Nationalistic Labor Policies Hinder Financial Innovation*

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Abstract

Hiring restrictions for high-skilled foreign nationals hinder domestic banks' production of cutting-edge innovation. We document this fact using the Employ American Workers Act (EAWA), which banned US financial institutions participating in the Troubled Asset Relief Program (TARP) from hiring *new* high-skilled foreign nationals until the full repayment of TARP funding. We exploit the differential pre-crisis exposure of similarly troubled TARP institutions to the unforeseen EAWA ban to show that the ban not only impeded the hiring of new foreign talent but also led to a reduction in both the quantity and quality of patent filings, including new products and processes in cutting-edge fields such as FinTech, cybersecurity, and payment systems. The effect is concentrated among individual inventors who filed patents for the first time during their tenure at a bank. Banks more exposed to EAWA did not substitute their internal innovation with the acquisition of external patents. In terms of labor market implications, rather than replacing new high-skilled foreign nationals with domestic employees—the stated goal of EAWA—banks paid higher wage premia to retain pre-crisis foreign hires than the prevailing wages of US workers in the same occupations and locations.

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Hiring American workers for limited available jobs should be a top priority for businesses taking taxpayer money through the TARP bailout program. [...] there is no need for companies to hire foreign guest workers through the H1-B program when there are plenty of qualified Americans looking for jobs.

Senator C. Grassley (February 6, 2009)

Buried in the American Recovery and Reinvestment Act of 2009 was the Employ American Workers Act... This act foolishly hurt hundreds of finance companies by limiting their talent pool precisely when they needed new talent the most.

Wall Street Journal (June 20, 2012)

A key driver of the bank's patent growth is its diverse workforce. More than 6,700 inventors across 42 states and 14 countries are inventors on the bank's 5,837 patents.

Bank of America (February 9, 2023)

1 Introduction

Innovation is a fundamental driver of economic growth (e.g., Romer, 1990; Aghion and Howitt, 1992; Jones, 1995; Griliches, 2007; He and Tian, 2020) and has been increasingly important to preserve corporations' and national security in the information economy era (e.g., Weiss, 2014). Many argue high-skilled immigrants play an important role in fostering a country's innovation production by contributing talent and specialized knowledge that is often not available in domestic inventors' pools.[1] At the same time, over the last decade, restrictions on both high- and low-skilled immigration have been at the forefront of the political agenda of many Western economies. Support for these restrictions is often based on the idea that foreign workers' reservation wage is lower than otherwise similarly skilled domestic workers, including high-skilled workers, and hence, foreign workers force domestic ones to either accept lower salaries or be unemployed.[2]

These two opposite views stem from different assumptions about the relative skill level of immigrant and domestic workers, that is, whether immigrants provide skills that are not available in the pool of domestic workers or whether immigrants replicate skills that are available domestically. Whereas low skills are standardized and tend to be homogeneous within and across countries, high skills, such as those needed to produce innovation, are specialized, scarce, and hard to replicate. To assess these statements empirically, an ideal experiment would randomly ban a group of firms from hiring high-skilled workers, such as high-skilled inventors, and compare the hiring of foreign inventors, innovation production, and wage offers across banned firms and others. If specialized skills can be found domestically, banned firms' innovation would not decline as long as the value of domestic wages is not higher than the expected

[1] For instance, see Hunt and Gauthier-Loiselle (2010), Hunt (2011), Borjas and Doran (2012), Moser et al. (2014), Laeven et al. (2015), Akcigit et al. (2018), Bernstein et al. (2019), and D'Acunto and Frésard (2019).

[2] Using large-scale surveys and experiments across six countries, Alesina et al. (2023) discover prevalent misperceptions about the skill levels of immigrants relative to domestic workers and examine how these misperceptions influence domestic citizens' support for various redistribution policies.

value of the innovation to be produced that accrues to firms. Firms would merely end up facing a higher wage bill to replace foreign skills with domestic skills. By contrast, if specialized skills cannot be found domestically, banned firms' innovation activities might be compromised, and banned firms would still face higher wage bills to retain the foreign high-skilled workers they hired before the ban was imposed.

In this paper, we consider a natural experiment that mimics this ideal experiment—a US regulation that banned some domestic firms, but not others, from hiring new foreign workers over staggered time periods—to assess if hindering firms from hiring new high-skilled immigrants results in a decline of the quantity and quality of firms' innovation. We also assess whether firms can substitute foreign skills with domestic ones and/or with existing foreign employees, for whom the regulation allowed firms to renew the immigrant worker status.

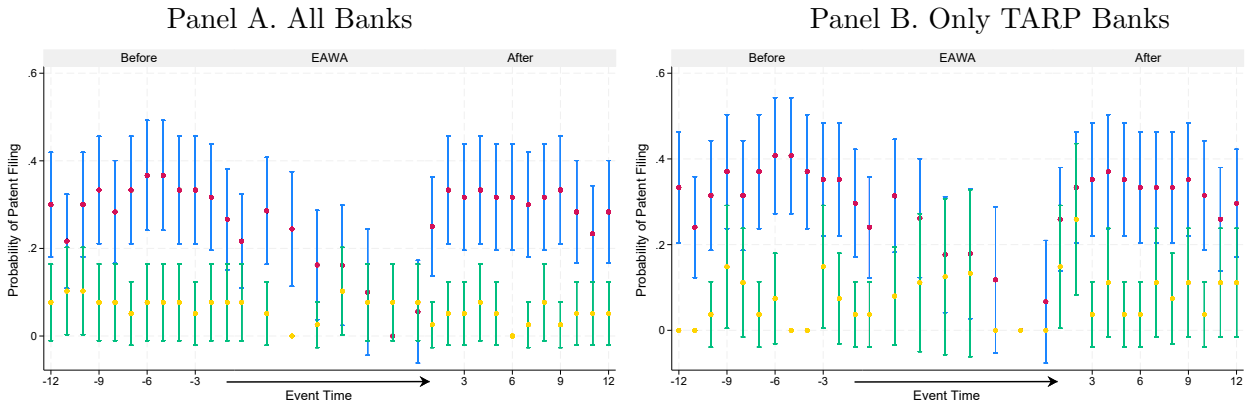
Specifically, we exploit the *Employ American Workers Act* (EAWA), which banned new foreign hires by US financial institutions, primarily commercial banks, that had enrolled in the *Troubled Asset Relief Program* (TARP) during the 2008-2009 financial crisis. As we elaborate in more detail below, EAWA was an ancillary piece of regulation that was approved and executed after the TARP program had started. For this reason, at the time of entering TARP, most financial institutions were not aware that a ban on new foreign hires would be imposed on them at a later date. The ban was active from EAWA's approval date until a bank's full repayment of TARP funds.

We find that after the EAWA ban, affected banks reduced their innovation production at both the extensive margin (number of patents produced) and intensive margin (subsequent citations of filed patents). This drop in innovation production reverted after the ban was lifted.[3] Clearly, EAWA differs from the ideal experiment in that financial institutions were not assigned to receive TARP funds at random. Moreover, during and after the 2008-2009 financial crisis, institutions were subject to major shocks to which they were differentially exposed and that were likely to affect their innovation activities as well as many other outcomes.

To tackle these endogeneity concerns, we propose two empirical strategies. Our first strategy compares innovation activities before and after the EAWA ban and between TARP and non-TARP recipients that had hired some foreigners among their high-skilled workers (STEM workers) before the financial crisis. This strategy can be interpreted as assessing the "extensive margin" of the EAWA ban across affected and unaffected institutions. The left panel of Figure 1 depicts the results of this assessment. Although the average frequency of patent filing for both groups of banks followed similar trends outside the EAWA

[3]One might argue that the timing of banks exiting from the EAWA program might be endogenous to bank CEOs' desire to resume innovation to reboot profitability. However, apart from the lengthy process of patent application, we verify that the profits generated by these bank patents might not be significant enough to influence the timing of exiting the EAWA — the average private value of these patents only represents 0.3% of a bank assignee's assets.

Figure 1: **Patenting Activity by U.S. Banks Around EAWA**



The figure plots the average frequency of patent filing by US banks (y-axis). The reported averages are calculated across bank-year-month observations within each event quarter (x-axis). Panel A includes both TARP and non-TARP recipients that sponsored at least one H-1B STEM job during 2004-2006. The blue (light-green) line represents TARP (non-TARP) recipients. Panel B only includes TARP recipients. The blue (light-green) line represents TARP recipients that had high (low) exposure to EAWA (see section 3.1 for how high and low exposures are constructed). The time periods are categorized as "Before," "EAWA (Event Time)," and "After," corresponding to quarters before, during, and after banks' compliance with EAWA. The Event Time period for TARP recipients is institution-specific (refer to Table A.1), whereas the period of non-TARP recipients is calculated from February 17, 2009, through February 17, 2011. See section 2.1 for the selection of our sample banks. Confidence intervals are calculated at the 95% level.

period, that is, both before and after the ban was active, TARP banks (red diamonds) filed patents at a substantially lower frequency while the EAWA ban was active. By contrast, the patenting frequency of non-TARP banks (yellow dots) faced minimal disruption during the same period.

A simple comparison of innovation trends between TARP and non-TARP banks might confound the effects of EAWA with major economic shocks that caused some banks to access TARP. To mitigate this concern, our second strategy limits the analysis to TARP recipients and compares the innovation activities of TARP banks that, prior to the onset of the financial crisis, had a higher share of high-skilled immigrant employees relative to all high-skilled employees with TARP banks that had a lower share. All TARP recipients in our analysis faced similar adverse economic shocks. However, banks that relied relatively more on immigrants to fulfill their high-skilled jobs before the crisis were more affected by the EAWA ban than other banks. This second strategy can be interpreted as an assessment of the "intensive margin" of the EAWA ban within banks that were hit significantly enough by the crisis to need access to TARP.

The right panel of Figure 1 visualizes the results of our second empirical strategy. It compares TARP recipients that employed more immigrants among their high-skilled workers before the crisis (red diamonds) with TARP recipients that employed fewer immigrants among their high-skilled workers (yellow

dots).[4] Similar to the left panel of Figure 1, we find patenting trends were similar across the two groups of banks before and after the EAWA was active, whereas patent productivity dropped substantially for TARP banks that were more exposed to the EAWA ban relative to TARP banks that were less exposed during the period in which the EAWA ban was active.

Our analysis is based on two main data sources. First, we obtain detailed data on H1-B visa applications from the US Citizenship and Immigration Services (USCIS). Using visa-level job classifications, we identify bank employees specializing in the fields of science, technology, engineering, and mathematics (STEM) to capture high-skilled immigrants. Second, we compile a dataset on inventions at the level of each US financial institution using information from the US Patent and Trademark Office (USPTO). This dataset includes 3,694 patents and 3,592 distinct inventors responsible for producing such patents. Overall, these patents carry an average market value of US$282 million based on stock-market reactions to news about their granting to banks.[5] This dataset enables us to observe the filing of patents originally assigned to financial institutions, along with the employment affiliations and trajectory of inventors over time.

Incidentally, the raw data on US banks' innovation production are of interest by themselves (e.g, Chen et al., 2019; Lerner et al., 2023). They unveil that US banks produce a substantial amount of cutting-edge innovation, especially in areas such as cybersecurity, mobile information technologies, mobile transaction technologies (e.g., robo-advising), data analytics, payment systems, FinTech applications, and several other fields that impact the efficiency, effectiveness, and security of the financial system and the overall economy.

Before proceeding with the analysis, we verify that TARP banks' compliance with the EAWA ban was universal; that is, applications for new H-1B visas to sponsor foreign STEM workers in domestic jobs dropped suddenly and dramatically for banks subject to the EAWA ban. By contrast, non-TARP banks with a similar level of pre-crisis foreign-STEM workers did not experience such a drop in H-1B visa applications, which dismisses the possibility that the lack of foreign workers was due to unobserved effects of the financial crisis on foreign workers' ability and willingness to migrate to the US. However, following the lifting of the EAWA ban, affected institutions gradually resumed hiring foreign STEM workers and eventually reverted to their pre-EAWA foreign hiring levels.

[4]Because hiring is positively correlated with bank size, we use size-adjusted cutoffs to define whether, before EAWA, a TARP bank hired more or fewer foreign STEMs relative to their peers of similar size. Specifically, we follow Begley and Srinivasan (2022) to classify domestic banks into small, medium, and large banks based on cutoffs of US$10 billion, US$50 billion, and US$1 trillion.

[5]The distribution of the private value of financial institutions from patenting is highly skewed, ranging from US$16.9 million at the 10th percentile to US$526.1 million at the 90th percentile of the sample distribution. For data on patent value capturing financial institutions' private return on patenting, we employ estimates by following Kogan et al.'s (2017) work.

We next establish that during the EAWA ban, TARP banks filed patents at a considerably lower frequency than non-TARP banks, with a difference of 6.5 percentage points, which is approximately 30.8% of the sample mean. These results remain robust when limiting the variation within banks over time and within year-months across banks as well as absorbing banks' foreign-hire outcomes over the preceding three years.

We then move on to interpret these results. A fundamental potential confounder in our setting is that the financial crisis was a significant adverse economic shock and especially so for TARP recipients, whose capacity to invest in innovation was likely compromised irrespective of the ban on foreign hires. Against this concern, note that our second empirical strategy does not rely on a simple comparison of outcomes within banks before and after EAWA, which would raise concerns about unobservable crisis- or TARP-related shocks that might have influenced banks' innovation (e.g., Calomiris and Khan, 2015; Berger and Roman, 2015, 2017; Berger et al., 2020; Ma et al., 2022). By contrast, our second strategy only uses banks that accessed TARP and faced similarly large negative shocks during the same time period. In particular, our analysis holds the amount of TARP funding constant, which we interpret as a direct proxy for the severity with which banks were hit by the crisis, and compares two groups of banks that obtained the same amount of TARP funds. One group relied less on immigrants to fulfill their high-skilled positions before the crisis hit, whereas the other relied more on immigrants to fulfill the same positions.

In our second strategy, we document that TARP banks with high EAWA exposure—those that hired more foreign STEMs than their peers of similar size before the financial crisis—cut their patenting activities significantly, whereas less exposed TARP banks barely cut them. The likelihood of filing any patents was lower for more exposed TARP banks, and, crucially, this effect was largely driven by missing patent filings by inventor teams that included new inventors (individuals who had never appeared as USPTO inventors before).

We further corroborate our interpretation of the baseline results with the following additional evidence. First, we find that during the EAWA ban, the quality of patents filed by TARP banks—measured by subsequent technology-cohort-adjusted citation counts—was lower relative to the quality of patents filed by non-TARP banks. This difference is detected for patents not covering business methods and patents on financial technology (FinTech). Second, we show that banks with high EAWA exposure might discontinue innovation activities in general during the ban. However, we document that the drop in patenting was concentrated among individual inventors who submitted patents for the first time within their tenure at a bank, whereas patenting by existing inventors barely changed during the same period. This finding is

consistent with the fact that the EAWA ban only restricted banks from sponsoring new visas for foreign STEM workers. Third, we find no evidence indicating TARP banks subject to the EAWA ban were more likely to purchase patents from external sources during the EAWA ban period, which would have allowed them to substitute in-house innovation production with externally-produced patents.

We then move on to assess the implications of the EAWA ban on the labor market for high-skilled workers. If domestic banks could replace foreign high-skilled immigrants with domestic high-skilled workers, we should have observed no effects of the EAWA ban on firms' innovation. By contrast, if banks faced a shortage of high skills in the domestic labor market, given that existing foreign STEM workers' visas could be renewed under EAWA, we should see that the price of existing foreign STEM workers' labor (wage) became higher than non-STEM workers' wages, as a result of banks trying hard to retain at least the limited pool of foreign STEM workers to which they had access. Existing foreign workers hired before EAWA had outside opportunities both within the US (non-EAWA-banned banks and non-financial firms) and abroad.

Our visa-level data enable us to compute the wage premium associated with each visa application filed by banks on behalf of foreign workers relative to the prevailing domestic wage for similar jobs.[6] We find that during the EAWA ban TARP banks began offering a higher wage premium to their existing STEM foreign workers than their existing non-STEM foreign workers.

Overall, our empirical results appear consistent with the view that banning the hire of foreign high-skilled workers (*nationalistic labor policies*) reduces firms' ability to produce innovation, presumably because foreign high-skilled employees cannot be found in the US workforce or their cost would be so high that it would exceed the expected value of innovation that accrues to the firm.[7] At the same time, banned firms also face a higher wage bill because they pay relatively higher wage premia to their existing pool of foreign high-skilled workers to avoid their departure from the firm. We do not find any evidence consistent with the view that nationalistic labor policies might favor domestic high-skilled workers by providing them with more or better paid jobs.

A. Related Literature

Our paper builds on several strands of literature in economics and finance. First, it relates to the literature studying the impact of policy interventions and regulation on innovation (see He and Tian, 2020 for a

[6]The prevailing wage in the H-1B data is visa-specific information and is self-reported by firms (visa petitioners) who provide the source of information for the prevailing wage to the immigration office. The immigration office assesses whether the reported domestic prevailing wage is plausible as part of the visa approval/denial process.

[7]Of course, the loss for the US economy overall is much higher than for the firm given that the social benefits of the innovation that was not produced would have likely been higher than the benefits the firm could have appropriated.

recent review as well as Bayazitova and Shivdasani, 2012; Amore et al., 2013; Agarwal et al., 2014; Mayer et al., 2014; Lucca et al., 2014; Agarwal et al., 2017; Genin et al., 2022; Denes et al., 2023; Babina et al., 2023). Consistent with the arguments in Lerner et al. (2023), we find post-financial crisis regulation may have led to lower investment in innovation. Rather than studying policies intentionally designed to influence innovation, such as place-based policies (e.g., Lerner, 1996; Tian and Xu, 2022; Xu, 2021; D'Acunto et al., 2021, 2019), our focus is on a labor-market restriction that produced unintended and yet substantial consequences for innovation production. We draw upon research documenting the unintended impacts of labor-market policy interventions on firms' innovation and productivity, such as Bena, Ortiz-Molina, and Simintzi (2022), who show labor protection laws prompt firms to pursue process innovation and automation rather than increase wages and job security. In the same vein, Hombert and Matray (2018) and Bena and Simintzi (2019) explore the innovation and labor-market ramifications of U.S. free-trade agreements with China. Given the pivotal role of financial innovation for product development and transaction security within an information-driven economy, the unintended consequences of nationalistic labor policies we uncover could have far-reaching implications for the profitability and security of the financial services industry.

Second, our paper is among the first to shed light on the extensive amount of innovation produced by US financial institutions. Many authors explore the causes and consequences of financial innovation at the micro level, including both patentable and non-patentable ideas (e.g., Tufano, 1989, 1995; Lerner, 2002; Tufano, 2003; Lerner, 2006, 2010; Rysman and Schuh, 2016; Pérignon and Vallée, 2017; Calvet et al., 2018; D'Acunto, 2020; Lerner et al., 2023).[8] In a recent study, Chen et al. (2019) employ machine learning to identify and classify innovations in the financial industry. The authors highlight that banks emerge as the most active innovators in the financial services sector among public firms. Jiang et al. (2023) use the text information from FinTech patents to study the labor-market outcomes of FinTech disruption.

Third, we show the important role of high-skilled immigrants in the advancement of US FinTech. This study speaks to an emerging body of literature emphasizing the contribution of domestic and foreign talent to U.S. innovation and productivity (e.g., Kerr, 2008; Kerr and Lincoln, 2010; Stuen et al., 2012; Moser et al., 2014; Peri et al., 2015; Jaimovich and Siu, 2017; Dimmock et al., 2022; Bernstein et al., 2019; Burchardi et al., 2020; Arkolakis et al., 2012; D'Acunto et al., 2023; Canayaz et al., 2024). Specifically, our work builds upon studies employing H-1B visa data in the US, such as Bernstein et al. (2019), which delineate immigrants' impact on US innovation, and Dimmock et al. (2022) and Chen et al. (2021), who

[8] Frame and White (2004), Frame and White (2012), and Lerner and Tufano (2012) provide extensive literature reviews.

find H-1B visa lottery winners generate more patents and patent citations than the average US domestic innovator. We also relate to Ouimet and Zarutskie (2020), who document that acquiring labor skills can be vital to firms to motivate their merger and acquisition activity.

2 Data

We employ several sources of data that cover information about the hiring policies and patenting activities of financial institutions.

2.1 Selecting the Sample of Financial Institutions

To obtain a homogeneous sample of financial institutions, we apply a set of filtering criteria. First, we exclude TARP participants that do not fall under the category of commercial banks, such as mutual funds, insurance companies, and trading companies. Second, we filter institutions that do not produce any innovation by keeping only institutions that submitted at least one patent application to the USPTO during our sample period (2002-2016). Third, to ensure we consider banks that had any scope for producing innovation during the EAWA period, we further exclude banks that had filed no patents prior to December 31, 2006. These selection steps lead us to include 27 TARP recipients in our sample, whose characteristics we discuss below and report in Table A.1.

Table A.1 provides a comprehensive list of the 21 TARP recipients included in our sample, along with timelines detailing their entry into and exit from TARP. The table also includes statistics such as patent fillings before 2006, foreign STEM hires during 2004-2006, total assets (millions USD) recorded as of end of 2009,[9] and the number of days of exposure to EAWA.

2.2 Timing of Exposure to the EAWA Foreign Hiring Ban

The duration of the restriction on TARP participants from hiring new H-1B workers under EAWA varies across institutions. EAWA came into effect on February 17, 2009, and ceased on February 17, 2011. Because financial institutions entered and exited the TARP program on different dates, exposure to the EAWA foreign hiring ban varies across institutions (see Figure A.1 in the Online Appendix for a graphical depiction of the staggered ban exposure).

In Table A.1, we list the timing of the beginning and end of the EAWA ban restrictions for the 27 selected TARP banks in our sample. The vast majority of institutions started facing the EAWA ban

[9]Initial financial data for the banks were primarily sourced from bank regulatory records and augmented with information from BvD banks scope, Compustat North American, and Global. Because Washington Mutual was acquired by JP Morgan on September 25 2008, the bank's assets as of 2009 was not available. We thus use Washington Mutual's assets in December 31, 2007.

on the day it entered into effect, because they had entered TARP before the US Congress debated and approved the ban. Note that before deciding to access TARP, most TARP institutions were unaware they would face a foreign hiring ban, which reduces the concern that considerations regarding foreign hiring policies and innovation production might have influenced their decision to access TARP. For this reason, institutions could not have considered their innovation activities an outcome potentially affected by TARP when deciding whether to enter the program.

In the second last column of Table A.1, we compute the number of days for which the EAWA was effective for each TARP participant. Substantial variation exists in the length of EAWA-ban exposure across TARP institutions.

2.3 Patents Data

Building on existing literature (see recent surveys by Bernstein et al., 2019; He and Tian, 2020), we measure innovation activity based on patent applications and outcomes. Our data, sourced from PatentsView, includes US patents filed by both TARP participants and other financial institutions over the period 2002–2014. The USPTO later granted these patents. Patent applications lack distinct firm-level or inventor-level identifiers for consistent tracking of assignees and inventors over time. Nevertheless, PatentsView employs a disambiguation algorithm that facilitates the association of the same inventor or patent assignee with multiple patents by pooling similar individual and firm names.

We create the sample of patents filed by financial institutions in several steps. First, we compile a list of names of institutions that filed and published at least one patent during the period 2002–2016 based on bank names in BANKSCOPE by Bureau van Dijk. Second, we use the list of institutions to search for assignee identifiers on the PatentsView platform. Third, we extract the patents filed by our sample's institutions.[10] The information we extract includes application/patent number, filing date, patent classification, assignee location, inventors' identities and addresses, and other details. When information is missing on PatentView, we search for it directly in the USPTO patent list.

The final sample consists of 8,097 patents filed between January 2000 and December 2014, all of which were eventually granted. For these patents, we also gather citation data from Google Patents, which is current as of January 2022. Most of our empirical analysis focuses on the period of January 2007–December 2014, during which the institutions in our sample filed 3,649 patents.

Panel A of Figure 2 shows the cumulative number of patents in our sample over the period 2002Q1–2014Q4. Similar to Lerner et al. (2023), we detect a surge in innovation production, measured by the

[10] https://patentsview.org/download/data-download-tables.

number of filed patents that were ultimately granted, in the first decade of the 21^{th}century. This trend appears to have flattened since 2010. Panel B lists the top 20 financial institutions ranked by the number of patents produced from January 2007 to December 2014. The patent distribution is heavily skewed, and sizable variation in innovative activities also exists among larger banks.

Panel A of Table 1 presents the top 20 classifications of patents filed by the financial institutions. Panel B of Table 1 presents information on the assignee and abstract for the top 20 patents by citations in our dataset. We present details in section A.1.2 of the Online Appendix.

2.4 H-1B Visa Applications Data

The US H-1B Program operates on an employer-centric model; that is, employers submit applications on behalf of the prospective employees. For this reason, H-1B visa applications lack demographic details specific to the foreign worker on behalf of which they are submitted. Our H-1B visa data are sourced from USCIS and are organized at the firm-location-job-application-date level. Each visa application provides information such as the sponsoring company's name, the date on which the application was filed, the occupation title the prospective employees would obtain, and the location of the H-1B applicant (sponsor). We also have access to data regarding the effective commencement and conclusion dates of the visa, the wages that were offered to applicants, the US prevailing wages for the same occupations and location, the number of employees associated with each visa, the designated location for employee deployment, and the application outcome (i.e., approval or rejection).

2.5 Descriptive Statistics

As discussed above, we require that the banks in our sample had filed at least one patent that was eventually granted by the USPTO prior to December 31, 2006, in order to capture banks that had scope to produce innovation during the EAWA. As such, we end up with 20 TARP and 13 non-TARP banks for the sample in which we implement our first empirical strategy (i.e., equation (3.1) in section 3.1). Note that in this sample, we also require that banks had hired at least one foreign STEM during 2004-2006. Instead, we end up with 27 TARP banks for the sample in which we implement the second strategy (i.e., equation (3.2) in section 3.1), which only includes TARP participants.

Table 2 presents a set of descriptive statistics of our main analysis at the bank-year-month level. The sample period is from January 2007 through December 2014. We start in January 2007 to ensure the outcome variables (e.g., H-1B STEM hiring and patenting activities) do not overlap with the pre-crisis period in which we measure banks' exposure to the EAWA shock, which is 2004–2006, as we define below.

In Panel A of Table 2, we see about 9.4% of bank-year-month observations subject to the EAWA period, 37.6% of observations are associated with the employment of H-1B STEM occupations, the average number of foreign STEMs hired is seven, and 20.5% of observations are linked to at least one patent filing. In Panel B of Table 2, we provide statistics for the sample in which we conduct analysis within TARP banks that were differentially exposed to EAWA. The frequencies with which banks hired foreign STEMs and applied for patents mirror those reported in Panel A. In terms of sample composition, 67% of bank-time observations exhibited high EAWA exposure; that is, TARP banks hired above the median of subsamples (stratified by bank size) account for 67% of our second sample. On average, TARP banks obtained funds from the government that accounted for 2.5% of total assets measured by the end of 2009.

3 Empirical Strategies

In this section, we discuss our two difference-in-differences (DiD) strategies and provide evidence about the compliance of TARP recipients with the EAWA ban on hiring foreign workers until the full repayment of TARP funds.

3.1 First Difference-in-Differences Strategy: TARP vs. Non-TARP Banks

We implement the first empirical strategy by estimating a set of linear specifications that exploit within-bank variation in both dependent and independent variables. To exclude banks that are not subject to the EAWA ban, we require that institutions hired at least one foreign employee for a STEM job through the H-1B visa program during the period of 2004–2006.[11] The most complete specification is as follows:

$$\begin{aligned} Outcome_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times TARP_i + \beta_3 Post_{i,s} + \\ \beta_4 Post_{i,s} \times TARP_i + X' \times \beta_5 + \eta_i + \eta_s + \epsilon_{i,s}, \end{aligned} \tag{3.1}$$

where $EAWA_{i,s}$ is a dummy variable that equals 1 if institution i is subject to the EAWA ban on hiring foreign workers during year-month s, and zero otherwise. $TARP_i$ is a dummy variable that equals 1 if institution i accessed the TARP program, and 0 otherwise. $Post_{i,s}$ is a dummy variable that equals 1 during year-month s after the EAWA is no longer binding for i, and 0 otherwise. $EAWA_{i,s}$ and $Post_{i,s}$ are set to 0 for institutions that never borrowed funds through TARP.[12] We also incorporate full sets of institution-

[11] We follow Cheng et al. (2014) and use the years 2004–2006 to measure the pre-crisis period, but our results are similar if we consider other time periods before 2008.

[12] Because only TARP banks were subject to the EAWA restriction, the two variables $EAWA_{i,s}$ and $EAWA_{i,s} \times TARP_i$ are perfectly correlated. For this reason, we only report the estimates of $EAWA_{i,s} \times TARP_i$ in all tables. The same logic applies to the variables of $Post_{i,s}$ and $Post_{i,s} \times TARP_i$.

and year-month fixed effects, represented by η_i and η_s respectively. The inclusion of institution-fixed effects absorbs systematic and time-invariant cross-sectional differences across institutions. Year-month fixed effects allow us to absorb economy-wide aggregate and time-varying shocks that affect all banks uniformly. Given the span of our sample period, covering the financial crisis and the Great Recession, unobservable time-varying aggregate shocks are likely to be important drivers of banks' outcomes, including their innovation activities. $Outcome_{i,s}$ are a set of outcomes measured at the level of institution i in year-month s, including patenting and other innovation activities.

In equation (3.1), the coefficient of interest is β_2, which captures the within-bank change in outcomes during the EAWA period relative to before EAWA entered into effect and across TARP and non-TARP recipients.

3.2 Second Difference-in-Differences Strategy: Varying Pre-Exposure to EAWA among TARP Banks

An important concern with our first empirical strategy is that the coefficient β_2 in equation (3.1) might capture the effect of time-varying bank-specific shocks that affect TARP and non-TARP institutions in a systematically different way. For instance, if TARP and non-TARP recipients' innovation activities were affected differently by monetary policy interventions during the period of interest or if TARP banks were exposed to shocks that instead did not affect non-TARP banks during the period of interest, the coefficient of interest in equation (3.1) might capture such differences.

To address this concern, our second empirical strategy only considers TARP recipients, which dismisses by construction the concern that TARP and non-TARP recipients might have faced different time-varying shocks that affected their innovation activities during the EAWA ban. Within this subset of institutions, we compare innovation outcomes across banks that had different pre-determined exposure to EAWA before EAWA was approved and entered into effect. We capture exposure with the share of bank-level STEM workers who were foreign in the pre-crisis period. The rationale for this strategy is that irrespective of whether banks might have been able to foresee the financial crisis, the implementation of a ban on foreign worker hiring was barely foreseeable in the pre-crisis period. Indeed, the EAWA ban was largely the result of political negotiations in the US Congress to secure the number of votes needed to pass the broader set of subsidies and other financial aid to institutions during the financial crisis, including subsequent waves of financing of TARP as well as other funds/programs. For this reason, banks could not have chosen the share of foreign workers among their STEM workforce in the pre-crisis period based on their expectations about the future EAWA ban. At the same time, once the ban was implemented, banks that relied more

than others on foreign STEM workers to fill their STEM job openings were affected more than other banks. Moreover, the number of pre-crisis STEM workers who were foreign, after controlling for other systematic differences in bank characteristics with the inclusion of institution-level fixed effects, seems unlikely to capture differential exposure to time-varying shocks within the group of TARP recipients.

To implement this strategy, we face the concern that both the distribution of bank sizes and of patenting activities are heavily skewed. Suppose, for instance, a small bank only employs two STEM workers and one of them is a foreign national. The share of foreign STEM workers would be 50% for this bank. This bank would appear highly exposed to EAWA, but at the same time, its patenting activities would be very low and volatile irrespective of the EAWA ban. By contrast, a very large bank that produces many patents regularly might hire hundreds of STEM workers, and the fraction of foreign workers among them is likely lower than 50% given the frictions and costs firms face to hire foreign workers. If we were capturing exposure to the EAWA ban with the raw ratio of foreign STEM workers, we would by construction attribute high exposure to a group of banks whose patenting activities are not comparable to those of the largest innovators, and vice versa.

To tackle this issue, we follow Begley and Srinivasan (2022) and classify domestic banks into small, medium, and large banks. Small banks have assets below US$10 billion, medium banks have assets between US$10 and US$50 billion, and large banks have assets above US$1 trillion. Within each of the three groups, we then compute a dummy variable, $High\ Exposure_i$, that equals 1 if the number of foreign STEM workers bank i hired in 2004-2006 was above the median of the distribution of foreign STEM workers within the group of banks of similar size. The median cutoffs for the number of foreign STEM hires by small, medium, and large banks are 0, 1, and 10.5, respectively. In this way, the categorization of TARP banks into different levels of exposure to EAWA is conditional on banks' size.

Based on these considerations, we implement our second strategy by estimating the following DiD specification:

$$\begin{aligned} Outcome_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times High\ Exposure_i + \beta_3 Post_{i,s} + \\ \beta_4 Post_{i,s} \times High\ Exposure_i + X' \times \beta_5 + \eta_i + \eta_s + \epsilon_{i,s}. \end{aligned} \tag{3.2}$$

One concern underlying this strategy is that banks' reliance on STEM human capital for operations other than innovation activities may be correlated with the deterioration of financial conditions during the crisis (3.2). For instance, recent studies indicate firms tend to lose talented workers, which might include STEM workers who innovate as well as STEM workers in other occupations, as they approach bankruptcy (e.g., Baghai et al., 2021, 2023). In fact, the shortage of high-skilled immigrants and financial

constraints may represent two distinct channels that force TARP banks to cut innovation.

To fully control for the bank-specific change in financial conditions during the crisis, we gathered data on the upfront funding obtained by each TARP recipient. We construct a continuous variable ($TARP\ Fund\%_i$) calculated as the proportion of (troubled) assets purchased by the US Department of the Treasury from institution i, scaled by i's total assets as of 2009.[13] We consider this measure the most direct proxy of the full extent of bank-level observed and unobserved deterioration of financial conditions during the crisis because, given the physical and reputational costs of accessing TARP funds, banks had the incentive to only access them to the minimal extent needed to weather the crisis. Other balance-sheet-level proxies would not provide such direct information on the deterioration of each bank's financial conditions during the crisis.

4 Foreign Hiring Restrictions and Innovation

We now move on to assess the effects of the EAWA ban on banks' innovation production. First, we confirm that TARP recipients complied with the EAWA ban on hiring foreign workers; that is, the EAWA was effectively enforced and banks stopped hiring new foreign workers while subject to it. Second, we report the results for implementing the empirical strategies discussed above.

4.1 Compliance with EAWA: New Foreign Workers Hiring by TARP Banks

Panel A of Figure 3 contrasts the quarterly average number of H-1B STEMs hired by the TARP banks with those hired by the non-TARP banks in our sample. When EAWA was passed, TARP banks experienced a large and abrupt drop in foreign STEM hires, but they gradually returned to the pre-EAWA hiring levels after EAWA ended. By contrast, non-TARP banks' foreign hiring was similar across different time periods.

Panel B of Figure 3 contrasts the TARP banks that had employed more foreign STEM workers during 2004-2006 with similarly troubled TARP banks that had employed fewer foreign STEM workers during the same period. Notably, TARP banks with lower EAWA exposure barely hired any foreign STEM workers before, during, and after the EAWA restriction, which is why the U-shaped curve of foreign

[13]The data on troubled assets (e.g., toxic assets and equity) purchased by the Treasury were obtained from the "TARP Investment Program Transaction Reports," available at: https://home.treasury.gov/data/troubled-assets-relief-program/reports/tarp-investment-program-transaction-reports. Due to acquisitions or mergers involving some TARP participants, individual funding data were are not available for acquired banks in the following cases: (i) Bank One Corporation acquisition by JPMorgan on July 1, 2004; (ii) Merrill Lynch acquisition by Bank of America in September 2009; (3) Wachovia Corporation acquisition by Wells Fargo on December 31, 2008; (4) Washington Mutual acquisition by JPMorgan Chase by the end of 2009; and (5) Chase Manhattan Bank acquisition by JPMorgan Chase on December 31, 2000. In such cases, we utilized the TARP funding data of their respective acquirers.

STEM hires was driven by TARP banks.

In Panels C and D of Figure 3, we consider the quarterly frequency at which banks sponsored at least one H-1B STEM visa. We observe similar patterns: relative to non-TARP banks, TARP banks cut the likelihood of hiring in response to their compliance with EAWA, and relative to TARP banks that were less exposed to EAWA, more exposed TARP banks halted their hiring of foreign STEMs during the EAWA ban.

To be consistent with the subsequent analysis, we perform this "first-stage" analysis using equations (3.1) and (3.2). The first dependent variable is the natural logarithm of 0.001 plus $\#STEM_{i,s}$. $\#STEM_{i,s}$ is the number of foreign STEMs sponsored by bank i in year-month s. If a bank does not sponsor any H-1B visas in s, the count is 0.001. However, we refrain from interpreting the economic meaning of this type of estimates, due to limitations associated with commonly used linear specifications in which the outcome is the logarithm of a count variable (e.g., Cohn et al., 2022). To assess the robustness of our estimates, we also introduce an alternative dependent variable, $STEM\ H1B_{i,s}$, which is a dummy variable that equals to 1 if bank i sponsored at least one H-1B visa in s, and 0 otherwise.

Panel A of Table 3 presents our estimates of equation (3.1), with the coefficients of interest highlighted in grey. During the EAWA ban, TARP banks cut foreign STEM hires more than non-TARP banks did (columns (1)-(3)). Our within-TARP-bank analysis suggests a stronger EAWA effect on TARP banks that had employed more foreign STEM workers in 2004-2006 (columns (4)-(6)).

Panel B of Table 3 presents our estimates of equation (3.2) where the dependent variable captures foreign STEM hires. Columns (1)-(4) indicate that during the EAWA ban, TARP banks were 14-24 percentage points less likely to hire foreign STEM workers relative to non-TARP banks. This number is about 37%-64% of the sample mean (0.376, as indicated in Table 2) and 29%-50% of a standard deviation (0.484, as indicated in Table 2). Columns (5)-(8) of Panel B reveal a similar pattern within TARP recipients that differed in their reliance on foreign and domestic STEM workers before the crisis. In column (8), for example, TARP banks with high EAWA exposure were 20.8 percentage points less likely to sponsor H-1B STEM visas during EAWA, which is about 57.6% of the sample mean sponsorship.

4.2 Ban on New Foreign Workers Hiring and Banks' Innovation

We use $Patent\ Filed_{i,s}$ as the dependent variable in equation (3.1). $Patent\ Filed_{i,s}$ is a dummy variable that equals 1 if bank i filed at least one patent in year-month s, and 0 otherwise. The specification implies a linear probability model for the likelihood of patenting, which we prefer to non-linear estimators, due to the need to include a large set of bank- and time-fixed effects.

We report the results in Table 4. Columns (1)-(4) report the impact of EAWA on patenting for TARP recipients relative to non-TARP recipients, both of which had sponsored some H-1B STEM jobs in 2004-2006. In the most restrictive specification (column (4)), we find a 5.9-percentage-point decrease in the likelihood of TARP recipients filing patents. In terms of economic magnitude, this estimate accounts for 28.8% of the sample mean (0.205, as indicated in Table 2) and about 14.6% of a standard deviation of the patenting dummy (0.404, as indicated in Table 2).

Columns (5)-(8) report the results from estimating equation (3.2), that is, implementing our second empirical strategy. TARP recipients with higher EAWA exposure — banks that hired more foreign STEMs than the size-adjusted sample median in the pre-crisis period — experienced a significant drop in patent filing relative to otherwise similar TARP recipients with a lower EAWA exposure. In terms of economic significance, moving from banks for which $High\ Exposure$ equals 0 to those for which it equals 1 leads to a 10.1-percentage-point drop in patent filings. This number represents 40.9% of the sample mean likelihood of patent filing in a year-month (0.247, as indicated in Table 2) and 23.4% of a standard deviation of the patenting dummy (0.432, as indicated in Table 2).

Beyond the baseline results, we assess if exposure to the EAWA ban affected patenting activities differently or similarly across patenting areas. Specifically, we consider business-method patents (classified as US patent class 705), non-business-method patents (classified as US patent classes other than 705), and FinTech patents filed by bank i in year-month s. Details about the keyword list we use to classify patent filings across areas are provided in Table A.2 of the Online Appendix.[14] Our analysis identifies 1,312 FinTech patents filed from 2007 to 2014, with Figure A.2 in the Online Appendix showcasing the top 20 financial institutions in terms of FinTech patent filings. Note a patent may be classified as both FinTech and business method, so to address potential overlap, we treat all business-method patents as non-FinTech, regardless of the keywords.

Table 5 reports the results. Columns (1)-(3) estimate equation (3.1) separately for the filing of patents belonging to the areas indicated on top of each column. We can see the drop in patent filings for TARP banks during the EAWA ban appears to have been uniform across patenting areas, even though individual estimated coefficients are not statistically significant from zero. Similarly, when moving to the second empirical strategy in columns (4)-(6), we find patent filing dropped similarly across all patenting areas for TARP banks that had higher pre-crisis EAWA exposure than other banks, and in this case, we can

[14]Inspired by Chen et al. (2019), we employ a keyword-based approach, examining seven classes: cybersecurity, mobile transaction, data analytics, blockchain, peer-to-peer lending, robo-advising, and the internet of things. We classify patents based on the presence of keywords in their title, abstract, and claims. For example, the term "authentication" defines the keyword for "cybersecurity." If a patent contains the keyword "authentication" in its title, abstract, or claims, it is categorized as related to cybersecurity.

reject the null that each individual estimated coefficient equals zero statistically.

4.3 Intensive Margin of Innovation: Patent Citations

The results so far referred to the extensive margin of innovation production, that is, the number of new patents banks file. The intensive margin of innovation, namely, the importance of the innovation in terms of generating future follow-up ideas and patents and impacting markets, is also important. In our setting, one might wonder whether TARP banks exposed to the EAWA ban on hiring new foreign workers changed their innovation strategy and focused their patenting activities to produce fewer but individually more important patents, thus concentrating the limited resources available for patent production into higher-return projects. Such a change in patenting strategy would provide a nuanced interpretation of the effects of foreign hiring bans on banks' innovation production. Conversely, if not only the quantity of innovation but also its quality declined during the period of exposure to the EAWA ban, we would detect and quantify yet another dimension along which banning the hiring of new foreign workers impacts innovation activities negatively.

To capture the intensive margin of patenting activity, we use a standard proxy for patent quality, namely, patent citations after their granting. Figure A.3 of the Online Appendix plots the distribution of patent citations for the patents in our sample. For this analysis, we cannot use the bank-year-month level sample that also includes periods during which banks submitted no granted patents, which would be vacuously associated with zero citations. Instead, we restrict the sample to observations specifically tied to at least one granted patent application.

We estimate the effect of the EAWA ban on patent quality using equation (3.1) to compare patent citations between TARP and non-TARP banks, and equation (3.2) to compare patent citations across TARP banks with different pre-set exposure to EAWA. In both regression specifications, the dependent variable is $\overline{Adj.Cites}_{i,s}$—the mean of *Adj.Cites* for all granted patents submitted by bank i in year-month s. Following Bernstein et al. (2019), we determine *Adj.Cites* by normalizing the number of citation counts based on the average citations within a specific technology-class-year. We transform $\overline{Adj.Cites}$ into a percentile-rank form.[15] Table 6 reports a set of summary statistics for our measures of patent citations.

Table 7 reports the results, which, in parallel with what we showed in Table 5 for the extensive margin

[15] We aggregate variables at the new level of observation, that is, bank-year-month observations associated with at least one filed patent eventually granted. Here, the year corresponds to the filing year of all patents belonging to the same technology class. Our citation data are observed up until January 2022. Figure A.3 of the Online Appendix plots the distribution of citation counts for patents submitted by institutions in our sample spanning the years 2007–2014. As anticipated, our findings reveal a pronounced positive skewness in the distributions of both raw and adjusted citation counts.

of innovation, also include separate estimates for patents in different technological areas. As shown in columns (1)-(4), when comparing patent quality between TARP and non-TARP recipients, we fail to detect an increase in post-filing patent citations for banks exposed to EAWA. Banks facing more limited resources to patent did not change their innovation strategy by focusing on more path-breaking and impactful projects.

By contrast, when we compare patent quality within the group of TARP banks with high or low exposure to the EAWA ban, we estimate a positive coefficient of interest (0.085 in column (5)), which suggests citation counts for patents filed during the EAWA period by more affected banks were higher than those of other banks and during the pre-crisis period. This positive coefficient is small, though, and masks substantial heterogeneity across categories. TARP recipients that hired more high-skilled immigrants before the crisis produce business-method patents that have higher average citation counts but non-business-method and FinTech patents that have lower average citation counts.

Although our setting does not allow for a direct test, one conjecture in interpreting these results is that when banks face restrictions to their factors of innovation production, such as new foreign inventors, they focus their innovation activities on developing cost-cutting methods to manage existing processes, which would fall under business-method patents. By contrast, when unconstrained, banks might focus their innovation activities on developing new products and new future commercial opportunities, which would fall under the FinTech/non-business-method patent categorization.

5 Interpreting The Effects of Banning New Foreign Hires on Innovation

In this section, we provide additional tests and evidence that help us interpret the economic channels that drive the baseline results we discussed above.

5.1 Are New Foreign Hires Relevant above and beyond Existing Foreign Workers?

As we discussed in the institutional setting (see section A.1), EAWA imposed restrictions exclusively on the sponsorship of *new* H-1B visas, whereas the renewal of H-1B visas for foreign workers who were already employed before EAWA was implemented remained unaffected. In other words, EAWA did not affect the existing stock of foreign workers whom banks employed in innovation activities, who continued working on their innovation production tasks after the EAWA ban was implemented. Can new hires be so important for innovation activities above and beyond the existing stock of foreign innovators whom banks employ?

Our evidence indicates the stifling of innovation during EAWA was indeed predominantly due to the absence of new foreign hires in STEM fields. We produce this evidence by estimating our baseline specification with the outcome variable being *First Filer*$_{i,s}$, which is a dummy variable that equals to 1 if, in year-month s, at least one patent filed by individual inventors who submitted patents for the first time within their tenure at bank i. This dummy variable thus captures the patents filed by banks in which a new innovator was part of the patenting team.

We present the results in Table 8. The analysis reveals a consistent pattern regardless of whether we compare *First Filer* between TARP and non-TARP banks or within TARP banks by varying their EAWA exposures. Specifically, financial institutions subjected to a more pronounced impact from the EAWA ban experienced a larger drop in the likelihood of filing patents for which new inventors were part of the patenting team. Importantly, the estimated effects closely align with our baseline estimates for the likelihood of banks filing any patents (see Table 4). The results in Table 8 suggest a significant portion of the patents that EAWA-exposed banks did not file when banned from hiring new workers were patents that, indeed, would normally include new inventors as part of the patenting team.

One of the mechanisms through which new hires might be important for patenting activities is agreements that assign to employers the ownership rights over inventions created by employed. If these agreements are signed (which we cannot observe in our data), banks would have an incentive to identify and recruit inventors whose innovative ideas might already be conceived but whose development or patenting process the foreign inventor cannot finance or navigate.

We are not aware of data sources that would enable us to observe whether newly hired inventors bring pre-existing innovative ideas that can be patented within the company. In the absence of such data, we proxy these instances with patent applications filed by financial institutions wherein an inventor who files for the first time during year-month s of their tenure with bank i is not only part of the team but also serves as the lead inventor; that is, s/he is listed as the first name in the inventors' team. The rationale is that lead inventors typically play a significant role in driving the innovation the patent protects. Therefore, when lead inventors are newly hired employees, the likelihood that the new hires contributed their existing innovation ideas to the bank once recruited is higher.[16]

Table A.3 of the Online Appendix estimates the effect of EAWA on patenting conducted by new inventors who are also listed as the lead inventor. We find a substantial share of the patents that EAWA-exposed banks did not file during the EAWA period were patents for which new employees would have been part of the team as lead inventors.

[16]To identify a lead inventor, we do not consider patents that list inventors alphabetically, in which the order of names does not indicate the importance of the specific inventor in developing the patent.

5.2 Did Banks Substitute Internal Patents with External Patent Purchases?

In principle, EAWA-exposed banks could have reacted to the drop in internally-produced patents during the EAWA ban by turning to the secondary market to purchase patents developed by others. Indeed, an emerging body of research shows firms frequently acquire innovation from counterparts that are more efficient at innovation (e.g., Aghion and Tirole, 1994; Bowen III, 2016; Cunningham et al., 2021; Sevilir and Tian, 2023).

To assess this possibility, we compile the patent transaction histories of each bank in our sample using the Patent Assignment Dataset sourced from the USPTO. This dataset enables parties to record inter-firm patent assignments, ensuring a comprehensive record of claimed interests in a given patent.[17] To precisely measure inter-firm patent purchases, we exclude inter-bank assignments caused by banks' acquisition of collateralized patents and patents from acquired firms. The summary statistics presented in Table 2 indicate the monthly frequency with which banks acquire at least one patent from external parties is 4.9% for all banks and 6.2% for TARP banks, which suggests this potential channel is not economically negligible.

Table 9 presents the estimation results based on our two proposed empirical strategies in equations (3.1) and (3.2). The dependent variable in this case is $Purchased_{i,s}$, which is a dummy that equals 1 if bank i acquired at least one patent from external parties in year-month s, and 0 otherwise.

Not only are the results inconsistent with the possibility that EAWA-exposed banks replaced internal patenting production with higher purchases of external patents, but, in fact, the likelihood of external purchases declined *more* for EAWA-exposed banks than for other banks during the crisis.

5.3 Labor-Market Implications: Wage Premia to Foreign STEM Workers

In the final two sets of analyses, we aim to shed light on the labor-market implications of the EAWA ban on banks' ability to engage in new foreign hires. In particular, because EAWA banned TARP banks from hiring new foreign workers, and because foreign workers in the US are not allowed to carry H-1B visas from one company to the other, TARP recipients could only employ high-skilled immigrants by retaining their existing H-1B-visa holders, that is, the foreign workers they had hired before the crisis.

Because the bargaining power between TARP banks and existing foreign workers shifted in favor of the latter group, the EAWA ban might have resulted in TARP banks paying a relatively higher wage premium to existing foreign workers relative to non-TARP banks after being affected by the ban. Based

[17] The data are available for download on the official website: https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-assignment-dataset.

on these considerations, we analyze the wage premia foreign STEM workers could extract during and after the EAWA period.[18]

We exploit information about wage premia (i.e., the difference between the wage offered to the visa holder and the prevailing wage for the same occupation in the US at the onset of visa application), job location and classification, and the number of immigrants sponsored in each petition from the H-1B visa data. From the sample from January 2007 through December 2014, we have collected a total of 50,545 H-1B petitions filed by our sample banks with USCIS. The prevailing wage rate is petition-specific and is defined as the average wage paid to similarly employed workers in the requested occupation in the area of intended employment.[19] Panel A of Table 10 reports summary statistics for the wage premium and other crucial covariates in this sample.

We estimate the following regression specification:

$$\begin{aligned}\overline{\text{Wage Premium}}_{i,l,s} = \alpha + \beta_1 \text{EAWA}_{i,s} \times \text{TARP}_i \times \text{STEM}_{i,l,s} + \beta_2 \text{EAWA}_{i,s} \times \text{TARP}_i + \beta_3 \text{EAWA}_{i,s} \times \text{STEM}_{i,l,s} \\ + \beta_4 \text{EAWA}_{i,s} + \beta_5 \text{Post}_{i,s} \times \text{TARP}_i \times \text{STEM}_{i,l,s} + \beta_6 \text{Post}_{i,s} \times \text{TARP}_i + \beta_7 \text{Post}_{i,s} \times \text{STEM}_{i,l,s} + \\ \beta_8 \text{Post}_{i,s} + \beta_9 \text{STEM}_{i,l,s} \times \text{TARP}_i + \beta_{10} \text{STEM}_{i,l,s} + \beta_{11} \text{TARP}_i + \eta_l + \eta_i + \eta_s + \epsilon_{i,l,s},\end{aligned} \tag{5.1}$$

where $\overline{Wage\ Premium}_{i,l,s}$ is the weighted-average wage premium over the prevailing wage for H-1B visas within the same job category l, submitted by bank i in year-month s. The weight is determined by the number of immigrants sponsored under each H-1B visa. $STEM_{i,l,s}$ is a dummy variable that equals 1 if job category l for visas sponsored by bank i in year-month s falls within the STEM classification, and 0 otherwise.

Panel B of Table 10 reports the estimates. Across columns (1)-(5), we detect a pattern consistent with TARP recipients paying a higher wage premium to existing STEM foreign employees during the EAWA period. By contrast, the wage premium TARP banks paid to foreign STEM workers after the EAWA ban was lifted did not differ from the wage premium they paid to others. The economic magnitude of these findings is illustrated in the last column: while TARP recipients paid foreign non-STEM workers (an insignificant) 3.5 percentage points less than the prevailing wage during EAWA, they compensated existing foreign STEM jobs with a 5.6-percentage-point higher premium.[20]

[18] Shifts in bargaining power between existing immigrants and bank employers might also be reflected in changing labor-contract covenants such as non-compete agreements and equity-based compensation (e.g., D'Acunto et al., 2021). Unfortunately, because these covenants are unobserved in H-1B visas, we cannot assess them in our setting.

[19] The prevailing wage rate is usually obtained by contacting either the State Workforce Agency (SWA) or from other legitimate sources of information.

[20] In Panel B of Table 10, *EAWA* and *Post* are absorbed because their perfect correlation with *EAWA* × *TARP* and *Post* × *TARP*, respectively. For the same reason, *EAWA* × *STEM* and *Post* × *STEM* are absorbed because their perfect correlation with *EAWA* × *TARP* × *STEM* and *Post* × *TARP* × *STEM*, respectively.

5.4 An Anatomy of STEM Jobs' Skill and Knowledge Sets

Our findings, considering both patenting activities and labor-market implications, imply that STEM immigrants could potentially play a more significant role in driving innovation within financial institutions than non-STEM immigrants. To investigate this possibility more directly, we conduct a comparative analysis of the skill and knowledge profiles of STEM jobs with those of non-STEM jobs. Both STEM and non-STEM positions in the US are sponsored under the H-1B visa program, which was subject to the EAWA ban for TARP funds recipients.

We obtain information on skills at the occupation level from ONET. Within the Standard Occupational Classification (SOC) system, each occupation's ONET rating quantifies the extent to which a specific skill or knowledge component is unique to that occupation. Skill components include basic skills (e.g., reading, facilitating the acquisition of new knowledge) and cross-functional skills (e.g., problem-solving, spanning across various domains of activities). These skills are evaluated across diverse areas such as business and management, manufacturing and production, engineering and technology, mathematics and science, health services, and others.[21]

Drawing from these occupation-level ratings, we measure the differences in skill and knowledge between foreign-born employees in STEM and non-STEM occupations. More precisely, we employ numerical ratings to quantify the level of a descriptor (a skill or knowledge component) h to N STEM occupations relative to the level of the same descriptor to M non-STEM occupations.

For an intra-bank comparison, both types of occupations must be sponsored by financial institutions i in the 2004-2006 period. We compute the following:

$$Difference_{h,i} = \frac{\frac{\sum_{k=1}^{N}\sum_{1}^{n} Rating_{h,k}}{\sum_{N}\sum_{n} 1}}{\frac{\sum_{k=1}^{M}\sum_{m} Rating_{h,k}}{\sum_{M}\sum_{m} 1}} - 1, \tag{5.2}$$

where $Rating_{h,k}$ represents the rating assigned to the level corresponding to descriptor h for occupation k. Financial institution i sponsors n H-1B workers for each STEM occupation and m H-1B workers for each non-STEM occupation. Using equation (5.2), we compute the average of $Difference_{h,i}$ across J financial institutions to determine the rating of descriptor h for STEM occupations relative to non-STEM occupations:

$$Differenceh = \frac{\sum_{J} Difference_{h,i}}{J}, \tag{5.3}$$

where J is the number of financial institutions sponsoring H-1B jobs in our sample.

[21] To synchronize with the timeline of STEM-dependence that we measure, we obtained O*NET version 11.0 as of December 2006 from ONET.

Our null hypothesis posits that ratings for the skill component h are consistent across various occupations, and as a result, $Difference_h$ in equation (5.2) is 0.

Panel A of Figure 4 illustrates $Difference_h$ calculated using skill ratings across 20 skill elements. Note skills such as "Science," "repairing," "installation," "equipment maintenance," and "programming" emerge as particularly advantageous for an average STEM occupation. In Panel B of Figure 4, t-statistics for the mean, computed according to equation (5.3), are plotted, revealing the majority of skill differences between STEM and non-STEM occupations are statistically significant. Moving to Panel C of Figure 4, $Difference_h$ is calculated using knowledge ratings across 20 elements. Similar to the skill ratings, "Science," "repairing," "installation," "equipment maintenance," and "programming" are identified as advantageous skill sets for an average STEM occupation. In Panel D, $Difference_h$ is constructed using knowledge ratings across 33 elements. Here, STEM occupations exhibit a performance exceeding 200% in various knowledge areas, including "biology," "physics," "chemistry," "fine arts," and "design." However, these differences are only marginally statistically significant.

Overall, our findings indicate STEM and non-STEM workers contribute significantly distinct skillsets to the financial institutions that employ them. As a result, these workers are not readily interchangeable.

6 Conclusions

We find nationalistic labor policies, which impose limitations on the ability of domestic firms to hire specialized foreign workers, can significantly impede financial institutions' capacity to produce innovation, including patenting products and services that would allow them to compete with FinTech companies or to enhance the security of the US financial sector.

Our paper offers a set of paths for future research. First, assessing and estimating the effects of lower patenting activities by financial companies that cannot hire specialized foreign STEM workers in terms of investment and profitability in the long-run would be important to quantify fully the magnitude of the negative effects of nationalistic labor policies.

Moreover, the increasing global threat of cyberattacks against financial corporations and other threats to the security of national financial sectors emphasize the national-security scope of banks' innovation activities: losing the edge on the frontier of technology production in this realm might have far-reaching negative implications above and beyond the short- and medium-run economic effects on banks and employees. Assessing the size of these effects is crucial to inform regulators of the potentially unintended consequences of their nationalistic policies.

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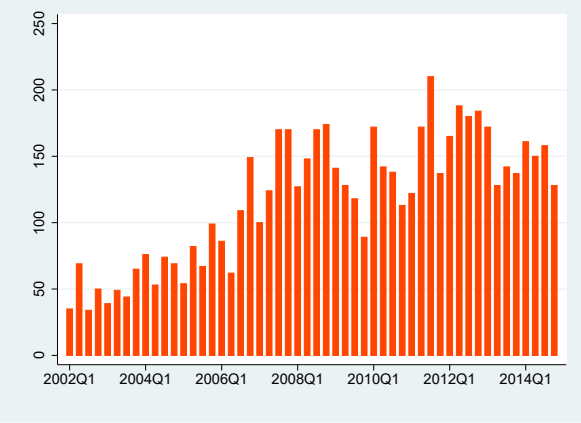
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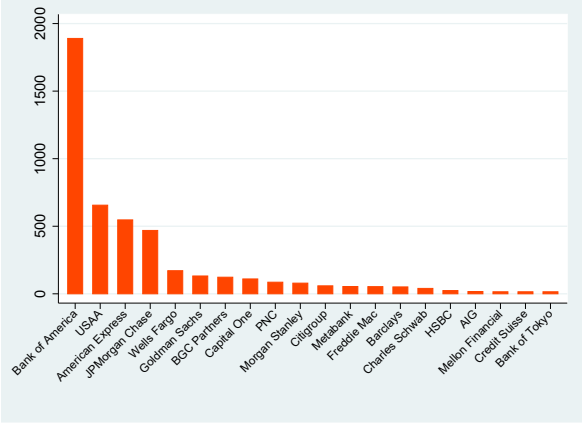
Figure 2: **Aggregated Patents and Top 20 Innovative Financial Institutions**

This figure presents the aggregated number of patents filed by the financial institutions in our sample over time (Panel A), the top 20 financial institutions that filed the most patents from January 2007 through December 2014 (Panel B), the aggregated number of inventors who filed patents for financial institutions over time (Panel C), and the top 20 financial institutions that hired the most inventors from January 2007 through December 2014 (Panel D). In Panels A and C, the x-axes measure time at the year-quarter level; in Panels B and D, the x-axes report institution names. In Panels A and B, y-axes are the number of patents filed; in Panels C and D, y-axes are the number of inventors.

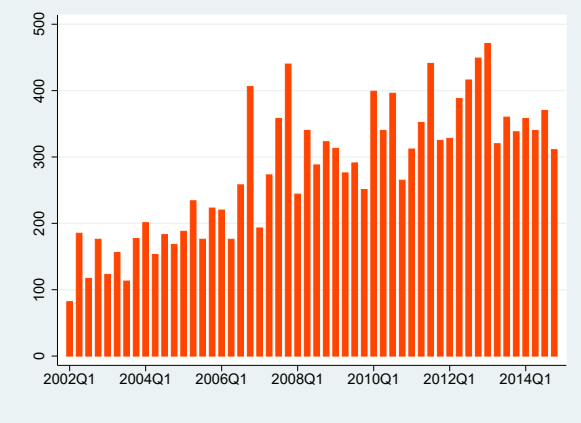
Panel A: Aggregated Patents



Panel B: Top 20 Banks, Patents



Panel C: Aggregated Inventors



Panel D: Top 20 Banks, Inventors

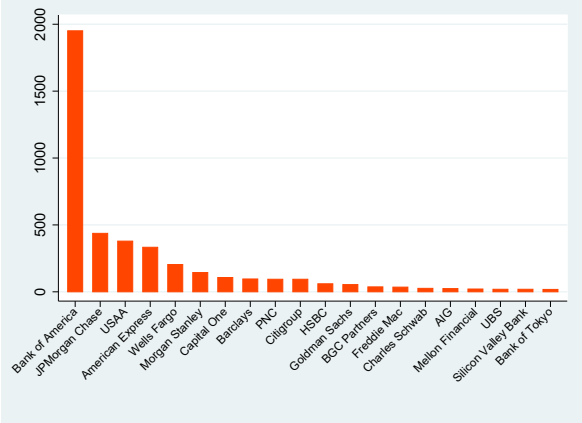
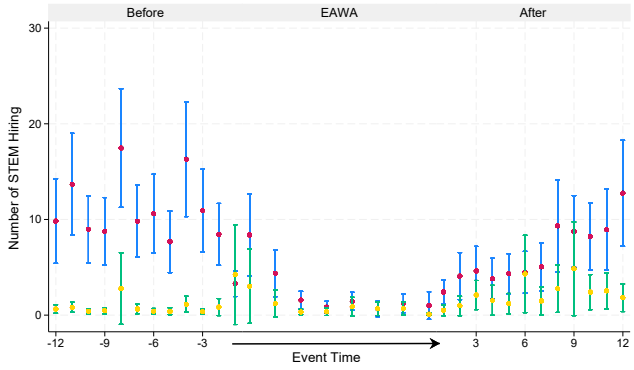


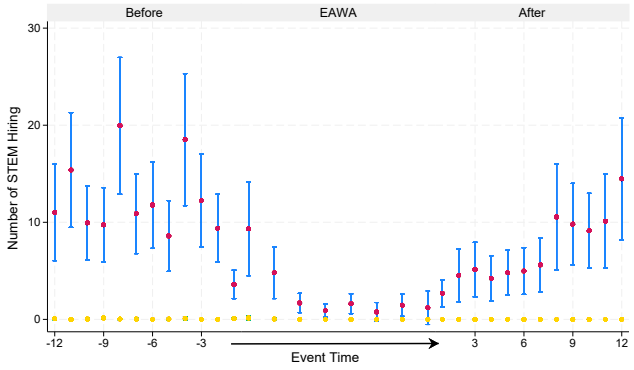
Figure 3: **H1-B STEM Hiring**

The figure plots the average number (Panels A and B) of H-1B STEM jobs that US banks hire and average frequency (Panels C and D) with which US banks hire H-1B STEM jobs (y-axis). The reported averages are calculated across bank-year-month observations within each event quarter (x-axis). Panel A and C include both TARP and non-TARP recipients that sponsored H-1B STEM jobs during 2004-2006. The blue (light-green) line represents TARP (non-TARP) recipients. Panels B and D only include TARP recipients. The blue (light-green) line represents TARP recipients that had high (low) exposure to EAWA (see section 3.1 for how high and low exposures are constructed). The time periods are categorized as "Before," "EAWA (Event Time)," and "After," corresponding to quarters before, during, and after banks' compliance with EAWA. The Event Time period for TARP recipients is institution-specific (refer to Table A.1), whereas the period of non-TARP recipients is calculated from February 17, 2009, through February 17, 2011. See section 2.1 for the selection of our sample banks. Confidence intervals are calculated at the 95% level.

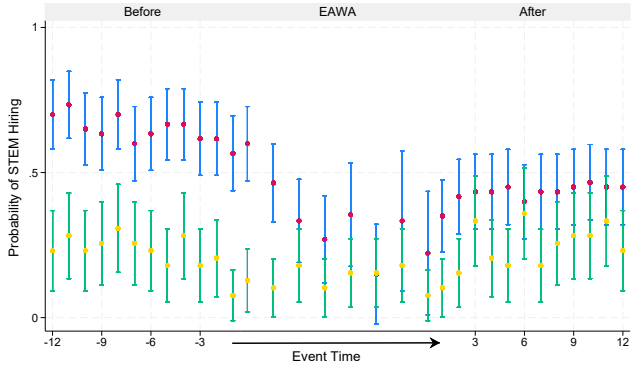
Panel A. All Banks, # Hire



Panel B. TARP Banks, # Hire



Panel C. All Banks, Prob. Hire



Panel D. TARP Banks, Prob. Hire

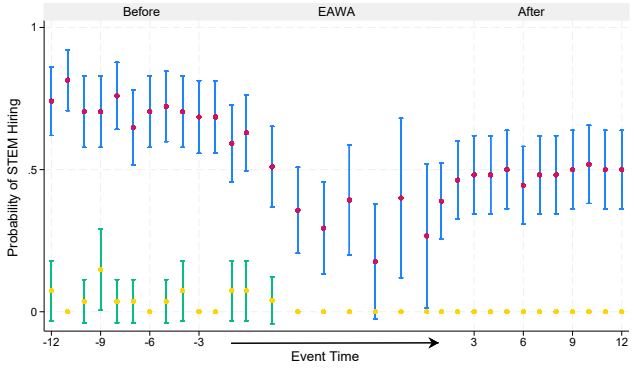


Figure 4: **STEM Skills**

*This figure plots the difference in O*NET ratings for the level of each skill or knowledge element of STEM occupations relative to non-STEM occupations. We use information from H-1B visas sponsored by our sample financial institutions through the H-1B program over the period of 2004-2006. For each skill or knowledge element h corresponding to institution i sponsoring N STEM occupations and M non-STEM occupations, the "Difference" score is calculated as follows:*

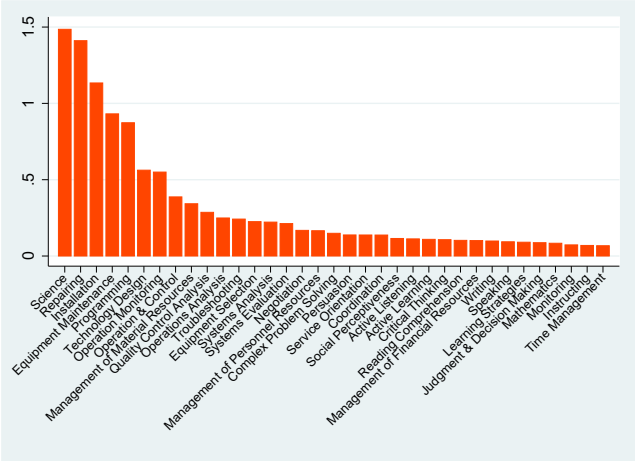
$$Difference_{h,i} = \frac{\frac{\sum_{k=1}^{N} \sum_{1}^{n} Rating_{h,k}}{\sum_{N} \sum_{n} 1}}{\frac{\sum_{k=1}^{M} \sum_{m} Rating_{h,k}}{\sum_{M} \sum_{m} 1}} - 1,$$

*where $Rating_{h,k}$ is the mean of ratings across all survey participants rated by O*NET with respect to element h required by occupation k. For each STEM or non-STEM occupation, institution i sponsors n and m individual H-1B visas, respectively. The mean of difference for element h across J banks is calculated as follows:*

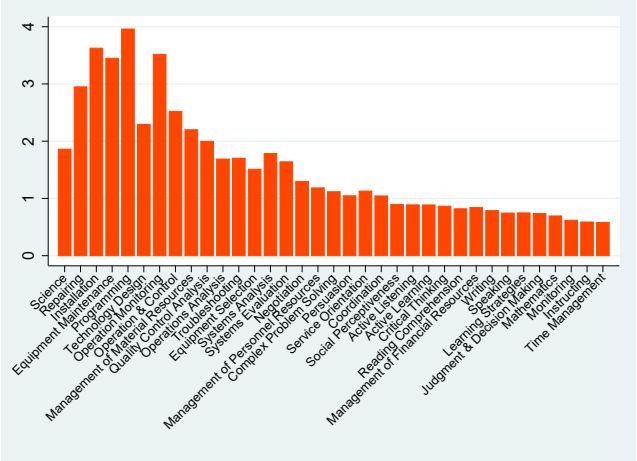
$$Difference_{h} = \frac{\sum_{J} Difference_{h,i}}{J}.$$

t-statistics for the mean of each skill or knowledge element h across L financial institutions is provided in the figure. In Panels A and B, the x-axes are skill elements; in Panels C and D, the x-axes are knowledge elements. In Panels A and B, the y-axes are $Difference_{h}$; in Panels C and D, the y-axes are t-statistics.

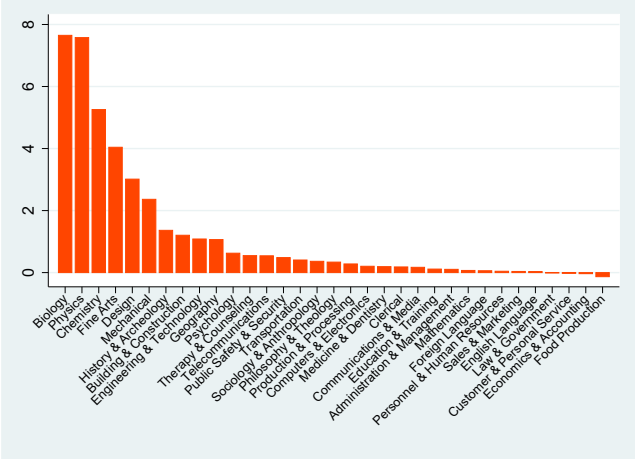
Panel A: Skill difference



Panel B: Skill difference, t-statistics



Panel C: Knowledge difference



Panel D: Knowledge difference, t-statistics

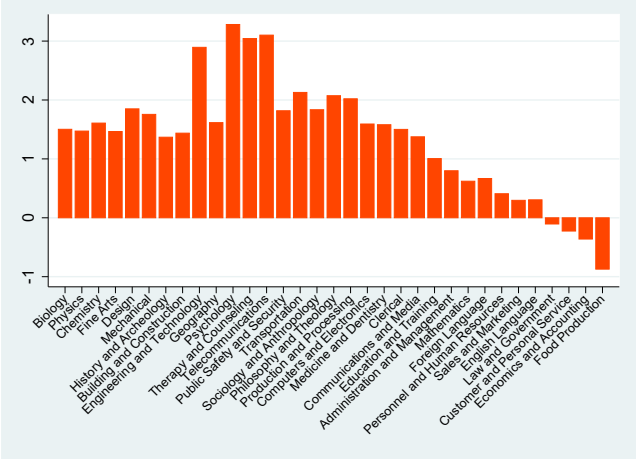


Table 1: **Qualitative Evidence on Patents Filed by Banks**

Panel A of this table reports the 20 most frequent classifications for patents granted by the US Patent and Trademark Office (USPTO) to the financial institutions in our sample. These patents were filed over the period of 2007-2014. Panel B of this table reports the top 20 patents by citations that were filed by financial institutions in our sample in one year (2012).

Panel A: Top 20 Patent Classification

Classification	Description	#Patents
705	Data processing: financial, business practice, management, or cost/price determination	2,440
235	Registers	416
709	Electrical computers and digital processing systems: multi-computer data transferring	231
726	Information security	222
707	Data processing: database and file management or data structures	219
382	Image analysis	132
370	Multiplex communications	118
717	Data processing: software development, installation, and management	109
714	Error detection/correction and fault detection/recovery	103
713	Electrical computers and digital processing systems: support	90
398	Optical communications	89
379	Telephonic communications	82
375	Pulse or digital communications	81
715	Data processing: presentation processing of document, operator interface processing, and screen saver display processing	76
455	Telecommunications	75
706	Data processing: artificial intelligence	60
340	Communications: electrical	48
718	Electrical computers and digital processing systems: virtual machine task or process management or task management/control	38
703	Data processing: structural design, modeling, simulation, and emulation	37

Panel B: Top 20 Patents Filed in 2012

Assignee Name	Patent Number	Filling Date	# Citations	Description
JPMorgan Chase	8433652	Mar 29, 2012	705	Method and system for processing internet payments using the electronic funds transfer network
JPMorgan Chase	8781543	Mar 26, 2012	694	Manual and automatic probe calibration
American Express	8401898	Aug 16, 2012	598	System and method for using loyalty rewards as currency
JPMorgan Chase	8602301	Sep 13, 2012	516	Selectable multi-purpose card
Bank of America	8839363	Mar 16, 2012	404	Trusted hardware for attesting to authenticity in a cloud environment
JPMorgan Chase	8469265	Jun 21, 2012	285	Method and system for implementing a card product with multiple customized relationships
American Express	8589255	Nov 6, 2012	279	Virtual reality shopping experience
Bank of America	8666895	Feb 21, 2012	277	Single action mobile transaction device
American Express	8191778	Feb 2, 2012	269	System and method for immediate issuance of transaction cards
American Express	8478639	Oct 23, 2012	248	System and method for a multiple merchant stored value card
JPMorgan Chase	8639017	Sep 14, 2012	157	Method and system for duplicate check detection
Bank of America	9043609	Jul 19, 2012	152	Implementing security measures for authorized tokens used in mobile transactions
Bank of America	8919643	Sep 14, 2012	146	Method and apparatus for using at least a portion of a one-time password as a dynamic card verification value
JPMorgan Chase	8826371	Aug 6, 2012	139	Authentication system and method
American Express	8572712	Mar 7, 2012	129	Device independent authentication system and method
American Express	8401889	Mar 28, 2012	124	Estimating the spend capacity of consumer households
American Express	8401539	Jan 31, 2012	118	Servicing attributes on a mobile device
JPMorgan Chase	8548886	Apr 26, 2012	113	Account opening system, method and computer program product
BGC Partners	8732069	Sep 14, 2012	111	Systems and methods for monitoring credit of trading counterparties

Table 2: **Sample Descriptive Statistics**

This table presents descriptive statistics for our sample. The sample unit is bank i as of year-month s. The sample period is 2007-2014. We require banks to have submitted at least one patent application with the US patent and trademark office (USPTO) before December 31, 2006. Panel A describes the sample for our first empirical strategy, which includes 20 TARP and 13 non-TARP banks, all of which had hired at least one H-1B STEM worker during 2004-2006. Panel B describes the sample for our second empirical strategy, which includes 27 TARP banks. TARP is a dummy variable that equals 1 if bank i accessed the Troubled Asset Relief Program (TARP), and 0 otherwise. EAWA is a dummy variable that equals 1 if bank i was subject to the Employ American Workers Act (EAWA) in year-month s, and 0 otherwise. Post is a dummy variable that equals 1 for all year-months after the EAWA ban ended, and 0 otherwise. Patent Filed is a dummy variable that equals 1 if bank i filed at least one granted patent in year-month s, and 0 otherwise. Patent Purchase is a dummy variable that equals 1 if bank i engaged with at least one inter-firm patent purchase in year-month s, and 0 otherwise. H1B STEM is a dummy variable that equals 1 if bank i hired at least one H-1B-sponsored STEM worker in year-month s, and 0 otherwise. #H1B STEM is the number of H-1B-sponsored STEM workers hired by the bank i in year-month s. First Filer is a dummy variable that equals 1 if patents filed by bank i in year-month s include at least one investor who filed for the first time for bank i, and 0 otherwise. Non-First Filer is a dummy variable that equals 1 if all patents filed by bank i in year-month s do not have any investors who filed for the first time for bank i, and 0 otherwise. First Leader is a dummy variable that equals 1 if patents filed by bank i in year-month s include at least one inventor who not only filed for the first time for bank i but also was listed as the lead inventor, and 0 otherwise. Non-First Leader is a dummy variable that equals 1 if patents filed by bank i in year-month s include at least one inventor who filed for the first time for bank i but was not listed as the lead inventor, and 0 otherwise. $H1B_{-3}$ is a dummy variable that equals 1 if bank i as of year-month s hired at least one H-1B-sponsored worker over the previous three years, and 0 otherwise. $STEM_{-3}$ is a dummy variable that equals 1 if bank i as of year-month s hired at least one H-1B-sponsored STEM worker over the previous three years, and 0 otherwise. TARP Fund% is the amount of funding over total assets measured in 2009 that TARP bank i obtained via the program. High $Exposure_i$ is a dummy variable that equals 1 if the number of H-1B STEM workers bank i hired in 2004-2006 is above the median of the distribution over a subsample of banks of similar size. Banks are classified into small, medium, and large if their assets are below \$10 billion, between US\$10 and US\$50 billion, and above US\$1 trillion, respectively.

	N	Mean	Std	Min	P10	P25	P50	P75	P90	Max
					Panel A. All Banks					
TARP	3,168	0.606	0.489	0	0	0	1	1	1	1
EAWA	3,168	0.094	0.292	0	0	0	0	0	0	1
Post	3,168	0.349	0.477	0	0	0	0	1	1	1
Patent Filed	3,168	0.205	0.404	0	0	0	0	0	1	1
Patent Purchase	3,168	0.0480	0.214	0	0	0	0	0	0	1
H1B STEM	3,168	0.376	0.484	0	0	0	0	1	1	1
#H1B STEM	3,168	6.874	23.440	0	0	0	0	4	19	392
First Filer	3,168	0.148	0.355	0	0	0	0	0	1	1
First Filer Leader	3,168	0.085	0.279	0	0	0	0	0	0	1
Non First Filer	3,168	0.058	0.233	0	0	0	0	0	0	1
Non First Filer Leader	3,168	0.120	0.325	0	0	0	0	0	1	1
$H1B_{-3}$	3,168	0.840	0.367	0	0	1	1	1	1	1
$STEM_{-3}$	3,168	0.753	0.431	0	0	1	1	1	1	1
					Panel B. TARP Banks					
High Exposure	2,592	0.667	0.471	0	0	0	1	1	1	1
TARP Fund%	2,592	0.025	0.023	0	0.011	0.013	0.021	0.026	0.063	0.110
EAWA	2,592	0.159	0.365	0	0	0	0	0	1	1
Post	2,592	0.571	0.495	0	0	0	1	1	1	1
Patent Filed	2,592	0.247	0.432	0	0	0	0	0	1	1
Patent Purchase	2,592	0.0610	0.239	0	0	0	0	0	0	1
H1B STEM	2,592	0.361	0.480	0	0	0	0	1	1	1
#H1B STEM	2,592	7.428	24.530	0	0	0	0	4	21	392
First Filer	2,592	0.177	0.382	0	0	0	0	0	1	1
First Filer Leader	2,592	0.102	0.303	0	0	0	0	0	1	1
Non First Filer	2,592	0.070	0.255	0	0	0	0	0	0	1
Non First Filer Leader	2,592	0.145	0.352	0	0	0	0	0	1	1
$H1B_{-3}$	2,592	0.678	0.467	0	0	0	1	1	1	1
$STEM_{-3}$	2,592	0.633	0.482	0	0	0	1	1	1	1

Table 3: **Employ American Workers Act (EAWA) and Hiring of Foreign STEM Workers**

This table reports the estimates of the effect of EAWA on foreign STEM hiring. Columns (1)-(4) report estimates from the following ordinary least squares (OLS) specification:

$$Y_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times TARP_i + \beta_3 Post_{i,s} + \beta_4 Post_{i,s} \times TARP_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}.$$

The sample in columns (1)-(4) consists of 20 TARP and 13 non-TARP banks that sponsored at least one STEM job through the H-1B program during 2004-2006. Columns (5)-(8) report estimates from the following OLS specification:

$$Y_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times High\ Exposure_i + \beta_3 Post_{i,s} + \beta_4 Post_{i,s} \times High\ Exposure_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}.$$

The sample in columns (5)-(8) consists of 27 TARP banks. In Panel A, the dependent variable is Ln(#H1B STEM+0.001)$_{i,s}$, which is the logarithm of the number of H-1B STEM workers sponsored by bank i in year-month s plus 0.001. In Panel B, the dependent variable is a dummy variable (H-1B STEM$_{i,s}$) that equals 1 if bank i sponsored at least one H-1B visa in year-month s, and 0 otherwise. See Table 2 for definitions of other variables. Standard errors are clustered at the bank level.

Panel A: Dependent Variable: *Ln(#H1B STEM+0.001)*

	All Banks				TARP Banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA × TARP	-2.954***	-3.202***	-2.455***	-1.828**				
	(-3.87)	(-2.98)	(-3.89)	(-2.19)				
Post × TARP	-0.548	-2.052**	-1.940**	-2.302**				
	(-0.61)	(-2.09)	(-2.38)	(-2.66)				
EAWA × High Exposure					-3.566***	-3.671***	-2.502***	-2.605***
					(-3.93)	(-3.99)	(-3.44)	(-3.62)
EAWA					0.960	3.040***	-0.058	1.590**
					(1.19)	(2.82)	(-0.09)	(2.40)
Post × High Exposure					-1.613	-1.532	-1.889**	-1.842*
					(-1.53)	(-1.40)	(-2.07)	(-1.98)
Post					0.317	1.393	-0.076	0.759
					(0.47)	(0.78)	(-0.25)	(1.40)
EAWA × TARP Fund%					-29.974	-32.121	-4.423	-6.538
					(-1.48)	(-1.63)	(-0.26)	(-0.42)
Post × TARP Fund%					-1.613	-1.532	-1.889**	-1.842*
					(-1.53)	(-1.40)	(-2.07)	(-1.98)
TARP	3.642***	4.515***						
	(2.89)	(3.50)						
High Exposure					4.909***	4.617***		
					(3.66)	(3.43)		
TARP Fund%					12.483	10.892		
					(0.46)	(0.38)		
H1B$_{-3}$	1.402	1.600*	0.340	0.639	0.862	0.573	0.289	0.234
	(1.65)	(1.79)	(0.99)	(1.45)	(1.38)	(0.88)	(0.91)	(0.78)
STEM$_{-3}$	4.285***	4.619***	0.547**	0.778**	3.807***	4.457***	0.490	0.829
	(4.66)	(4.63)	(2.58)	(2.23)	(3.47)	(3.86)	(1.22)	(1.62)
Constant	-11.139***	-11.538***	-4.787***	-5.145***	-11.072***	-12.038***	-4.471***	-5.403***
	(-12.68)	(-12.56)	(-9.66)	(-9.35)	(-11.67)	(-7.78)	(-8.78)	(-9.83)
Year × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
N	3,168	3,168	3,168	3,168	2,592	2,592	2,592	2,592
adj. R^2	0.27	0.30	0.66	0.69	0.40	0.41	0.74	0.76

Panel B: Dependent Variable: Probability of H-1B STEM Hiring

	All Banks				TARP Banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA × TARP	-0.239***	-0.261**	-0.198***	-0.144*				
	(-3.32)	(-2.57)	(-3.33)	(-1.81)				
Post × TARP	-0.059	-0.182*	-0.181**	-0.202**				
	(-0.72)	(-2.03)	(-2.37)	(-2.50)				
EAWA × High Exposure					-0.289***	-0.299***	-0.199***	-0.208***
					(-3.46)	(-3.55)	(-2.84)	(-3.02)
EAWA					0.087	0.252**	0.001	0.127*
					(1.11)	(2.48)	(0.02)	(1.84)
Post × High Exposure					-0.140	-0.135	-0.165*	-0.163*
					(-1.48)	(-1.39)	(-1.90)	(-1.85)
Post					0.009	0.121	-0.027	0.072
					(0.16)	(0.80)	(-0.76)	(1.32)
EAWA × TARP Fund%					-2.770	-2.932	-0.688	-0.844
					(-1.36)	(-1.49)	(-0.40)	(-0.53)
Post × TARP Fund%					1.297	1.435	-0.076	-0.012
					(1.30)	(1.41)	(-0.06)	(-0.01)
TARP	0.306***	0.377***						
	(2.84)	(3.37)						
High Exposure					0.420***	0.402***		
					(3.72)	(3.54)		
TARP Fund%					0.655	0.557		
					(0.35)	(0.28)		
$H1B_{-3}$	0.115	0.127*	0.031	0.046	0.077	0.057	0.020	0.017
	(1.65)	(1.76)	(0.97)	(1.19)	(1.48)	(1.07)	(0.64)	(0.57)
$STEM_{-3}$	0.387***	0.415***	0.051**	0.068**	0.332***	0.374***	0.052	0.064
	(4.85)	(4.90)	(2.52)	(2.16)	(3.53)	(3.84)	(1.29)	(1.30)
Constant	-0.154**	-0.184**	0.393***	0.370***	-0.141*	-0.232*	0.417***	0.336***
	(-2.10)	(-2.44)	(8.55)	(7.34)	(-2.01)	(-1.89)	(8.77)	(6.61)
Year × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
N	3,168	3,168	3,168	3,168	2,592	2,592	2,592	2,592
adj. R^2	0.26	0.28	0.61	0.63	0.40	0.40	0.70	0.71

Table 4: **Employ American Workers Act (EAWA) and Patenting Activities**

This table reports the estimates of the effect of EAWA on patenting activities. Columns (1)-(4) report estimates from the following ordinary least squares (OLS) specification:

$$Patent\ Filed_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times TARP_i + \beta_3 Post_{i,s} + \beta_4 Post_{i,s} \times TARP_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}.$$

The sample in columns (1)-(4) consists of 20 TARP and 13 non-TARP banks that sponsored at least one STEM job through the H-1B program during 2004-2006. Columns (5)-(8) report estimates from the following OLS specification:

$$Patent\ Filed_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times High\ Exposure_i + \beta_3 Post_{i,s} + \beta_4 Post_{i,s} \times High\ Exposure_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}.$$

The sample in columns (5)-(8) consists of 27 TARP banks. Patent Filed$_{i,s}$ is a dummy variable that equals 1 if bank i filed at least one granted patent in year-month s, and 0 otherwise. See Table 2 for definitions of other variables. Standard errors are clustered at the bank level.

	All Banks				TARP Banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA × TARP	-0.123***	-0.177***	-0.065**	-0.059*				
	(-3.81)	(-3.33)	(-2.50)	(-1.84)				
Post × TARP	0.075*	0.049	-0.020	0.003				
	(1.80)	(1.05)	(-0.79)	(0.10)				
EAWA × High Exposure					-0.175***	-0.176***	-0.103**	-0.101**
					(-3.02)	(-2.94)	(-2.50)	(-2.47)
EAWA					0.065	0.125	0.032	-0.010
					(1.12)	(1.17)	(0.80)	(-0.19)
Post × High Exposure					-0.034	-0.032	-0.053*	-0.054*
					(-0.61)	(-0.56)	(-1.91)	(-1.95)
Post					0.053	0.200	0.016	0.007
					(0.96)	(1.48)	(0.79)	(0.20)
EAWA × TARP Fund%					-1.380	-1.265	-0.173	-0.108
					(-1.40)	(-1.20)	(-0.31)	(-0.19)
Post × TARP Fund%					1.322	1.266	0.257	0.224
					(1.36)	(1.25)	(0.55)	(0.51)
TARP	0.210**	0.234**						
	(2.48)	(2.52)						
High Exposure					0.162	0.160		
					(1.65)	(1.58)		
TARP Fund%					0.439	0.478		
					(0.21)	(0.22)		
H1B$_{-3}$	0.106	0.113	-0.007	-0.005	0.009	0.001	-0.009	-0.010
	(1.66)	(1.66)	(-0.46)	(-0.23)	(0.12)	(0.01)	(-0.54)	(-0.69)
STEM$_{-3}$	0.166***	0.168***	-0.006	-0.017	0.232**	0.237**	-0.004	-0.012
	(3.03)	(2.94)	(-0.71)	(-1.25)	(2.71)	(2.57)	(-0.25)	(-0.54)
Constant	-0.151**	-0.159**	0.229***	0.227***	-0.048	-0.139	0.270***	0.288***
	(-2.20)	(-2.21)	(10.82)	(8.78)	(-0.53)	(-1.17)	(12.81)	(12.24)
Year × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
N	3,168	3,168	3,168	3,168	2,592	2,592	2,592	2,592
adj. R^2	0.16	0.15	0.62	0.61	0.13	0.12	0.60	0.59

Table 5: **Employ American Workers Act (EAWA) and Patenting Activities by Patent Categories**

This table reports the estimates of the effect of EAWA on patenting activities. Columns (1)-(3) report estimates from the following ordinary least squares (OLS) specification:

$$\begin{aligned} \textit{Patent Filed}_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times TARP_i + \beta_3 Post_{i,s} \\ + \beta_4 Post_{i,s} \times TARP_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}. \end{aligned}$$

The sample in columns (1)-(3) consists of 20 TARP and 13 non-TARP banks that sponsored at least one STEM job through the H-1B program during 2004-2006. Columns (4)-(6) report estimates from the following OLS specification:

$$\begin{aligned} \textit{Patent Filed}_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times \textit{High Exposure}_i + \beta_3 Post_{i,s} + \\ \beta_4 Post_{i,s} \times \textit{High Exposure}_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}. \end{aligned}$$

The sample in columns (4)-(6) consists of 27 TARP banks. Patent-Filed$_{i,s}$ is a dummy variable that equals 1 if bank i filed at least one granted patent in year-month s, and 0 otherwise. For each patent category (i.e., business method (705), non-business method (Non-705), and FinTech), Patent Filed$_{i,s}$ is a dummy variable that equals 1 if bank i filed at least one granted patent in that category in year-month s, and 0 otherwise. See Table 2 for definitions of other variables. Standard errors are clustered at the bank level.

	All Banks			TARP Banks		
	705	Non 705	FinTech	705	Non 705	FinTech
	(1)	(2)	(3)	(4)	(5)	(6)
EAWA × TARP	-0.061	-0.010	-0.014			
	(-1.57)	(-0.37)	(-0.62)			
Post × TARP	-0.068	0.062**	0.044**			
	(-1.65)	(2.52)	(2.05)			
EAWA × High Exposure				-0.076*	-0.057*	-0.045*
				(-1.93)	(-1.79)	(-1.81)
EAWA				0.000	-0.008	-0.002
				(0.01)	(-0.14)	(-0.03)
Post × High Exposure				-0.139***	0.055*	0.051*
				(-3.35)	(1.88)	(1.95)
Post				0.126**	-0.077	-0.073
				(2.54)	(-1.45)	(-1.28)
EAWA × TARP Fund%				-0.289	-0.092	-0.643
				(-0.84)	(-0.22)	(-1.13)
Post × TARP Fund%				-0.847*	0.693	-0.559
				(-1.81)	(1.50)	(-1.38)
$H1B_{-3}$	-0.093**	0.042**	0.039**	-0.004	-0.007	0.017
	(-2.65)	(2.09)	(2.09)	(-0.13)	(-0.40)	(0.79)
$STEM_{-3}$	-0.036	0.014	0.020	-0.104***	0.043*	0.032
	(-1.40)	(0.84)	(1.45)	(-3.20)	(1.73)	(1.24)
Constant	0.263***	0.089***	0.049*	0.228***	0.185***	0.140***
	(6.84)	(3.32)	(1.81)	(6.19)	(6.44)	(3.89)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,168	3,168	3,168	2,592	2,592	2,592
adj. R^2	0.48	0.57	0.51	0.47	0.56	0.50

Table 6: **Sample Descriptive Statistics: Patent Citation**

This table presents descriptive statistics for our sample of patent citations. The sample unit is bank i as of year-month s in which at least one granted patent was filed. The sample period is 2007-2014. We require banks to have submitted at least one patent application with the US Patent and Trademark Office (USPTO) before December 31, 2006. Panel A includes 20 TARP and 17 non-TARP banks, both of which had hired at least one H-1B STEM worker during 2004-2006. Panel B includes 27 TARP banks. TARP is a dummy variable that equals 1 if bank i had ever accessed the Troubled Asset Relief Program (TARP), and 0 otherwise. EAWA is a dummy variable that equals 1 if bank i complied with the Employ American Workers Act (EAWA) in year-month s, and 0 otherwise. Post is a dummy variable that equals 1 for all year-months after the EAWA was ineffective, and 0 otherwise. For each patent category (i.e., all patents, business method (705), non-business method (Non-705), and FinTech), $\overline{Raw\ Cites}$ is the averaged raw citation counts for all patents filed by bank i in year-month s that were later granted. $\overline{Adj\ Cites}$ is the averaged adjusted citation counts for all patents filed by bank i in year-month s that were later granted. For each patent, adjusted citation is the number of citations divided by the average number of citations in a given technology-class-year (the year in which all patents of the same technology were applied). Technology domain is defined at the 4-digit International Patent Classification. The end of the observation period for patent citation is January, 2022. $H1B_{-3}$ is a dummy variable that equals 1 if bank i as of year-month s hired at least one H-1B-sponsored worker over the last three years, and 0 otherwise. $STEM_{-3}$ is a dummy variable that equals 1 if bank i as of year-month s hired at least one H-1B-sponsored STEM worker over the last three years, and 0 otherwise. TARP Fund% is the amount of funding over total assets measured in year 2009 that TARP bank i obtained from the government through entering into the TARP program. High $Exposure_i$ is a dummy variable that equals 1 if the number of H-1B STEM workers hired by bank i during 2004-2006 is above the median of the distribution over a subsample of banks of similar size. Banks are classified into small, medium, and large if their assets are below US$10 billion, between US$10 and US$50 billion, and above US$1 trillion, respectively.

	N	Mean	Std	Min	P10	P25	P50	P75	P90	Max
					Panel A. All Banks					
TARP	651	0.897	0.304	0	0	1	1	1	1	1
EAWA	651	0.088	0.283	0	0	0	0	0	0	1
Post	651	0.556	0.497	0	0	0	1	1	1	1
$\overline{\text{Raw Cites}}$	651	38.877	51.373	0	3	9	22.333	49	94	643
$\overline{\text{Raw Cites}}$ (705)	404	50.128	70.812	0	3.750	9	24	58.917	127	643
$\overline{\text{Raw Cites}}$ (Non-705)	493	36.202	43.832	0	3	9.667	21.500	45.333	93.600	391
$\overline{\text{Raw Cites}}$ (FinTech)	354	43.334	59.495	0	3	9.333	22.111	53	107	520
$\overline{\text{Adj Cites}}$	651	1.034	1.258	0	0.089	0.255	0.636	1.319	2.411	11.650
$\overline{\text{Adj Cites}}$ (705)	404	1.114	1.548	0	0.081	0.193	0.510	1.370	2.803	11.650
$\overline{\text{Adj Cites}}$ (Non-705)	493	1.101	1.259	0	0.095	0.321	0.680	1.341	2.776	8.998
$\overline{\text{Adj Cites}}$ (FinTech)	354	1.307	1.727	0	0.084	0.308	0.699	1.603	3.461	15.460
$H1B_{-3}$	651	0.980	0.140	0	1	1	1	1	1	1
$STEM_{-3}$	651	0.975	0.155	0	1	1	1	1		
					Panel B. TARP Banks					
EAWA	641	0.105	0.306	0	0	0	0	0	1	1
Post	641	0.618	0.486	0	0	0	1	1	1	1
$\overline{\text{Raw Cites}}$	641	38.736	50.978	0	4	9.500	22.333	49	93.778	643
$\overline{\text{Raw Cites}}$ (705)	404	51.207	70.522	0	4	9.875	25.917	60.250	127	643
$\overline{\text{Raw Cites}}$ (Non-705)	484	35.057	43.048	0	3	9	20.750	44	87.500	391
$\overline{\text{Raw Cites}}$ (FinTech)	348	41.877	59.109	0	2.778	9	21.625	52	102.667	520
$\overline{\text{Adj Cites}}$	641	1.027	1.242	0	0.100	0.258	0.636	1.308	2.355	11.654
$\overline{\text{Adj Cites}}$ (705)	404	1.141	1.545	0	0.089	0.208	0.546	1.424	2.805	11.654
$\overline{\text{Adj Cites}}$ (Non 705)	484	1.069	1.238	0	0.097	0.313	0.651	1.298	2.729	8.998
$\overline{\text{Adj Cites}}$ (FinTech)	348	1.269	1.724	0	0.076	0.287	0.677	1.555	3.359	15.459
$H1B_{-3}$	641	0.910	0.287	0	1	1	1	1	1	1
$STEM_{-3}$	641	0.899	0.302	0	0	1	1	1	1	1
TARP Fund%	641	0.027	0.028	0.009	0.011	0.014	0.020	0.026	0.063	0.110
High Exposure	641	0.891	0.312	0	0	1	1	1	1	1

Table 7: **Employ American Workers Act (EAWA) and Patent Citations**

This table reports the estimates of the effect of EAWA on patent citations. Columns (1)-(4) report estimates from the following ordinary least squares (OLS) specification:

$$\overline{Adj.Cites}_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times TARP_i + \beta_3 Post_{i,s} + \beta_4 Post_{i,s} \times TARP_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}.$$

The sample in columns (1)-(4) consists of 20 TARP and 17 non-TARP banks that sponsored at least one STEM job through the H-1B program during 2004-2006. Columns (5)-(8) report estimates from the following OLS specification:

$$\overline{Adj.Cites}_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times High\ Exposure_i + \beta_3 Post_{i,s} + \beta_4 Post_{i,s} \times High\ Exposure_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}.$$

The sample in columns (5)-(8) consists of 27 TARP banks. For each patent category (i.e., all patents, business method (705), non-business method (Non-705), and FinTech), $\overline{Adj.Cites}$ is the averaged Adj.Cites for patents filed by bank i in year-month s. $\overline{Adj.Cites}$ is transformed into percentile ranks. Adj.Cites is the number of citation counts divided by the average number of citation counts in a given technology-class-year (i.e., the year in which all patents of the same technology were applied). Technology domain is defined at the 4-digit International Patent Classification. The end of the observation period for patent citation is January, 2022. See Table 6 for definitions of other variables. Standard errors are clustered at the bank level.

	All Banks				TARP Banks			
	All	705	Non 705	FinTech	All	705	Non 705	FinTech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA × TARP	-0.022	0.069	-0.058	-0.070				
	(-0.51)	(0.73)	(-0.76)	(-0.41)				
Post × TARP	0.005	-0.017	-0.004	0.108				
	(0.08)	(-0.29)	(-0.09)	(0.95)				
EAWA × High Exposure					0.085**	0.268*	-0.217**	-0.555**
					(2.51)	(1.92)	(-2.89)	(-2.63)
EAWA					-0.028	-0.240***	0.264***	0.380
					(-0.44)	(-2.98)	(3.44)	(1.46)
Post × High Exposure					0.042	0.025	-0.065	-0.594***
					(0.83)	(0.38)	(-1.37)	(-12.56)
Post					-0.008	-0.086	0.119*	0.601***
					(-0.10)	(-0.95)	(1.86)	(14.15)
EAWA × TARP Fund%					-0.854	0.523	-4.490**	2.924
					(-1.06)	(0.95)	(-2.83)	(0.35)
Post × TARP Fund%					1.442***	0.267	0.231	2.620***
					(3.47)	(0.65)	(0.56)	(3.37)
$H1B_{-3}$	-0.053	-0.340***	-0.279*	-0.732***	-0.203***	-0.335***	-0.265*	-0.732***
	(-0.84)	(-2.96)	(-2.03)	(-4.92)	(-2.86)	(-3.85)	(-1.85)	(-4.82)
$STEM_{-3}$	0.034	0.245**			0.161**	0.151		
	(0.45)	(2.65)			(2.56)	(1.56)		
Constant	0.495***	0.597***	0.788***	1.197***	0.473***	0.716***	0.699***	1.171***
	(7.90)	(10.18)	(5.93)	(6.65)	(7.88)	(8.96)	(6.19)	(6.00)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	651	404	493	354	641	404	484	348
adj. R^2	0.19	0.35	0.15	0.16	0.20	0.32	0.18	0.17

Table 8: **Employ American Workers Act (EAWA) and First Patent Filers**

This table reports the estimates of the effect of EAWA on the likelihood of patents being filed by first-time filers. Columns (1)-(4) report estimates from the following ordinary least squares (OLS) specification:

$$\begin{aligned} \textit{First Filer}_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times TARP_i + \beta_3 Post_{i,s} \\ + \beta_4 Post_{i,s} \times TARP_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}. \end{aligned}$$

The sample in columns (1)-(4) consists of 20 TARP and 13 non-TARP banks that sponsored at least one STEM job through the H-1B program during 2004-2006. Columns (5)-(8) report estimates from the following OLS specification:

$$\begin{aligned} \textit{First Filer}_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times \textit{High Exposure}_i + \beta_3 Post_{i,s} + \\ \beta_4 Post_{i,s} \times \textit{High Exposure}_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}. \end{aligned}$$

The sample in columns (5)-(8) consists of 27 TARP banks. In Panel A, the dependent variable is First Filer$_{i,s}$, which is a dummy variable that equals 1 if patents filed by bank i in year-month s include at least one investor who filed for the first time for bank i, and 0 otherwise. In Panel B, the dependent variable is Non-First Filer$_{i,s}$, which is a dummy variable that equals 1 if all patents filed by bank i in year-month s do not have any investors who filed for the first time for bank i, and 0 otherwise. See Table 2 for definitions of other variables. Standard errors are clustered at the bank level.

Panel A: Dependent Variable: First Filer

	All Banks				TARP Banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA × TARP	-0.111***	-0.124***	-0.074***	-0.046				
	(-3.57)	(-2.83)	(-3.35)	(-1.68)				
Post × TARP	0.017	-0.002	-0.050*	-0.033				
	(0.49)	(-0.06)	(-1.80)	(-1.07)				
EAWA × High Exposure					-0.145***	-0.149***	-0.093**	-0.094**
					(-2.95)	(-2.92)	(-2.70)	(-2.76)
EAWA					0.022	0.078	0.010	0.013
					(0.48)	(0.86)	(0.29)	(0.22)
Post × High Exposure					-0.034	-0.031	-0.055	-0.054
					(-0.61)	(-0.55)	(-1.53)	(-1.48)
Post					0.043	0.109	0.010	-0.006
					(0.77)	(0.97)	(0.33)	(-0.12)
EAWA × TARP Fund%					-0.159	-0.127	0.142	0.138
					(-0.19)	(-0.15)	(0.26)	(0.23)
Post × TARP Fund%					-0.362	-0.341	-0.848**	-0.832**
					(-0.36)	(-0.33)	(-2.75)	(-2.74)
TARP	0.181**	0.195**						
	(2.50)	(2.39)						
High Exposure					0.127	0.119		
					(1.61)	(1.49)		
TARP Fund%					-0.821	-0.851		
					(-0.60)	(-0.60)		
H1B$_{-3}$	0.081*	0.095*	-0.003	0.013	0.057	0.048	0.023	0.024
	(1.74)	(1.87)	(-0.17)	(0.72)	(1.17)	(0.98)	(1.37)	(1.33)
STEM$_{-3}$	0.113***	0.112**	-0.013	-0.022	0.122*	0.139*	-0.054***	-0.049*
	(2.77)	(2.61)	(-1.16)	(-1.67)	(1.78)	(1.89)	(-3.06)	(-2.01)
Constant	-0.110**	-0.122**	0.184***	0.169***	0.004	-0.043	0.231***	0.236***
	(-2.06)	(-2.14)	(8.34)	(7.18)	(0.06)	(-0.47)	(10.31)	(6.88)
Year × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
N	3,168	3,168	3,168	3,168	2,592	2,592	2,592	2,592
adj. R^2	0.11	0.10	0.51	0.51	0.09	0.07	0.49	0.48

Panel B: Dependent Variable: Non-First Filer

	All Banks				TARP Banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA × TARP	-0.012	-0.053*	0.009	-0.013				
	(-0.83)	(-1.94)	(0.56)	(-0.65)				
Post × TARP	0.058**	0.052**	0.030*	0.036**				
	(2.61)	(2.34)	(1.94)	(2.27)				
EAWA × High Exposure					-0.029	-0.027	-0.010	-0.007
					(-1.37)	(-1.25)	(-0.43)	(-0.29)
EAWA					0.043*	0.047	0.023	-0.023
					(1.96)	(1.53)	(1.01)	(-1.14)
Post × High Exposure					0.001	-0.000	0.002	-0.000
					(0.03)	(-0.01)	(0.09)	(-0.01)
Post					0.010	0.091**	0.006	0.014
					(0.62)	(2.08)	(0.29)	(0.43)
EAWA × TARP Fund%					-1.221**	-1.138*	-0.315	-0.245
					(-2.22)	(-2.05)	(-0.57)	(-0.48)
Post × TARP Fund%					1.684***	1.607***	1.104**	1.057**
					(7.09)	(6.39)	(2.44)	(2.44)
TARP	0.029	0.039						
	(1.22)	(1.53)						
High Exposure					0.035	0.041		
					(1.25)	(1.34)		
TARP Fund%					1.260	1.329		
					(1.29)	(1.38)		
$H1B_{-3}$	0.025	0.019	-0.004	-0.018	-0.048	-0.047	-0.032***	-0.034**
	(1.08)	(0.79)	(-0.46)	(-1.29)	(-1.08)	(-1.10)	(-3.08)	(-2.73)
$STEM_{-3}$	0.054**	0.056**	0.006	0.005	0.110***	0.098**	0.050***	0.037**
	(2.48)	(2.54)	(1.36)	(0.84)	(3.00)	(2.52)	(3.57)	(2.32)
Constant	-0.041	-0.037	0.045***	0.057***	-0.052	-0.097**	0.039**	0.052**
	(-1.62)	(-1.48)	(3.30)	(3.95)	(-1.62)	(-2.22)	(2.68)	(2.20)
Year × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
N	3,168	3,168	3,168	3,168	2,592	2,592	2,592	2,592
adj. R^2	0.04	0.04	0.19	0.19	0.07	0.07	0.18	0.18

Table 9: **Employ American Workers Act (EAWA) and Patent Purchase**

This table reports the estimates of the effect of EAWA on patent purchase. Columns (1)-(4) report estimates from the following ordinary least squares (OLS) specification:

$$Patent\ Purchased_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times TARP_i + \beta_3 Post_{i,s} + \beta_4 Post_{i,s} \times TARP_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}.$$

The sample in columns (1)-(4) consists of 20 TARP and 13 non-TARP banks that sponsored at least one STEM job through the H-1B program during 2004-2006. Columns (5)-(8) report estimates from the following OLS specification:

$$Patent\ Purchased_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times High\ Exposure_i + \beta_3 Post_{i,s} + \beta_4 Post_{i,s} \times High\ Exposure_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}.$$

The sample in columns (5)-(8) consists of 27 TARP banks. $Patent\ Purchased_{i,s}$ is a dummy variable that equals to 1 if bank i purchased at least one granted patent in year-month s, and 0 otherwise. See Table 2 for definitions of other variables. Standard errors are clustered at the bank level.

	All Banks				TARP Banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA × TARP	-0.002	-0.022	0.011	0.000				
	(-0.07)	(-0.91)	(0.49)	(0.01)				
Post × TARP	0.023	0.017	0.006	0.006				
	(0.64)	(0.56)	(0.18)	(0.20)				
EAWA × High Exposure					-0.034	-0.038	-0.013	-0.016
					(-1.28)	(-1.33)	(-0.51)	(-0.60)
EAWA					0.021	0.028	0.019	0.018
					(0.90)	(0.71)	(0.88)	(0.56)
Post × High Exposure					0.000	-0.000	-0.009	-0.010
					(0.00)	(-0.01)	(-0.27)	(-0.28)
Post					0.028	0.058	0.019	0.033
					(1.06)	(1.20)	(0.89)	(1.46)
EAWA × TARP Fund%					0.123	0.159	0.051	0.068
					(0.21)	(0.23)	(0.08)	(0.10)
Post × TARP Fund %					-0.057	-0.056	-0.092	-0.089
					(-0.10)	(-0.10)	(-0.19)	(-0.18)
TARP	0.062**	0.070**						
	(2.46)	(2.55)						
High Exposure					0.030	0.030		
					(1.13)	(1.08)		
TARP Fund %					-0.278	-0.285		
					(-0.57)	(-0.55)		
$H1B_{-3}$	0.040*	0.046*	0.013	0.020	0.029	0.028	0.014	0.016
	(1.81)	(1.79)	(1.11)	(1.21)	(1.25)	(1.13)	(0.84)	(0.79)
$STEM_{-3}$	0.019	0.017	-0.000	-0.004	0.042	0.043	0.000	-0.001
	(1.28)	(1.08)	(-0.03)	(-0.39)	(1.30)	(1.18)	(0.02)	(-0.07)
Constant	-0.046	-0.049	0.034	0.032	-0.014	-0.032	0.044	0.036*
	(-1.64)	(-1.58)	(1.28)	(1.14)	(-0.76)	(-0.96)	(1.61)	(1.87)
Year × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
N	3,168	3,168	3,168	3,168	2,592	2,592	2,592	2,592
adj. R^2	0.04	0.03	0.31	0.31	0.03	0.02	0.28	0.28

Table 10: **Wage Premia of H1-B Employees**

This table reports estimates from the following ordinary least squares (OLS) specification:

$$\begin{aligned}\overline{Wage\ Premia}_{i,l,s} = \alpha + \beta_1 EAWA_{i,s} \times TARP_i \times STEM_{i,l,s} + \beta_2 EAWA_{i,s} \times TARP_i + \beta_3 EAWA_{i,s} \times STEM_{i,l,s} \\ + \beta_4 EAWA_{i,s} + \beta_5 Post_{i,s} \times TARP_i \times STEM_{i,l,s} + \beta_6 Post_{i,s} \times TARP_i + \beta_7 Post_{i,s} \times STEM_{i,l,s} + \\ \beta_8 Post_{i,s} + \beta_9 STEM_{i,l,s} \times TARP_i + \beta_{10} STEM_{i,l,s} + \beta_{11} TARP_i + \eta_l + \eta_i + \eta_s + \epsilon_{i,l,s}.\end{aligned}$$

The sample consists of TARP and non-TARP banks that sponsored at least one visa for STEM jobs through the H-1B program from January 2004 through December 2006. $\overline{Wage\ Premia}_{i,l,s}$ *is the weighted-average wage premia for H-1B visas within the same job category* l*, submitted by bank* i *in year-month* s*. The weight is determined by the number of immigrants sponsored under each H-1B visa. Wage premium of each visa is wage divided by prevailing wage.* $STEM_{i,l,s}$ *is a dummy variable that equals 1 if job category* l *for visas sponsored by bank* i *in year-month* s *falls into the STEM classification, and 0 otherwise. See Table 6 for definitions of other variables. Standard errors are clustered at the bank level.*

Panel A: Descriptive Statistics

	N	Mean	Std	Min	P10	P25	P50	P75	P90	Max
Wage Premia	8,981	1.266	0.208	1	1.068	1.122	1.211	1.348	1.541	2.091
EAWA	8,981	0.088	0.283	0	0	0	0	0	0	1
Post	8,981	0.540	0.498	0	0	0	1	1	1	1
STEM Job	8,981	0.511	0.500	0	0	0	1	1	1	1
TARP	8,981	0.900	0.299	0	1	1	1	1	1	1

Panel B: Regression Analysis

	(1)	(2)	(3)	(4)	(5)
EAWA × STEM × TARP	0.073**	0.081**	0.072**	0.049*	0.056**
	(2.16)	(2.29)	(2.29)	(1.87)	(2.05)
EAWA × TARP	-0.030**	-0.044	-0.034**	-0.020*	-0.035
	(-2.21)	(-1.52)	(-2.40)	(-1.92)	(-1.32)
Post × STEM × TARP	0.016	0.022	0.008	0.005	0.012
	(0.60)	(0.68)	(0.32)	(0.23)	(0.42)
Post × TARP	0.005	-0.065**	0.013	0.021	-0.030
	(0.24)	(-2.20)	(0.55)	(1.11)	(-0.90)
TARP	-0.058	-0.014			
	(-1.43)	(-0.45)			
STEM	-0.008	-0.006	0.004	0.006	0.010
	(-0.53)	(-0.35)	(0.79)	(0.98)	(1.56)
STEM × TARP	-0.011	-0.013	-0.020*	-0.007	-0.010
	(-0.58)	(-0.70)	(-1.89)	(-0.62)	(-1.08)
Constant	1.321***	1.318***	1.265***	1.254***	1.280***
	(36.83)	(35.61)	(107.51)	(109.30)	(59.41)
Bank FE	No	No	Yes	Yes	Yes
City FE	No	No	No	Yes	Yes
Year × Month FE	No	Yes	No	No	Yes
N	8,981	8,981	8,981	8,981	8,981
adj. R^2	0.01	0.02	0.08	0.19	0.20

Online Appendix:
Nationalistic Labor Policies Hinder Financial Innovation

Francesco D'Acunto, Hengyi Huang, Michael Weber, Jin Xie, and Liu Yang

Not for Publication

A.1 Institutional Setting

Our empirical setting is influenced by two key institutional features: the timing and motivations governing the approval of TARP and EAWA, and the scope for patenting activity within the US financial sector.

A.1.1 TARP and Employ American Workers Act

On October 3, 2008, US President George W. Bush enacted the Troubled Asset Relief Program (TARP), granting the US government the authority to acquire toxic assets and equity from financial institutions.[1] Predominantly consisting of commercial banks, TARP participants saw the government acquiring preferred stocks in eight major banks: Goldman Sachs, Morgan Stanley, J.P. Morgan Chase, Bank of America, Citigroup, Wells Fargo, Bank of New York Mellon, and State Street. TARP assistance also extended to a major utility (General Electric) and three leading car manufacturers (GM, Ford, and Chrysler). We exclude these two groups from our analysis, due to the distinct nature of their innovation and their extensive coverage by various government programs during the financial crisis and the Great Recession.

On February 17, 2009, President Obama signed the Employ American Workers Act (EAWA) into law, which was valid for two years and was not subsequently renewed. The legislation specifically targeted TARP recipients seeking to hire H-1B workers. Although the original intent of the Act was to completely prohibit TARP recipients from applying for any H-1B visas, the final legislation permitted such employment with certain imposed restrictions. Irrespective of their exposure and reliance on H-1B employees, all TARP recipients were subjected to the same regulations as "H-1B Dependent Employers."[2] The foreign hiring ban stipulated by the EAWA did not extend to workers seeking to extend their H-1B stay; however, it was binding for employers filing H-1B petitions for new foreign-born employees.

In the US, an employer with a significant proportion of H-1B workers relative to its total domestic workforce is categorized as "H-1B dependent." Such employers are required to make specific attestations on the Labor Condition Application (LCA). However, under the EAWA, TARP recipients are also treated

[1] Originally, the program authorized an expenditure of US$700 billion. The Dodd-Frank Wall Street Reform and Consumer Protection Act later reduced this amount to US$475 billion. The program essentially concluded on December 19, 2014, when the US Treasury sold its remaining holdings of Ally Financial.

[2] Certain non-TARP recipients are considered "H-1B dependent" if H-1B workers make up more than 15% of their workforce.

as H-1B dependent employers in relation to *new* petitions filed, irrespective of the number of H-1B workers in their US workforce. Precisely, the EAWA stipulates that no TARP recipient can hire an H-1B non-immigrant unless the recipient has made certain LCA attestations, which were previously mandated only for H-1B dependent employers.

The extra obligations required by EAWA include the following:

- Prior to filing an H-1B petition, the employer must take *bona fide* steps to recruit US workers for the position for which an H-1B worker is sought and offer a wage that is at least as high as that offered to the H-1B worker.
- The employer must also attest that, in connection with their *bona fide* recruitment efforts, they have actually offered the same job to any US worker who has applied and who is equally or better qualified for the position.
- Employers were also hindered from laying off any US workers in jobs equivalent to the H-1B position within the period beginning 90 days before and ending 90 days after the H-1B petition filing.

In summary, H-1B petitioning under EAWA imposed significantly higher compliance costs, requiring detailed information and documents for each prospective worker. Additionally, conducting a documented search for US applicants with specific skills, if rare within the domestic workforce, could be both costly and time-consuming. As demonstrated below, the EAWA ban indeed resulted in the near-complete elimination of new foreign high-skilled hires by US financial institutions.

A.1.2 Patenting in the Financial Sector

Our primary focus is on the innovation of financial institutions. Although the innovation activities of traditional banks are sometimes overlooked, note that banks are frequent patent filers (e.g., Chen et al., 2019; Lerner et al., 2023). The aftermath of the 2008-2009 financial crisis witnessed an unprecedented surge in patenting activity by commercial banks in the US According to a *Wall Street Journal* article dated May 10, 2016, large banks and credit companies have submitted applications for at least 2,679 patents since 2013, particularly in areas such as mobile systems, the Internet of Things, and data analytics.[3]

To illustrate the areas in which financial institutions, particularly banks, have been innovative, we categorize granted patents based on US classifications and rank these classifications by the number of patents within each category. In Panel A of Table 1, we present the top 20 classifications of patents filed by the financial institutions in our sample, utilizing the US Patent and Trademark Office (USPTO) patent

[3] "Big Banks Stake Fintech Claims with Patent Application Surge," *The Wall Street Journal*, May 10, 2016.

topic classifications. These classifications account for approximately 95% of patents filed by commercial banks headquartered in the US Common categories include various forms of data processing methods and information security.[4]

Financial institutions are driven by incentives to participate in FinTech innovation for several reasons. First, due to security threats, the risk of data breaches, and potential litigation, banks cannot rely solely on third-party vendors to develop patents. Second, FinTech companies pose competition to incumbent traditional financial institutions in various areas, including mortgage and loan originations. Banks have actively filed patents over the past decade in domains where startup FinTech firms are flourishing. Some of these inventions have already been commercialized into financial products. For instance, the cloud wallet security technology developed by J.P. Morgan Chase has been integrated into the Chase Pay mobile payments system. On the other hand, some patent applications by financial institutions are more speculative. For example, MasterCard International has applied for a patent on a method that utilizes big data to predict customers' political affiliations based on their shopping patterns.[5]

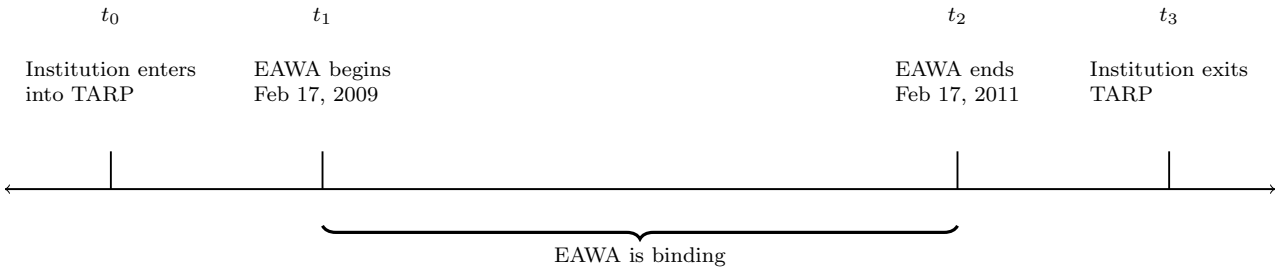
To provide additional insight into the type of assignees and inventions covered by the patents in our sample, Panel B of Table 1 presents information on the assignee and abstract for the top 20 patents by citations in our dataset. For instance, the most cited patent, filed by J.P. Morgan Chase in March 2012, introduces a "method and system for processing internet payments using the electronic funds transfer network." Additionally, a series of patents filed by American Express, focusing on customer loyalty reward systems, are among the most cited. In summary, this table highlights patents that broadly address payment systems, the cybersecurity of financial institutions' client data, and online customer loyalty programs.

Figure A.4 in the Online Appendix presents the front page of the patent with the highest citation among all patents in our sample. This business-method patent, granted to JPMorgan Chase Bank, introduces a method and system for conducting financial transactions over a payment network. Figure A.5 in the Online Appendix showcases the front page of the patent with the highest citation among all FinTech patents in our sample. This particular patent, granted to Bank of America, focuses on inventing hardware for attesting to authenticity in a cloud environment.

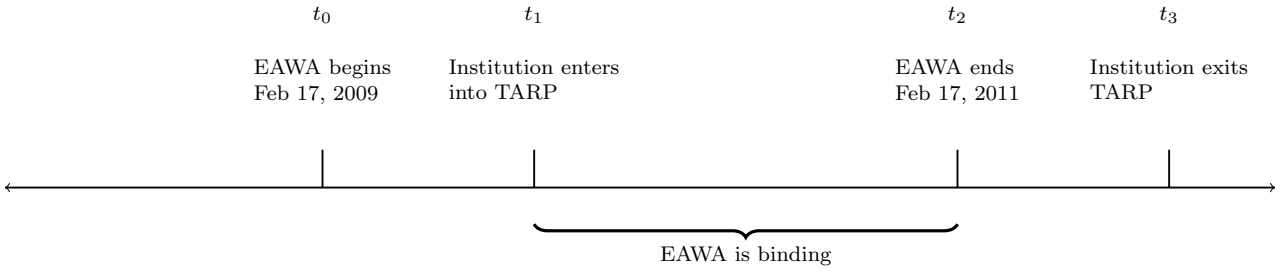
[4]The catch-all category includes patents that we cannot unequivocally assign to one of the USPTO categories.
[5]See "Big Banks Stake FinTech Claims with Patent Application Surge," *Wall Street Journal*, May 10, 2016.

Figure A.1: **Timelines**

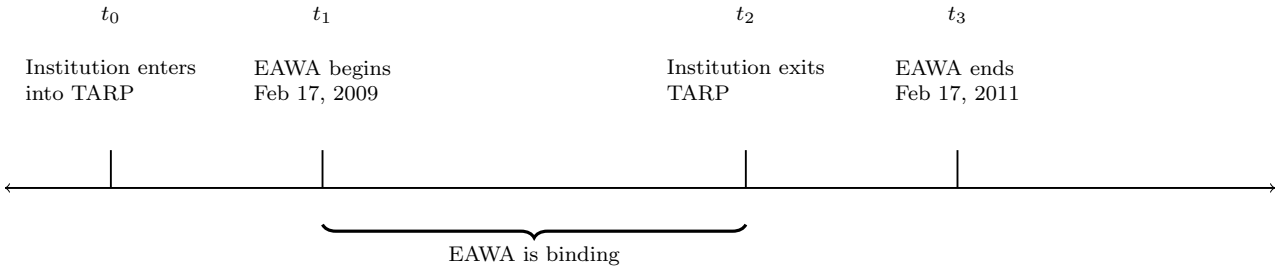
Panel A: Financial institution enters into TARP before Feb 17, 2009 & exits TARP after Feb 17, 2011



Panel B: Financial institution enters into TARP after Feb 17, 2009 & exits TARP after Feb 17, 2011



Panel C: Financial institution enters into TARP before Feb 17, 2009 & exits TARP before Feb 17, 2011



Panel D: Financial institution enters into TARP after Feb 17, 2009 & exits TARP before Feb 17, 2011

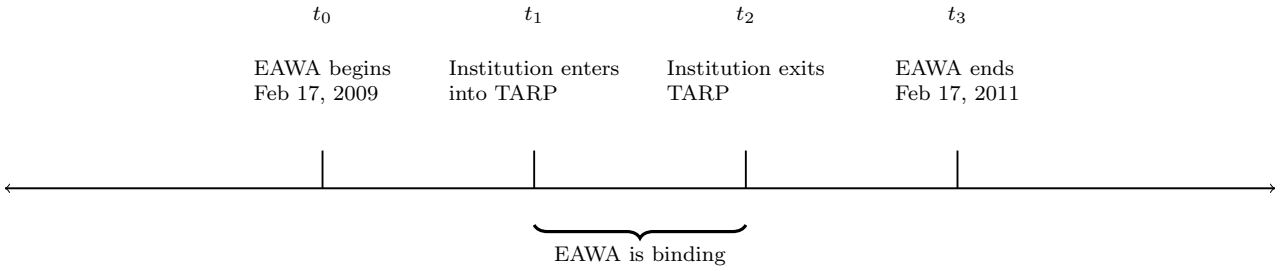


Figure A.2: **Top 20 Financial Institutions Ranked by FinTech Patents**

This figure presents the name of financial institutions (and their corresponding numbers) that filed the most patents from January 2007 through June 2015. These patents were granted by the US Patent and Trademark Office. The x-axes are institution names. The y-axes are the number of FinTech patents filed by institutions.

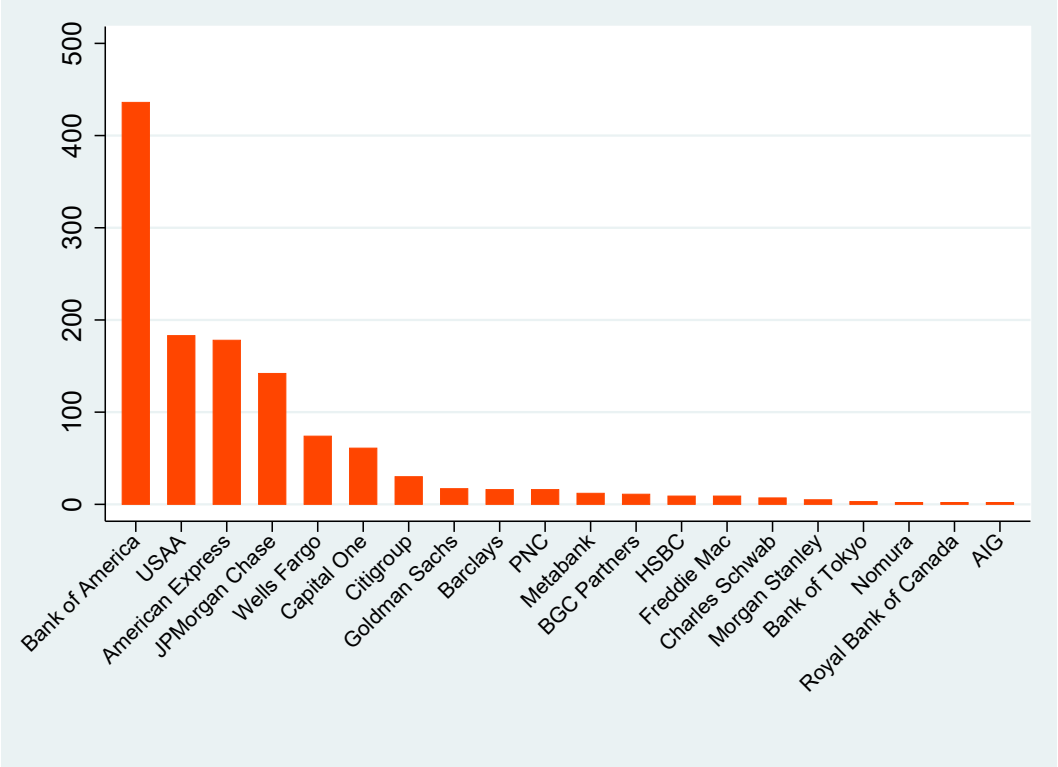
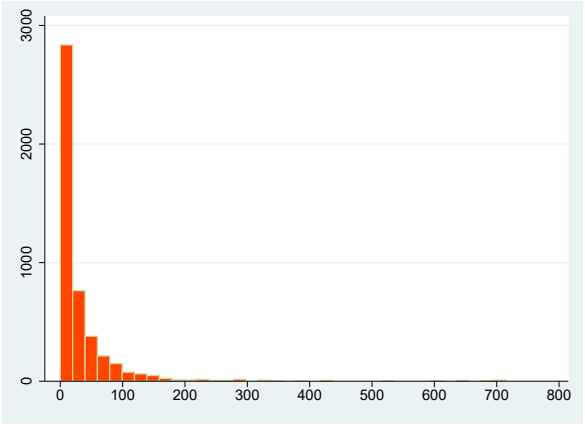


Figure A.3: **Distribution of Patent Citations**

This figure plots the distribution of patent citations across patents filed by sample financial institutions from January 2007 through December 2014. These patents were granted by the US Patent and Trademark Office. Panel A plots the distribution of the number of citation counts. Panel B plots the distribution of adjusted citations. Adjusted citation is the number of citations divided by the average number of citations in a given technology-class-year (the year in which all patents were applied).

Panel A: Raw Citation



Panel B: Adjusted Citation

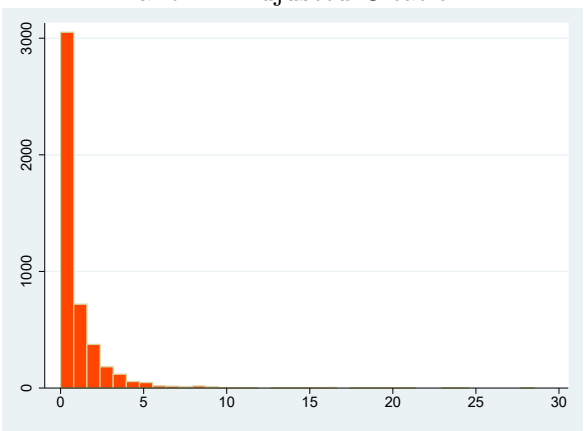


Figure A.4: **Front Page of Patent with the Highest Citation Count**

US008738521B2

(12) **United States Patent**
O'Leary et al.

(10) **Patent No.: US 8,738,521 B2**
(45) **Date of Patent: *May 27, 2014**

(54) **METHOD AND SYSTEM FOR PROCESSING INTERNET PAYMENTS USING THE ELECTRONIC FUNDS TRANSFER NETWORK**

(71) Applicant: **JPMorgan Chase Bank, N.A.**, New York, NY (US)

(72) Inventors: **Denis O'Leary**, New York, NY (US); **Vincent D'Agostino**, New York, NY (US); **S. Richard Re**, Westfield, NJ (US); **Jessica Burney**, New York, NY (US); **Adam Hoffman**, New York, NY (US)

(73) Assignee: **JPMorgan Chase Bank, N.A.**, New York, NY (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

This patent is subject to a terminal disclaimer.

(21) Appl. No.: **13/789,795**

(22) Filed: **Mar. 8, 2013**

(65) **Prior Publication Data**

US 2013/0191277 A1 Jul. 25, 2013

Related U.S. Application Data

(63) Continuation of application No. 13/443,179, filed on Apr. 10, 2012, now Pat. No. 8,452,703, which is a continuation of application No. 13/102,113, filed on May 6, 2011, now Pat. No. 8,190,521, which is a continuation of application No. 12/576,463, filed on Oct. 9, 2009, now Pat. No. 7,962,409, which is a continuation of application No. 10/356,171, filed on Jan. 31, 2003, now Pat. No. 7,676,431, which is a continuation of application No. 09/497,307, filed on Feb. 3, 2000, now Pat. No. 6,609,113.

(60) Provisional application No. 60/132,305, filed on May 3, 1999.

(51) **Int. Cl.**
G06Q 20/10 (2012.01)
G06Q 40/00 (2012.01)

(52) **U.S. Cl.**
USPC **705/39**; 705/35; 705/42

(58) **Field of Classification Search**
CPC G06Q 20/10; G06Q 40/00
USPC 705/39, 35
See application file for complete search history.

(56) **References Cited**

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Primary Examiner — Jagdish Patel
(74) *Attorney, Agent, or Firm* — Goodwin Procter LLP

(57) **ABSTRACT**

Embodiments of the invention include a method and system for conducting financial transactions over a payment network. The method may include associating a payment address of an account with an account holder name, the account residing at a financial institution and the associated payment address of the account configured to allow withdrawals by the account holder only and to allow a plurality of deposits to be made at different times. The method further includes freely publishing the payment address and making it available to users of an internet portal or search engine. The method further includes receiving data over a network identifying a deposit to be made to the account, assigning the deposit to the account using the payment address, and notifying the payer of the assignment. At least one directory is used for associating the account holder with the payment address.

24 Claims, 10 Drawing Sheets

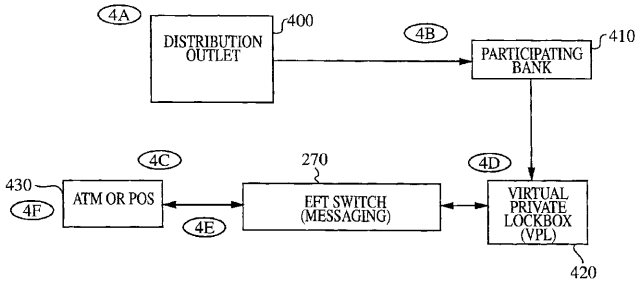


Figure A.5: **Front Page of FinTech Patent with the Highest Citation Count**



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

(10) **Patent No.: US 9,184,918 B2**
(45) **Date of Patent: *Nov. 10, 2015**

(54) **TRUSTED HARDWARE FOR ATTESTING TO AUTHENTICITY IN A CLOUD ENVIRONMENT**

(71) Applicant: **Bank of America Corporation**, Charlotte, NC (US)

(72) Inventors: **Bradford Thomas Spiers**, Bedminster, NJ (US); **Miroslav Halas**, Charlottesville, VA (US); **Richard A. Schimmel**, Glenmont, NY (US)

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

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

This patent is subject to a terminal disclaimer.

(21) Appl. No.: **14/305,611**

(22) Filed: **Jun. 16, 2014**

(65) **Prior Publication Data**

US 2014/0298439 A1 Oct. 2, 2014

Related U.S. Application Data

(63) Continuation of application No. 13/422,751, filed on Mar. 16, 2012, now Pat. No. 8,839,363.

(60) Provisional application No. 61/492,612, filed on Jun. 2, 2011, provisional application No. 61/476,747, filed on Apr. 18, 2011.

(51) **Int. Cl.**
H04L 29/06 (2006.01)
H04L 9/32 (2006.01)
(Continued)

(52) **U.S. Cl.**
CPC ***H04L 9/3247*** (2013.01); ***G06F 9/45533*** (2013.01); ***G06F 21/575*** (2013.01); ***H04L 9/28*** (2013.01); ***H04L 9/3234*** (2013.01);
(Continued)

(58) **Field of Classification Search**
None
See application file for complete search history.

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

(57) **ABSTRACT**

Apparatuses, computer readable media, methods, and systems are described for storing a first measurement of a virtualization platform, storing a second measurement of a measured virtual machine, generating a quote using a key, wherein the quote is based on the first measurement and the second measurement, and providing the quote for attesting to authenticity of the virtualization platform and of the measured virtual machine. In a further example, the quote may be generated based on a third measurement of a secure tunnel.

20 Claims, 9 Drawing Sheets

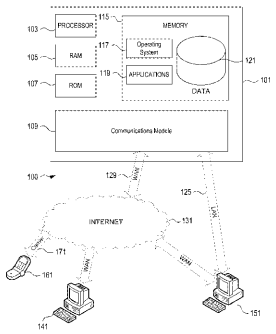


Table A.1: **TARP Banks in Our Sample**

This table presents a list of 27 TARP banks that filed at least one patent before December 31, 2006. #H-1B STEM 2004-2006 refers to the number of H-1B STEM workers that a bank had hired during 2004-2006. TARP Start refers to the date on which a financial institution agrees to receive funds from the Treasury. TARP End refers to the date on which a financial institution fully pays off the funds. EAWA Start and EAWA End refer to dates on which the EAWA act starts and ends to be ineffective for a bank. #EAWA Days is the number of days for which a TARP participant has been subject to EAWA. Assets 2009 (in millions) is a bank's total assets as of 2009.

	#H-1B STEM 2004-2006	TARP Start	TARP End	EAWA Start	EAWA End	#EAWA Days	Assets 2009
JPMorgan Chase	848	2008/10/28	2009/12/16	2009/02/17	2009/12/16	302	2,175,052
Chase Manhattan Bank	0	2008/10/28	2009/12/16	2009/02/17	2009/12/16	302	2,031,989
Citigroup	1,629	2008/10/28	2011/01/31	2009/02/17	2011/01/31	713	1,938,470
Bank of America	416	2008/10/28	2010/03/09	2009/02/17	2010/03/09	385	1,817,943
Wells Fargo	461	2008/10/28	2010/05/26	2009/02/17	2010/05/26	463	1,243,646
Morgan Stanley	718	2008/10/28	2009/08/12	2009/02/17	2009/08/12	176	658,812
Wachovia	245	2008/10/28	2010/05/26	2009/02/17	2011/02/17	730	510,083
Washington Mutual	134	2008/10/28	2009/12/16	2009/02/17	2011/02/17	730	327,913
PNC Financial Services Group	0	2008/12/31	2010/05/05	2009/02/17	2010/05/05	442	291,081
US Bancorp	44	2008/11/14	2009/07/15	2009/02/17	2009/07/15	148	265,912
Merrill Lynch Inc	301	2008/10/28	2010/03/09	2009/02/17	2010/03/09	385	246,024
Bank of New York Mellon	0	2008/10/28	2009/08/05	2009/02/17	2009/08/05	169	237,512
Capital One	14	2008/11/14	2009/12/09	2009/02/17	2009/12/09	295	169,646
Branch Banking and Trust Company	5	2008/11/14	2009/07/22	2009/02/17	2009/07/22	155	147,484
American Express	100	2009/01/09	2009/07/29	2009/02/17	2009/07/29	162	126,074
KeyCorp	14	2008/11/14	2011/04/20	2009/02/17	2011/02/17	730	105,231
Goldman Sachs	1,266	2008/10/28	2009/07/22	2009/02/17	2009/07/22	155	91,016
Zions Bancorporation	0	2008/11/14	2012/12/05	2009/02/17	2011/02/17	730	55,093
Huntington Bancshares	0	2008/11/14	2011/01/19	2009/02/17	2011/01/19	701	54,353
Fifth Third Bank	3	2008/12/31	2011/03/16	2009/02/17	2011/02/17	730	54,116
Discover Financial Services	90	2009/03/13	2010/07/07	2009/03/13	2010/07/07	481	39,892
TCF Financial Corporation	5	2008/11/14	2009/12/21	2009/02/17	2009/12/21	307	16,740
Citizens Bank	11	2009/05/29	2013/03/26	2009/05/29	2011/02/17	629	12,267
Silicon Valley Bank	18	2008/12/12	2010/06/16	2009/02/17	2010/06/16	484	9,474
First American Financial Corporation	0	2009/07/24	2012/12/11	2009/07/24	2011/02/17	573	5,530
First American Corporation	0	2009/07/24	2012/12/11	2009/07/24	2011/02/17	573	218
Bank One	57	2008/10/28	2009/12/16	2009/02/17	2009/12/16	302	215

Table A.2: **FinTech Keywords**

This table presents the full keyword list to identify the following seven types of FinTech patents. We search these keywords in the abstracts and claims for each patent.

Fintech Class	Keywords	Fintech Class	Keywords
Cybersecurity	cybersecurity	Blockchain	blockchain
Cybersecurity	encryption	Blockchain	distributed ledger
Cybersecurity	tokenization	Blockchain	cryptocurrency
Cybersecurity	authentication	Blockchain	acyclic
Cybersecurity	biometrics	Blockchain	bitcoin
Moblie Transaction	mobile transaction	Peer-to-peer	peer-to-peer
Moblie Transaction	payment	Peer-to-peer	peer
Moblie Transaction	digital wallet	Peer-to-peer	p2p
Moblie Transaction	digital cash	Peer-to-peer	consumer-to-consumer
Moblie Transaction	virtual cash	Peer-to-peer	customer-to-customer
Moblie Transaction	automated clearing house	Peer-to-peer	crowdfunding
Moblie Transaction	automatic funds transfer	Peer-to-peer	crowd funding
Moblie Transaction	automatic investment program	Robo-advising	robo-adivising
Moblie Transaction	automatic reinvestment	Robo-advising	automatic
Moblie Transaction	electronic depository transfers	Robo-advising	portfolio
Moblie Transaction	electronic funds transfer	Robo-advising	future investment opportunities
Data Analytics	data analytics	Robo-advising	investment adviser
Data Analytics	big data	Robo-advising	investment advisory
Data Analytics	cloud computing	Robo-advising	investment strategy
Data Analytics	artificial	Robo-advising	market timing
Data Analytics	machine learning	Robo-advising	passive investment strate
Data Analytics	credit history	Robo-advising	passive portfolio strate
Data Analytics	credit scoring	Robo-advising	replicating portfolio
Blockchain	crypto currency	Robo-advising	well-diversified portfolio
Blockchain	digital currency	Internet of things	internet of things
Blockchain	digital currencies	Internet of things	smart devise
Blockchain	virtual currency	Internet of things	sensor
Blockchain	virtual currencies	Internet of things	actuators

Table A.3: **Employ American Workers Act (EAWA) and First Patent Filers as Lead Inventors**

This table reports the estimates of the effect of EAWA on the likelihood of patents being filed by first-time filers. Columns (1)-(4) report estimates from the following ordinary least squares (OLS) specification:

$$\begin{aligned} \textit{First Filer}_{\ i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times TARP_i + \beta_3 Post_{i,s} \\ + \beta_4 Post_{i,s} \times TARP_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}. \end{aligned}$$

The sample in columns (1)-(4) consists of 20 TARP and 13 non-TARP banks that sponsored at least one STEM job through the H-1B program during 2004-2006. Columns (5)-(8) report estimates from the following OLS specification:

$$\begin{aligned} \textit{First Filer}_{i,s} = \alpha + \beta_1 EAWA_{i,s} + \beta_2 EAWA_{i,s} \times \textit{High Exposure}_i + \beta_3 Post_{i,s} + \\ \beta_4 Post_{i,s} \times \textit{High Exposure}_i + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}. \end{aligned}$$

The sample in columns (5)-(8) consists of 27 TARP banks. In Panel A, the dependent variable is First Filer$_{i,s}$, which is a dummy variable that equals 1 if patents filed by bank i in year-month s include at least one investor who filed for the first time for bank i, and 0 otherwise. In Panel B, the dependent variable is Non-First Filer$_{i,s}$, which is a dummy variable that equals 1 if all patents filed by bank i in year-month s do not have any investors who filed for the first time for bank i, and 0 otherwise. See Table 2 for definitions of other variables. Standard errors are clustered at the bank level.

Panel A: Dependent Variable: First Leader

	All Banks				TARP Banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA × TARP	-0.075***	-0.085**	-0.059**	-0.047				
	(-2.90)	(-2.50)	(-2.44)	(-1.69)				
Post × TARP	-0.014	-0.018	-0.054***	-0.033				
	(-0.56)	(-0.58)	(-2.74)	(-1.33)				
EAWA × High Exposure					-0.068*	-0.070*	-0.038	-0.039
					(-1.83)	(-1.88)	(-1.20)	(-1.27)
EAWA					-0.043	-0.025	-0.050	-0.056
					(-1.27)	(-0.48)	(-1.69)	(-1.39)
Post × High Exposure					-0.028	-0.026	-0.042*	-0.042*
					(-0.78)	(-0.73)	(-1.82)	(-1.80)
Post					0.007	0.035	-0.016	-0.012
					(0.20)	(0.51)	(-0.91)	(-0.34)
EAWA × TARP Fund%					1.200	1.226	1.258	1.276
					(1.53)	(1.57)	(1.62)	(1.55)
Post × TARP Fund%					-0.037	-0.037	-0.242	-0.263
					(-0.07)	(-0.06)	(-1.12)	(-1.21)
TARP	0.126**	0.130**						
	(2.33)	(2.11)						
High Exposure					0.086	0.083		
					(1.68)	(1.60)		
TARP Fund%					-1.221	-1.229		
					(-1.25)	(-1.21)		
H1B$_{-3}$	0.049	0.059*	-0.006	0.004	0.052	0.049	0.020*	0.022*
	(1.60)	(1.70)	(-0.68)	(0.28)	(1.66)	(1.55)	(2.02)	(1.79)
STEM$_{-3}$	0.060**	0.056**	-0.014*	-0.028***	0.052	0.058	-0.053***	-0.058***
	(2.30)	(2.04)	(-2.03)	(-2.87)	(1.06)	(1.05)	(-5.00)	(-3.65)
Constant	-0.065*	-0.071*	0.125***	0.119***	0.025	0.006	0.158***	0.159***
	(-1.76)	(-1.73)	(8.50)	(6.69)	(0.68)	(0.11)	(9.75)	(7.11)
Year × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
N	3,168	3,168	3,168	3,168	2,592	2,592	2,592	2,592
adj. R^2	0.06	0.05	0.43	0.43	0.06	0.04	0.42	0.42

Panel B: Dependent Variable: Non-First Leader

	All Banks				TARP Banks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA × TARP	-0.048*	-0.091**	-0.007	-0.012				
	(-1.92)	(-2.50)	(-0.26)	(-0.36)				
Post × TARP	0.089***	0.067**	0.033	0.036*				
	(2.84)	(2.20)	(1.53)	(1.79)				
EAWA × High Exposure					-0.107**	-0.106**	-0.065	-0.062
					(-2.32)	(-2.20)	(-1.41)	(-1.32)
EAWA					0.107*	0.150	0.082	0.045
					(2.06)	(1.68)	(1.64)	(0.80)
Post × High Exposure					-0.006	-0.005	-0.011	-0.013
					(-0.17)	(-0.16)	(-0.47)	(-0.51)
Post					0.047	0.166*	0.032*	0.019
					(1.67)	(1.99)	(1.76)	(0.91)
EAWA × TARP Fund%					-2.581**	-2.491**	-1.431	-1.383
					(-2.50)	(-2.18)	(-1.45)	(-1.40)
Post × TARP Fund%					1.358**	1.303**	0.498	0.488
					(2.65)	(2.40)	(1.15)	(1.17)
TARP	0.085*	0.103**						
	(1.85)	(2.12)						
High Exposure					0.076	0.077		
					(1.35)	(1.32)		
TARP Fund%					1.660	1.707		
					(1.09)	(1.13)		
$H1B_{-3}$	0.057	0.055	-0.001	-0.008	-0.042	-0.048	-0.029*	-0.032*
	(1.42)	(1.29)	(-0.08)	(-0.47)	(-0.73)	(-0.83)	(-1.84)	(-2.00)
$STEM_{-3}$	0.107***	0.113***	0.008	0.012	0.180***	0.180***	0.049**	0.047**
	(2.93)	(2.97)	(1.26)	(1.32)	(3.42)	(3.03)	(2.46)	(2.42)
Constant	-0.086*	-0.088*	0.104***	0.107***	-0.073	-0.145*	0.112***	0.129***
	(-1.97)	(-1.94)	(5.77)	(4.85)	(-1.22)	(-1.80)	(5.69)	(6.40)
Year × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	3,168	3,168	3,168	3,168	2,592	2,592	2,592	2,592
adj. R^2	0.09	0.08	0.34	0.33	0.09	0.08	0.32	0.32