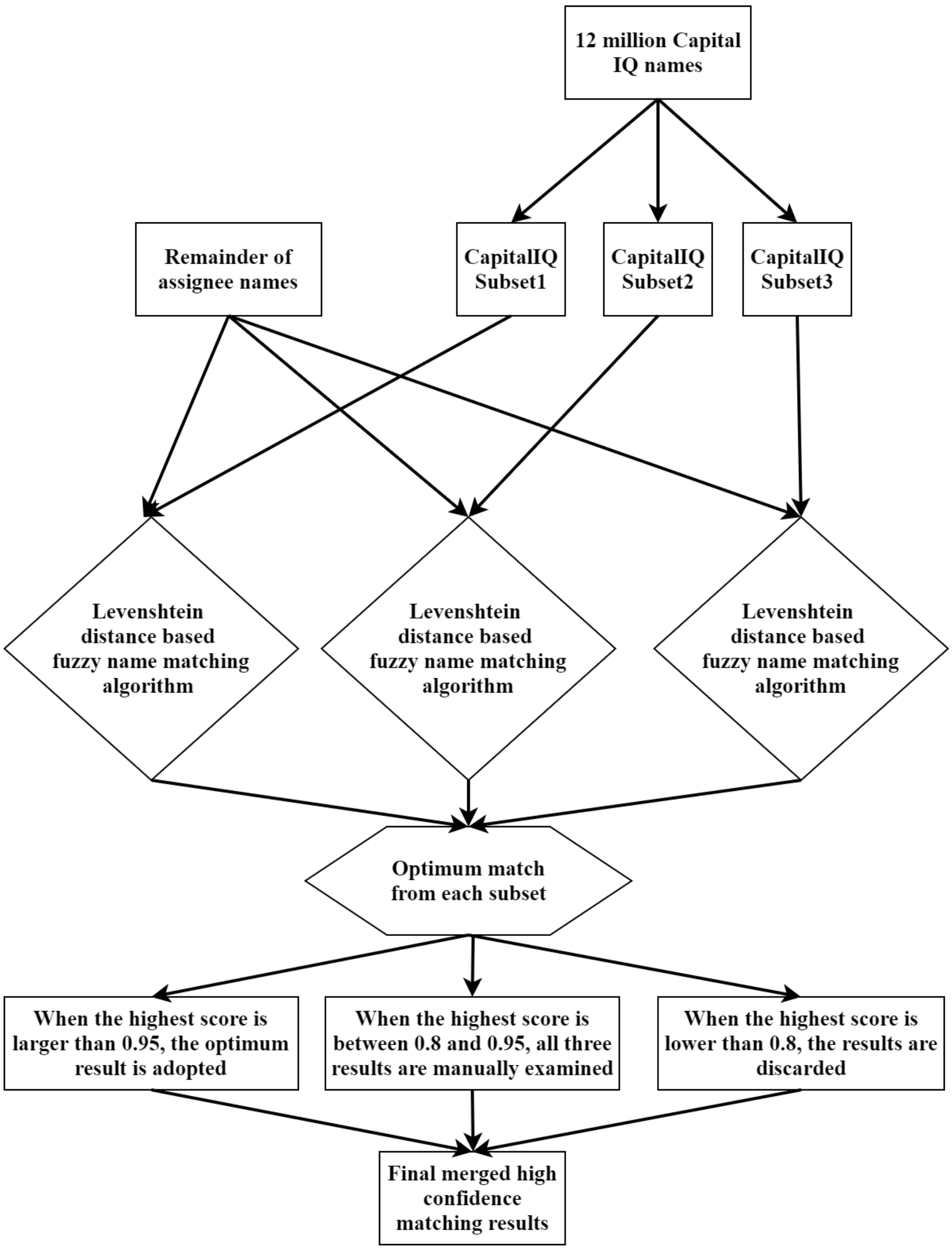


Figure A-6. An Overview of the Financial Dataset Construction Procedure. The first step in our process was to obtain additional patent-level data on financial patents from Derwent. We obtained from Patentsview the patent assignee type and a host of other information. Then the assignee's Capital IQ ID was obtained from either the UVA dataset or fuzzy name matching with Capital IQ company names. The detailed Capital IQ data were merged using a crosswalk file. Finally, we used keywords to describe the patent.

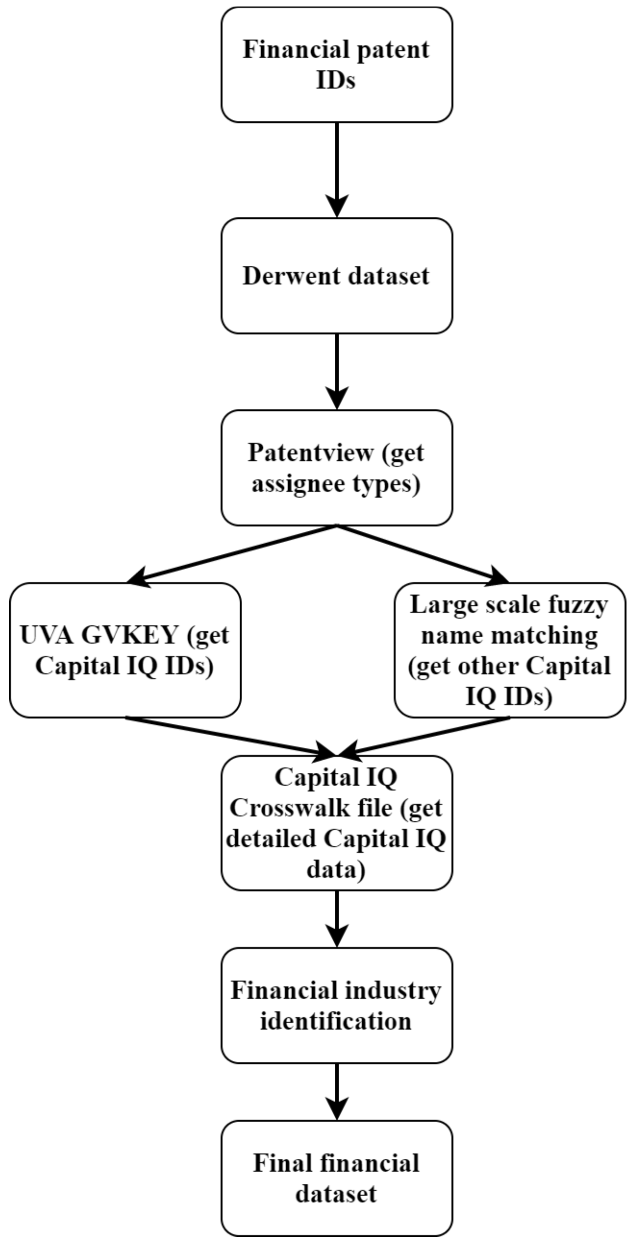
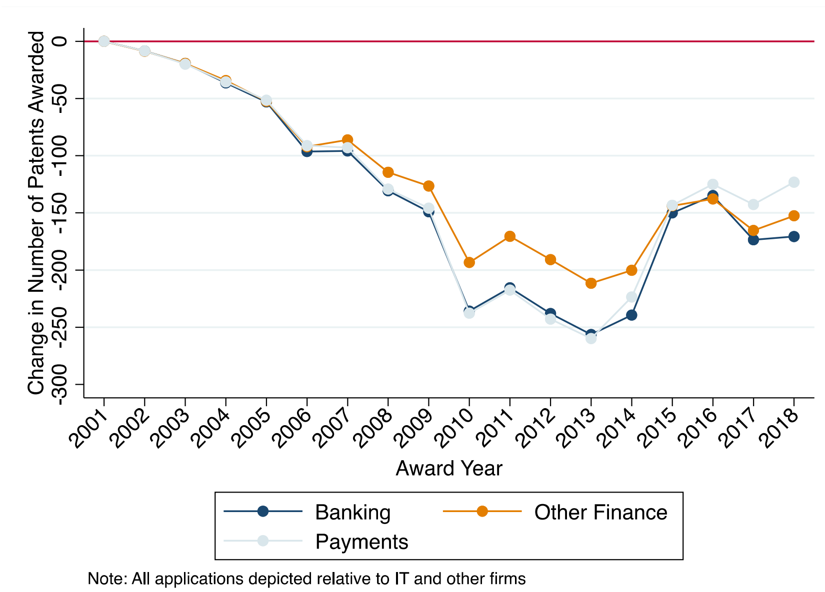


Figure A-7. Decomposition of the rise of financial patenting. The charts depict the results of a regression analysis of the rise of patenting, where the dependent variable is the number of financial patents awarded by each year-assignee firm industry-patent type-inventor location cell. The charts depict the interactions between year with assignee industry (Panel A; relative to "IT and Other Industries") and inventor location (Panel B, relative to "Non-U.S. Inventors").

Panel A: Financial patenting by assignee industry



Panel B: Financial patenting by geography

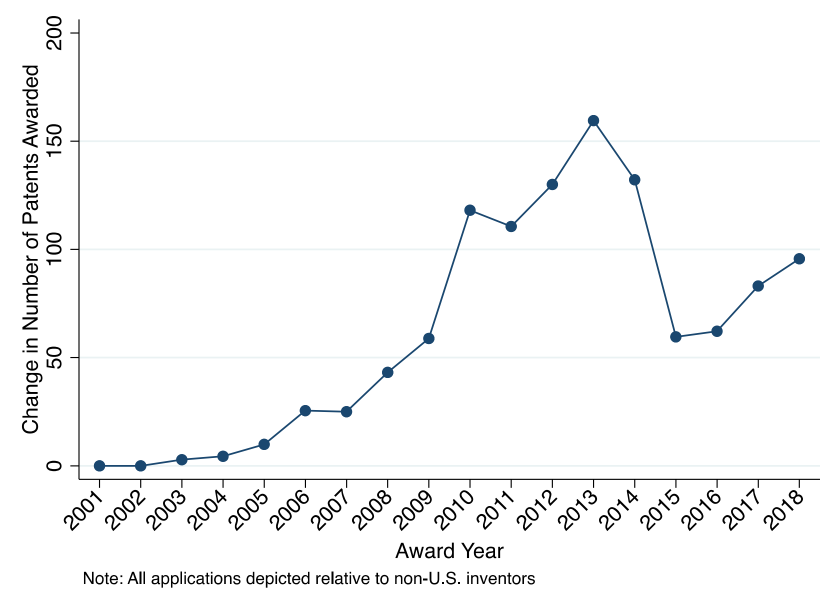


Figure A-8. Trends in patent citations to academic articles in finance patents. Panel A presents the number of academic citations per finance patent over time, for publications in business, economics, and finance, information technology, and other fields, by application year, normalized by the number of academic citations in non-finance patents. Each series is set to 100 for applications in the year 2000. Panel B and depicts the results of a regression analysis of the overall trends in patent citations to academic articles by banks over time, where the dependent variables are the number of academic citations (blue line) and the number of citations to business/economics/finance journals (orange line) in these patents assigned to banks, respectively. Both regressions include controls for patent type, inventor location, and assignee characteristics. The charts depict the interactions between the application year with the banks (relative to the other assignees and with 2001 normalized as zero).

Panel A: Normalized academic citations, by application year and academic publication type.

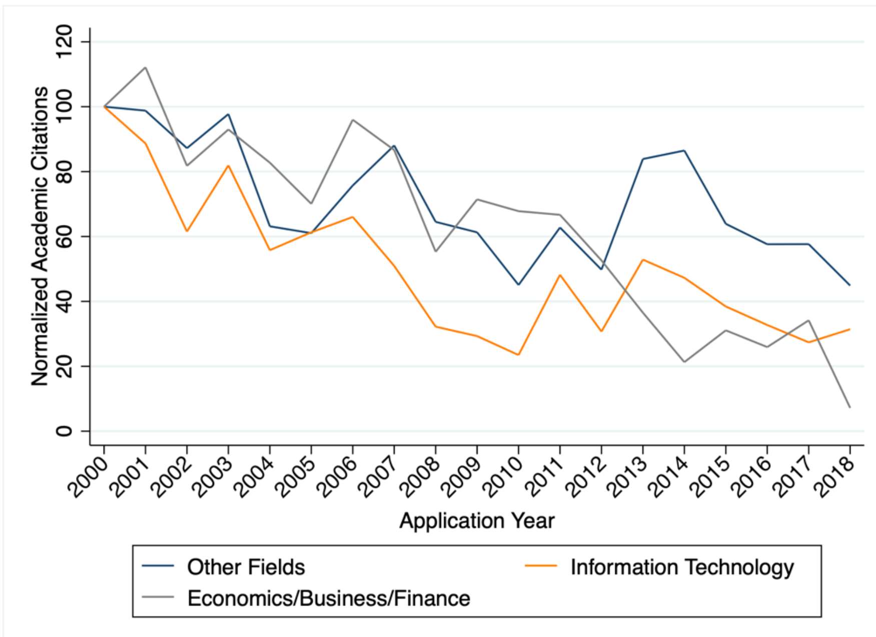


Figure A-8 (continued).

Panel B: Academic article citations in finance patents by Banks over time (**relative to other firms**)

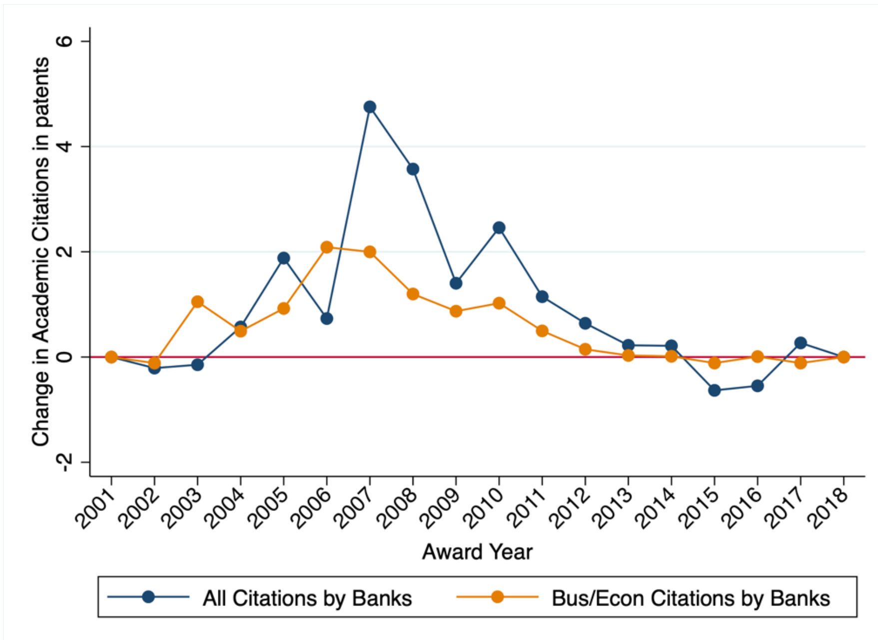


Table A-1. The extent of patent change between application publication and award. The table reports the number of independent claims at the time of application publication and award, the length of the shortest independent claim at these two points, and the change in these measures for finance and non-patents patents. The sample consists of all patents applied for between 2000 and 2014, and issued by February 2019 with an original review by the USPYO. It reports as well the significance of t-tests of the equality of these measures for finance and non-finance patents. * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

	Finance Patents	*Non-Finance Patents*
Application publication		
Count of independent claims	3.60	3.00***
Length of shortest independent claim	117.60	111.52**
Patent		
Count of independent claims	3.07	2.66***
Length of shortest independent claim	201.18	160.55***
Change, count of independent claims	-0.53	-0.33***
Change, length of shortest independent claim	83.58	49.04***
Count of patents	15,922	2,600,032

Table A-2. Comparison of the finance patent samples in Lerner (2002) and this paper. Information is derived from Patentsview, as well as the methodologies described in the paper.

	Lerner (2002) sample	*This sample*
Number of patents:	445	24,255
Patent age:		
First Application Year	1968	2000
Last Application Year	1999	2018
First Award Year	1971	2001
Last Award Year	2000	2019
Median Application Year	1995	2009
Median Award Year	1998	2013
First inventor foreign:	13.9%	21.0%
First inventor U.S. location:		
East North Central	10.4%	14.1%
East South Central	0.3%	0.6%
Middle Atlantic	27.4%	16.7%
Mountain	4.2%	7.1%
New England	10.4%	7.3%
Pacific	23.0%	27.5%
South Atlantic	15.7%	15.4%
West North Central	2.6%	4.4%
West South Central	6.0%	6.9%
Assignee type:		
U.S. corporation	62.5%	81.3%
Foreign corporation	12.6%	17.4%
Individual	24.9%	8.7%
U.S. government	0.0%	0.1%
Foreign government	0.0%	0.0%
U.S. university	0.0%	0.2%
Foreign university	0.0%	0.1%
Assignee corporate type:		
Banking	18.5%	7.5%
Capital markets	18.5%	7.6%
Other finance	10.7%	8.6%
IT	33.8%	39.1%
Payments	3.9%	10.3%
Other	14.6%	26.9%
Mean impact:		
Citation weight	1.97	1.25
Kogan et al. weight	63.41	23.61
Kelly et al. weight	2.62	0.86

Top 3 assignees:	Merrill Lynch	Bank of America
	Citigroup	Trading Technologies International
	Hitachi	Visa

Note: The assignment of patentee type differs slightly from Lerner (2002), as this classification is now based on USPTO reporting in Patentsview. The 2002 paper classified patents based on the author's own research. In particular, a small number of patents that were assigned to holding companies associated with a single inventor were classified in that paper as being individual patents, but by the USPTO (and Patentsview) as corporate ones.

Table A-3: List of keywords.

Accounting	**Consumer Banking**	**Communications**	**Cryptocurrencies**	**Currency**	**Investment Banking**
Accounting	Bridge Finance	Broadcast	Altcoin	Currency Conversion	Asset Analysis
Accounts Payable	Commercial Loan	Broadcasts	Bitcoin	Exchange Rate	Asset Characterization
Accounts Payables	Covenant	Communication	Blockchain	Foreign Exchange	Bid Ask
Accounts Receivable	Debtor Finance	Communications	Cryptocurrency	Forex	Bond
Accounts Receivables	Debtor In Possession	Message	Distributed Ledger	Swap	Call Option
Audit	Default	Messages	Initial Coin Offering		Chinese Wall
Auditor	Event	News Feed	Token		Derivative
Bookkeeper	Indicator Lending Rate	News Feeds			Dummy Order
Budget	Interest Coverage				Dummy Orders
Budgeting	Letter Of Credit				Gilt
Cash Flows	Line Of Credit				Hair Cut

Controller	Material Adverse Change				Hedge Fund
FIFO	Sweep Account				Hidden Liquidity
Financial Controls	Term Loan				Initial Public Offering
First In First Out	Zero Balance Account				Liquidity Pool
Forecasting					Liquidity Provider
Free Cash Flows					Margin
GAAP					Moving Average
Generally Accepted Accounting Principles					Option
Gross Margin					Order Book
Information System					Price Level
Interest Coverage					Price Levels
Inventory					Private Equity
Last In First Out					Put Option

LIFO					Short Selling
Net Present Value					Trading Protocol
Net Working Capital					Trading Protocols
Payables					Valuation
Payback					
Payroll Taxes					
Quick Ratio					
Working Capital					

Table A-3 (continued).

Insurance	Payments	Real Estate	Retail Banking	Security	Wealth Management
Actuarial	Authorized	Appraisal	ATM	Authentic	Active Management
Auto Insurance	Card Reader	Cap Rate	Automatic Teller Machine	Authenticate	Asset Allocation
Beneficiary	Cash Register	Closing Costs	Availability Policy	Authenticating	Asset Class
Catastrophe Bond	Contactless	Closing Fee	Balance Transfer	Biometric	Back-End Load
Catastrophe Loss	Credit Transaction	Conforming Loan	Certificate Of Deposit	Cipher	Benchmark
Claims Adjustment	Customer	Cumulative Loan To Value	Check	Ciphers	Capital Appreciation
Coinsurance	Debit Transaction	Deed	Checking	Credential	Capital Preservation
Crash	Interbank Fee	Delinquency	Checks	Credentials	Custodian
Disability	Keypad	Dual Agency	Credit Score	Cryptographic	ETF
Driving Behavior	Kiosks	Easement	Direct Deposit	Decipher	Exchange Traded Fund
Driving Environment	Merchant	Eminent Domain	Direct Payroll Deposit	Deciphers	Financial Industry Regulatory Authority

Earned Premium	NFC	Escrow	Interbank Fee	Decrypt	FINRA
Home Insurance	Payment	Eviction	Money Market	Decryption	Front-End Load
Homeowners Insurance	Point Of Sale	Foreclosure	NOW Account	Detection	Index Fund
Indemnity	POS	Home Equity	Online Banking	Encrypt	Individual Retirement Account
Insurance Risk		Home Warranty	Overdraft	Encryption	Mutual Funds
Life Insurance		Jumbo Loan	Passbook	Fraud	Prospectus
Life Settlement		Loan To Value	Savings	Fraudulent	Prospectuses
Long-Term Care		Mortgage	Student Loan	Identifier	Target Date Fund
Malpractice		Non-Conforming Loan	Time Deposit	Identity	Tax Avoidance
Reinsurance		Prepayment	Withdrawal Fee	Public Key	Tax Benefits
Structured Settlement		Real Estate Investment Trust		Secure Key	Tax Cost
Term Insurance		Realtor		Security	Tax Costs
Umbrella Liability		Refinancing		Spoofing	Tax Deduction

Vehicle Damage		REIT		Symmetric Key	Tax Deductions
		Tax Lien		Theft	Wrap Fee
		Title Search		Token	
		Zoning		Verify	

Table A-4. Searching strategy for patent categorization. We search each section of the patent in sequence, for those patents without a keyword match in the earlier sections. We classify the remaining 345 patents without a keyword match through a manual review of the patent text.

	Section of the Patent Examined			
	Abstract	*First 100 Words of Background*	*Entirety of Background Section*	*Entirety of Patent Text*
Patents Searched	24288	5062	2107	1030
Keywords Found:				
0	5062	2107	1030	345
1	9179	1891	321	11
2	6805	866	263	28
3	2606	166	244	70
4	555	30	120	122
5	74	2	64	140
6	6	0	53	146
7	1	0	9	115
8	0	0	3	42
9	0	0	0	8
10	0	0	0	3

Table A-5. Number of keywords found. The table reports the number of cases with zero, one, and more than one keywords, and the mean number of keywords found.

Patent Section Examined:	*Total Search Space*	*# with 0 Keywords*	*# with 1 Keyword*	*# with >1 Keyword*	*Mean Keyword Count for >1 Cases*
Abstract	24288	5062	9179	10047	2.39
First 100 Words of Background	5062	2107	1891	1064	2.22
Entirety of Background Section	2107	1030	321	756	3.26
Entirety of Patent Text	1030	345	11	674	5.30

Table A-6. Decomposition of the rise of financial patenting. The table presents results of a regression analysis of the finance patenting, where the dependent variable is the number of financial patents awarded in each year-assignee industry-patent type-inventor location cell. The table reports the results of F-tests of the joint significance of the various sets of independent variables.

Set of Independent Variables	*F-statistic*	*p-Value*
Year Fixed Effects	34.47	0.000
Assignee Industry Fixed Effects	110.82	0.000
Patent Type Fixed Effects	17.00	0.000
Inventor Location Fixed Effect	216.67	0.000
Year * Assignee Industry Fixed Effects	6.43	0.000
Year * Patent Type Fixed Effects	1.37	0.081
Year * Inventor Location Fixed Effects	11.45	0.000

Table A-7. Keywords associated with finance patents that we designated as consumer-oriented.

401k or 401(k)
Annuity or annuities
ATM or teller machine
Auto[mobile] insurance or car insurance
Auto[mobile] loan
College savings
Credit card
Credit report
Credit score
Customer
Debit card
Defined benefit
Defined contribution
e-Commerce
Financial adviser
Financial literacy
Health insurance
Home equity
Homeowner's insurance
Identity theft
Individual
Life insurance
Lottery payment
Medical loan or medical debt
Mobile phone
Mutual fund
Payday loan
Pension
Prepaid card
Policy holder or policyholder
Renter's insurance
Retail
Retirement account
Reverse mortgage
Savings account
Social security
Student loan or student debt
Unemployment insurance

Table A-8. Correlation between patent characteristics. The construction of the software measure is described in the text. The rows present the mean of the software measure in the same, the correlation of the software variable with the application and award date, the assignee industry, and interactions. * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Mean	86.5%
Correlation coefficient between patent type and…	
Application date	0.137***
Award date	0.146***
Assignee in banking industry	0.020**
Assignee in capital markets	0.068***
Assignee in IT, payments, or other	-0.071***
Correlation of IT/payment/other assignee and date for software patents	
Application date	-0.024***
Award date	-0.026***

Table A-9. Most frequently cited academic journals in finance patents. The table present the ten journals most frequently cited in finance patents applied for between 2000 and 2018 and awarded by February 2019. In addition to the journal citations, there are 257 citations to working papers archived at www.ssrn.org. The prominent role of the *Journal of Animal Sciences* reflects the presence of one dozen patents that are continuations (or continuations-in-part) of a single application originally filed by Micro Beef Technologies, relating to an accounting system for cattle farms. Each of the patents cites an (almost identical) list of approximately 40 papers from the *Journal of Animal Science*.

Journal Name	*Number of Citations*
Communications of the ACM	949
Journal of Finance	633
Journal of Animal Science	499
Financial Analysts Journal	363
IEEE Computer	301
Journal of Portfolio Management	279
ABA Banking Journal	242
Computers & Security	216
Journal of Financial Economics	191
Management Science	190

Table A-10. Number of academic citations in finance patents and all patents. The table presents the mean number of citations to academic output, the number in publications with an above-median impact factor, the number in publications of various types (all business, economics, and finance journals, all business, economics, and finance journals with an above-median impact factor, and "Top 3" finance journals), and the lag between article publication and patent application filing. The totals are reports for finance patents, all patents, and all patents in the 53 four-digit CPC patent classes in which universities most frequently file patents. All analyses use patents applied for between 2000 and 2018 and awarded by February 2019. * denotes statistical significance of the differences in t-tests at the 10% level; ** at the 5% level; and *** at the 1% level.

	Financial Patents	*All Other Patents*	*All Other Patents in Academic Classes*
Total Citations	2.45	6.17***	10.36***
Total Citations to High-Impact Factor Journals	0.07	1.38***	2.53***
Total Citations to Business/Economics/Finance Journals	0.54	0.02***	0.02***
Total Citations to High-Impact Bus/Econ/Fin Journals	0.07	0.00***	0.00***
Total Citations to Top 3 Finance Journals	0.04	0.00***	0.00***
Article-Patent Application Lag (years)	9.38	10.50***	10.02***
Number of Observations	24,255	3,781,439	1,823.420

Table A-11. OLS regression analyses of academic citations and patent characteristics. The sample consists of all patents applied for between 2000 and 2018 and awarded by February 2019. The dependent variables are the number of academic citations in these patents, the number of citations to business, economics, and finance journals, the number to Top 3 finance journals, and the mean age of the citations in each patent (years between the article publication and patent application date). In Panel A, the key independent variable is a dummy whether the patent is financial; in Panel B, the key independent variables are dummies whether the patent is financial, the assignee is a U.S. corporation, a foreign corporation, a U.S. university or another type, and the interactions between assignee type and the financial patent dummies (other assignees is the omitted category); and in Panel C, the key independent variables are dummies whether the patent is financial, the assignee is venture backed, and the interactions between the dummies. All regressions control for the time period and inventor location. Robust standard errors are in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

	Academic Citations		*Bus/Econ/Fin Citations*		*Top 3 Citations*		*Citation Age*
Panel A							
Financial patent	-8.15***		0.71***		0.07***		-0.63***
	[0.45]		[0.01]		[0.001]		[0.13]
Panel B							
Financial patent	-1.70		0.47***		0.04***		-2.63**
	[1.36]		[0.02]		[0.003]		[1.24]
U.S. corporation	5.98***		0.04***		0.0001		-1.63***
	[0.16]		[0.002]		[0.0003]		[0.10]
Foreign corporation	2.93***		0.02***		-0.0001		-2.42***
	[0.23]		[0.0004]		[0.0004]		[0.11]
U.S. university	44.83***		0.04***		0.0001		-1.36***
	[0.31]		[0.005]		[0.0006]		[0.11]
Financial * U.S. corporation	-6.11***		0.28***		0.043***		2.04
	[1.44]		[0.02]		[0.000]		[1.25]
Financial * Foreign corporation	-3.10		0.05		-0.01***		1.44
	[2.63]		[0.05]		[0.005]		[1.38]
Financial * U.S. university	-36.23***		0.37***		0.03***		2.59
	[7.41]		[0.13]		[0.01]		[1.86]
Panel C							
Financial patent	-8.06***		0.80***		0.08***		-0.36***
	[0.52]		[0.01]		[0.0001]		[0.13]
Venture-backed firm	9.82***		0.02***		-0.0003		0.42***
	[0.21]		[0.004]		[0.0004]		[0.05]
Financial * Venture-backed	-8.67***		-0.02		0.05***		-3.78***
	[1.95]		[0.03]		[0.004]		[0.50]

Table A-12. Financial patenting in three key regions. Panel A presents the characteristics of patents applied for in each five-year period in San Jose-San Francisco-Oakland CSA; Panel B in the New York-Newark CSA; and Panel C in the South Atlantic and East North Central U.S. Census divisions. The table presents for finance patents applied for between 2000 and 2018 and awarded by February 2019 the share of all finance patents applied for from the region, the share of all finance patents assigned to a CSA, and the share of all finance patents assigned to a firm of a given type. We run a regression using each CSA in each five-year period as an observation, with the patent share in a given five-year period as the dependent variable and independent variables controlling for the CSA, the time tend, the interaction of these two measures, and various demographic characteristics of the CSA in that period. The t-statistic is from the interaction term. All shares are computed using patent counts, citation weights, and Kogan et al. (2017) weights. We assign patents based on the location of the first inventor.

Table A-12 (continued).

Panel A: San Jose-San Francisco-Oakland, CA CSA.

	2000-04	*2005-09*	*2010-14*	*2015-18*	*t-stat*
Unweighted					
Share of all patenting	8.5%	10.7%	15.7%	18.3%	20.37
Share of all CSA patenting	14.2%	16.9%	23.2%	28.0%	22.01
Normalized by CSA patenting of that type					
Small firms	19.5%	18.6%	21.4%	25.0%	4.11
Medium firms	18.2%	28.8%	34.0%	48.6%	16.00
Large firms	10.7%	11.0%	26.0%	22.9%	4.55
SIFIs	3.7%	3.6%	6.2%	6.4%	4.42
Banking industry	4.6%	3.3%	6.3%	6.6%	3.03
Other finance industry	8.1%	4.2%	6.5%	2.9%	-3.67
Payment industry	15.3%	39.0%	58.0%	63.9%	8.02
IT/other industry	16.1%	18.5%	22.3%	23.5%	8.93
Cite weighted					
Share of all patenting	11.5%	16.2%	21.3%	21.5%	5.66
Share of all CSA patenting	16.7%	23.4%	28.4%	29.6%	5.71
Normalized by CSA patenting of that type					
Small firms	21.2%	24.9%	26.9%	20.9%	-0.10
Medium firms	21.3%	45.8%	49.5%	72.4%	12.73
Large firms	10.2%	14.2%	30.6%	11.4%	0.58
SIFIs	6.2%	7.1%	8.4%	15.7%	4.34
Banking industry	5.4%	5.6%	8.9%	14.5%	5.52
Other finance industry	9.4%	5.3%	4.2%	0.0%	-7.97
Payment industry	26.4%	60.5%	72.1%	76.8%	4.81
IT/other industry	17.8%	21.7%	24.0%	33.8%	7.87
Kogan weighted					
Share of all patenting	8.4%	14.8%	25.0%	25.6%	7.41
Share of all CSA patenting	10.7%	18.7%	32.6%	34.4%	8.64
Normalized by CSA patenting of that type					
Small firms	33.9%	42.2%	16.7%	0.0%	-4.07
Medium firms	19.6%	55.5%	38.0%	42.1%	1.15
Large firms	8.1%	6.3%	31.7%	32.6%	6.32
SIFIs	6.4%	5.1%	13.0%	15.1%	6.28
Banking industry	9.2%	5.9%	13.9%	14.9%	3.57
Other finance industry	2.5%	1.9%	3.5%	0.4%	-1.06
Payment industry	11.4%	72.7%	63.4%	64.6%	2.08
IT/other industry	32.6%	35.6%	58.5%	40.4%	1.46

Table A-12 (continued).

Panel B: New York-Newark CSA.

	2000-04	*2005-09*	*2010-14*	*2015-18*	*t-stat*
Unweighted					
Share of all patenting	13.4%	11.6%	9.5%	5.7%	-8.49
Share of all CSA patenting	22.4%	18.4%	14.2%	8.7%	-15.74
Normalized by CSA patenting of that type					
Small firms	14.4%	16.5%	14.3%	25.0%	2.59
Medium firms	15.6%	11.6%	9.8%	6.2%	-14.46
Large firms	32.0%	23.2%	15.6%	5.6%	-33.64
SIFIs	63.3%	33.4%	24.1%	4.0%	-13.42
Banking industry	27.6%	18.0%	12.5%	6.0%	-22.74
Other finance industry	56.1%	46.2%	33.0%	4.4%	-7.71
Payment industry	11.1%	6.7%	6.8%	5.8%	-4.82
IT/other industry	16.7%	13.7%	11.6%	11.4%	-10.89
Cite weighted					
Share of all patenting	14.6%	7.8%	6.4%	5.7%	-5.04
Share of all CSA patenting	21.3%	11.3%	8.5%	7.8%	-5.01
Normalized by CSA patenting of that type					
Small firms	5.0%	6.5%	22.7%	42.5%	6.43
Medium firms	16.2%	6.5%	4.1%	6.0%	-3.11
Large firms	33.1%	12.3%	7.1%	1.7%	-5.86
SIFIs	50.8%	12.4%	7.1%	7.7%	-3.12
Banking industry	34.5%	12.3%	9.4%	14.7%	-2.13
Other finance industry	54.1%	33.8%	9.6%	0.0%	-14.64
Payment industry	17.0%	3.1%	3.2%	5.7%	-2.17
IT/other industry	16.0%	10.2%	9.6%	15.0%	-0.68
Kogan weighted					
Share of all patenting	34.6%	19.8%	14.4%	5.7%	-12.87
Share of all CSA patenting	44.2%	25.0%	18.9%	7.7%	-12.09
Normalized by CSA patenting of that type					
Small firms	28.2%	10.5%	6.6%	0.0%	-7.50
Medium firms	14.9%	12.9%	18.1%	12.0%	-0.90
Large firms	52.0%	29.1%	18.9%	6.5%	-12.70
SIFIs	57.7%	30.7%	24.0%	5.5%	-12.63
Banking industry	34.5%	19.2%	16.3%	6.0%	-11.90
Other finance industry	77.9%	65.8%	52.1%	4.8%	-5.64
Payment industry	16.1%	8.4%	13.2%	7.6%	-3.33
IT/other industry	7.4%	5.3%	5.8%	18.3%	-1.89

Table A-12 (continued).

Panel C: Charlotte-Concord CSA.

	2000-04	*2005-09*	*2010-14*	*2015-18*	*t-stat*
Unweighted					
Share of all patenting	0.3%	1.7%	2.3%	4.2%	13.52
Share of all CSA patenting	0.5%	2.7%	3.3%	6.5%	11.76
Normalized by CSA patenting of that type					
Small firms	0.0%	0.0%	0.0%	0.0%	-0.55
Medium firms	0.0%	0.2%	0.4%	0.3%	0.68
Large firms	0.7%	10.0%	11.0%	16.9%	8.36
SIFIs	2.3%	27.0%	36.1%	54.9%	16.63
Banking industry	3.1%	25.3%	33.1%	52.2%	17.95
Other finance industry	0.4%	1.0%	0.3%	1.0%	-0.75
Payment industry	0.0%	0.0%	0.6%	0.6%	1.54
IT/other industry	0.3%	0.3%	0.3%	0.7%	0.77
Cite weighted					
Share of all patenting	0.4%	1.5%	3.2%	1.6%	1.32
Share of all CSA patenting	0.6%	2.2%	4.3%	2.3%	1.31
Normalized by CSA patenting of that type					
Small firms	0.0%	0.0%	0.0%	0.0%	-0.60
Medium firms	0.0%	0.0%	0.0%	0.0%	0.16
Large firms	1.2%	9.0%	6.9%	4.7%	0.59
SIFIs	3.8%	32.3%	43.7%	63.0%	14.73
Banking industry	0.4%	2.2%	3.7%	2.3%	35.36
Other finance industry	0.8%	0.8%	0.0%	0.0%	-2.42
Payment industry	0.0%	0.0%	0.0%	0.0%	0.24
IT/other industry	0.2%	0.1%	3.2%	0.4%	0.64
Kogan weighted					
Share of all patenting	0.4%	11.0%	8.7%	13.7%	4.15
Share of all CSA patenting	0.5%	13.9%	11.4%	18.3%	4.69
Normalized by CSA patenting of that type					
Small firms	0.0%	0.0%	0.0%	0.0%	-0.25
Medium firms	0.0%	0.1%	3.8%	1.1%	1.33
Large firms	0.7%	18.5%	13.6%	22.8%	4.07
SIFIs	0.9%	22.9%	23.6%	39.5%	8.94
Banking industry	1.3%	26.8%	25.2%	39.2%	6.08
Other finance industry	0.0%	0.1%	0.0%	1.3%	0.32
Payment industry	0.0%	0.0%	3.3%	1.8%	2.31
IT/other industry	0.0%	0.0%	0.1%	0.1%	0.32

Table A-13. Financing patenting by U.S. region over time. The table presents the share of patenting by region for the nine U.S. Census regions. All analyses use patents applied for between 2000 and 2018 and awarded by February 2019. The table presents financial patents as a share of all patents, computed using patent counts, citation weights, and Kogan et al. (2017) weights. We assign patents based on the location of the first inventor.

	Patent Count				Citation Weighted				Kogan et al. Weighted			
	2000-04	*2005-09*	*2010-14*	*2015-18*	*2000-04*	*2005-09*	*2010-14*	*2015-18*	*2000-04*	*2005-09*	*2010-14*	*2015-18*
East North Central	8.2%	11.0%	13.0%	10.9%	9.2%	9.2%	13.6%	27.9%	4.7%	6.9%	6.2%	6.1%
East South Central	0.6%	0.6%	0.4%	0.3%	0.5%	0.6%	0.2%	0.2%	0.4%	0.2%	0.3%	0.1%
Middle Atlantic	15.6%	14.9%	12.0%	7.1%	16.4%	12.4%	13.7%	9.3%	42.4%	26.8%	19.3%	7.3%
Mountain	5.9%	5.9%	5.2%	5.3%	7.5%	5.8%	4.0%	2.8%	6.3%	5.6%	3.1%	2.7%
New England	6.4%	5.5%	6.0%	4.5%	6.5%	4.0%	4.0%	2.9%	4.7%	3.2%	3.9%	2.2%
Pacific	16.7%	19.2%	25.5%	26.9%	22.4%	27.4%	34.6%	32.6%	11.3%	19.0%	32.7%	33.5%
South Atlantic	11.2%	12.3%	11.7%	15.2%	12.5%	15.4%	11.8%	6.4%	15.1%	21.1%	16.9%	23.9%
West North Central	3.2%	4.0%	3.3%	3.3%	2.6%	4.0%	3.2%	1.0%	3.6%	4.8%	4.1%	7.2%
West South Central	5.4%	6.6%	4.8%	4.4%	5.6%	9.0%	5.5%	7.4%	5.8%	5.3%	2.8%	4.1%
Outside the US	26.8%	20.0%	18.1%	22.1%	16.8%	12.2%	9.4%	9.5%	5.7%	7.1%	10.7%	12.9%

Table A-14. OLS regression analyses of the impact of regulatory actions on financial patenting. Panel A uses observations at the state-industry (banks, other finance, payments, and IT/other)-patent type (banking, payments, and other)-application year (2000-18) level, for a total of 11,400 observations. The dependent variable is the number of patents in a given cell. The key independent variables are the count of number of banking enforcement actions in a given state in year t interacted with assignee industry and patent type. Panel B uses the same observations as Panel A, but the dependent variables is the number of average citations of patents in a given cell. The key independent variables are the count of number of banking enforcement actions in a given state in year t interacted with patent type. All regressions include fixed effects for time, state patent type, and assignee industry. Clustered standard errors (at the state-year level) are in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Panel A: State formal enforcement actions and financial patenting.

	Patent count		
	Time t	*Time t+1*	*Time t+2*
Enforcement Actions$_t$ x Bank Firms	-0.471***	-0.491***	-0.497***
	[0.087]	[0.095]	[0.105]
Enforcement Actions$_t$ x Other Finance Firms	-0.378***	-0.391***	-0.397***
	[0.085]	[0.097]	[0.109]
Enforcement Actions$_t$ x Payments Firms	-0.393***	-0.404***	-0.397***
	[0.064]	[0.069]	[0.075]
Enforcement Actions$_t$ x Banking Type	-0.063**	-0.074**	-0.087**
	[0.031]	[0.035]	[0.038]
Enforcement Actions$_t$ x Other Type	-0.004	-0.000	0.001
	[0.008]	[0.008]	[0.008]
Observations	11,400	11,400	11,400
R-squared	0.423	0.431	0.434
Time FEs	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Patent type FEs	Yes	Yes	Yes
Assignee industry FEs	Yes	Yes	Yes
Data sample period	2000-2018	2000-2018	2000-2018
Test Equality of Coefficients (F Statistic Reported)			
Interaction with Bank vs. IT/Other	29.50***	26.84***	22.43***
Interaction with Other Finance vs. IT/Other	19.77***	16.19***	13.17***
Interaction with Payments vs. IT/Other	37.26***	34.38***	28.31***
Interaction with Banking vs. Payment Type	4.06**	4.57**	5.17**
Interaction with Other vs. Payment Type	0.21	0.00	0.02

Table A-14 (continued).

Panel B: State formal enforcement actions and financial patent quality.

	Patent quality		
	Time t	*Time t+1*	*(Time t+2*
Enforcement Actions$_t$ x Banking Type	-0.006	-0.023	0.001
	[0.019]	[0.019]	[0.017]
Enforcement Actions$_t$ x Other Type	0.027	-0.004	0.026
	[0.031]	[0.030]	[0.031]
Enforcement Actions$_t$ x Payment Type	0.000	0.000	0.000
Observations	11,400	11,400	11,400
R-squared	0.158	0.159	0.160
Time FEs	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Patent type FEs	Yes	Yes	Yes
Assignee industry FEs	Yes	Yes	Yes
Data sample period	2000-2018	2000-2018	2000-2018
Test Equality of Coefficients (F Statistic Reported)			
Interaction with Banking vs. Payment Type	0.10	1.47	0.00
Interaction with Other vs. Payment Type	0.75	0.02	0.68

Table A-15. OLS regression analyses of the impact of regulatory actions on financial patenting, by patent type in given industries. Panel A and Panel B are identical to those in Table 7 and Panel A of Table A-14, but with the addition of interactions between the banking and payments industry dummies and the patent type dummy (consolidated into banking and non-banking and payments and non-payments respectively). Clustered standard errors (at the CSA level (Panel A) and state-year level (Panel B)) are in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

Panel A: CSA-Level regulatory burdens and financial patenting, by patent type in given industries.

	Patent count				
	(1)		*(2)*		*(3)*
∆ Capital Ratio x Banks x Banking Type	-2.754*				
	[1.529]				
∆ Capital Ratio x Payments x Payment Type	-0.061				
	[1.417]				
% MSR x Banks x Banking Type			-2.812		
			[1.727]		
% MSR x Payments x Payment Type			-1.069		
			[1.852]		
% OTS x Banks x Banking Type					-5.129**
					[2.499]
% OTS x Payments x Payment Type					-0.030
					[3.039]
Observations	1,452		1,452		1,452
R-squared	0.466		0.466		0.467
CSA FEs	Yes		Yes		Yes
Patent type FEs	Yes		Yes		Yes
Assignee industry FEs	Yes		Yes		Yes
Assignee industry x Patent type FEs	Yes		Yes		Yes
Data Sample Period	2008-15		2008-15		2008-15

Table A-15 (continued).

Panel B: State enforcement actions and financial patenting, by patent type in given industries.

	Patent count		
	Time t	*Time t+1*	*Time t+2*
Enforcement Actions$_t$ x Banks x Banking Type	-0.179***	-0.190***	-0.195***
	[0.028]	[0.030]	[0.031]
Enforcement Actions$_t$ x Payments x Payment Type	-0.035	-0.027	-0.011
	[0.036]	[0.041]	[0.047]
Observations	11,400	11,400	11,400
R-squared	0.362	0.364	0.365
Time FEs	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Patent type FEs	Yes	Yes	Yes
Assignee industry FEs	Yes	Yes	Yes
Assignee industry x Patent type FEs	Yes	Yes	Yes
Data Sample Period	2000-2018	2000-2018	2000-2018

Table A-16. The impact of technology progress on financial patenting. The table is identical to that in Table 8, but with the key independent variables being interactions between another four STSI technology indexes in a given state in year t and assignee industry. All regressions include fixed effects for time, state, patent type, and assignee industry. Clustered standard errors (at the state-year level) are in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

	Patent count						
	(1)		*(2)*		*(3)*		*(4)*
Technology Concentration x Payments Firms	0.038***						
	[0.015]						
Technology Concentration x IT/Other Firms	0.179***						
	[0.035]						
Entrepreneurial Capacity x Payments Firms			0.047***				
			[0.017]				
Entrepreneurial Capacity x IT/Other Firms			0.240***				
			[0.041]				
Technology Workforce x Payments Firms					0.035**		
					[0.014]		
Technology Workforce x IT/Other Firms					0.179***		
					[0.034]		
Human Capital Investment x Payments Firms							0.032***
							[0.009]
Human Capital Investment x IT/Other Firms							0.109***
							[0.024]
Observations	6,600		6,600		6,600		6,600
R-squared	0.395		0.402		0.390		0.362
Time FEs	Yes		Yes		Yes		Yes
State FEs	Yes		Yes		Yes		Yes
Patent type FEs	Yes		Yes		Yes		Yes
Assignee industry FEs	Yes		Yes		Yes		Yes
Data sample period	2008-18		2008-18		2008-18		2008-18
Test Equality of Coefficients (F Statistic Reported)							
Interaction with Payments vs. Bank	6.90***		7.12***		6.16**		12.23***
Interaction with IT/Other vs. Bank	26.52***		33.94***		27.09***		20.87***

Table A-17. Movement of financial patentees. Panel A reports the number of firms and the number of total patents awarded to these firms, divided into those that filed a successful financial patent application in 2000-04 but not 2015-18, those that did so in 2015-18 but not 2000-04, those that did so In both periods, and the subset that moved their modal location of patenting between these two periods. In Panel B, for the switchers only, the three most common departure and destination CSAs are also reported. We assign patents based on the location of the first inventor.

Panel A: Breakdown of firms and associated patents.

	Firms	*Total patents*
Firms that patented in 2000-04, but not in 2015-18	792	3876
Firms that patented in 2015-18, but not in 2000-04	306	1895
Firms that patented in 2000-04 and in 2015-18	130	16539
Of these, firms that shifted modal CSA	26	9137

Panel B: Departure and arrival city of switchers.

	Firms	*Total patents*
Three most frequently departed 2000-04 CSAs:		
New York-Newark, NY-NJ-CT-PA	9	8283
Denver-Aurora, CO	1	297
San Jose-San Francisco-Oakland, CA	3	188
Three most frequently arrived 2015-18 CSAs:		
San Jose-San Francisco-Oakland, CA	4	5562
Charlotte-Concord, NC-SC	1	652
Rochester-Austin, MN	1	589

Table A-18. Counterfactuals regarding the movement of financial patentees. The first two columns present the unweighted share of patent applications by CSA for the ten CSAs with the most financial patents overall for 2000-04 and 20015-18 (from Table 8). The third column presents the distribution of patenting in 2015-18 had the 29 firms that switched their modal location of financial patenting between 2000-04 and 2015-18 retained the distribution as it was in 2000-04. The fourth column presents the distribution of patenting in 2015-18 had all 130 firms that patented in 2000-04 and 2015-18 retained the distribution as it was in 2000-04. All analyses use patents applied for between 2000 and 2018 and awarded by February 2019.

	2000-04		2015-18		
	Actual		*Actual*	*If switchers stayed in place*	*If all continuers stayed in place*
San Jose-San Francisco-Oakland, CA	8.5%		18.3%	18.1%	13.5%
New York-Newark, NY-NJ-CT-PA	13.4%		5.7%	7.8%	8.4%
Chicago-Naperville, IL-IN-WI	3.4%		3.9%	3.9%	2.9%
Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	4.0%		4.0%	4.1%	4.2%
Cleveland-Akron-Canton, OH	2.4%		1.7%	1.6%	2.4%
Los Angeles-Long Beach, CA	2.4%		1.8%	1.9%	1.6%
Atlanta--Athens-Clarke County--Sandy Springs, GA	2.0%		2.8%	2.6%	2.4%
Seattle-Tacoma, WA	1.9%		1.8%	1.6%	1.9%
Denver-Aurora, CO	2.2%		1.3%	2.0%	2.4%
Charlotte-Concord, NC-SC	0.3%		4.2%	0.2%	0.2%

Table A-19. Probit regression analysis of the determinants of the movement of financial patentees. The sample consists of 130 firms that filed financial patents in 2000-04 and 2015-18. The dependent variable is a dummy indicating if the firm shifted its modal CSA for patent application filed in these two periods. The independent variables include dummies for firm industry (payments is the omitted category), whether the firm is venture-backed or publicly traded (all of the time of the first patent filing in the 2000-04 period), and whether its modal patenting location in 2000-04 were the New York or San Francisco CSAs, as well as the volume of finance venture capital investments in 2000 in the modal CSA. The observations are weighted by the number of patents filed in 2000-04. Robust standard errors are in brackets; * denotes statistical significance at the 10% level; ** at the 5% level; and *** at the 1% level.

	Did the firm switch CSAs?		
Is firm a bank?	0.609***	-0.170	0.659***
	[0.168]	[0.144]	[0.173]
Is firm other financial service?	-0.214	-1.149***	-0.334*
	[0.142]	[0.160]	[0.187]
Is firm IT or other?	-1.093***	-1.105***	-0.310**
	[0.112]	[0.111]	[0.140]
Is firm venture-backed?	-0.360	-0.296	0.216
	[0.485]	[0.495]	[0.417]
Is firm publicly traded?	-0.017	-0.713***	-0.712***
	[0.089]	[0.099]	[0.110]
Is modal patent in 2000-04 in NY CSA?		2.235***	1.928***
		[0.093]	[0.095]
Is modal patent in 2000-04 in SJ/SF CSA?		0.173*	-1.934***
		[0.104]	[0.228]
2000 Finance VC investments in modal CSA			0.002***
			[0.000]
Number of observations	130	130	130
Weighted observations	2176	2176	2176
p-Value, χ^2-test	0.000	0.000	0.000
Pseudo R^2	0.136	0.395	0.417