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How Technological Innovation Shapes Financial Innovation: Substitution Effects Versus Knowledge Diffusion

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Abstract

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Keywords: technological innovation, financial innovation, substitution effects, knowledge diffusion, patents, inventors, human capital
JEL Classification: O33, O16, O30, G30

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1. Introduction

Financial innovation plays a critical role in fostering economic growth (Silber, 1983; Merton, 1992; Laeven et al., 2015; Beck et al., 2016; Lerner et al., 2024). Such innovation stimulates the development of the financial sector by introducing new products and services that can improve risk sharing (Allen and Gale, 1994), better address the needs of customers (Tufano, 2003), and help complete securities markets (Duffie and Rahi, 1995; Elul, 1995; Grinblatt and Longstaff, 2000). Additionally, financial innovation can enhance the efficiency of capital allocation (Ross, 1976; Houston et al., 2010), thus helping to reduce frictions and costs associated with financing corporate investment and, ultimately, technological progress.

The existing literature provides theoretical, empirical, and historical perspectives on the co-evolution of technological and financial innovation, suggesting that these two innovation types are synergistically linked (e.g., Allen and Gale, 1994; Tufano, 2003; Frame and White, 2004; Laeven et al., 2015). Perhaps the most obvious explanation of this positive linkage is that financial market development can facilitate and guide technological innovation (e.g., Hsu et al., 2014; Clò et al., 2022). There is much evidence suggesting that financial sector development contributes positively to technological innovation. For instance, Mezzanotti and Simcoe (2023) examine the adverse effects of the 2008 financial crisis on technological innovation and high-tech firms. Chang et al. (2019) document that the development of markets for derivative securities (i.e., credit default swaps) contributed to the funding and development of high-tech industries. In addition, as shown by Lerner and Wulf (2007) and Zona (2016), the rise of stock-based executive compensation among research personnel helped strengthen incentives to invest in R&D and innovation.

Whether it is also true that technological progress itself drives financial innovation is less clear. The notion that technology does facilitate financial innovation is at least consistent with anecdotal evidence that new technologies are playing large and growing roles in the provision of financial services. For example, it is evident that innovations in digital computing, including AI and machine learning, are being increasingly used in areas such as mobile payments, algorithmic trading, and automated lending. Also, recent studies document the application of information technology, cloud computing, and blockchain to areas such as high-frequency trading (Jones, 2013; Kauffman et al., 2015), invoicing and payments (Cong and He, 2019; Cong et al., 2021), and robot-based or AI-based investing (Bartram et al., 2020). Nevertheless, despite the insights these studies provide about the growing connection between technology and finance, there remains relatively little systematic, large-scale evidence that speaks directly to the impact of technological innovation on financial innovation.

We posit that there are two main ways in which technological innovation can affect financial innovation. The first relates to the diffusion of technology-related knowledge that enhances firms' ability to implement financial innovation. A substantial body of research studies the transfer of technology-based knowledge across firms and industries, showing that downstream innovation can benefit from knowledge diffusion through reduced uncertainty, shorter research time, lower innovation costs, and other advantages (e.g., Mansfield, 1961; Rogers, 1962; Cohen and Levinthal, 1990; Caballero and Jaffe, 1993). Technology spillovers via knowledge diffusion are more prevalent among firms that operate in related fields or share technological foundations (Jaffe, 1986; Bloom et al., 2013). Thus, with the recent increase in the integration of financial products with other technological domains, financial innovation has likely become a more direct beneficiary of knowledge diffusion arising from technological innovation.

A second way in which technological innovation could impact financial innovation is via a "crowding out" effect. Firms that pursue financial innovation, like virtually all other firms, operate under resource constraints and need to strategically allocate key innovation inputs. For these financial innovating firms, the arrival of new technology can disrupt existing lines of innovation, reducing their future profitability (Christensen, 1997; Adner and Zemsky, 2005; Christensen et al., 2015) and increasing the relative attractiveness of new business opportunities not directly related to finance. As a result, firms may, in the aggregate, reallocate innovation efforts away from finance and towards non-financial domains, leading to an overall decline in financial innovation relative to other technological areas.

When technological advances alter the dynamic interplay between financial and non-financial innovation, this process naturally reshapes the demand for associated innovation inputs—most notably, inventor human capital. Prior research highlights that inventors are an essential prerequisite and a driving force for innovation (e.g., Becker, 1964; Romer, 1990; Jaffe and Trajtenberg, 2002; Kim and Marschke, 2005; Bhaskarabhatla et al., 2021; Matray, 2021). By recruiting inventors across different areas, firms can integrate new research capabilities, accelerating expansion in emerging technological spaces (Acs and Audretsch, 2003; Matray, 2021; Li and Wang, 2023). Therefore, if technological innovation leads to the substitution of financial innovation with non-financial innovation, a central mechanism may very well be that new technologies make it more economical for firms to hire inventor human capital in emerging, non-financial domains rather than financial ones.

In this paper, we use longitudinal data on patenting and inventor-level movements to investigate how technological innovation can shape financial innovation. A key element of our approach is that we exploit major waves of non-financial innovation, which represent rapid, dramatic increases in technology that may potentially lead to changes in financial innovation. Based on comprehensive data on U.S. patent flows and patent citation activity between 2005 and

2021, we use time-series segmentation methods to objectively characterize three major waves of non-financial innovation. The waves begin in different years—2007, 2014, and 2016—which enables us to study the waves' impact using interrupted time series (ITS) regression analysis. The ITS method is an empirical design that has been widely used across a variety of disciplines (e.g., social sciences, health sciences, and public policy) to estimate the effects of phenomena or interventions.[1] In our setting, ITS is an appropriate method to employ since the weekly frequency of our patent data allows us to credibly estimate both pre-event and post-event trends.

Our results indicate that, in the earlier part of the sample, substitution effects dominate in terms of both patenting and new employment of inventors. Specifically, following the onsets of the 2007 and 2014 non-financial innovation waves, financial patent applications by U.S. public firms experienced an aggregate decrease, both in absolute terms and as a proportion of overall patents. Importantly, we also document a substitution effect in the market's demand for financial inventors: the proportion of newly employed financial inventors relative to all newly hired inventors declined sharply after both wave starts, consistent with the notion that strategic shifts in inventor employment are a key mechanism through which firms realign their innovation focus.

Given the critical role that inventors play in driving innovation, economic constraints that limit firms' ability to access inventor human capital are likely to shape innovation outcomes and, consequently, how firms respond to technological change. Building on this insight, we next examine whether the economic frictions that firms face influence their ability to substitute financial inventors with non-financial ones. We focus on three key constraints that pertain to firms' ability to attract and recruit talent: (1) internal resource constraints; (2) financial constraints; and (3) labor-market constraints. We find that the decline in the proportion of newly hired financial inventors is

[1] For instance, ITS models have been used by studies within epidemiology (Bernal et al., 2017), healthcare (Hudson et al., 2019), psychology (Jebb et al., 2015), criminology (Sliva and Plassmeyer, 2021), and numerous other fields.

especially pronounced among firms that are less profitable or less financially constrained. This heterogeneity is consistent with the idea that firms experiencing a relaxation of internal resource constraints have stronger incentives to redirect innovation resources, and they have a greater ability to do so when financially unconstrained. Moreover, firms located near research universities, which benefit from better access to inventor talent across fields, exhibit a more substantial decline in the share of newly hired financial inventors (and, correspondingly, an increase in the share of non-financial inventors). This result suggests that access to an abundant supply of inventor human capital facilitates strategic shifts in inventor composition.

In contrast to the first two technological innovation waves, the most recent wave does not appear to be associated with a substitution away from financial patenting or the hiring of financial inventors. Indeed, the results show that, beginning in 2016, technological innovation generally has had no significant association with firms' subsequent financial innovation or their new employment of financial inventors. Additionally, we find that the average breadth of financial patents increased most sharply—both in level and slope—following the second technology wave. By the onset of the third wave, financial patents had become significantly broader, and high-breadth financial patents had become disproportionately more valuable in aggregate. We interpret these findings as indicative of a fundamental change in the nature of financial innovation in recent years (Lerner et al., 2024), reflecting an increasing integration of financial products with other technological domains such as digital computing (e.g., FinTech), biological sciences, e-commerce, and manufacturing. These changes have transformed the financial services landscape, enabling firms to switch among areas within the financial innovation space as financial patents become broader, more valuable, and more synergistically related to emerging technologies.

Our study contributes in several ways to an improved understanding of the interplay between financial and technological innovation. First, we help to fill a gap in the literature by providing some of the first large-scale evidence on how technological innovation relates to subsequent changes in financial innovation. The notion that technology and finance co-evolve in a synergistic manner has long been a theme in the literature (Allen and Gale, 1994; Tufano, 2003; Frame and White, 2004; Laeven et al., 2015), but our findings suggest that the two types of innovation can also sometimes interact in non-obvious ways. Indeed, over much of the sample period that we study, there is ample evidence that technological advancements are associated with the crowding-out of firms' financial innovation, perhaps by enabling them to pursue new, more profitable opportunities in non-finance domains.

Second, our cross-sectional analysis echoes arguments from earlier literature (Lerner, 2006; Lerner and Tufano, 2011; Bhaskarabhatla et al., 2021) and confirms that firm-level characteristics (e.g., profitability, financial constraints, and labor market constraints) play crucial roles in shaping financial innovation activity. In particular, firms' demand for financial inventors—who are arguably the single most important input into the financial innovation process—appears to respond to new technologies in ways that depend on both financial and non-financial constraints. While technological innovations may alleviate non-financial constraints, only firms that are financially unconstrained and have access to inventor talent will rationally choose to hire new inventors with specialized expertise to fully capitalize on such advancements. These findings support and extend the general conclusion emerging from prior research that a firm's financial and labor market resources are key determinants of its ability to drive innovation (Brown et al., 2009; Chava et al., 2013; Amore et al., 2013; Howell, 2017; Matray, 2021).

Lastly, the findings of our study contribute to a deeper understanding of the growing integration between finance and technology, a trend that has been well-documented in existing literature (e.g., Philippon, 2016; Chen et al., 2019; Thakor, 2020; Chemmanur et al., 2020). Our results point to a fundamental change in the nature of financial innovation in recent years. Whereas crowding-out effects appear to dominate in the earlier part of our sample period, the increasing convergence between finance and technology has likely enhanced the appeal of financial innovation and reduced the degree of substitution away from it.

The remainder of the paper is organized as follows. Section 2 develops our main hypotheses. Section 3 explains our empirical strategy. Section 4 outlines our sample construction, describes our data sources, and provides descriptive statistics. Section 5 presents our results. Section 6 concludes.

2. Hypothesis development

2.1. Substitution versus knowledge diffusion

We propose that financial innovation can be associated with technological innovation in two distinct and opposite ways. The first relates to technological spillovers and knowledge diffusion.[2] When technological innovation occurs, existing lines of innovation can benefit from the diffusion of knowledge by building on previous ideas, reducing uncertainty, and achieving success with fewer research inputs such as time and capital (e.g., Mansfield, 1961; Rogers, 1962; Cohen and Levinthal, 1990; Caballero and Jaffe, 1993). Additionally, such diffusion effects can be strengthened when firms operate in overlapping fields or share technological spaces (e.g., Jaffe, 1986; Bloom et al., 2013). In the case of financial innovation, diffusion effects may have become

[2] An extensive literature empirically documents knowledge spillovers using R&D and patenting activity. See, for instance, Jaffe, 1986; Jaffe et al., 1993; Majumdar and Venkataraman, 1998; Griffith et al., 2006; Bloom et al., 2013.

particularly important in recent years as the financial services sector has grown more deeply integrated with key technologies such as digital computing (see, e.g., studies of FinTech by Philippon, 2016; Chen et al., 2019; Thakor, 2020; Chemmanur et al., 2020).[3]

The second possible effect is substitution, whereby technological innovation may cause firms to de-prioritize financial innovation. Specifically, constraints on human capital or technical resources can limit the types of innovation that a firm can pursue. As a result, a firm with finite resources may be compelled to ration its investment spending, foregoing some worthwhile projects and focusing solely on those that are most profitable or least costly. However, significant technological advancements can create new, more profitable business opportunities (e.g., Bergek et al., 2013; Kang and Song, 2017).[4] These advancements can also reduce the future profitability of established innovation agendas by causing business disruption (Christensen, 1997; Adner and Zemsky, 2005; Christensen et al., 2015). Thus, firms that previously pursued financial innovation might find it beneficial to shift their focus to other business endeavors, thus leading to a "crowding out" of financial innovation activity. Accordingly, we propose the following two hypotheses:

H1a. (Diffusion effect) Financial innovation increases with technological innovation.

H1b. (Substitution effect) Financial innovation decreases with technological innovation.

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[3] Recent empirical studies have documented specific applications of new technologies to financial services, including high-frequency trading, mobile banking, cloud-based financial software, blockchain, and investment robo-advising (e.g., Jones, 2013; Kauffman et al., 2015; Cong and He, 2019; Bartram et al., 2020; Cong et al., 2021).

[4] One example in the context of financial innovation is the decline of automated teller machines (ATMs). As internet technologies enable online banking and digital-wallets, ATMs become less profitable, prompting innovators to shift away from ATM innovation toward other opportunities.

2.2. Inventor human capital and resource reallocation

When firms collectively adjust their innovation focus, this entails a systematic reallocation of innovation resources, giving rise to an aggregate change in the demand for associated inputs. The most important of these inputs into innovation is inventor human capital. Prior research suggests that adjusting inventor talent inputs and engaging with inventor labor markets is a key channel through which firms can implement their innovation strategies (Griliches, 1990; Teece, Pisano, and Shuen, 1997). By hiring inventors from diverse technological fields, firms gain access to novel knowledge, facilitating entry into new technological domains (Acs and Audretsch, 2003; Matray, 2021; Li and Wang, 2023). Therefore, when technological waves shape firms' innovation decisions—either by encouraging or discouraging financial innovation—the primary channel of adjustment is likely to be through changes in the demand for different types of inventors. We thus expect to observe aggregate changes in the hiring of financial inventors (i.e., inventors with recent experience in financial innovation) in response to changes in innovation focus.

H2a. (Diffusion effect) The hiring of financial inventors increases with technological innovation.

H2b. (Substitution effect) The hiring of financial inventors decreases with technological innovation.

2.3. Heterogeneity across firms

While technological waves may shape financial innovation through the two opposing effects discussed above, the net change in financial innovation can depend on the economic frictions that firms face. Most obviously, constraints on firms' access to inventor talent may limit their ability to adjust their innovation strategies and, in turn, affect how they respond to technological change. This insight motivates us to investigate how different types of firm-level constraints may moderate the impact of technological innovation on the hiring of financial inventors. Drawing on prior literature that links firm characteristics to financial innovation (e.g., Lerner, 2006), we focus on three specific types of constraints, as detailed below.

2.3.1. Operating performance

Operating performance serves as an important indicator of the internal resource constraints that firms face. Underperforming firms can struggle to achieve economies of scale, suffer from limited internal funding, and operate less efficiently (Audretsch, 1995; Davidsson et al., 2005; Jang and Park, 2011; Lee and Johnson, 2013). For such firms, financial innovation can be particularly appealing as it typically requires lower upfront input costs and offers relatively higher returns on R&D investment (Lerner and Tufano, 2011; Lerner et al., 2024). As a result, these underperforming firms may be more inclined to specialize in employing financial inventors to pursue financial innovation. In contrast, more profitable firms are likely to have already optimized their human capital allocation across a broader set of innovation areas. Such firms can also more easily capitalize on existing consumer demand for their products, and hence they have less incentive to shift focus away from their current innovation space and mix of inventor types.

However, a major wave of technological innovation can change the cost-profitability tradeoff between financial innovation and alternative business opportunities, thereby reshaping firms' demand for inventor talent. For the reasons outlined above, underperforming firms, compared to their better-performing counterparts, will be more responsive to these changes and more likely to adjust the composition of their inventor workforce. If the knowledge diffusion effect dominates, technological innovation may enhance the profitability of financial innovation, increasing demand for the inputs required to support it. In this case, underperforming firms may respond by hiring more financial inventors. On the other hand, if substitution effects are more important, technological advancements may diminish the comparative advantage of financial innovation, thereby increasing underperforming firms' demand for non-financial inventors. In this case, underperforming firms will pivot away from employing financial inventors and choose to hire more inventors who specialize in non-financial innovation.

2.3.2. Financial constraints

Another factor that may deter firms from acquiring inventor human capital is the presence of financial constraints. A substantial body of literature highlights that insufficient financial resources can cause firms to forego promising innovation opportunities (Hall and Lerner, 2010; Brown et al., 2012; Hottenrott and Peters, 2012) and limit their capacity to invest in necessary inventor human capital (Garmaise, 2008; Hut, 2019). In contrast, firms with better access to external financing are more capable of expanding innovation efforts (Brown et al., 2009; Chava et al., 2013; Amore et al., 2013; Howell, 2017), including increasing investment in highly-demanded talent (Bäurle et al., 2018). As a result, financially unconstrained firms have greater flexibility to reallocate inventor resources and shift their innovation focus in response to changing opportunities.

When technological innovation creates more profitable opportunities in new areas, it does not alleviate the financial constraints that some firms face. As such, it may be the case that only financially unconstrained firms can meaningfully employ new inventors and aggressively pursue new, highly profitable innovation opportunities. In the context of financial innovation, if technological advances primarily act as substitutes, financially unconstrained firms can respond to shifting demand by disproportionately hiring inventors in non-financial domains, while financially constrained firms may be unable to do so. Conversely, if technological advances enhance the profitability of financial innovation through knowledge diffusion, financially unconstrained firms are more likely to increase the hiring of financial inventors, whereas constrained firms may lack the capacity to respond in kind.

2.3.3. Labor market constraints

The new employment of inventors is also influenced by labor market frictions. Proximity to top-tier research universities (e.g., R1 institutions) provides firms with access to a steady supply of highly-skilled graduates—many of whom are potential future inventors—and facilitates connections with academic expertise and local innovation networks. Prior studies suggest that geographic clustering near universities fosters informal knowledge spillovers and collaborative research (Zucker, 1987; Audretsch and Feldman, 1996), and that firms located near leading research institutions are more likely to produce high-impact patents and experience faster technological progress (Azoulay et al., 2011). These findings highlight the importance of university-industry proximity as a key channel for accessing innovation inputs. Consequently, when a technological wave emerges, firms near research universities are better positioned to adapt their inventor composition accordingly, either by hiring more financial inventors if a technology wave leads to knowledge diffusion effects or by shifting toward non-financial inventors when substitution effects dominate.

Based upon the above discussion of the three types of constraints, we propose the following hypotheses:

H3a. (Diffusion effect) Following technological innovation, underperforming firms, less financially constrained firms, and firms closer to research universities exhibit greater increases in the hiring of financial inventors.

H3b. (Substitution effect) Following technological innovation, underperforming firms, less financially constrained firms, and firms closer to research universities exhibit greater declines in the hiring of financial inventors relative to the hiring of non-financial inventors.

3. Empirical design

To test our hypotheses, we identify major technological waves—periods of time in which technological, non-financial innovation exhibited a rapid and substantial increase. Using time-series segmentation methods, we objectively identify three major technological innovation waves (see Section 4.2). Each wave features a significant upswing in a specific technological innovation category with widespread impact, as measured by patent citations. For each wave, we track financial patenting activity following the start of the wave. Sections 4.1 and 4.2, respectively, provide details on how we identify financial patents and the onsets of the three technological waves.

To examine the effects of these technological innovation waves on financial innovation, we employ interrupted time series (ITS) analysis, a research design that is widely and increasingly used in various fields such as epidemiology (Bernal et al., 2017), healthcare (Hudson et al., 2019), psychology (Jebb et al., 2015), criminology (Sliva and Plassmeyer, 2021), public policy (Dee and Jacob, 2011) and ecology (Wauchope, et al., 2021). Comprehensive overviews of ITS methodology can be found in surveys such as Linden, A. (2015), Hategeka et al. (2020), Bernal et al. (2017), and Penfold and Zhang (2013), as well as in texts such as Morgan and Winship (2015) and

McDowall et al. (2019). Compared to other quasi-experiment methods like difference-in-differences (DID), the ITS method has two important distinguishing features. First, it does not necessarily require the use of a control group. Second, it typically uses higher-frequency observations over longer time windows, enabling the model to explicitly account for secular trends in the data.

ITS analysis enables the study of the impact of events or phenomena by incorporating the following factors into one regression model: (1) the baseline trend prior to any events; (2) the immediate effect of each event; and (3) the gradual impact of each event over time. Since it explicitly models pre-event and post-event trends, ITS analysis addresses the concern that pre-existing trends may disguise the true impact of an event. Compared to estimation methods that rely on simple pre-post comparisons, ITS regressions are more informative as they enable the detection of effects that emerge gradually over time.

ITS is particularly well-suited for our empirical setting on account of several considerations. First, we measure patenting activities at a high frequency (weekly) over a 15-year interval. ITS estimation is more powerful and less vulnerable to confounding historical events when the frequency of data points is higher (see, e.g., Shadish et al., 2002). This high frequency design yields a large number of observations before and after each of the three major events in our sample, an essential condition for obtaining valid inferences in the ITS model (Baicker and Svoronos, 2019). Second, since the United States Patent and Trademark Office (USPTO) discloses patent applications every week, the time series is well-balanced and does not require extrapolation or interpolation to fill in any gaps in the time series. Third, the weekly count of patent applications is an aggregate measure, which accords with the typical ITS requirement that observations are made at the population level. Lastly, ITS analysis can measure both immediate and delayed responses of financial innovation to the onset of intense technological innovation periods, which accounts for the fact that a patent application filing might not occur until some time after the underlying innovation takes place.

We implement an ITS model by estimating a segmented regression as specified in the following equation:

$$Y_t = \beta_0 + \beta_1 V_t + \sum_{k=1}^{N} \beta_{2,k} I_{t,k} + \sum_{k=1}^{N} \beta_{3,k} I_{t,k} X_{t,k} + \epsilon_t, \quad (1)$$

where Y_t is the main outcome variable in week t (e.g., the number and share of financial patent applications, the share of newly employed financial inventors, the average breadth of financial patents, or the total value of high-breadth financial patents); V_t is the number of weeks between week t and the beginning of the sample; $I_{t,k}$ is a binary variable equal to one if and only if week t is after event k (which corresponds in our setting to the onset of intense technological innovation period k); $X_{t,k}$ is the number of weeks between time t and the week of event k; and N is the total number of events. Here, the main coefficient of interest for each event k is $\beta_{2,k}$ which captures the event's immediate, short-run impact on the outcome variable. A positive coefficient $\beta_{2,k}$ implies that the outcome level increases immediately in the short run in response to event k. Note that the interaction term $I_{t,k}X_{t,k}$ equals zero for all weeks before and up to event k, and it equals 1 for the first week after the event, 2 for the second week after the event, 3 for the third week after the event, and so on. Therefore, the coefficient $\beta_{3,k}$ estimates the impact of event k on the outcome variable's trend. In estimating Eq. (1), we use Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors with the lag length set to five weeks. The main results remain robust when using alternative lag lengths of one, four, or six weeks, as reported in Table IA.1 of the Internet Appendix.

As further discussed in Sections 5.1 and 5.5, we conduct several validity and robustness tests for our ITS model. In particular, a key requirement for valid inference in ITS analysis is the stationarity of the time series (Jandoc, Burden, Mamdani, Lévesque, and Cadarette, 2015). We check the stationarity of our data by running Augmented Dickey–Fuller (ADF) tests. As detailed in Section 5, the results reject the null hypothesis that residual terms follow a unit-root process, confirming that our ITS analyses are not affected by nonstationarity. ITS inferences could also be invalidated if the events of interest are confounded by macroeconomic variables or other salient events. To address this concern, we conduct additional tests and confirm that our main ITS regression results are robust to the inclusion of various macroeconomic control variables such as GDP growth, price level, employment growth, trade openness, schooling, and weekly stock market return and volatility. In addition, landmark Supreme Court rulings such as Alice vs. CLS Bank International (2014) significantly influenced patenting activities by imposing limits on the patentability of software-related innovations. To rule out potential effects from such legal changes, we exclude software innovations from our sample and again confirm the robustness of our main findings. (See Section 5.5 for details of the above robustness and validity checks.)

4. Data and sample

4.1 Sample construction

We begin with the set of all U.S. patent applications filed between 2005 and 2019 that are published by 2021. Patent information is sourced from the full-text applications and grant filings available through the Bulk Data Storage System (BDSS) of the U.S. Patent and Trademark Office (USPTO) (https://bulkdata.uspto.gov/). From the BDSS data, we extract information on filing and disclosure dates, patent grant dates, applicants, assignees, and other related details. We exclude patent applications where the assignees are not U.S. entities[5]. Additionally, we obtain information on patent inventors from PatentsView (www.patentsview.org) and then merge the data with the USPTO sample.

To identify financial patent filings, we apply a straightforward, easily replicated approach that relies on text-based filtering to exclude any patent applications unlikely to be related to financial services.[6] For this purpose, we use a list of financial terms from Chen et al. (2019) and follow their filtering process to exclude non-financial patent applications. We then obtain IPC code information from BDSS and the PatentsView and use the information to further restrict our sample to financial patent applications that contain at least one IPC code from Class G or Class H. Out of 45,548 applications that remain after term filtering, 43,527 belong to these two patent classes. Additional details of the procedure for identifying financial patent applications are provided in the Appendix.

Next, we merge the remaining financial patent applications with Compustat using the procedure outlined in Chen et al. (2023), which combines string matching, manual verification, and machine learning algorithms to construct a crosswalk between USPTO patent assignees and Compustat firms (see the Appendix for further details.) This crosswalk enables us to identify firms engaged in financial innovation and to trace the Compustat firms that employ individual inventors of financial patents. This, in turn, facilitates analyses of how the employment of financial inventors responds to technological innovation and how these responses vary across firms. From Compustat, we extract firm-level characteristics such as industry classification, headquarter location, total

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[5] U.S. entities are identified using the organization code (2 for U.S. entities) recorded in patent fillings. If the organization code is missing, we consider an assignee to be a U.S. entity if the organization name is present and the assignee has a U.S. address.

[6] Other approaches for identifying financial patents include using technology classification codes, filtering based on the industries of assignees, or employing machine-learning models to conduct text-based analysis. See, for instance, Lerner (2002), Lerner (2006), Duffy and Squires (2008), Hall (2009), Hall et al. (2009), and Lerner et al. (2024).

assets, and operating performance. We exclude firms with non-positive total assets from the Compustat sample. We construct a measure of financial constraints following the methodology of Kaplan and Zingales (1997). In addition, we construct a proxy for access to local inventor talent by computing the geographic distance from each firm's headquarters to the nearest Tier-1 research (R1) university.[7]

Last, to explore firms' strategic hiring of inventor human capital as a key mechanism underlying substitution (or diffusion) effects of technological waves, we track inventor employment in our sample. Since detailed employment histories of patent inventors are unavailable in the PatentsView or USPTO data, we infer inventor-employer relationships based on patent assignment information. Specifically, if an individual is listed as an inventor on a patent application and a firm is identified as the assignee, we assume the inventor is employed by that firm at the time of the patent's filing.

Panel A of Table 1 presents the number of financial patent applications by different groups of filers. As seen in the table, both public firms and non-Compustat entities play significant roles in financial innovation, accounting for 49% and 51%, respectively, of all financial patent applications. The table also shows that non-financial firms are significant contributors to financial innovation, representing over 57% of all financial patent applications filed by Compustat firms. In Fig. IA.1 of the Internet Appendix, we further break down the number of patent applications by the business sector, as defined by the SIC divisions from the Occupational Safety and Health Administration (OSHA) (https://www.osha.gov/data/sic-manual). As seen in Panel B of Fig. IA.1, the finance sector (i.e., Finance, Insurance, and Real Estate), along with the services and manufacturing sectors, accounts for the majority of financial innovation. Notably, the services

[7] The list of R1 universities is obtained from https://www.aeaweb.org/resources/institution_classifications/r1.

sector initially led financial innovation in the early years but was surpassed by the finance sector after 2008, with the latter's dominance peaking around 2014.

Panel B of Table 1 presents the number of new hirings of financial patent inventors, categorized by different groups of employers. Each observation represents a new, unique employment relationship between a given firm and a financial patent inventor. New employment includes both the first appearances of inventors in the sample as well as transitions from other employers. Financial patent inventors are defined as those who previously filed financial patent applications at prior employers or, in the case of first-time employment, those who file financial patent applications during their initial employment week.

As shown in the table, approximately 42% of financial patent inventors are hired by public firms, while the remaining 58% are employed by non-Compustat entities. Within Compustat firms, both the financial sector (identified using SIC codes 6000-6999) and the non-financial sector play significant roles in employing financial patent inventors, accounting for 51% and 49% of inventor employment, respectively. Among firms with non-missing data for the corresponding variable, those for which ROA is outside the top quartile, financial constraints are low ($\leq 75^{th}$ percentile), or an R1 university is nearby ($\leq$ 100 km) contribute 61%, 96%, and 89% of new hiring of financial patent inventors, respectively. These patterns highlight the potential importance of firm characteristics in shaping financial innovation activity through inventor employment.

To construct the outcome variables for our empirical tests, we calculate weekly totals of financial patent applications filed within each group from Panel A of Table 1. We thus obtain, for each group, a time series of 780 observations from 2005-2019, with each observation representing an aggregate number of patent applications filed in a given week. Panel A of Table 2 presents summary statistics for weekly financial patent application filings within the various groups.

Some of our empirical tests (see, in particular, Section 5.4) also rely on grouping financial innovations by technological breadth. We measure patent breadth by the number of unique (full-digit) IPC codes or, alternatively, the number of unique 4-digit IPC codes. For each week, we compute the average patent breadth across all financial patent applications filed during that period. As shown in Panel A of Table 2, financial innovations tend to be relatively narrow in scope, with the median of weekly average breadth falling below 2 for both measures. To further explore high-breadth patents, we define them as those containing more than one unique (full-digit) IPC code or, alternatively, more than one unique 4-digit code. We impute individual patent values using stock-market announcement returns following the methodology of Kogan et al. (2017).[8] We then aggregate the values of all high-breadth patent applications filed in each week and report the corresponding statistics (in millions of dollars) in Table 2.

Panel B of Table 2 presents statistics on the weekly new employment of financial inventors across different groups of employers. In this table, the new employment of financial inventors is defined as the initial week in which a financial inventor files a patent with a given firm for the first time. This includes both first-time employment and job transitions from other employers. We then count each new employment episode for a given week to calculate the total number of new employment records for the week.

4.2 Identifying major waves of technological innovation

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[8] To estimate the economic value for a given patent application, we first calculate the (0,0) cumulative abnormal return (CAR) around the public announcement date of the patent application, using a market-adjusted model. Then we estimate the dollar value of a patent as the CAR multiplied by the firm's market capitalization 5-days before the application disclosure, adjusted for anticipation and for the firm's total patent announcements on the same day. Specifically, for each patent we use Eq. (3) in Kogan et al. (2017) to calculate its value as $Economic\ value = \left(1 - \underline{\pi}\right)^{-1} \frac{1}{N_j} E[v_j | R_j] M_j$, where $\underline{\pi}$, the unconditional probability of successful patent application, is taken to be 56%; N_j is the number of patent applications a firm filed on the same day; and M_j is the firm's market capitalization five trading days prior to the application announcement date *t*.

We use an objective, data-driven procedure to identify the onset of the most significant technological innovation waves occurring during the sample period. The advantage of this approach is that it limits subjective bias in characterizing which episodes of technological innovation qualify as being highly influential. To implement our approach, we begin by pinpointing innovation categories that are most prominent as measured by the total number of citations they received. Using information from BDSS and PatentsView, we count all citations received by 2021 for each granted patent published between 2005 and 2019. Next, we exclude financial patents by removing those containing financial terms listed in Chen et al. (2019). We then group the remaining patents based on their 3-digit IPC codes (IPC3) and rank the groups according to the aggregate number of citations received by patents within each group.

All of the top 10 IPC3 groups fall within five IPC classes: Class A, Class B, Class C, Class G, and Class H.[9] Among them, Classes G and H are the most likely to be associated with or affected by financial innovation (see Appendix for details). Therefore, we focus on the top three IPC3 groups within Classes G and H as being the groups of greatest interest. (Similar results are obtained when using the top five IPC3 groups.) Panel A of Table 3 shows information for these technologies, including their IPC codes, category names, numbers of citations received, and examples of a highly cited patent within the group. As seen in the table, the top IPC3 code, G06, is for "Computing; Calculating; Counting," which includes sub-categories related to digital data processing, recognition, and presentation. The second and the third most influential IPC3 codes

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[9] Class A is "Human Necessities", which encompasses sub-areas such as agriculture, foodstuffs, personal or domestic articles, and health. Class B refers to "Performing Operations and Transporting", which includes fields like liquid/gas separation, shaping, printing, transporting, and microstructural technology. Class C is "Chemistry and Metallurgy", which covers areas such as chemistry, metallurgy, and combinatorial technology. Class G, "Physics", and Class H, "Electricity", are detailed in the Appendix. For more details, see: https://www.wipo.int/en/web/classification-ipc.

are H04, "Electric communication technique," and H01, "Basic electric elements."[10] To the extent that many financial services functions relate to record-keeping and fact-checking, the identified categories of technological innovations seem likely to have ripple effects on financial innovation. In contrast, among the top three innovation categories in non-G/H classes (i.e., "Medical or veterinary science; hygiene" (A61), "Organic chemistry" (C07), and "Vehicles in general" (B60)), none is closely related to financial innovation. In Panel B of Table 3, we classify the filers of the top three IPC3 groups in G/H classes by the OSHA SIC division and report the division names along with the corresponding number of patents filed for each group.

Next, we identify the onset of each technological innovation wave using an approach that combines a time-series segmentation method with the detection of extrema.[11] Specifically, we first calculate the total number of (non-financial) patent applications published each week within the three top IPC3 categories and scale it by the total number of all patent applications published in the same week. To smooth short-term fluctuations, we use a four-week moving average for the resulting time series. We then apply a change-point detection algorithm that has been widely used by researchers to identify points at which the statistical properties of the data undergo important shifts (Lescisin and Mahmoud, 2018; Park et al., 2020; Perry and Muller, 2022).[12] Application of the algorithm results in segmentation of the overall sample into four distinct time periods separated

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[10] An example patent of category G06, titled "multipoint touchscreen," relates to an electronic device's handling of simultaneous touches and near-touches. Under category H04, an example patent is a technology on associating fictitious usernames to real identities. In category H01, an example patent focuses on smaller and more efficient semiconductor devices.

[11] We thank an anonymous referee for suggesting the use of time-series segmentation methods.

[12] The algorithm is implemented using the Python library *ruptures*, which is designed for detecting structural changes in time series data. We use a method based on the Radial Basis Function (RBF) kernel, which detects change points by measuring pairwise, high-dimensional similarity between time segments. RBF is effective in capturing complex and subtle shifts in the data distribution. To control the sensitivity of the method, we use a penalty value of 30. In general, a higher penalty helps prevent over-segmentation but may also miss relatively subtle or short-lived changes. For robustness, we tested penalties of 20 and 40 and obtained consistent results. For further details on the RBF kernel, see, for instance, Schölkopf and Smola (2002).

by three boundaries. We interpret each of the three boundaries between segments as indicating a technological wave since it is a notable point in time during which major structural change is occurring.

For each of the three waves detected in this manner, we proceed to identify the start of the wave. Specifically, we identify the absolute minimum point in the time series occurring within six months prior to each segment boundary. Each of these minimum points is considered the onset of a technological innovation wave and is designated as an event week. Using this approach, we identify three event weeks: the 45th week of 2007, the 36th week of 2014, and the 30th week of 2016.

To validate that each of the three identified event dates marks the onset of a highly important technological change, we proceed as follows. First, we use the same time series to identify all local minima, where a local minimum is defined as the lowest point within all rolling nine-week windows (spanning from week –4 to +4, including week 0) over the sample period. Second, for each local minimum found, we calculate the difference between it and the maximum observed in the next 52 weeks. This captures the extent of the subsequent surge in patenting activities. Third, we then rank weeks based on the sizes of their subsequent surges. Notably, the three event weeks identified by our algorithm rank as the top three local minima in terms of the largest subsequent increases. This gives further credence to the idea that the three event dates we identified indeed represent the beginnings of important technological waves.

5. Results

5.1. Responses of financial innovation to technological innovation waves

According to Hypothesis 1, financial innovation may be linked to technological developments in two distinct ways. On the one hand, the diffusion of new technologies can inspire new ideas and enable firms to build on existing advancements, thereby enhancing financial innovation. On the other hand, technological innovation may disrupt existing business lines or foster new, more profitable opportunities, potentially driving resource-constrained firms to shift their focus away from financial innovation. To test these hypotheses, we first calculate the total number of financial patent applications filed each week and estimate ITS regressions as specified in Eq. (1).

Panel A of Table 4 presents the results. The sample period spans from 2005 to 2019. In Columns (1)-(3), the dependent variable is the weekly aggregate number of financial patent applications filed by the following three groups: (1) U.S. (non-individual) entities; (2) Compustat firms; and (3) Compustat firms filing a financial patent for the first time. To identify first-time financial patents, we track patent filings back to 2001, the earliest year available in our patent application data. The dependent variables in each regression in the table are winsorized at 1% and 99%. The key explanatory variables include *Event_k*, an indicator for the period after the onset of a technological wave *k*, and the interaction term *WeeksPost_k* × *Event_k*, which captures the number of weeks elapsed since the beginning of the event *k*. *k* denotes one of the three technological innovation waves in the sample, with *Event_07, Event_14,* and *Event_16* corresponding to the 45th week of 2007, the 36th week of 2014, and the 30th week of 2016, respectively. Additionally, we include *Weeks*, a variable that measures the number of weeks elapsed since the beginning of the sample period (the 1st week of 2005). The coefficients on the interaction terms exhibit mixed trends across time periods and firm groups, while the coefficients on *Event_k* reveal a clear pattern. Specifically, the coefficients on *Event_07* and *Event_14* are negative and statistically significant across all three groups of firms. For *Event_16*, the results are mixed. The coefficient is only marginally significant for all U.S. entities and statistically insignificant for Compustat firms.

To account for the possibility that the observed trends in financial patents merely reflect broader trends in overall patenting activity, we scale the count of financial patents by the total number of all patents (both financial and non-financial) filed in the same week and run the ITS regressions again using Eq. (1).

Fig. 1 provides a visual summary of our findings from this analysis. Each dot represents an observed weekly proportion of financial patents during the sample period (2005 to 2019), calculated as the number of financial patents filed in a week divided by the total number of patents filed in the week and expressed as a percentage. The solid line segments show the fitted trend lines. In Panels A through C, respectively, patenting is measured and aggregated among a given group of entities. Panel A focuses on financial innovation by all U.S. non-individual entities. While the slopes do not exhibit a clear pattern, the graph shows striking changes in the levels. Following the onsets of technological innovation waves, the share of financial patent filings clearly declines relative to total patent filings, although the magnitude of the decline is smaller after the 2016 event. These results indicate that financial innovation exhibits an immediate drop after the start of the technological innovation waves, particularly in the earlier part of the sample period, consistent with the hypothesis of a substitution effect (Hypothesis 1b).

Panel B of Fig. 1 focuses on financial innovation by Compustat firms. The graph once again shows a significant drop in the proportion of financial patent filings following the onset of the first two technological waves. However, no visually significant change is observed after the 2016 event, suggesting that technological innovation had little relation with Compustat firms' financial innovation for the more recent period. To explore this pattern further, Panel C of Fig. 1 restricts the sample to Compustat firms that filed at least one financial patent in a given week. The results are similar to what is shown in Panel B: these financial innovating firms exhibit a decline in the share of financial innovation after the 2007 and 2014 events; however, there is no significant decline observed after the 2016 event, reinforcing the earlier finding that financial innovation among Compustat firms had limited correlation with the 2016 wave. In the more recent period, technological innovation seems to coincide with a new trend in Compustat firms' financial innovation. In Section 5.4, we relate this observation to the growing integration between finance and technology, which is likely to enhance the appeal of financial innovation and mitigate the extent of substitution effects.

Panel A in Table 4 reports the detailed ITS regression results that enable quantitative conclusions about the magnitudes and statistical significance of observed effects. The dependent variable is the total number of weekly financial patent filings (Columns (1)-(3)) or the weekly financial patent filings as a percentage of the total patent filings in the same week (Columns (4)-(6)). Financial and total patenting activity are measured from patenting among the following groups: (1) U.S. (non-individual) entities; (2) Compustat firms; and (3) Compustat firms that filed at least one financial patent in a given week. The dependent variables are winsorized at 1% and 99%. Consistent with the patterns observed in Fig. 1, the coefficients on *Event_07* and *Event_14* are significantly negative across all three columns. In contrast, the coefficients on *Event_16* are insignificant and remarkably smaller in magnitude for Compustat firms, indicating that the 2016 event had no substantial effect on their financial innovation activity. These findings based on the proportion of financial patents are consistent with the results in Panel A, reinforcing the idea that the observed trends are not simply driven by overall changes in patenting activity. Throughout the remainder of the paper, we use proportion-based measures—rather than raw counts—as the dependent variable.

For robustness, we conduct a series of tests replicating the analysis in Panel A of Table 4. First, to address concerns about confounding from other factors, we incorporate macroeconomic control variables, including GDP growth, the Consumer Price Index, schooling, employment growth, population growth, and trade openness. GDP growth (*Quarterly GDP growth*) is the quarterly percentage change in U.S. GDP. Consumer Price Index (*Monthly CPI*) is the log-transformed U.S. consumer price index, measured monthly. Schooling (*College or above*) is the percentage of the U.S. population aged 25 and above that have graduated from college or another high education institution in a given year. Employment growth (*Monthly employment growth*) is the percentage change in total U.S. nonfarm employment, measured monthly. Population growth (*Yearly population growth*) is the annual percentage change in the U.S. population. Trade openness (*Trade openness*) is the sum of exports and imports in the U.S. as a percentage of U.S. GDP. Data on population, quarterly GDP, and monthly CPI and employment are from the Federal Reserve Bank of St. Louis, while schooling and trade openness data come from the World Bank. For each given week, we also control for both the mean and the standard deviation of daily returns, excluding all distributions, on a value-weighted market portfolio (CRSP item *VWRETX*).[13] As shown in Panel B of Table 4, our results remain robust. We also estimate regressions that control for the Weekly Economic Index (*WEI*) from the Federal Reserve Bank of Dallas. (The WEI is not available before 2008, so we only apply it to the latter two shocks.) The results remain similar (see Table IA.7 of the Internet Appendix for details).

[13] For robustness, we replace the return and volatility of the value-weighted portfolio with the equal-weighted measures and obtain consistent results, as reported in Table IA.6 of the Internet Appendix.

In addition, to address concerns about potential non-stationarity in the time series, we perform Augmented Dickey-Fuller (ADF) tests on all specifications in Table 4. As shown at the bottom of the table, the results reject the null hypothesis that the residuals follow a unit-root process, supporting the stationarity of our models. We also conduct additional tests that use a four-week moving average of the proportion of financial patents as the dependent variable. The results remain robust. Furthermore, we find similar results when we (1) use monthly data rather than weekly data; (2) exclude software patents from our sample; (3) apply the Prais-Winsten (PW) method (Prais and Winsten, 1954); or (4) incorporate one-week, four-week, or six-week lags in the autocorrelation structure using the Newey-West method. (The results from all of these additional robustness checks are reported in the Internet Appendix.)

5.2. New employment of inventors

Our results thus far suggest that, prior to 2016, technological innovation was associated with a strong substitution effect that diminished financial innovation (Hypothesis 1b). However, the manner in which this substitution effect comes about remains to be established. To empirically explore the underlying mechanism, we now turn our focus to firms' employment of inventor human capital. While firms' strategic shifts in innovation focus are difficult to observe directly, changes in the allocation of inventor talent—a critical input for innovation—can precede observable outputs. Compared to patents, which are relatively delayed outcomes influenced by various factors, shifts in inventor employment can provide a more immediate and informative signal of firms' evolving innovation priorities.

As posited in Section 2.2, when waves of technological innovation create more profitable opportunities outside the financial domain, firms may shift their innovation focus by systematically reallocating inventor human capital from financial areas to non-financial domains. Therefore, we expect the crowding-out of financial innovation to occur primarily through the strategic redeployment of inventors. To test this hypothesis, we define the new employment of inventors as the first week in which an inventor files a patent with a given firm. This definition includes both initial hires and job transitions from other employers. We then calculate the weekly percentage of newly employed inventors who are financial inventors. Financial inventors are defined as those who previously filed financial patent applications at prior employers or, in the case of first-time employment, those who file financial patent applications during their initial week. Based on our percentage measure of newly-employed financial inventors, we then estimate ITS regressions as specified in Eq. (1).

We begin by illustrating our findings from the ITS analysis in Fig. 2. Each dot represents the weekly percentage of newly employed inventors at Compustat firms who are financial inventors, while the solid line segments show the fitted trend lines. The graph shows that, in the aggregate, firms significantly reduce their new employment of financial inventors relative to all inventors following the onsets of the first two waves, suggesting a negative impact of technological innovation on financial inventor hiring. In contrast, an increase is observed following the 2016 event, but the increase appears to be very slight.

Table 5 reports the formal regression results. The dependent variable, winsorized at 1% and 99%, is the weekly percentage of newly employed inventors who are financial inventors, reported separately for three groups of employers: (1) all Compustat firms, (2) financial innovating firms, and (3) non-financial innovating firms. Financial innovating firms are defined as Compustat firms that have filed at least one financial patent before the employment week, while non-financial innovating firms are those that have not filed any financial patents before that time. Consistent with the patterns observed in Fig. 2, the coefficients on *Event_k* in Column (1) are significantly negative for the 2007 and 2014 events, indicating a substantial decline in the new employment of financial inventors relative to non-financial inventors. When Compustat firms are further split into financial innovating firms and non-financial innovating firms in Columns (2) and (3), we find a notable divergence: the crowding-out effects after the first two events are only significant among financial innovating firms, while non-financial innovating firms exhibit no significant change in hiring financial inventors. As shown at the bottom of the table, the ADF tests for all specifications reject the null hypothesis that the residuals follow a unit-root process. These results suggest that, as a response to technological shocks, financial innovating firms, in the aggregate, actively reallocate their human capital to shift their innovation focus away from finance. In contrast, non-financial innovating firms likely have already allocated their inventor talent across a broader set of innovation areas, leaving them with less incentive to adjust employment strategies. Overall, the results for the first two events support Hypothesis 2b: emerging technological waves are associated with reduced hiring of financial inventors, particularly by firms that have previously engaged in financial innovation. The findings also indicate that reallocating inventor human capital is a plausible way in which firms can bring about rapid shifts in their innovation focus.

5.3. Firm-level heterogeneity and new employment of inventors

In this section, we turn to hypotheses about whether firm-level constraints affect firms' ability to substitute between different types of inventor human capital. We focus on three key constraints that may hinder firms' ability to attract and hire skilled inventors: (1) internal resource constraints, captured by return on assets (ROA); (2) financial constraints; and (3) labor market constraints. As detailed in Section 4.1, we define high-ROA firms as those with ROA above the

75th percentile in a given year among all Compustat firms with non-missing ROA data. We measure financial constraints following Kaplan and Zingales (1997) with highly constrained firms similarly defined as those above the 75th percentile.[14] Labor market constraints are proxied for by whether or not a top research university is nearby: firms are considered less constrained if they are headquartered within 100 kilometers (and, for robustness, 50 kilometers) of at least one R1 university. We then calculate, for specific subsamples of Compustat firms, the weekly percentages of newly employed inventors who are financial inventors.

Panel A of Fig. 3 shows a clear difference in the new employment of financial inventors by high-ROA firms (Panel A.1) versus that by underperforming firms (Panel A.2). As hypothesized in Section 2.3.1, firms with weaker operating performance—those facing internal resource constraints such as limited economies of scale and technological expertise— may be more reliant on financial innovation, as they are less capable of pursuing potentially more profitable alternatives. When major technological innovations lower the barrier to entry into other fields or threaten to disrupt traditional financial services, resource-constrained firms may be strongly incentivized to shift their focus away from financial innovation and thus employ more non-financial inventors. Consistent with this hypothesis (Hypothesis 3b), low-ROA firms exhibit a significant decline in the new employment of financial inventors following the three events, although the magnitude of the drop is smaller after 2016 compared to the first two waves. In contrast, high-ROA firms show no clear pattern: there is no visible effect after the 2007 event, a mild decline following the 2014 wave, and an increase after the 2016 wave.

[14] For robustness, we employ two alternative measures of financial constraints: the WW index of Whited and Wu (2006) and the SA index of Hadlock and Pierce (2010). As reported in Table IA.8 of the Internet Appendix, our findings remain consistent with these alternative measures.

Next, we examine the impact of financial constraints. As hypothesized in Section 2.3.2, financial constraints can deter firms from pursuing costly adjustments in their human capital investments. When technological innovation occurs, it may present new, profitable opportunities, but it does not simultaneously alleviate firms' financial constraints. As a result, firms with fewer financial constraints are better positioned to reallocate resources and prioritize the hiring of inventors who have expertise outside the financial domain.

The graphs in Panel B of Fig. 3 support this hypothesis. Following the events in 2007 and 2014, less financially constrained firms (Panel B.2) show a tendency to shift away from hiring financial inventors, whereas highly constrained firms (Panel B.1) do not exhibit a similar response. After the 2016 event, however, there is no obvious shift among less-constrained firms. This notable difference may be attributable to the growing integration between financial and technological innovation in the more recent part of the sample period. We provide further discussion on this point in Section 5.4.

The detailed regression results behind Panels A and B of Fig. 3 are reported in Table 6. The dependent variable in each specification is winsorized at 1% and 99% and represents, for a given group of Compustat firms, the weekly percentage of newly employed inventors who are financial inventors. In Columns (2) and (4), the coefficients *Event_07* and *Event_14* yield significantly negative coefficients for firms with low ROA and low financial constraints. In contrast, the coefficients are insignificant for firms with high ROA and high financial constraints, except for *Event_14* in the high ROA group, which is marginally significant. This suggests that, relative to their counterparts, underperforming firms and financially unconstrained firms have the incentive and ability to reduce the recruitment of financial inventors in response to the first two technological innovation waves.

Lastly, we examine whether constraints on firms' access to inventor human capital can moderate substitution effects. As discussed in Section 2.3.3, a firm located near a research university benefits from better access to skilled graduates, academic expertise, and local innovation networks. These resources facilitate the firm's adjustments to its inventor composition in response to technological shocks. Consistent with this hypothesis, Fig. 4 reveals a clear difference between firms near R1 universities and those more distant: firms in close proximity (Panel A) significantly decrease their share of newly-employed financial inventors following the events in 2007 and 2014, while no declines are observed for their counterparts after the events (Panel B). However, following the event in 2016, neither group shows a significant change in the new employment of financial inventors.

The detailed regression results corresponding to Fig. 4 are reported in Table 7. The dependent variable, winsorized at 1% and 99%, is the weekly percentage of inventors newly employed by those firms who are financial inventors. Columns (1) and (3) are based on Compustat firms located within 50 kilometers and 100 kilometers, respectively, of at least one R1 university. Distance is measured from a firm's headquarters to the campus of a given R1 university. In contrast, Columns (2) and (4) are based on Compustat firms that do not meet the corresponding proximity criteria. As shown in the table, *Event_07* and *Event_14* yield significantly negative coefficients for firms located near R1 universities, whereas the coefficients are either positive or insignificantly negative for firms with no local R1 university. This suggests that firms with better access to local human capital resources can more easily reallocate inventor employment from financial to non-financial domains.

Overall, the results in this section confirm the view that different constraints faced by firms affect their responses to technological waves. However, the consistent absence of significant substitution effects after the third event suggests that recent years saw a fundamental change to the financial innovation landscape. We turn to an exploration of this issue in the next section.

5.4. The changing nature of financial innovation

Why did financial innovation and the new employment of inventors respond so differently to technological waves before 2016 versus afterwards? One possible explanation is that the financial innovation landscape as a whole was broadening and evolving during the years leading up to 2016.[15] With the increasing integration of finance and technology, the overall domain of financial innovation was enlarged, generating a wide array of new opportunities within financial services. These developments may have enhanced the attractiveness of financial innovation itself, reducing firms' incentives to reallocate resources toward non-financial domains and thereby weakening substitution effects. Compared to traditional financial innovations that lacked cross-sector synergies, new types of financial innovation were broader in scope, more synergistic vis-à-vis computing technology, and more able to incorporate benefits from technology diffusion. This notion is consistent with the recent increase in the private return of financial patents documented by Lerner et al. (2024).

To investigate this potential explanation, we examine trends in financial patent breadth and how this breadth responded to the three major technological innovation waves. As detailed in Section 4.1, we measure an individual patent's breadth by the number of unique full IPC codes (or, for robustness, the number of unique 4-digit IPC codes) associated with the patent. We then calculate the average patent breadth across financial patent applications filed in a given week and

[15] See, for example, "Financial services technology 2020 and beyond", PWC, December 2019; "Forging new pathways: The next evolution of innovation in financial services", Deloitte and the World Economic Forum, 31 August 2020.

examine its time-series changes around the onset of the three major waves of technological innovation. Fig. 5 reveals a striking trend: while financial patent breadth increases around the 2007 event, it increases more dramatically—both in terms of magnitude and growth rate—around the 2014 event. By the onset of the 2016 technological wave, the average breadth of financial patents surpasses that of any earlier period within our sample. Table 8 reports the regression results. In Columns (1) and (2), the dependent variable, winsorized at 1% and 99%, is the average financial patent breadth, calculated based on full IPC codes and 4-digit IPC codes, respectively. As seen in Column (1), the average breadth of financial patents responds significantly and positively to technological innovation waves. Meanwhile, consistent with the sharp growth observed after the 2014 event in Fig. 5, the interaction between *WeekPost_14* and *Event_14* is significantly positive. Overall, these findings support the view that the scope of financial innovation has experienced a dramatic broadening that may have fundamentally changed firms' responses to technological waves.

To examine whether increased patent breadth encourages firms to continue engaging in financial innovation rather than shifting to non-financial areas, we further explore the value of high-breadth patents around the three technological shocks. High-breadth patents are defined as those containing more than one unique full IPC code (or, for robustness, unique 4-digit IPC codes). Specifically, we aggregate the value of high-breadth financial patents filed in a given week and scale it by the total value of all financial patents filed in the same week. Patent values are imputed from stock-market announcement returns following the methodology of Kogan et al. (2017).

Fig. 6 reveals a trend similar to that in Fig. 5: the relative value of high-breadth patents rises notably in the latter part of the sample period, with the most pronounced acceleration occurring after the 2014 event. By the time the third wave begins, high-breadth financial patents account for a disproportionately large share of the total value of financial patents. We present the formal regression analysis in Table 8. The dependent variable in Columns (3) and (4), winsorized at 1% and 99%, is the weekly proportion of patent value attributable to high-breadth financial patent applications. Consistent with the visual evidence, the regression results show that the value share of high-breadth financial patents increases significantly following the 2007 and 2014 events. Indeed, the interaction between *WeekPost_14* and *Event_14* is significantly positive, indicating a sustained upward trend in the dependent variable after the 2014 wave. These findings support the notion that financial patents become more attractive in the later period, thus reducing firms' incentives to shift away from financial innovation.

Overall, the results in this section highlight a significant shift in the nature of financial innovation during the later part of the sample period, as evidenced by the broader scope of financial patents and the increased value of high-breadth financial patents. This evolving landscape may offer a potential explanation for why financial innovation responded differently to the 2016 technological wave compared to how it responded to previous waves: firms simply found it more advantageous to invest in new types of financial innovation that had greater value and more commercial applicability but that were still within the wide expanse of financial innovation.

5.5. Possible alternative explanations

In this section, we address the possibility that our findings could be spurious due to the presence of confounding factors such as macroeconomic conditions or regulatory changes.

One potential concern is that the onset of the first innovation wave is close to the 2008 financial crisis, which caused a severe economic downturn and could plausibly explain the observed decline in financial innovation and the "crowd-out" effect we observe after the first event.

However, our first event date is in the 45th week of 2007 (early November), while the National Bureau of Economic Research (NBER) marks December 2007 as the official start of the recession, coinciding with the peak of overall economic activity. The actual economic decline began modestly and did not reach its most acute phase until the fall of 2008 (see, e.g., Weinberg, 2013). In contrast, our interrupted time series (ITS) analysis indicates a significant drop in financial patent application filings shortly after the event date (November 2007). Given that patent applications are a lagging output of innovation activity, the decline in financial innovation must have commenced even earlier. Therefore, the timing suggests that the financial crisis is not likely to have been an important driver of the observed decline in financial innovation after the first event. To further address concerns related to macroeconomic confounding, we include controls for key macroeconomic variables. As shown in Panel B of Table 4, our main results remain robust after incorporating these controls.

Another potential alternative explanation involves changes in patent regulation during our sample period. Notably, Supreme Court decisions in *Alice Corp. v. CLS Bank International* (2014) imposed stricter limits on the patentability of software-related innovations, particularly those deemed to claim abstract ideas or ineligible subject matter. An earlier case, *Bilski v. Kappos* (2010), also contributed to this shift, as the Court ruled that the abstract investment strategy described in the patent application did not qualify as patentable subject matter.[16]

Given that financial innovations often involve algorithmic processes or conceptual methods, these rulings may have contributed to a decline in financial patent filings—potentially offering an alternative explanation for the "crowd-out" effect we observe. However, we argue that there are two reasons this explanation is unlikely to account for our findings. First, our dependent variable

[16] The *Bilski v. Kappos* decision is less of a concern for our tests because it occurred in 2010, approximately three years after the first event and four years before the second. Therefore, this court decision is unlikely to have been the primary driver of the decline in financial patents that we observe immediately following the first two events.

is constructed as the proportion of financial patents relative to all patents, not the raw count. Thus, the regulatory changes would only bias our results if financial patents were disproportionately more affected by the rulings compared to patents in other domains. But there is no a priori reason to believe this is true, given that non-financial patents can also involve abstract subject matter. Second, we have verified that our qualitative results continue to hold if we exclude software-related patents (identified using IPC classifications as in Graham and Mowery, 2003) from both the financial and total patent counts when constructing the percentage-based dependent variable. As we report in Table IA.5 of the Internet Appendix, our main results are robust to excluding software patents from the construction of the dependent variable. Since software patents are the category most likely to be affected by the two Supreme Court decisions, the persistence of a "crowding-out" effect even after excluding such patents suggests that the court decisions are unlikely to be driving the patterns we observe.

6. Conclusion

Despite the importance of financial innovation as a driver of economic growth, little systematic evidence exists on whether financial innovation itself benefits from technological progress or is inhibited by it. To address this gap in the literature, our paper employs interrupted time series (ITS) analysis and patent data during 2005-2019 to provide large-scale evidence on how technological innovation impacts financial innovation. We find that, prior to 2016, financial innovation declines following the start of major technological innovation waves, suggesting a strong substitution effect whereby technological innovation creates more profitable opportunities outside the financial domain and prompts firms to shift their efforts away from financial innovation. This substitution appears to occur through the reallocation of the inventor human capital, as evidenced by the significant drop in the proportion of newly employed financial inventors following these waves. This drop is especially pronounced among less profitable firms, financially unconstrained firms, and firms with better access to the inventor labor market. The technological wave in 2016, however, has a more nuanced correlation with financial innovation, likely due to the increasing scope of financial innovation and the rising value of high-breadth financial patents.

Our results shed light on the interplay and co-evolution of technological and financial innovations, helping to fill gaps identified in the earlier literature regarding the determinants of financial innovation (e.g., Lerner, 2006; Lerner and Tufano, 2011). In particular, our findings highlight a potentially critical mechanism underlying substitution effects: firms, in the aggregate, shift innovation focus by adjusting their inventor employment strategies.

Finally, we note two inherent limitations of our study. First, not all innovation activities pursued by firms are aimed at acquiring patents. Indeed, firms may choose to develop certain innovations as trade secrets rather than seek formal patent protection for them. To the extent that some innovating firms and their inventors avoid the patenting process altogether, both financial innovation and non-financial innovation alike might be underrepresented in our sample. Second, the technological, non-financial waves that we study occur solely within IPC patent classes G and H. Although these are very broad technological classes that are of direct relevance to financial services and the rise of FinTech, it seems likely that consequential scientific and technological advances in other patent classes can also shape how firms and inventors pursue financial innovation.

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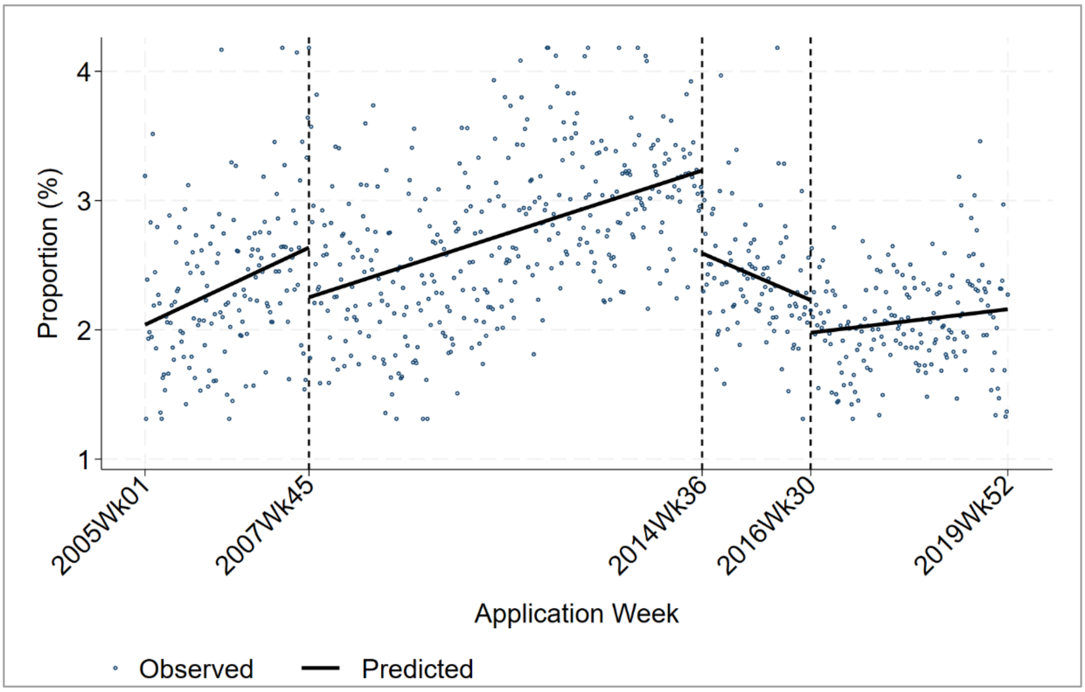
Fig. 1. Response of financial innovation to technological innovation

Notes: Each observation measures the financial patents filed in a week as a percentage of total patents filed in the week.

Panel A. Financial innovation by U.S. (non-individual) entities



Panel B. Financial innovation by Compustat firms

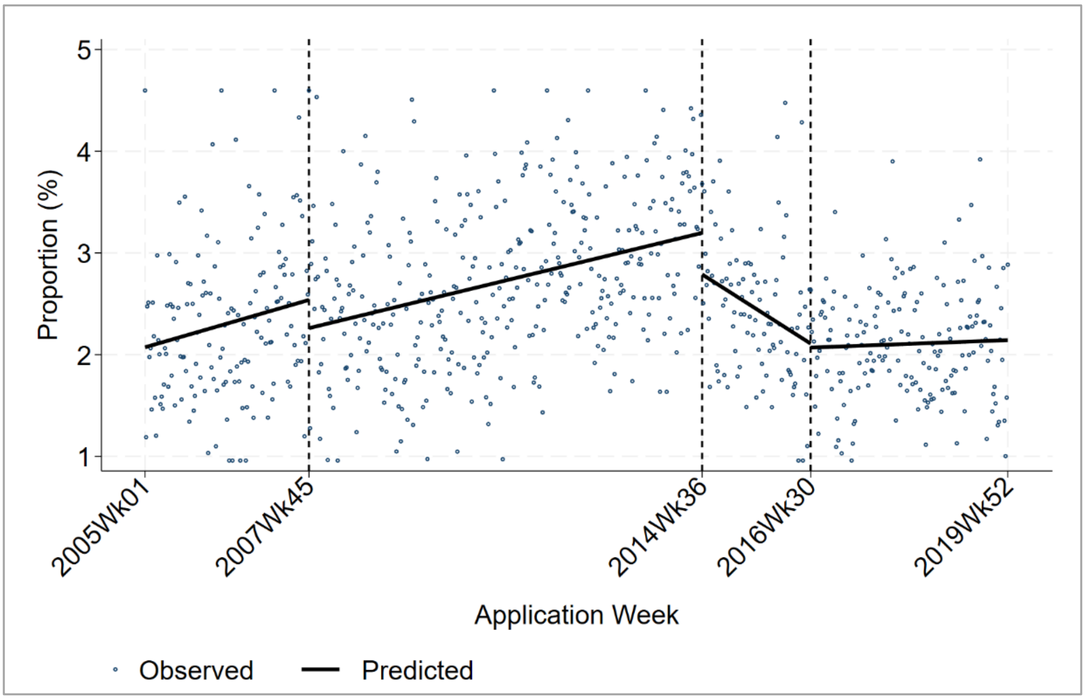


Fig. 1, continued

Panel C. Financial innovation by Compustat firms with at least one financial patent in a given week

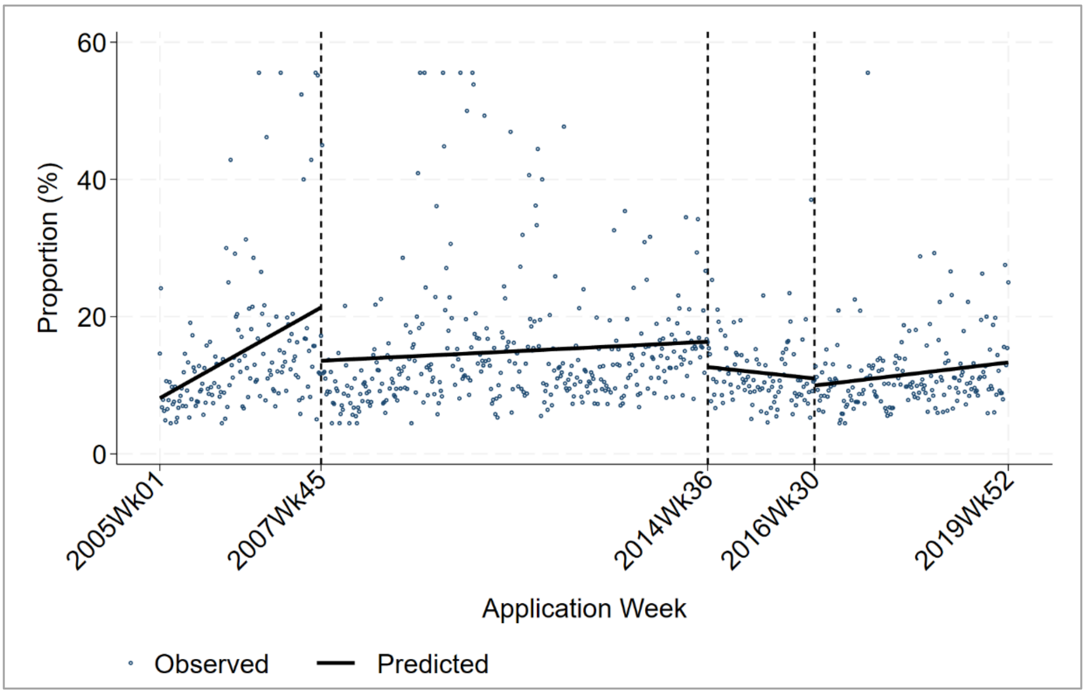


Fig. 2. Technological innovation and new employment of financial inventors

Notes: Each observation represents the weekly percentage of Compustat firms' newly-employed inventors who are financial inventors.

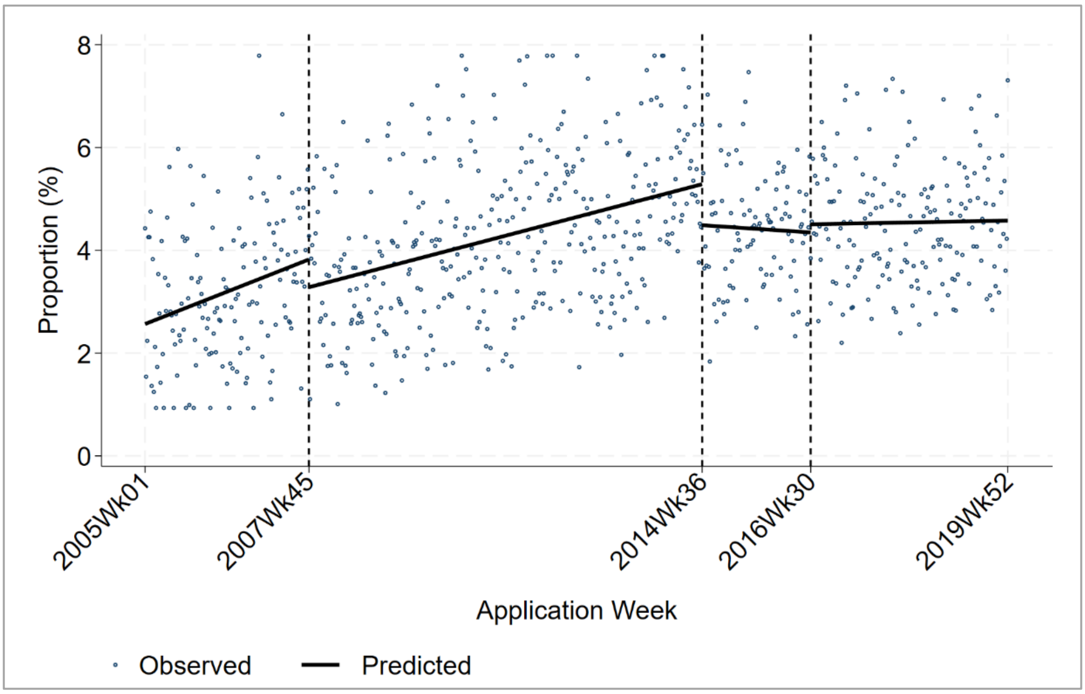
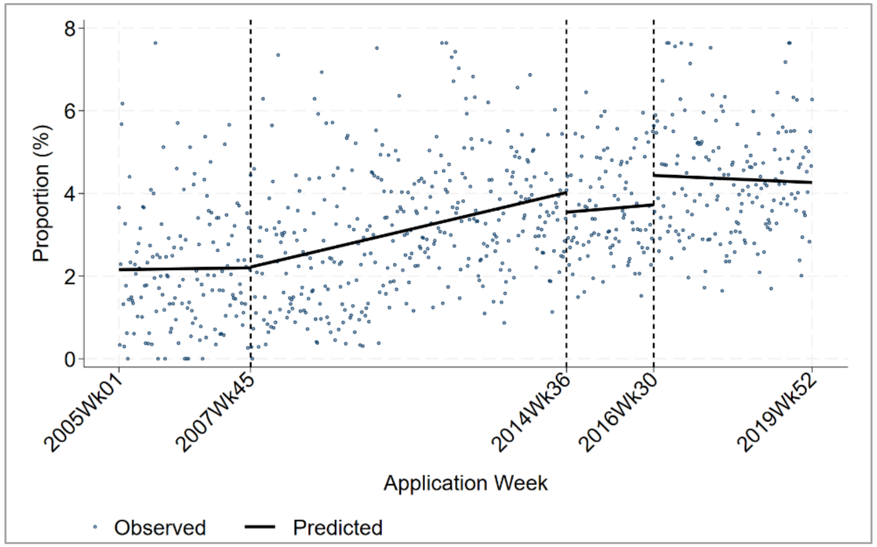


Fig. 3. Technological innovation and new employment of financial inventors: the role of firm-level heterogeneity

Notes: Each observation represents, for a given group of Compustat firms, the weekly percentage of newly employed inventors who are financial inventors.

Panel A. High vs. Low ROA

Panel A.1. High-ROA firms



Panel A.2. Low-ROA firms

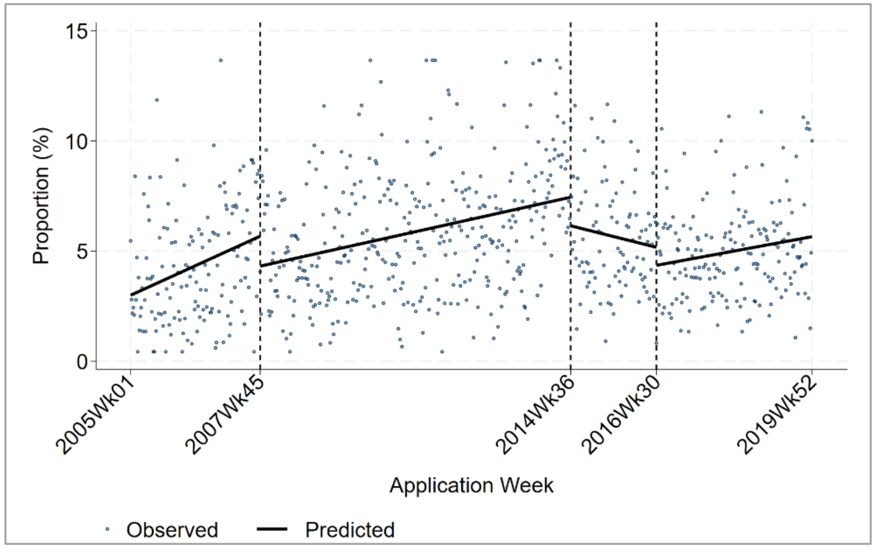
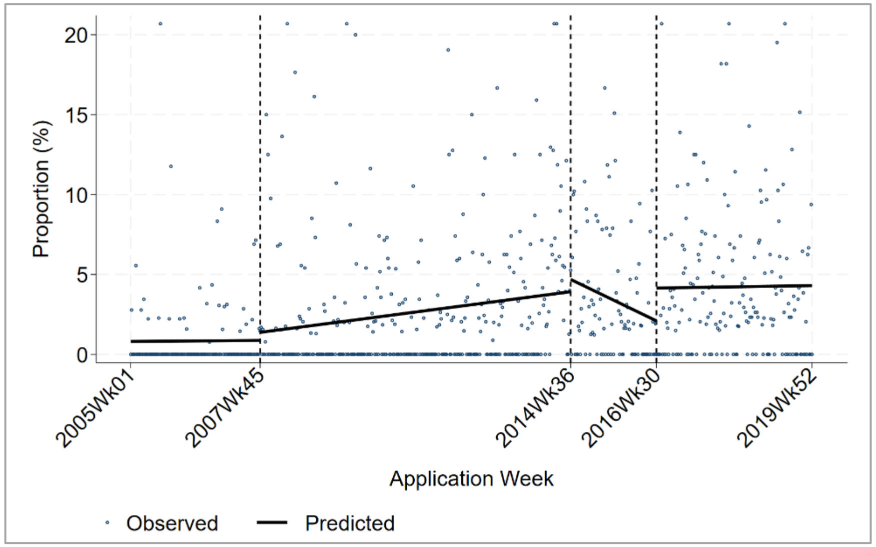


Fig. 3, continued

Panel B. High vs. Low Financial Constraints

Panel B.1. Firms with high financial constraints



Panel B.2. Firms with low financial constraints

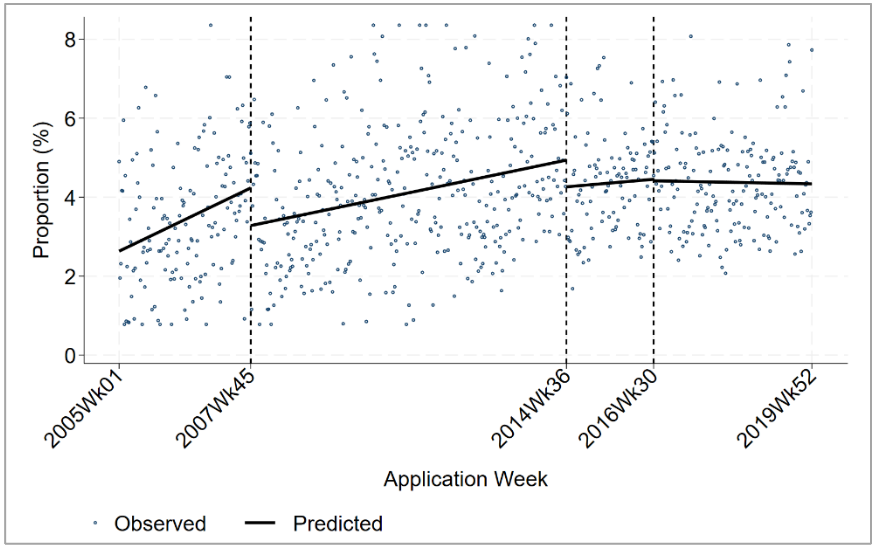
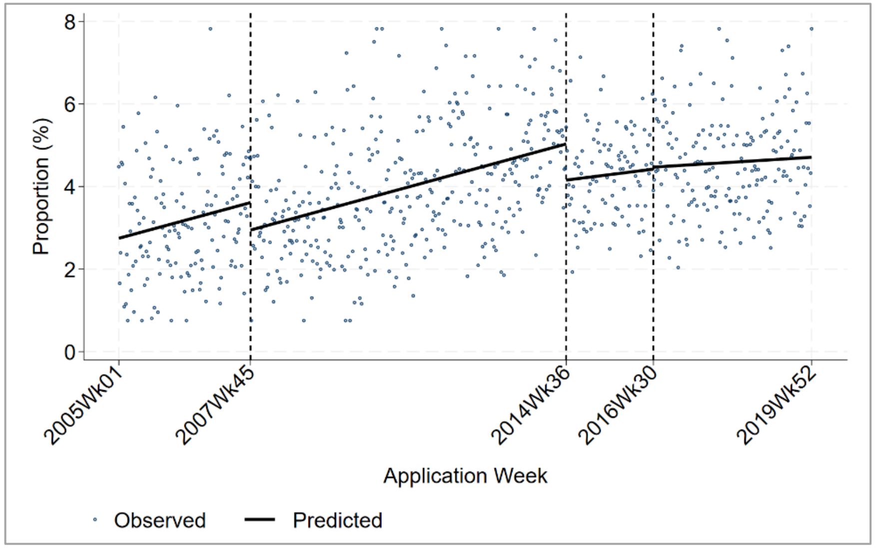


Fig. 4. Technological innovation, local labor supply, and new employment of financial inventors

Notes: Each observation represents, for a given group of Compustat firms, the weekly percentage of newly employed inventors who are financial inventors.

Panel A. Firms headquartered within 100 km of the nearest R1 university



Panel B. Firms headquartered over 100 km from the nearest R1 university

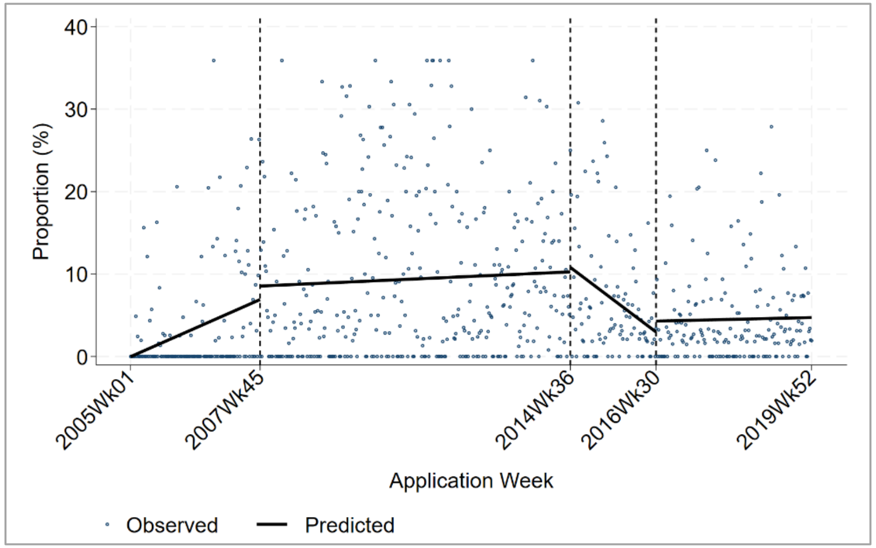


Fig. 5. The changing nature of financial innovation: patent breadth

Notes: Each observation represents the average patent breadth across financial patent applications filed in a given week.

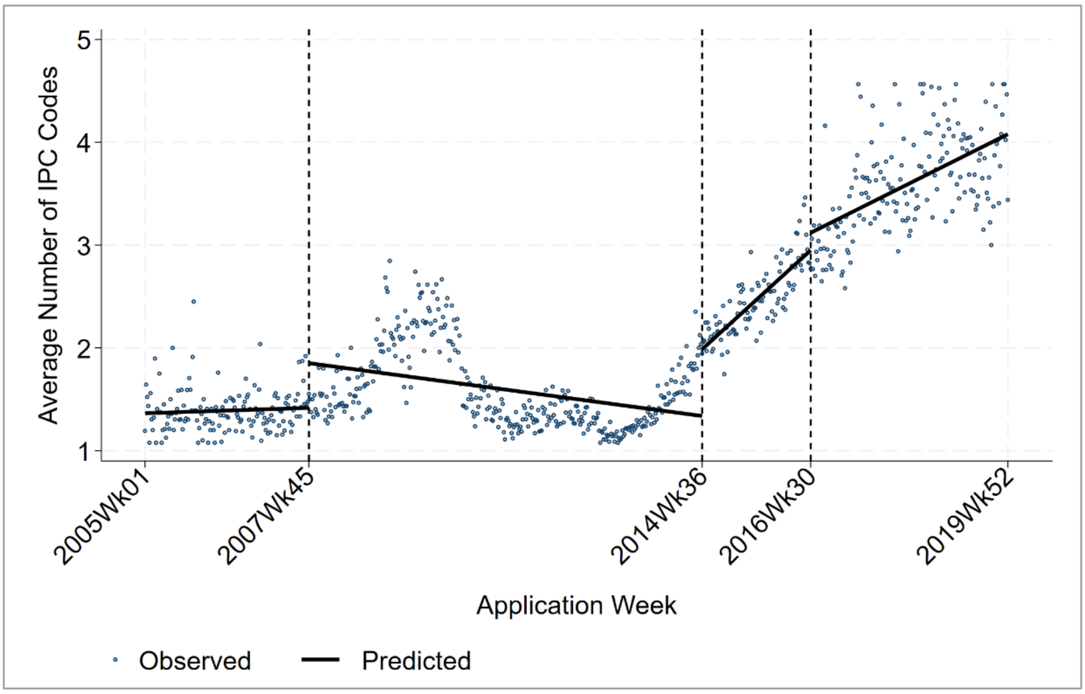


Fig. 6: Changes in the relative value of high-breadth patents

Notes: Each observation represents the total value of high-breadth financial patent applications during a given week as a proportion (%) of the total value of all financial patent applications during the week.

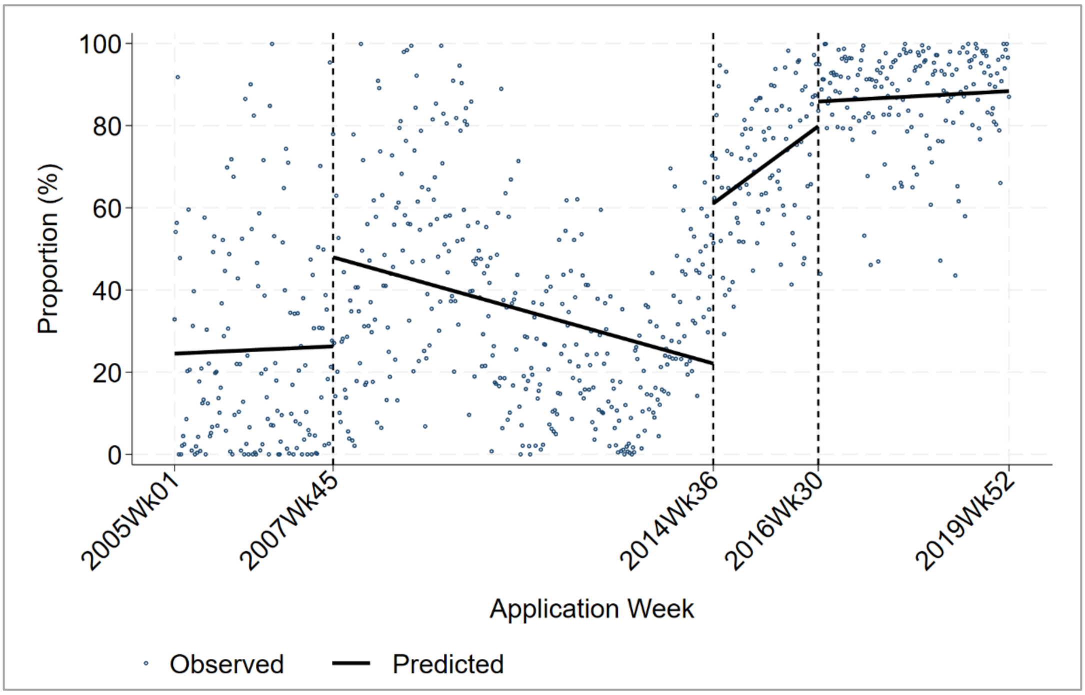


Table 1. Frequency distribution of financial patents and employment of financial inventors

Notes: The sample consists of patent- and inventor-level observations from 2005-2019.

Panel A. Number of financial patent applications			
Financial patent applications filed by:			
Non-individual entities in the U.S.		43,527	
Non-Compustat entities		22,134	
Compustat firms		21,393	
Compustat subsamples:	*Yes*		*No*
Within financial sector	9,114		12,279

Panel B. Number of newly-employed financial inventors			
Financial inventors hired by:			
Non-individual entities in the U.S.		39,781	
Non-Compustat entities		22,889	
Compustat firms		16,892	
Compustat subsamples:	*Yes*		*No*
Within financial sector	8,551		8,341
High ROA	6,574		10,248
With low financial constraints	12,709		506
Headquartered near (≤ 50 km) any R1 university	14,813		2,079
Headquartered near (≤ 100 km) any R1 university	14,987		1,905

Table 2. Summary statistics of financial patenting activity and inventor employment

Notes: The sample consists of weekly observations from 2005-2019.

Panel A. Financial patent applications						
	N	Mean	S.D.	p5	Median	p95
# of patent applications						
By U.S. non-individual entities	780	55.80	29.61	23	53	93
By Compustat firms	780	27.43	14.84	9	26	50.5
Within the financial sector	780	11.69	8.28	1.5	11	26
Outside the financial sector	780	15.74	8.81	5	14	29
Average patent breadth						
Full IPC	780	2.13	0.98	1.17	1.71	4.02
4-digit IPC	780	1.39	0.30	1.05	1.30	1.96
Value of high-breadth patents						
Full IPC	777	1,186.16	1,239.72	15.02	733.95	3,884.16
4-digit IPC	776	600.46	754.62	0	311.73	2,135.62

Panel B. New employment of financial inventors						
	N	Mean	S.D.	p5	Median	p95
By U.S. non-individual entities	780	50.96	28.14	22	47	86
By Compustat firms	780	35.20	19.59	10.5	33	66
By firms in the financial sector	780	10.94	8.04	1	10	25
By firms with high ROA	780	16.03	11.13	2	15	34
By firms with low financial constraints	780	27.13	15.43	7	25	52
By firms headquartered near (≤ 50 km) any R1 university	780	31.69	18.59	9	29.5	60.5
By firms headquartered near (≤ 100 km) any R1 university	780	32.15	18.66	9	30	60.5

Table 3. Technology groups with the most active innovation activities

Panel A. Details on the most active technological innovation groups

3-Digit IPC	Categories	Number of citations	Examples of highly cited patents
G06	Computing; Calculating; Counting	6,097,120	US7663607B2, “Multipoint touchscreen”
H04	Electric communication technique	3,695,558	US7024609B2, “System for protecting the transmission of live data streams, and upon reception, for reconstructing the live data streams and recording them into files”
H01	Basic electric elements	2,598,313	US8646103B2, “Method and system for securing online identities”

Panel B. Innovation in the most active technology groups, by SIC division

SIC Division	All Three Top IPCs	IPC = G06	IPC = H04	IPC = H01
Manufacturing	198,971	80,802	81,712	51,514
Services	191,134	144,423	50,391	17,174
Transportation, Communications, Electric, Gas, And Sanitary Services	27,949	10,682	19,997	737
Finance, Insurance, And Real Estate	21,494	16,836	6,729	675
Retail Trade	8,796	7,039	2,966	133
Public Administration	8,533	4,887	1,868	2,468
Mining	2,196	1,615	262	381
Wholesale Trade	704	556	96	89
Construction	233	58	26	155
Agriculture, Forestry, And Fishing	14	14	2	0

Table 4. The response of financial innovation to technological innovation

Notes: Panel A reports the main results of the Interrupted Time Series (ITS) analysis examining the response of financial innovation to the onset of three major waves of non-financial, technological innovation. Panel B reports the results of robustness checks that add macroeconomic control variables to the regressions. Newey-West standard errors with a lag of five weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A. Baseline

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities (1)	Compustat (2)	First-time financial patents (3)	U.S. Entities (4)	Compustat (5)	Financial innovating firm-week (6)
Event_07	-18.931***	-7.573***	-0.611**	-0.385***	-0.277*	-7.768***
	(3.390)	(1.848)	(0.256)	(0.124)	(0.158)	(2.086)
Event_14	-11.665***	-4.535*	-0.748***	-0.641***	-0.408***	-3.690***
	(3.874)	(2.531)	(0.250)	(0.083)	(0.123)	(1.150)
Event_16	-6.827*	0.586	-0.200	-0.252**	-0.039	-1.026
	(3.772)	(2.747)	(0.208)	(0.116)	(0.192)	(1.492)
WeekPost_07 × Event_07	0.040	0.027*	0.001	-0.001	-0.001	-0.082***
	(0.033)	(0.014)	(0.003)	(0.001)	(0.001)	(0.016)
WeekPost_14 × Event_14	-0.267***	-0.188***	-0.000	-0.006***	-0.010***	-0.025
	(0.051)	(0.039)	(0.003)	(0.001)	(0.002)	(0.019)
WeekPost_16 × Event_16	0.133**	0.106**	-0.002	0.005***	0.007***	0.036*
	(0.058)	(0.042)	(0.004)	(0.002)	(0.003)	(0.020)
Weeks	0.142***	0.060***	0.001	0.004***	0.003**	0.089***
	(0.029)	(0.012)	(0.003)	(0.001)	(0.001)	(0.016)
ADF Z-statistic **(**1% Critical Value = -3.430)	-8.818	-9.520	-10.805	-10.111	-10.393	-8.700
Observations	780	780	780	780	780	780

(continued on the next page)

Table 4 *(continued)*

Panel B. Baseline with macroeconomic controls						
	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities (1)	Compustat (2)	First-time financial patents (3)	U.S. Entities (4)	Compustat (5)	Financial innovating firm-week (6)
Event_07	-17.400***	-5.686***	-0.495*	-0.368**	-0.202	-7.367***
	(3.842)	(2.163)	(0.274)	(0.146)	(0.188)	(2.156)
Event_14	-16.487***	-8.832***	-0.883***	-0.531***	-0.458***	-3.991***
	(4.042)	(2.564)	(0.272)	(0.094)	(0.140)	(1.502)
Event_16	-8.635**	-1.022	-0.144	-0.359***	-0.150	-0.762
	(3.750)	(2.626)	(0.226)	(0.132)	(0.193)	(1.614)
WeekPost_07 × Event_07	0.222***	0.141***	0.003	-0.000	0.001	-0.127***
	(0.047)	(0.025)	(0.003)	(0.002)	(0.002)	(0.023)
WeekPost_14 × Event_14	-0.234***	-0.156***	-0.005	-0.003*	-0.007**	-0.019
	(0.064)	(0.046)	(0.004)	(0.002)	(0.003)	(0.028)
WeekPost_16 × Event_16	0.191***	0.159***	0.001	0.002	0.007**	0.039
	(0.071)	(0.048)	(0.005)	(0.002)	(0.003)	(0.031)
Weeks	-0.012	0.007	-0.005	0.002	0.003	0.175***
	(0.056)	(0.033)	(0.003)	(0.002)	(0.002)	(0.031)
Quarterly GDP growth	29.453	104.964	3.658	3.522	11.744	126.795
	(165.974)	(111.220)	(10.170)	(4.656)	(7.388)	(92.809)
Monthly CPI	139.960*	27.854	1.648	-0.572	-5.290	-91.258*
	(76.634)	(47.731)	(5.130)	(2.800)	(4.007)	(55.394)
College or above	-47.376	-216.457	54.378***	3.847	2.012	-236.431
	(303.697)	(195.691)	(17.994)	(8.740)	(14.370)	(155.284)

(continued on the next page)

Table 4 *(continued)*

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities (1)	Compustat (2)	First-time financial patents (3)	U.S. Entities (4)	Compustat (5)	Financial innovating firm-week (6)
Monthly employment growth	-952.818	-812.435*	23.429	-29.914	-46.427	140.353
	(687.516)	(430.973)	(42.682)	(25.190)	(32.185)	(376.168)
Yearly population growth	9,580.886***	6,902.378***	280.777**	-11.110	130.432	-1,349.417
	(2,142.188)	(1,359.686)	(130.997)	(70.953)	(112.215)	(1,185.917)
Trade openness	198.281***	149.146***	0.097	8.334***	9.692***	-27.626
	(55.606)	(35.433)	(4.068)	(2.321)	(3.433)	(44.600)
Weekly average market return	55.238	12.181	-6.568	5.276	1.505	-0.822
	(91.435)	(63.178)	(7.253)	(3.766)	(5.234)	(56.381)
Weekly market volatility	9.678	-15.275	-0.460	-0.053	0.638	58.910
	(85.830)	(58.687)	(6.332)	(3.320)	(5.471)	(56.588)
ADF Z-statistic **(**1% Critical Value = -3.430)	-9.901	-10.571	-11.731	-10.889	-10.797	-9.602
Observations	780	780	780	780	780	780

Table 5. Technological innovation and employment of financial inventors

Notes: Newey-West standard errors with a lag of five weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Compustat firms		
	All (1)	Financial innovating (2)	Non-financial innovating (3)
Event_07	-0.540** (0.267)	-0.994** (0.417)	-0.192 (0.205)
Event_14	-0.798*** (0.276)	-1.251*** (0.370)	-0.195 (0.180)
Event_16	0.159 (0.253)	0.019 (0.363)	-0.107 (0.258)
WeekPost_07 × Event_07	-0.003 (0.003)	-0.008* (0.005)	0.003 (0.002)
WeekPost_14 × Event_14	-0.007* (0.004)	-0.009* (0.005)	0.001 (0.003)
WeekPost_16 × Event_16	0.002 (0.004)	0.008 (0.005)	-0.004 (0.004)
Weeks	0.008*** (0.002)	0.013*** (0.004)	-0.001 (0.002)
ADF Z-statistic **(**1% Critical Value = -3.430)	-10.901	-10.890	-11.585
Observations	780	780	780

Table 6. Technological innovation, firm-level heterogeneity, and employment of financial inventors

Notes: Newey-West standard errors with a lag of five weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	ROA		Financial constraints	
	High (1)	Low (2)	High (3)	Low (3)
Event_07	0.019 (0.260)	-1.361*** (0.495)	0.505 (0.605)	-0.954*** (0.300)
Event_14	-0.476* (0.280)	-1.297** (0.613)	0.770 (1.056)	-0.677* (0.349)
Event_16	0.710** (0.276)	-0.819* (0.488)	2.053** (0.917)	-0.039 (0.308)
WeekPost_07 × Event_07	0.005* (0.003)	-0.009** (0.005)	0.007 (0.005)	-0.006** (0.003)
WeekPost_14 × Event_14	-0.003 (0.004)	-0.019** (0.008)	-0.034** (0.013)	-0.003 (0.005)
WeekPost_16 × Event_16	-0.003 (0.004)	0.017** (0.008)	0.027* (0.015)	-0.002 (0.005)
Weeks	0.000 (0.003)	0.018*** (0.004)	0.000 (0.004)	0.011*** (0.003)
ADF Z-statistic **(**1% Critical Value = -3.430)	-9.968	-10.268	-10.389	-10.170
Observations	780	780	780	780

Table 7. Technological innovation, local labor supply, and the employment of financial inventors

Notes: Newey-West standard errors with a lag of five weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Headquarters ≤ 50 km from a R1 university		Headquarters ≤ 100 km from a R1 university	
	Yes (1)	No (2)	Yes (3)	No (4)
Event_07	-0.817*** (0.256)	2.787** (1.366)	-0.665*** (0.248)	1.639 (1.643)
Event_14	-0.865*** (0.264)	-0.347 (1.133)	-0.875*** (0.257)	0.543 (1.882)
Event_16	0.056 (0.271)	0.757 (0.789)	0.049 (0.253)	1.315 (1.223)
WeekPost_07 × Event_07	-0.000 (0.003)	-0.032*** (0.011)	0.000 (0.003)	-0.042*** (0.013)
WeekPost_14 × Event_14	-0.005 (0.004)	-0.034*** (0.013)	-0.003 (0.003)	-0.085*** (0.022)
WeekPost_16 × Event_16	-0.000 (0.004)	0.037*** (0.013)	-0.001 (0.004)	0.082*** (0.023)
Weeks	0.007*** (0.002)	0.028*** (0.010)	0.006** (0.002)	0.047*** (0.012)
ADF Z-statistic (1% Critical Value = -3.430)	-10.696	-10.451	-10.972	-10.792
Observations	780	780	780	780

Table 8. The changing nature of financial innovation: shifts in patent breadth and value

Notes: Newey-West standard errors with a lag of five weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Average patent breadth		Total value of high-breadth patents	
	# of Unique IPCs (1)	# of Unique 4-digit IPCs (2)	# of Unique IPCs (3)	# of Unique 4-digit IPCs (4)
Event_07	0.435*** (0.106)	0.137*** (0.045)	21.691*** (5.951)	14.810*** (3.900)
Event_14	0.649*** (0.086)	0.195*** (0.038)	38.960*** (5.571)	13.382*** (2.978)
Event_16	0.170* (0.102)	0.060 (0.052)	6.018 (4.126)	-0.587 (4.908)
WeekPost_07 × Event_07	-0.002*** (0.001)	-0.001*** (0.000)	-0.085 (0.057)	-0.044 (0.035)
WeekPost_14 × Event_14	0.011*** (0.001)	0.005*** (0.001)	0.265*** (0.073)	0.330*** (0.059)
WeekPost_16 × Event_16	-0.004*** (0.001)	-0.003*** (0.001)	-0.178** (0.072)	-0.212*** (0.066)
Weeks	0.000 (0.000)	0.000 (0.000)	0.012 (0.053)	-0.024 (0.032)
ADF Z-statistic (1% Critical Value = -3.430)	-4.898	-5.717	-7.287	-8.430
Observations	780	780	777	776

Appendix. Methodology for identifying financial patents

To identify financial patent filings, we start with a list of financial terms from Chen, Wu, and Wang (2019), who compile this list by first gathering financial terms from Campbell R. Harvey's *Hypertextual Finance Glossary* and the online *Oxford Dictionary of Finance and Banking (5th Edition)* and then excluding terms with semantic ambiguity. The authors augment this list with additional terms that have recently gained recognition as financial terminology (e.g., "bitcoin", "cryptocurrency", or "crowdfunding"). The final list comprises 487 unique financial terms, including single-word terms as well as two- and three-word phrases.

We follow the patent filtering process of Chen, Wu, and Wang (2019) by using the financial terms list to exclude non-financial patent applications. After completing the filtering process, we further restrict our sample to financial patent applications that contain at least one IPC code from Class G or Class H. Class G pertains to "Physics" and covers technical areas such as computing, calculating, counting, information and communication technology, and others. Class H relates to "Electricity" and includes areas such as basic electric elements, generation of electricity, applied electricity, basic electronic circuits and their control, radio or electric communication techniques, among others. We restrict financial patents to those within these categories as the three technological innovation waves identified in our sample all belong to IPC Classes G or H (see details in Section 4.2). Focusing on patents within these same classes allows us to observe the direct effects of these innovations. This approach is also consistent with findings from previous literature that seeks to identify financial innovation. For example, Lerner et al. (2024) employ a machine-learning approach to identify 24,288 financial patents, all of which fall within Class G or Class H. (We note that Lerner et al. (2024) report Cooperative Patent Classification (CPC) code subclasses for financial patents in their sample, which can be converted to IPC codes.)

Next, we follow the procedure used by Chen, Hu, Wang, and Wu (2023) to merge the remaining financial patent applications with Compustat. This matching procedure combines simple string matching, manual verification, and various machine-learning algorithms to create a name-matching crosswalk between USPTO patent applications and Compustat firms (including their subsidiaries). As part of this process, we merge Compustat and USPTO data separately to a third database, Data Axle, which provides detailed information on corporate parents, subsidiaries, branches, and hierarchical positioning within the corporate family. Because a significant fraction of patent assignees may be subsidiaries or branches of Compustat firms (see, e.g., Lerner and Seru, 2022), this approach of using Data Axle to build a crosswalk yields a more complete picture of innovation activity than would be available from directly matching between Compustat firm names and USPTO assignee names.

Internet Appendix for

"How Technological Innovation Shapes Financial Innovation: Substitution Effects Versus Knowledge Diffusion"

This Internet Appendix includes figures on firm innovation activities and additional robustness checks that support our findings in the main text of the paper.

Figure IA.1 illustrates the time-series distribution of innovation activity by SIC division. Panel A presents the time series of patent applications in the top three IPC3 groups within Classes G and H (as defined in Table 3 in the main text), excluding financial patent applications. Panel B presents the time series of financial patent applications.

Tables IA.1–IA.5 provide robustness checks for Panel A of Table 4 using, respectively, the following approaches: (1) applying Newey–West standard errors with lag lengths of one, four, and six weeks; (2) employing the Prais–Winsten method, which is a generalized least-squares technique that corrects for AR(1) serial correlation in the error terms (Prais and Winsten, 1954); (3) measuring the dependent variables as four-week moving averages; (4) using monthly rather than weekly data; and (5) excluding software patents from our sample.

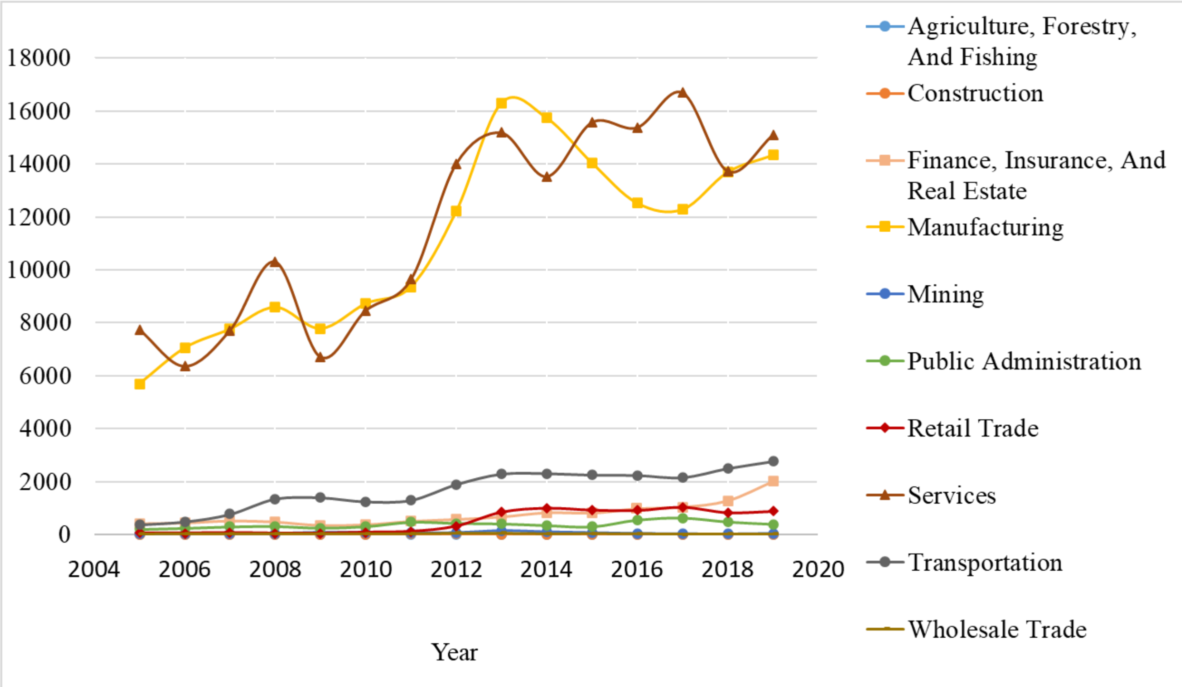
Tables IA.6 and IA.7 report robustness test results for Panel B of Table 4 by (1) replacing the return and volatility of the value-weighted portfolio with their equal-weighted counterparts and (2) replacing the market return and volatility control variables with the Weekly Economic Index (WEI) from the Federal Reserve Bank of Dallas.

Finally, Table IA.8 shows regressions similar to those in Columns (3) and (4) of Table 6 except that the KZ measure of financial constraints is replaced by one of two alternative measures of financial constraints—the Whited and Wu (2006) WW index and the Hadlock and Pierce (2010) SA index.

Fig. IA.1. Time-series distribution of innovation activity, by SIC division

Notes: In the legends for Panels A and B, "Transportation" encompasses the divisions of transportation, communications, electric, gas, and sanitary services.

Panel A. Patent applications (Non-financial) in the top three IPC3 groups within Classes G and H



Panel B. Financial patent applications

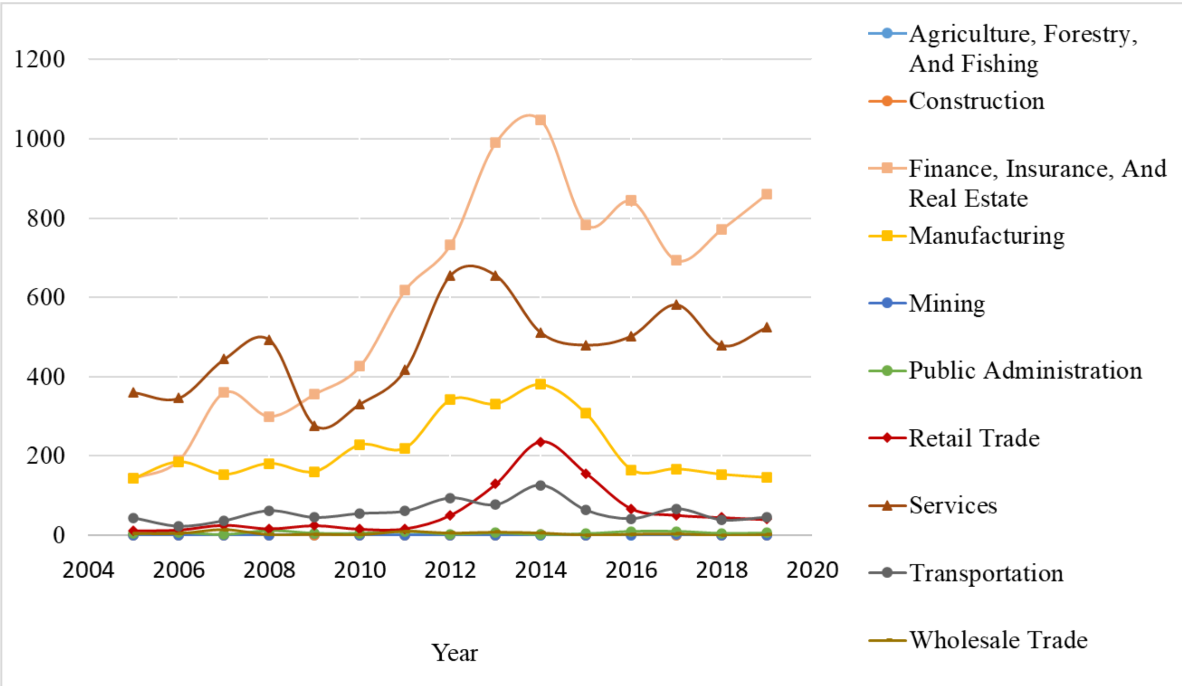


Table IA.1. The response of financial innovation to technological innovation – Newey-West standard errors with different lags

Notes: Newey-West standard errors with a lag of one, four, or six weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A. Lag of one week

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities	Compustat	First-time financial patents	U.S. Entities	Compustat	Financial innovating firm-week
	(1)	(2)	(3)	(4)	(5)	(6)
Event_07	-18.931***	-7.573***	-0.611***	-0.385***	-0.277*	-7.768***
	(3.510)	(1.801)	(0.235)	(0.124)	(0.155)	(2.069)
Event_14	-11.665***	-4.535*	-0.748***	-0.641***	-0.408***	-3.690***
	(3.968)	(2.609)	(0.247)	(0.109)	(0.147)	(1.282)
Event_16	-6.827*	0.586	-0.200	-0.252**	-0.039	-1.026
	(4.100)	(2.891)	(0.206)	(0.116)	(0.193)	(1.556)
WeekPost_07 × Event_07	0.040	0.027*	0.001	-0.001	-0.001	-0.082***
	(0.034)	(0.016)	(0.003)	(0.001)	(0.001)	(0.017)
WeekPost_14 × Event_14	-0.267***	-0.188***	-0.000	-0.006***	-0.010***	-0.025
	(0.059)	(0.043)	(0.003)	(0.002)	(0.003)	(0.022)
WeekPost_16 × Event_16	0.133**	0.106**	-0.002	0.005***	0.007***	0.036
	(0.063)	(0.045)	(0.003)	(0.002)	(0.003)	(0.023)
Weeks	0.142***	0.060***	0.001	0.004***	0.003**	0.089***
	(0.032)	(0.014)	(0.002)	(0.001)	(0.001)	(0.017)
Observations	780	780	780	780	780	780

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Table IA.1. *(continued)*

Panel B. Lag of four weeks

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities (1)	Compustat (2)	First-time financial patents (3)	U.S. Entities (4)	Compustat (5)	Financial innovating firm-week (6)
Event_07	-18.931***	-7.573***	-0.611**	-0.385***	-0.277*	-7.768***
	(3.308)	(1.802)	(0.255)	(0.123)	(0.158)	(2.128)
Event_14	-11.665***	-4.535*	-0.748***	-0.641***	-0.408***	-3.690***
	(3.927)	(2.580)	(0.248)	(0.091)	(0.133)	(1.168)
Event_16	-6.827*	0.586	-0.200	-0.252**	-0.039	-1.026
	(3.825)	(2.815)	(0.207)	(0.116)	(0.195)	(1.474)
WeekPost_07 × Event_07	0.040	0.027*	0.001	-0.001	-0.001	-0.082***
	(0.032)	(0.014)	(0.003)	(0.001)	(0.001)	(0.017)
WeekPost_14 × Event_14	-0.267***	-0.188***	-0.000	-0.006***	-0.010***	-0.025
	(0.052)	(0.040)	(0.003)	(0.001)	(0.003)	(0.019)
WeekPost_16 × Event_16	0.133**	0.106**	-0.002	0.005***	0.007***	0.036*
	(0.059)	(0.043)	(0.004)	(0.002)	(0.003)	(0.020)
Weeks	0.142***	0.060***	0.001	0.004***	0.003**	0.089***
	(0.029)	(0.012)	(0.003)	(0.001)	(0.001)	(0.016)
Observations	780	780	780	780	780	780

(continued on next page)

Table IA.1. *(continued)*

Panel C. Lag of six weeks

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities (1)	Compustat (2)	First-time financial patents (3)	U.S. Entities (4)	Compustat (5)	Financial innovating firm-week (6)
Event_07	-18.931***	-7.573***	-0.611**	-0.385***	-0.277*	-7.768***
	(3.407)	(1.872)	(0.259)	(0.123)	(0.157)	(2.068)
Event_14	-11.665***	-4.535*	-0.748***	-0.641***	-0.408***	-3.690***
	(3.911)	(2.537)	(0.249)	(0.079)	(0.119)	(1.142)
Event_16	-6.827*	0.586	-0.200	-0.252**	-0.039	-1.026
	(3.806)	(2.646)	(0.208)	(0.119)	(0.188)	(1.486)
WeekPost_07 × Event_07	0.040	0.027*	0.001	-0.001	-0.001	-0.082***
	(0.033)	(0.015)	(0.003)	(0.001)	(0.001)	(0.016)
WeekPost_14 × Event_14	-0.267***	-0.188***	-0.000	-0.006***	-0.010***	-0.025
	(0.051)	(0.038)	(0.003)	(0.001)	(0.002)	(0.019)
WeekPost_16 × Event_16	0.133**	0.106***	-0.002	0.005***	0.007***	0.036*
	(0.059)	(0.041)	(0.004)	(0.002)	(0.002)	(0.020)
Weeks	0.142***	0.060***	0.001	0.004***	0.003**	0.089***
	(0.029)	(0.012)	(0.003)	(0.001)	(0.001)	(0.015)
Observations	780	780	780	780	780	780

Table IA.2. The response of financial innovation to technological innovation: the Prais-Winsten method

Notes: Standard errors are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities	Compustat	First-time financial patents	U.S. Entities	Compustat	Financial innovating firm-week
	(1)	(2)	(3)	(4)	(5)	(6)
Event_07	-19.426***	-7.639***	-0.610***	-0.376***	-0.260*	-7.730***
	(3.482)	(2.134)	(0.208)	(0.112)	(0.153)	(1.732)
Event_14	-11.446***	-4.591*	-0.749***	-0.634***	-0.408**	-3.673*
	(4.017)	(2.463)	(0.241)	(0.129)	(0.177)	(2.002)
Event_16	-6.519	0.618	-0.200	-0.249*	-0.041	-1.025
	(4.457)	(2.734)	(0.268)	(0.143)	(0.196)	(2.224)
WeekPost_07 × Event_07	0.037	0.027	0.001	-0.001	-0.000	-0.081***
	(0.035)	(0.022)	(0.002)	(0.001)	(0.002)	(0.018)
WeekPost_14 × Event_14	-0.272***	-0.188***	-0.000	-0.007***	-0.010***	-0.025
	(0.064)	(0.039)	(0.004)	(0.002)	(0.003)	(0.032)
WeekPost_16 × Event_16	0.136**	0.106**	-0.002	0.005**	0.007**	0.036
	(0.068)	(0.042)	(0.004)	(0.002)	(0.003)	(0.034)
Weeks	0.145***	0.061***	0.001	0.004***	0.003**	0.089***
	(0.034)	(0.021)	(0.002)	(0.001)	(0.002)	(0.017)
Observations	780	780	780	780	780	780

Table IA.3. The response of financial innovation to technological innovation: dependent variables measured as four-week moving averages

Notes: Newey-West standard errors with five-week lags are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities	Compustat	First-time financial patents	U.S. Entities	Compustat	Financial innovating firm-week
	(1)	(2)	(3)	(4)	(5)	(6)
Event_07	-16.821***	-6.774***	-0.588**	-0.388***	-0.281**	-4.874***
	(3.149)	(1.748)	(0.244)	(0.120)	(0.135)	(1.087)
Event_14	-13.656***	-4.290	-0.833***	-0.619***	-0.321**	-2.104**
	(4.083)	(2.804)	(0.222)	(0.089)	(0.136)	(0.852)
Event_16	-8.467**	0.764	-0.237	-0.244**	0.037	-0.162
	(3.777)	(2.429)	(0.189)	(0.118)	(0.170)	(1.135)
WeekPost_07 × Event_07	0.066***	0.036***	0.002	-0.002	-0.001	-0.042***
	(0.023)	(0.011)	(0.003)	(0.001)	(0.001)	(0.008)
WeekPost_14 × Event_14	-0.261***	-0.204***	-0.000	-0.006***	-0.010***	-0.043***
	(0.051)	(0.039)	(0.003)	(0.002)	(0.002)	(0.015)
WeekPost_16 × Event_16	0.125**	0.121***	-0.002	0.004***	0.008***	0.046***
	(0.057)	(0.041)	(0.003)	(0.002)	(0.002)	(0.015)
Weeks	0.122***	0.054***	0.000	0.004***	0.004***	0.053***
	(0.017)	(0.008)	(0.003)	(0.001)	(0.001)	(0.008)
Observations	777	777	777	777	777	777

Table IA.4. The response of financial innovation to technological innovation: monthly observations

Notes: Newey-West standard errors with a lag of one week are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities	Compustat	First-time financial patents	U.S. Entities	Compustat	Financial innovating firm-week
	(1)	(2)	(3)	(4)	(5)	(6)
Event_07	-90.595***	-33.735***	-2.704**	-0.466***	-0.288*	-2.293***
	(17.341)	(9.450)	(1.129)	(0.123)	(0.164)	(0.493)
Event_14	-68.082***	-21.901	-3.403***	-0.643***	-0.359**	-0.691
	(23.384)	(16.007)	(1.047)	(0.105)	(0.159)	(0.433)
Event_16	-36.576*	1.796	-0.869	-0.224	0.028	0.042
	(20.818)	(12.555)	(0.842)	(0.138)	(0.201)	(0.854)
WeekPost_07 × Event_07	0.849	0.573*	0.027	-0.009*	-0.005	-0.071***
	(0.646)	(0.299)	(0.054)	(0.005)	(0.006)	(0.018)
WeekPost_14 × Event_14	-4.933***	-3.772***	-0.011	-0.028***	-0.044***	-0.123***
	(1.340)	(0.990)	(0.065)	(0.008)	(0.012)	(0.040)
WeekPost_16 × Event_16	2.098	2.178**	-0.035	0.018**	0.033***	0.125***
	(1.479)	(1.044)	(0.070)	(0.008)	(0.012)	(0.043)
Weeks	2.815***	1.141***	0.014	0.021***	0.015***	0.093***
	(0.545)	(0.248)	(0.053)	(0.005)	(0.006)	(0.017)
Observations	180	180	180	180	180	180

Table IA.5. The response of financial innovation to technological innovation: excluding software patents

Notes: Newey-West standard errors with a lag of five weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities	Compustat	First-time financial patents	U.S. Entities	Compustat	Financial innovating firm-week
	(1)	(2)	(3)	(4)	(5)	(6)
Event_07	-20.648***	-8.714***	-0.623***	-0.480***	-0.328*	-6.957
	(3.530)	(1.810)	(0.237)	(0.134)	(0.168)	(4.442)
Event_14	-12.914***	-5.851**	-0.766***	-0.752***	-0.615***	-4.843***
	(3.660)	(2.281)	(0.225)	(0.098)	(0.141)	(1.738)
Event_16	-5.433	0.164	-0.222	-0.237**	-0.091	-2.900
	(3.346)	(2.482)	(0.173)	(0.116)	(0.203)	(2.166)
WeekPost_07 × Event_07	0.069**	0.041***	0.001	-0.000	0.000	-0.090**
	(0.034)	(0.014)	(0.002)	(0.001)	(0.001)	(0.045)
WeekPost_14 × Event_14	-0.326***	-0.204***	-0.001	-0.009***	-0.011***	0.026
	(0.047)	(0.036)	(0.003)	(0.001)	(0.003)	(0.024)
WeekPost_16 × Event_16	0.128**	0.100***	-0.002	0.005***	0.007***	0.035
	(0.052)	(0.037)	(0.003)	(0.002)	(0.003)	(0.026)
Weeks	0.128***	0.056***	0.002	0.005***	0.004***	0.074*
	(0.029)	(0.011)	(0.002)	(0.001)	(0.001)	(0.044)
Observations	780	780	780	780	780	780

Table IA.6. The response of financial innovation to technological innovation: with macroeconomic control variables

Notes: The mean and the standard deviation of daily returns are based on an equal-weighted market portfolio (CRSP item EWRETX). Newey-West standard errors with a lag of five weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities	Compustat	First-time financial patents	U.S. Entities	Compustat	Financial innovating firm-week
	(1)	(2)	(3)	(4)	(5)	(6)
Event_07	-17.276***	-5.667***	-0.492*	-0.370**	-0.208	-7.359***
	(3.825)	(2.154)	(0.274)	(0.148)	(0.188)	(2.166)
Event_14	-16.464***	-8.800***	-0.885***	-0.528***	-0.452***	-3.919***
	(4.036)	(2.566)	(0.273)	(0.094)	(0.141)	(1.495)
Event_16	-8.803**	-1.044	-0.143	-0.361***	-0.145	-0.756
	(3.760)	(2.629)	(0.226)	(0.133)	(0.194)	(1.606)
WeekPost_07 × Event_07	0.221***	0.141***	0.003	-0.000	0.001	-0.126***
	(0.047)	(0.025)	(0.003)	(0.002)	(0.002)	(0.023)
WeekPost_14 × Event_14	-0.232***	-0.155***	-0.005	-0.003*	-0.007**	-0.019
	(0.064)	(0.046)	(0.004)	(0.002)	(0.003)	(0.028)
WeekPost_16 × Event_16	0.190***	0.158***	0.001	0.002	0.007**	0.040
	(0.071)	(0.048)	(0.005)	(0.002)	(0.003)	(0.031)
Weeks	-0.010	0.006	-0.005	0.002	0.003	0.174***
	(0.056)	(0.033)	(0.003)	(0.002)	(0.002)	(0.031)
Quarterly GDP growth	21.925	102.700	3.351	3.700	11.960	124.708
	(165.621)	(112.367)	(10.111)	(4.749)	(7.498)	(93.432)
Monthly CPI	137.244*	29.102	1.607	-0.481	-4.996	-90.238
	(76.519)	(47.578)	(5.164)	(2.831)	(4.021)	(55.798)

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Table IA.6 *(continued)*

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities	Compustat	First-time financial patents	U.S. Entities	Compustat	Financial innovating firm-week
	(1)	(2)	(3)	(4)	(5)	(6)
College or above	-52.487	-219.688	54.573***	3.602	1.899	-235.835
	(302.898)	(195.906)	(18.068)	(8.747)	(14.406)	(154.818)
Monthly employment growth	-1,000.370	-813.088*	23.488	-29.790	-44.235	141.849
	(683.272)	(428.008)	(42.919)	(25.068)	(31.888)	(374.763)
Yearly population growth	9,537.574***	6,895.661***	280.443**	-10.755	134.087	-1,294.545
	(2,141.213)	(1,361.367)	(131.244)	(70.633)	(111.107)	(1,169.289)
Trade openness	200.069***	149.294***	0.001	8.413***	9.757***	-25.204
	(55.776)	(35.821)	(4.035)	(2.343)	(3.458)	(44.386)
Weekly average market return	31.614	28.108	-5.308	4.997	3.733	7.291
	(91.869)	(57.024)	(6.583)	(3.682)	(4.557)	(52.433)
Weekly market volatility	-24.693	-21.216	-0.607	0.010	2.140	68.254
	(96.408)	(63.394)	(7.447)	(4.015)	(6.231)	(69.918)
Observations	780	780	780	780	780	780

Table IA.7. The response of financial innovation to technological innovation: with macroeconomic control variables (WEI)

Notes: Newey-West standard errors with a lag of five weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities	Compustat	First-time financial patents	U.S. Entities	Compustat	Financial innovating firm-week
	(1)	(2)	(3)	(4)	(5)	(6)
Event_14	-17.531***	-9.507***	-0.869***	-0.569***	-0.498***	-3.814**
	(4.068)	(2.571)	(0.277)	(0.094)	(0.143)	(1.606)
Event_16	-8.322**	-0.734	-0.107	-0.355***	-0.130	-1.333
	(3.615)	(2.581)	(0.224)	(0.129)	(0.198)	(1.751)
WeekPost_14 × Event_14	-0.244***	-0.164***	-0.006	-0.004**	-0.008***	-0.024
	(0.064)	(0.046)	(0.004)	(0.002)	(0.003)	(0.029)
WeekPost_16 × Event_16	0.187***	0.158***	0.001	0.002	0.007**	0.034
	(0.071)	(0.048)	(0.005)	(0.002)	(0.003)	(0.033)
Weeks	0.223***	0.153***	-0.003	0.003**	0.005***	0.035*
	(0.050)	(0.030)	(0.002)	(0.001)	(0.002)	(0.020)
Quarterly GDP growth	35.933	108.911	0.452	4.271	7.293	45.440
	(201.112)	(136.061)	(11.716)	(5.438)	(8.726)	(98.411)
Monthly CPI	156.745	41.017	4.492	-1.094	-4.163	-78.480
	(102.440)	(61.969)	(5.869)	(3.144)	(4.808)	(59.252)
College or above	-69.569	-202.196	58.066***	3.263	0.064	-160.859
	(338.501)	(211.627)	(18.580)	(9.392)	(15.366)	(178.108)
Monthly employment growth	-1,322.221**	-991.182**	30.076	-46.735*	-54.555	-53.630
	(649.688)	(451.687)	(43.946)	(25.083)	(37.837)	(541.896)

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Table IA.7. *(continued)*

	Number of financial patents			Financial patents as a percentage of all patents		
	U.S. Entities	Compustat	First-time financial patents	U.S. Entities	Compustat	Financial innovating firm-week
	(1)	(2)	(3)	(4)	(5)	(6)
Yearly population growth	9,735.298***	7,136.122***	271.050**	-32.754	114.257	-1,824.286
	(2,263.828)	(1,422.757)	(128.933)	(71.326)	(115.101)	(1,255.080)
Trade openness	243.189***	173.235***	0.226	9.351***	9.668**	-65.212
	(88.017)	(54.245)	(5.014)	(2.810)	(4.138)	(45.366)
WEI	-0.705	-0.371	-0.025	-0.015	-0.013	0.635
	(0.688)	(0.448)	(0.046)	(0.030)	(0.041)	(0.599)
Observations	624	624	624	624	624	624

Table IA.8. Technological innovation, firm financial constraints, and employment of financial inventors: Robustness under alternative measures of financial constraints

Notes: Newey-West standard errors with a lag length of five weeks are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. The four missing observations in column (3) are caused by an absence of any inventor employment by highly constrained firms (measured by the SA index) in the 18th week of 2005, the 47th week of 2007, the 52nd week of 2010, and the 52nd week of 2015.

	WW index		SA index	
	High	Low	High	Low
	(1)	(2)	(3)	(3)
Event_07	0.469	-0.687**	1.359	-0.592**
	(0.604)	(0.274)	(0.903)	(0.275)
Event_14	-0.447	-0.796***	0.253	-0.847***
	(0.657)	(0.308)	(1.080)	(0.281)
Event_16	1.092	-0.067	0.865	-0.002
	(0.844)	(0.266)	(0.852)	(0.266)
WeekPost_07 × Event_07	0.005	-0.004	0.010	-0.003
	(0.005)	(0.003)	(0.008)	(0.003)
WeekPost_14 × Event_14	-0.014	-0.008**	-0.025*	-0.007*
	(0.010)	(0.004)	(0.014)	(0.004)
WeekPost_16 × Event_16	0.013	0.005	0.030**	0.003
	(0.012)	(0.004)	(0.015)	(0.004)
Weeks	-0.003	0.010***	-0.010	0.009***
	(0.005)	(0.003)	(0.008)	(0.003)
Observations	780	780	776	780