Nationalistic Labor Policies Hinder Innovation*

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Abstract

Hiring restrictions for high-skilled foreign nationals hinder domestic firms' 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 did not only hindered new foreign hires but also reduced the quantity and quality of patents filings, especially in fields such as FinTech, cybersecurity, and payment systems. In terms of labor market implications, instead of replacing new high-skilled foreign nationals with domestic employees—the stated goal of EAWA's proponents—banks paid higher wage premia to retain pre-crisis foreign hires relative to 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 (EAWA proponent) (February 6, 2009)

Big banks in the U.S., which have been seeking to hire more foreign workers in recent years under the H-1B visa program, are now being forced to reconsider their approach after the Trump administration made it harder to obtain the work permits.

Bloomberg News (February 22, 2018)

1 Introduction

High-skilled immigration provides talent and specialized knowledge that might be unavailable domestically but is needed to produce innovation (Laeven et al., 2015; Bernstein et al., 2019; D'Acunto and Frésard, 2019).[1] Innovation is a fundamental driver of economic growth (e.g., see Griliches (2007) and He and Tian (2020)) and has been increasingly important to preserve national security in the information economy era (Weiss (2014)). At the same time, since the Great Recession, restrictions to both high-skill and low-skill immigration have been at the forefront of the political agenda of many Western economies.

Does restricting domestic firms from hiring foreign high-skilled workers reduce the quantity and quality of domestic innovation? Or, can domestic firms substitute foreign nationals with domestic labor—the stated aim of nationalistic labor policies—to keep innovating? We tackle these questions in the context of the *Employ American Workers Act* (EAWA), which restricted US financial institutions that had entered the *Troubled Asset Relief Program* (TARP) during the 2008–2009 Financial Crisis from hiring new foreign workers until after TARP funds had been paid back in full.[2]

We first document the often neglected fact that US financial institutions produce substan-

[1] See also, for instance, "Immigrants for the Heartland", Matthew J Slaughter, *The Wall Street Journal*, April 29, 2019.

[2] EAWA allowed the renewal of pre-existing foreign hires, whose wage premia relative to US nationals with similar skills increased while EAWA was effective, as we discuss below.

tial innovation, especially in fields such as cybersecurity, mobile information technologies, mobile transaction technologies (e.g., robo-advising), data analytics, payment systems, and many other areas that affect the efficiency, effectiveness, and security of overall economy. We classify about 10,000 patent application documents submitted by US banks. About half of them are in the area of data processing methods. Other relevant areas include information security and electrical computers & digital processing systems. Interestingly, traditional banks have been patenting extensively in areas that FinTech companies have commercialized over the last decade.

A naive comparison of the innovation trends by institutions that accessed TARP and others would confound the effects of the EAWA ban with the major economic shocks that led institutions to access TARP. For this reason, our main analysis includes only institutions that accessed TARP and faced the EAWA ban. Within this group, we exploit two sources of variation. First, we use the fact that the EAWA ban affected TARP institutions at different points in time. Second, we compare institutions that, before the onset of the crisis, employed higher or lower shares of foreign workers in STEM-related research activities. All the institutions in our analysis thus faced similarly negative economic shocks, as we document in the data, but institutions that relied relatively more on foreign skilled workers before the crisis were affected by the EAWA ban more than other institutions, because the ban required them to find novel recruiting channels for innovators or hindered them completely from obtaining the highly specialized skills they needed, which might have not been available in the US domestic labor force.

As a first step, we verify that TARP institutions' compliance to EAWA was universal: applications for new H-1B visas dropped to zero for institutions subject to EAWA. At the same time, institutions that did not enter TARP did not experience this drop in H-1B-visa applications, which suggests that economy-wide shocks induced by the Financial Crisis and the Great Recession in the US and abroad cannot explain the drop in new foreign hires by

US financial institutions.

We next document that, during the EAWA period, foreign-STEM-dependent institutions—those whose foreign hires included more STEM workers—reduced their patenting activities substantially more than others: their probability of filing any patents during the EAWA period dropped and this drop was largely due to fewer patents filed by teams including inventors that had never filed patents in the US before. The quality of patents filed, as measured by citations over time, was lower and especially so for patents in the area of financial technology (FinTech). After the EAWA ban on hiring foreign workers was lifted, foreign-STEM-dependent institutions started to hire STEM foreigners again and reverted back to their pre-EAWA patenting frequency.

Our baseline results survive a set of robustness tests, such as weighing observations based on the pre-crisis amount of firms' patents, foreign hires during the pre-crisis period, or firm size. We also perform two falsification tests, whereby we randomly assign placebo STEM exposure ratios and placebo dates for the beginning and end of the EAWA restriction period across firms. We fail to replicate the baseline results in these falsification tests.

After establishing these baseline facts, we move on to assess a set of issues and concerns with interpreting them. First and foremost, the financial crisis was a major negative economic shock, especially for TARP participants, which must have impacted their ability to invest in R&D and innovation irrespective of the ban on foreign hires. Conversely, repaying the TARP funds in full might capture a time in which financial institutions' operations were back to normal. For this reason, it is important to stress that our strategy does *not* rely on a simple comparison of outcomes within institutions before and after being subject to EAWA, which would raise the concern of crisis-related unobservables that in turn affected firms' innovation patterns. Rather, we consider institutions that accessed TARP and hence faced similarly large negative economic shocks over the same time period. Our strategy compares the reactions to EAWA by institutions that happened to be differentially exposed to this regulation shock. Institution-level exposure is measured as the ratio of foreign STEM workers over total foreign workers in the pre-crisis period (2004—2006).[3] Ultimately, we compare two institutions, both of which accessed and exited TARP, but one of which happened to rely less on high-skilled foreign hires while the other relied more on high-skilled foreign hires to innovate at the time the EAWA ban on new foreign hires hit both institutions.

The identifying assumption of our difference-in-differences strategy is that any divergence in the trends of innovation across TARP firms that were more or less reliant on foreign STEM workers when the EAWA ban hit was due to the EAWA ban rather than to other shocks that affected such institutions differently. To corroborate the economic plausibility of this assumption, which we cannot test, we show that the trends of patent filings by TARP institutions sorted based on their reliance on foreign STEM workers were parallel before EAWA was passed. Our remaining assumption thus becomes that TARP firms with higher shares of foreign STEM workers reacted differently after the EAWA ban because they relied more on foreign workers to innovate and not due to other unobserved differences relative to less-foreign-STEM-reliant TARP firms.

Differences in the time length for which institutions were subject to the EAWA ban are also a source of concern, because they might be endogenous to institutions' willingness to innovate. That is, banks might choose to leave the TARP program earlier or later depending specifically on their innovation plans rather than other business considerations. The EAWA restriction period, however, was largely determined by the amount of toxic assets to which banks were exposed before the financial crisis and anecdotally all financial institutions tried to exit TARP as soon as they were able to reduce their exposure to toxic assets (Gennaioli et al., 2012; Cheng et al., 2014; Baron and Xiong, 2017).[4]

[3]We use the period 2004–2006 because existing empirical evidence suggests banks' hiring policies were unlikely to be affected by their anticipation of the 2008 financial crisis at that time. For example, using personal home transaction data, Cheng et al. (2014) find that mid-level managers in securitized finance were not aware of a large-scale housing bubble and a looming crisis in 2004–2006.

[4]Toxic assets include mortgage loans or securitized products that were issued by banks during the 2004–

When we estimate our difference-in-differences specification by ordinary least squares, we add a full set of firm and year fixed effects. Firm fixed effects allow us to absorb time-invariant firm-level unobservables that might determine the level of innovation as well as the systematic reliance of firms on foreign STEM workers. Absorbing time-varying shocks common to all firms, instead, allows us to exclude that economy-wide technological or macroeconomic shocks or monetary and fiscal policy interventions that all TARP firms faced drive our results.

In the last part of the paper, we propose an alternative way to corroborate our interpretation of the baseline results. Specifically, we consider the labor-market implications of the EAWA ban. If domestic institutions could replace foreign high-skilled hires with domestic hires, we should have observed no effects of EAWA on firms' innovation. By contrast, if domestic institutions faced a shortage of the high-skilled workers they needed to innovate, because existing foreign STEM workers' visas could be renewed under EAWA, we would expect that the price of existing foreign workers' labor (wages) increased substantially as institutions tried hard to retain the limited pool of foreign STEM workers they could access. For jobs that were less specialized, and hence for which replacing foreign workers with domestic workers should have been easier, we would not expect a substantial increase in the relative wages of foreign workers.

We find evidence consistent with these conjectured labor-market implications using visa-level data. Visa-level data allow us to compute the wage premium attached to each visa application institutions filed on behalf of workers—the wage the institution offered to such workers divided by the prevailing domestic wage in the workers' occupation.[5] Indeed, foreign-STEM-dependent institutions started to offer a higher wage premium to their existing STEM foreign workers during the EAWA period. By contrast, we do not find differentials in the

2006 period.

[5]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.

wage premia that the same foreign-STEM-reliant institutions offered to non-STEM foreign workers. Moreover, we find that the wage premium to foreign STEM workers continued after the EAWA was lifted—i.e., once new foreigners could be hired again—whereas it did not exist after the EAWA for non-STEM workers.

We cannot disentangle whether the wage dynamics we document after the EAWA ban was lifted are driven by the demand or supply of specialized labor. On the demand side, banks might have prioritized the hiring of foreign analysts and mid-level managers over STEM innovators shortly after the visa ban was over due to needs in core operations.[6] On the supply side, the 2008-2009 Financial Crisis and the Great Recession might have steered high-skilled STEM immigrants away from jobs in the financial industry and into other fields such as computing and technology companies.

1.1 Related Literature

Our paper builds on several strands of economics and finance literature, including FinTech, innovation, banking, immigration policies, and financial regulation.

First, our paper relates to the literature studying the effects of policy interventions and regulation on innovation (see He and Tian (2020) for a recent review as well as Bayazitova and Shivdasani (2012); Duchin and Sosyura (2014); Agarwal et al. (2014); Calomiris and Khan (2015); Agarwal et al. (2017); Mayer et al. (2014); Lucca et al. (2014); Granja et al. (2017)). Rather than studying a policy that was purposefully adopted to affect innovation, such as place-based policies (Lerner (1996); Tian and Xu (2022); Xu (2021); D'Acunto, Tate, and Yang (2021)), we study a labor-market restriction whose innovation implications were unintended and yet, as we document, quite sizable. We build on earlier work that has documented the unintended consequences of labor-market policy interventions on firms' in-

[6] Consistent with this possibility, Figure A.1 in the Online Appendix shows that banks submitted a large number of H-1B visa petitions to sponsor non-STEM workers immediately after the end of the ban.

novation and productivity, such as Bena, Ortiz-Molina, and Simintzi (2021), who show that labor protection laws incentivize firms to engage in process innovation and replace workers with machines rather than increasing wages and job security. See also Hombert and Matray (2018); Bena and Simintzi (2019), who study the innovation and labor-market consequences of US free-trade agreements with China. Because of the importance of innovation in the FinTech space to product development and transaction security in an information economy, the unintended consequence of immigration bans we document could have far-reaching implications for the competitive landscape in the financial services industry.

Second, this paper is one of the very few that shed light on the extensive amount and type of innovation financial institutions produce. Several authors explore the causes and consequences of financial innovation at the micro level, including both patentable and non-patentable ideas (Tufano, 1989, 1995; Lerner, 2002; Tufano, 2003; Lerner, 2006, 2010; Rysman and Schuh, 2016; Pérignon and Vallée, 2017; Calvet et al., 2018; D'Acunto et al., 2019; D'Acunto, 2020).[7] In a recent study, Chen et al. (2019) apply machine learning to identify and classify innovations in the financial industry. The authors document that banks are by far the most active innovators among public firms in the financial services industries. Market leaders and incumbents appear to invest heavily in innovation to avoid much of the negative value effect created by disruptive technologies from nonfinancial startups.

Third, we show that high-skilled immigrants play an important role in the development of financial technology. Our empirical evidence is particularly relevant to the assessment of the role of policies that restrict high-skilled immigration. The study relates to an emerging literature suggesting that foreign talent plays a key role in US innovation and productivity (Kerr and Kerr, 2010; Peri et al., 2015; Jaimovich and Siu, 2017; Dimmock et al., 2019; Bernstein et al., 2019). In particular, we build on studies using H-1B visa data in the US, such

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

as Bernstein et al. (2019), who document immigrants' contribution to US innovation, and Dimmock et al. (2019), who find that H-1B visa lottery winners who become entrepreneurs receive more venture capital funding, are more likely to have a successful exit via IPOs, and produce more patents and patent citations than the average US domestic entrepreneur.

2 Institutional Setting

Two institutional features shape our empirical setting—the timing and motivations for the approval of TARP and EAWA, as well as the scope for patenting activity in the US financial sector.

2.1 TARP and Employ American Workers Act

On October 3, 2008, U.S. President George W. Bush signed into law the Troubled Asset Relief Program (TARP). The program allowed the U.S. government to purchase toxic assets and equity from financial institutions.[8] The vast majority of TARP participants were commercial banks, among which the government bought preferred stocks in eight major banks, including Goldman Sachs, Morgan Stanley, J.P. Morgan Chase, Bank of America, Citigroup, Wells Fargo, Bank of New York Mellon and State Street. TARP beneficiaries also included a major utility (General Electric) and three top car manufacturers (GM, Ford, and Chrysler), which we exclude from our analysis given the completely different nature of their innovation and the fact that they were targeted by many other government programs during the Financial Crisis and the Great Recession.[9]

On February 17, 2009, President Obama signed the Employ American Workers Act (EAWA) into law. The Act had a validity of two years and was not renewed. It targeted

[8]The program originally authorized expenditure of $700 billion. The Dodd-Frank Wall Street Reform and Consumer Protection Act reduced the amount authorized to $475 billion. On December 19, 2014, the U.S. Treasury sold its remaining holdings of Ally Financial, essentially ending the program.

[9]All our results stay similar if we do not exclude these firms.

TARP recipients seeking to employ H1B workers. The initial goal of the legislation was to completely ban TARP recipients from applying for any H1B visas. The final legislation, however, allowed such employment but imposed several restrictions. Regardless of their exposure and reliance on H1B employees, all TARP recipients were subject to the same rules as "H1B Dependent Employers."[10] The foreign hiring ban under the EAWA did not apply to workers seeking to extend their H1B stay. However, the rule was binding for employers who filed H1B petitions for new foreign-born employees.

In the US, H1B dependent companies must sign several attestations on the Labor Condition Application (LCA). Prior to filing an H1B petition, the employer must take *bona fide* steps to recruit U.S. workers for the position for which an H1B worker is sought and offer a wage that is at least as high as that offered to the H1B worker. The employer must also attest that, in connection with their *bona fide* recruitment efforts, they have actually offered the same job to any U.S. worker who has applied and who is equally or better qualified for the position. Employers were also hindered from laying off any U.S. workers in jobs equivalent to the H1B position within the period beginning 90 days before and ending 90 days after the H1B petition filing. In short, H1B petitioning under EAWA imposed much higher costs of compliance in order to produced the detailed information and documents for each prospective worker, not to mention the fact that the documented search of U.S. applicants possessing specific skills the institution needed might have been very costly and long if such skills were rare within the US domestic workforce. As we show below, indeed the EAWA ban led to the almost full elimination of foreign high-skilled new hires by U.S. financial institutions.

[10]Certain non-TARP recipients are considered to be 'H1B dependent if H1B workers make up more than 15% of their workforce.

2.2 Patenting in the Financial Sector

Our main outcome of interest is the innovation of financial institutions. Although the innovation activities of traditional banks are often overlooked, banks are frequent patent filers. The aftermath of the 2008-2009 Financial Crisis witnessed an unprecedented wave of patenting activity marked by commercial banks in the US. According to a *Wall Street Journal* article dated May 10, 2016, large banks and credit companies have applied for at least 2,679 patents since 2013 in areas such as mobile systems, the Internet of Things, and data analytics.[11]

To illustrate the areas in which banks have been innovating, we categorize granted patents based upon US classifications and rank these classifications based on the number of patents within each classification. Panel A of Table 1 presents the top 20 classifications of patents filed by the financial institutions in our sample based on the USPTO patent topic classifications. These classifications count for about 95% of patents filed by commercial banks headquartered in the United States. Among the most common categories are various forms of data processing methods as well as information security.[12]

Financial institutions face incentives to engage in FinTech innovation for at least two reasons. First, due to security threats, the risk of a data breaches, and potential litigation, banks are not able to solely rely on third-party vendors to develop patents. Second, FinTech companies compete with incumbent traditional financial institutions in many areas, such as mortgage and loan originations. Banks have been filing patents over the last decade in areas in which startup financial technology firms are thriving. Some of these inventions have already been commercialized as financial products. For example, the cloud wallet security technology invented by J.P. Morgan Chase has been applied to Chase Pay mobile payments system. Other patent applications by financial institutions are more speculative. MasterCard

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

[12] Catch-all category includes the patents that we are unable to assign without doubt to one of the USPTO categories.

International, for example, has applied for a patent on a method that uses big data to predict customers' political affiliations based on where they shop.[13]

To provide additional intuition on the type of assignees and inventions the patents in our sample cover, in Panel B of Table 1 we report the assignee and abstract for the top 20 patents by citations in our sample. For instance, the most cited patent was filed by JP Morgan Chase in March 2012 and proposes a "method and system for processing internet payments using the electronic funds transfer network." Also, a set of patents filed by American Express and dealing with customer loyalty reward systems are among the most cited. Overall, this table describes patents that broadly deal with payment systems, the cybersecurity of financial institutions' clients data, and online customer loyalty programs.

In Appendix A.1, we also report a few patent abstracts in our sample. Although this list certainly is not representative of the entire sample of patents owned by banks, a glance at these abstracts suggests that many bank innovations are tightly linked to products that can be commercialized.

3 Data

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

3.1 Employ American Workers Act

The effective period in which banks receiving TARP funds were restricted from hiring H-1B workers due to the EAWA — which is crucial to our analysis — varies across institutions. As the EAWA started on February 17, 2009 and ended on February 17, 2011, banks that entered the TARP program at different dates faced different effective timing of their restriction from

[13]See "Big Banks Stake FinTech Claims with Patent Application Surge", *Wall Street Journal*, May 10, 2016.

hiring H-1B visa holders. If a bank repaid TARP money before February 17, 2011, they could hire foreign workers without restriction immediately after the repayment date; if a bank entered TARP after February 17, 2009, they could have hired without restriction before entering TARP.

In Table A.1, we present timelines with respect to the beginning and end of the EAWA period for all TARP participants that had filed at least one patent during our sample period. In the last column, we compute the number of days for which the EAWA was effective for each participant, and indeed the variation in the length of exposure is quite substantial. The vast majority of institutions were restricted by the EAWA on it approval day, Feb 17, 2009, which means that they had already entered TARP when the ban was implemented. Ultimately, most institutions did not know that they would have faced a foreign hiring ban before they decided to enter TARP, which dismisses the concern that banks might have decided whether or not to enter TARP and hence be subject to the ban based on their expected patenting activity going forward. Dismissing this concern is important because otherwise one might worry that only the banks that had planned to stop innovating irrespective of the EAWA ban accessed TARP.

3.2 Patents Data

Following prior literature (for a recent survey, see Bernstein et al., 2019), we measure innovation activity based on patent applications and patenting outcomes. We obtain data on PatentsView for U.S. patents that were filed by TARP and non-TARP banks from 2002 through 2015. These patents were later on granted by the United States Patent and Trademark Office (USPTO). PatentsView is a visualization, data dissemination, and analysis platform that is supported by the Office of the Chief Economist at the USPTO. USPTO patent applications do not include unique firm-level or inventor-level identifiers to track assignees and inventors over time. However, PatentsView uses a disambiguation algorithm to associate the same inventor or assignee with more than one patent by clustering like entities together.

Our sampling procedure for patents filed by banks consists of several steps. First, we obtain a list of bank names that filed and published at least one patent to the USPTO over the period of 2002 – 2016. For bank names, we refer to BANKSCOPE (Bureau van Dijk). Second, we search manually for assignee identifiers from the PatentsView platform for the banks in our sample. Third, we utilize the corresponding assignee identifiers to extract granted patents filed by these banks from PatentsView.[14] Specifically, we extract information about application/patent number, filing date, patent classification, assignee location, inventors' identity and address, and patent applicant (assignee). If these items are missing, we collect them directly from the USPTO.

The final sample consists of 8,097 patents filed from January 2000 through December 2016. For these patents, we collect citations data from Google Patents as of January 2022.

Panel A of Figure 1 plots the aggregate number of patents in our sample of financial firms from 2002Q1 through 2015Q2. This plot reveals that the amount of innovation, measured as the number of filed patents that were eventually granted, has increased dramatically in the first decade of the twenty-first century, and appears to have stabilized since 2010. Panel B of the figure lists the name of top 20 banks ranked by their granted patents filed from January 2007 through June 2015, which is our regression sample period. The distribution of patents is very skewed towards the largest banks with substantial variation even among those. For instance, Bank of America files a much hire number of patents than any other large banks.

3.3 H-1B Visa Applications Data

The H-1B Program is an employer-based program. Because the applications are filed by employers, they do not include demographic information specific to individual foreign work-

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

ers. We obtain the H-1B visa data from USCIS at the firm-location-job-application-date level. In each visa application, we have information about the sponsoring company's name, date in which the sponsor filed the application, job title and location of the H-1B applicant (sponsor), effective beginning and ending dates, wage offered to the foreign national and prevailing wage in the same occupation and location, number of employees for each visa, location of employees to be deployed, and application outcome (i.e., approval or rejection).

Panel A of Figure 2 plots the number of STEM workers for whom institutions in our sample filed H1B visa applications by quarter. The figure suggests that H-1B-visa application was abruptly halted during the financial crisis. Panel B lists the top 20 banks that hired the most STEM workers from January 2004 through December 2006. The distribution of STEM hiring among top banks is not as skewed as the distribution of patents. Citigroup, Goldman Sachs, and JPMorgan Chase are among the top 3 institutions that dominated sponsoring H1B visas for STEM immigrants. Panel C reports the H-1B-visa applications separately for applications of non-STEM foreign workers. Although the dynamics of these applications over time do not differ substantially, the level of STEM-related applications appears to be systematically higher. Panel D lists the top 20 banks that sponsored the most H1B visas to recruit non-STEM workers. Citigroup, Merrill Lynch, and Lehman Brothers had the largest share of non-STEM employees as portfolio managers, loan officers, analysts, accountants, and others.

3.4 Summary Statistics

Table 2 presents a set of descriptive statistics for the bank-month-level analysis. The sample period is from January 2007 through December 2014. We start in January 2007 to make sure that the outcome variables (e.g., STEM hiring and patenting activities) do not overlap with the pre-crisis period in which we measure the *Treated* condition, which is between 2004 and 2006, as we define below.

Eleven percent of observations are associated with hiring STEM jobs and 8.3% of observations are associated with at least one patent filling. In each bank months, the likelihood of observing business-method patents (USPTO classification 705), non-business-method patents, and FinTech patents is similar (6.5%, 6%, and 4%, respectively). On average, in the pre-crisis period (2004-2006) STEM jobs account for 20% of total H-1B-sponsored jobs, and the likelihood of sponsoring at least one STEM job through the H-1B program is 38.2%.

4 Empirical Strategy

In this section, we discuss our difference-in-differences empirical strategy, the assumptions it implies, and a set of potential concerns.

4.1 Difference-in-Differences Strategy

Our empirical design compares bank-level patenting activities before and after TARP banks complied to the EAWA (first difference) across banks with a higher (*Treated*) or lower share of STEM H1B workers before the Financial Crisis (second difference). In some analyses, we further split the period after EAWA implementation into two parts—the period during which the EAWA ban was in place and the period after the ban was lifted, i.e. after firms exited TARP—to assess the longer-term effects of the EAWA ban.

We implement this strategy by estimating a set of linear specifications that only exploit variation in outcome and control variables within banks:

$$\begin{aligned} \mathit{Outcome}_{i,s} = \alpha + \beta_1 \times \mathit{EAWA}_{i,s} + \beta_2 \times \mathit{EAWA}_{i,s} \times \mathit{Treated}_i + \beta_3 \times \mathit{Post}_{i,s} + \\ \beta_4 \times \mathit{Post}_{i,s} \times \mathit{Treated}_i + X' \times \beta_5 + \eta_i + \eta_s + \epsilon_{i,s}. \end{aligned} \tag{4.1}$$

where $\mathit{Outcome}_{i,s}$ indicates a set of outcomes for bank i as of time s. $\mathit{EAWA}_{i,s}$ is a dummy variable that equals 1 during the months (s) in which institution i is subject to the Employ American Workers Act (EAWA), and zero otherwise. $\mathit{Post}_{i,s}$ is a dummy variable that equals 1 in the months after the EAWA has ceased to be binding for institution i that was previously subject to the act and zero otherwise. $Treated_i$ is the number of STEM jobs as a percentage of total number of H1B-sponsored workers hired by firm i from January 2004 through December 2006 ($STEM_{0406}$). This variable aims to capture the extent to which the institutions in our sample relied on foreign STEM workers before the 2008-2009 Financial Crisis. We follow Cheng et al. (2014) in using the years between 2004 and 2006 to measure the pre-period, but our results are similar if we consider other time periods before 2008. In an alternative specification, to ensure that our results survive when we allow for nonlinear effects of the shares of STEM workers hired, we also define a dummy variable that equals 1 if $STEM_{0406}$ is greater than zero, and zero otherwise.

Finally, η_i and η_t are full sets of bank and time fixed effects. Bank fixed effects partial out systematic time-invariant cross-sectional differences across the banks that enter the analysis. Because the variable $Treated_i$ is defined at the bank level and is time invariant, its level is absorbed by the bank fixed effects. Time fixed effects allow us to partial out economy-wide aggregate time-varying shocks that affect all banks in the same way, and which are likely to be major during our sample period, which spans the Financial Crisis and the Great Recession.

Our coefficient of interests is β_2, which captures the change in each outcome variable within banks during the EAWA period relative to before and across banks with a higher or lower exposure to the EAWA foreign hiring ban.

4.2 Identifying Assumptions

A necessary condition to interpret the results of our difference-in-differences specification causally is the parallel-trends assumption. The assumption states that the evolution of firm-level outcomes of interest for treated and control banks would have followed common trends before and after the EAWA, had the policy not been enacted. This assumption is untestable given that the potential outcome absent EAWA implementation is unobservable. However, we can at a minimum test whether the pre-trends of outcomes before the EAWA implementation across banks that were more or less exposed to the foreign hiring shock were parallel. If pre-trends were parallel, our remaining identifying assumption would be that any divergence in the trends across the two groups of banks after EAWA is due to the ban on foreign hiring and not to other possible concurrent shocks.

We estimate the following specification:

$$STEM\ H1B_{i,t} = \alpha + \sum_{t=n}^{m} \beta_t \times Period_{i,t} \times Treated_i + \sum_{t=n}^{m} \gamma_t \times Period_{i,t} + X' \times \beta_5 + \eta_i + \eta_t + \epsilon_{i,t}, \quad (4.2)$$

where $\sum_{t=n}^{m} \beta_t \times Period_{i,t} \times Treated_i$ is a set of interactions of $Treated_i$ and event period dummies for n periods before and m periods after bank i is subject to the EAWA ban; $STEM\ H1B_{i,s}$ is the logarithm of the number of H1B-sponsored STEM workers ($\#STEM$) plus one; and η_i and η_t are full sets of financial institution and time fixed effects.

To understand the split across periods in equation 4.2, it is important to note that the length to which US institutions were subject to EAWA varied across banks depending on when banks entered and exited TARP (see Table A.1 for details). In event time, we therefore label $Period_{i,0}$ as the number of months that each institution i was subject to EAWA, which again includes a different number of months across institutions. Instead, each pre- and post-EAWA period spans 180 days. For instance, $Period_{i,-1}$ and $Period_{i,1}$ indicate the 180 days before institution i started to be subject to EAWA and after institution i exited TARP and EAWA, respectively.

Rather than in table form, we report the estimated coefficients from equation 4.2 in graphical form to make them easier to grasp. In Figure 3, red dots indicate the value of estimated coefficients $\hat{\beta}_t$ for each period. The solid-line segments around each point represent 2-standard-error confidence bounds. The period just before the EAWA period is the omitted category in the regression.

Two patterns are worth noticing. First, the pre-trends of foreign hiring outcomes are parallel across treated and control banks before the EAWA was implemented, as the estimated coefficient $\hat{\beta}_t$ in the pre-period does not change over time. In terms of levels, treated banks were hiring more foreign workers than other banks and hence $\hat{\beta}_t$ is positive, which is exactly what we would expect given our definition of treated and control firms. The second pattern is that treated firms were differentially hit more by the EAWA ban during the EAWA period, and caught up with pre-EAWA foreign hiring slowly over time. We will revisit this second pattern using our difference-in-differences specification below.

4.3 "First Stage": EAWA and H1B Hiring

Before considering bank-level innovative outcomes, we verify that banks indeed complied with the EAWA hiring ban, and hence that they were unable to hire new H1B-visa foreign workers while subject to the ban.

In terms of raw data, Figure A.1 proposes binscatter plots of the average number of H1B employees across event days around the beginning and end of the EAWA ban across two sample splits: (1) whether banks participated in TARP, and hence were subject to EAWA, and (2) whether H1B workers had STEM qualifications. Consistent with compliance with the EAWA hiring ban, the average number of H1B visa holding employees of US financial institutions dropped during the EAWA period.

We already documented in Figure 3 the dynamic differential evolution of foreign STEM hiring across banks that had different levels of exposure to the EAWA ban. For consistency with our differences-in-differences specification and the subsequent analysis, we repeat this "first stage" analysis using our difference-in-differences multivariate specifications:

$$\begin{aligned} \textit{STEM H1B}_{i,s} = \alpha + \beta_1 \times \textit{EAWA}_{i,s} + \beta_2 \times \textit{EAWA}_{i,s} \times \textit{Treated}_i + \beta_3 \times \textit{Post}_{i,s} + \\ \beta_4 \times \textit{Post}_{i,s} \times \textit{Treated}_i + X' \times \beta_5 + \eta_i + \eta_s + \epsilon_{i,s}, \end{aligned} \tag{4.3}$$

where $\textit{STEM H1B}_{i,s}$ indicates STEM-related hiring outcomes at the level of bank i as of month s. The first (continuous) version of this outcome variable is the logarithm of the number of H1B-sponsored STEM workers ($\#\textit{STEM}$) plus one. The second (binary) version is an indicator variable equal to 1 if bank i sponsors at least one STEM job through the H1B-program in month s.

Table 3 reports the estimates of equation 4.3, where the estimated coefficient of interest, $\hat{\beta}_2$, is highlighted in grey. For the continuous outcome, which captures the intensive margin of foreign STEM hiring, columns (1)-(4) propose the same pattern across alternative specifications: banks that relied more on foreign STEM workers before the financial crisis were hit more than others by the EAWA foreign hiring ban. In fact, those banks that did not have foreign STEM employees before the crisis were not affected at all, as captured by the coefficient attached to EAWA—they continued not hiring foreign workers during the ban, but this did not affect their employment structure because they were not hiring foreign STEM workers to begin with. Moreover, banks that relied more on H1B STEM employment before the crisis kept having fewer such workers also after the EAWA ban was lifted relative to before the crisis, which can be consistent with labor market frictions hindering firms from fully reverting bank in terms of foreign STEM recruiting as soon as the ban is over.

Columns (5)-(8) of Table 3 consider the binary version of the outcome variable—the extensive margin of foreign STEM hiring. Qualitatively, we detect the same patterns as in the intensive margin with the exception of foreign STEM hiring after the EAWA ban was lifted. This difference is not surprising, because as long as banks that relied substantially on foreign STEM workers before the crisis hired at least one foreign STEM worker after the

EAWA period, the binary variable would equal 1 both before the crisis and after the EAWA ban.

In Table A.2, we show our results are robust to using an alternative measure of foreign STEM hiring. That is, we define the dependent variable as a dummy equal to 1 if firm i in month s hires at least 1 H1B-sponsored STEM worker, and zero otherwise.

5 Extensive Margin of Patenting: Patent Filings

We now move on to assess the effects of the EAWA foreign hiring ban on financial institutions' innovation activities.

First, we consider the extensive margin of innovation, which we capture by using $Patent\ Filed_{i,s}$, i.e. a dummy variable that equals 1 if bank i filed at least one patent in month s, and zero otherwise as the outcome in the difference-in-differences specification. The specification implies a linear probability model for the likelihood of patenting, which we prefer to non-linear estimators due to the large number of fixed effects.

We report the results in Table 4, where, to be consistent with the estimates of EAWA on foreign STEM hiring discussed above, we consider both a continuous (columns (1)-(4)) and a discrete version (columns (5)-(8)) of the treatment variable. The continuous version is the number of STEM jobs as a percentage of total number of H1B-sponsored workers hired by firm i from January 2004 through December 2006 ($STEM_{0406}$). The discrete version is a dummy variable that equals 1 if $STEM_{0406}$ is greater than zero, and zero otherwise.

Across the board and irrespective of the specifications or definitions of treatment variable, we find that banks that hired more STEM foreign workers during the pre-crisis period were less likely to file any patents during the EAWA period relative to before (see coefficient estimates highlighted in grey).

To interpret the economic magnitude of our estimates, we note that a one-standard-deviation increase in *Treated* (0.318, see Table 2) corresponds to a drop in the likelihood of filling patents of about 5.5 percentage points (=0.318 × 0.1849), which is 14.5% of a standard deviation of the patenting dummy (27.6%, see Table 2). These estimated effects are similar when we use the discrete definition of our treatment. Specifically, banks hiring any STEM-skilled immigrants during the pre-crisis period experienced a drop of the likelihood of patenting in the months in which they were subject to the EAWA ban by about 10 percentage points. The number is about 36% of a standard deviation of the patenting likelihood in our sample.

Our specification also allows us to assess the dynamics of patenting across banks in the period after the EAWA ban was lifted, which is captured by the estimates attached to the variable $Post \times Treated$. We find that the likelihood of filing patents in that period is not systematically different relative to before EAWA, which is consistent with institutions starting to file patents again over time and reverting towards their pre-ban patterns of patenting once they were again free to hire foreign STEM workers.

5.1 Why Are New (Foreign) Hires So Relevant?

As we discussed in the institutional setting, the EAWA imposed restrictions only on the sponsoring of *new* H1B visas, whereas the renewal of foreign workers on H1B visas who were already employed at the institution before the EAWA was effective was not affected. But then, a natural question arises: can the lack of new hires be so important for patenting activities? After all, new hires might just be marginal additions to existing innovating teams in each institution.

Contrary to this possibility, we find that the lack of new hires drives almost completely the differential patterns of patenting during the EAWA period we have detected. We reach this conclusion by estimating our baseline difference-in-differences specification but replacing the outcome variable with *First Filer*$_{i,s}$, which is a dummy that equals 1 if, among the patents bank i field in month s, there is at least one in which one of the inventors on the patent files for the first time, i.e., recently-hired inventors.

Panel A of Table 5 reports the results. For brevity, we only show the estimated coefficient of interest $\hat{\beta}$ but the specifications are the same as above.[15] We can see that, irrespective of whether we define our treatment variable in the continuous format (columns (1)-(2)) or the discrete format (columns (3)-(4)), banks that relied more on foreign STEM workers before the crisis were substantially less likely to file patents that included new inventors relative to other banks, who were mostly recruiting domestic inventors and could keep recruiting domestic inventors through the EAWA period. Importantly, the estimated magnitudes of the effects are quite close to those we discussed above for the likelihood of filing any patents, which suggests that indeed most of the patents TARP banks reliant on foreign STEM workers did not file during the EAWA were patents that would have included new hires in the inventors' team.

One of the mechanisms through which new hires might be so important in overall patenting activities is the "pre-invention assignment agreement," which assigns to employers ownership rights over inventions created by their employers. Because of this rule, financial institutions, like any other firms, have an incentive to scout new inventors that have already produced innovation before being recruited and help them patent such innovation using the expertise of existing teams and patent lawyers that are already working with the bank. Foreign STEM workers might lack the financial and legal resources to file patents in the US and for this reason might accept to be hired and patent their existing innovation through banks.[16]

Unfortunately, we are not aware of data that are detailed enough to observe whether hired inventors access the company with pre-existing innovations that they can patent with

[15] In Table A.3, we report a full set of coefficients and t-statistics that we obtained from regression analysis.

[16] New hires are obviously likely to still retain some of the proceeds of their innovations through salary and benefits negotiations at the time they are hired.

the company. Absent these ideal data, we lever our patent information to construct a proxy for this situation. Specifically, we approximate these cases with patent applications filed by financial institutions in which not only an inventor who filed for the first time is part of the team, but he/she is in fact the lead inventor based on being listed as the first name in the inventors' team. The rationale is that lead inventors are likely to be major drivers of the innovation covered by the patent, and when lead inventors are recently hired employees, the likelihood that the invention already existed before being hired is higher. For this analysis, we do not consider patents that list inventors alphabetically, in which the order of names gives no indication about the importance of the specific inventor in developing the patent.

Panel B of Table 5 estimates the effect of EAWA on patenting conducted by new inventors who are also listed as the first inventor in patents where inventor names are non-alphabetically placed. Consistent with our conjecture, we find that a substantial share of the patent TARP banks that relied more on foreign STEM workers did not file during the EAWA period were patents in which new employees would have been part of the team as lead inventors.

5.2 Which Areas of Patenting Were Most Affected?

We also examine which areas of patenting were most affected by the EAWA ban on foreign hiring.

First, we compare the time series of patenting in the area of *business methods* (USPTO classification 705) relative to other areas. Business method patents are a class of process-innovation patents claiming new methods of doing business, which includes new types of e-commerce, banking, tax compliance procedures etc. Business methods do not necessarily require research and development investments to be produced, but often derive from intuitions of non-inventor employees that propose new ideas on how to better perform the processes of the bank. For this reason, both STEM and non-STEM workers might engage with innovative activities related to business-methods patents. Patents outside the business methods area, instead, which refer to the design and implementation of new technologies, new payment systems, etc., are likely to be mainly conducted by STEM workers.

Second, we propose a method to identify FinTech patents within our sample. Inspired by Chen et al. (2019), we search for FinTech patents based on the following seven classes: cybersecurity, mobile transaction, data analytics, blockchain, peer-to-peer lending, robo-advising, and internet of things. Our classification is based on a keyword list. We search for keywords in the title, abstract, and claim of 8,295 patents. For example, we take "authentication" as a keyword defining "cybersecurity". If we find the word of authentication in a patent's title, abstract, or claim, we classify that patent as being related to cybersecurity. According to this classification rule, a patent can be classified as both FinTech and business method. To avoid overlapping samples, we treat all business-method patents as non-FinTech patents, irrespective of the keywords in their title, abstract, and claims.

In Table A.4 of the Online Appendix, we present the full list of keywords we used to identify FinTech patents. We end up with 1,555 FinTech patents filed during the period of 2007-2014. Figure A.2 of the Online Appendix lists the top 20 banks that have filed the most FinTech patents in our sample, which are led by Bank of America, United Services Automobile Association (USAA), JPMorgan Chase, and American Express.

The estimates of the effect of EAWA on the likelihood that banks file business-methods patents (columns (1) and (4)), non-business-methods patents (columns (2) and (5)), and FinTech patents (columns (3) and (6)) are in Table 6. For the extensive margin of patent filings, we fail to detect systematic patterns in terms of different types of patents driving our results. In fact, for each group of patents we estimate negative coefficients of interest, indicating that all patenting areas might have been affected by the EAWA ban at the extensive margin, but for most estimated coefficients are not statistically significant.

6 Intensive Margin of Patenting: Patent Citations

We move on to consider the intensive margin of patenting activity with a proxy for patent quality—patent citations. For this analysis we cannot use the bank-month level sample that also includes months in which banks filed no patents, which would be vacuously associated with zero citations. Instead, we restrict the sample to bank-month observations associated with at least one patent application that was eventually granted. We use the following regression specification to estimate the impact of EAWA on patent quality:

$$\begin{aligned}\overline{PR\ Adj.\ Cites}_{i,s} = \alpha + \beta_1 \times EAWA_{i,s} + \beta_2 \times EAWA_{i,s} \times Treated_i + \beta_3 \times Post_{i,s} \\ +\beta_4 \times Post_{i,s} \times Treated_i + X' \times \beta_5 + \eta_i + \eta_t + \epsilon_{i,s},\end{aligned} \tag{6.1}$$

where $\overline{PR\ Adj.\ Cites}_{i,s}$ is the average *Adj. Cites* of granted patents filed by bank i in month s. $\overline{PR\ Adj.\ Cites}$ takes the form of percentile rank of the average *Adj. Cites*.

Following Bernstein et al. (2019), we calculate *Adj. Cites* as the number of citations normalized by the average number of citations in a given technology-class-year (the year in which all patent applications of the same technology were filed). We observe patent citations up to January 2022. To repeat the analysis across patenting areas for the intensive margin of patenting, we also separately calculate $\overline{PR\ Adj.\ Cites}_{i,s}$ for business-method, non-business-method, and FinTech patents filed by bank i in month s. Table A.5 in the Online Appendix presents the descriptive statistics of our measures of patent citations as well as of the observables we have used in the analysis so far but aggregated at the new level of observation.

We report the results for estimating equation 6.1 in Table 7. For brevity, we only report the estimates of the double-differences coefficient of interest across four panels for the full sample as well as for each of the business areas.[17] In the full sample of patents, we do not seem to observe a substantial drop in quality for patents filed during the EAWA period

[17] In Table A.6, we report all coefficients obtained from regression analysis.

(Panel A).

This non-result, however, masks substantial heterogeneity. In particular, Panel C and Panel D show that the average cites of non-business-method patents and FinTech-related patents—that is, the categories in which the contribution of actual inventors and hence STEM workers is important—are substantially lower over time for banks subject to EAWA that relied on foreign STEM workers before the crisis relative to other banks.

Table A.7 in the Online Appendix provides an alternative estimation. The left-hand-side variable is redefined as an indicator for $\overline{\text{Adj. Cites}} \geq 1$—it equals 1 if the mean of normalized citations for patents filed by bank i as of month s is above 1, and zero otherwise. In other words, the new dependent variable captures a scenario in which averaged patent quality associated with a sample unit outperforms the average. We find results that are qualitatively and quantitatively similar to those in Table 7.

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

Our final set of analyses aims to shed light on the labor-market consequences of the EAWA ban on new foreign hires. This margin is important to assess because if our results were indeed related to the dynamics of the labor market for foreign STEM workers, we should be able to detect effects of the EAWA restriction on the relative price of foreign labor during and after the restriction, i.e. on the wage premium financial institutions paid to foreign STEM workers.

In particular, because of the ban on hiring new foreign STEM workers, and because foreign workers in the US cannot carry their H1B visa from one company to the other, the only way in which TARP banks who relied on foreign STEM workers could employ them was to retain existing foreign workers hired before the financial crisis. The increased bargaining power of such workers should have resulted in higher wage premia paid to them.

Note that even after the EAWA ban was lifted we could expect to see a higher wage premium for foreign (new and existing) STEM workers, because all financial institutions competed to hire more foreign STEM workers than usual and foreign STEM workers are a scarce resource.

Based on these considerations, we analyze the wage premia foreign STEM workers could extract during and after the EAWA period. We perform this analysis at the level of H1B visa petition, which contains information about wage premia (the difference between the wage offered to the visa holder and the prevailing wage for the same occupation in the US at the time of the visa application), job location and classification, contract duration, and the number of workers sponsored in each petition. On the sample from January 2007 through December 2014, we have collected a total of 50,545 H1B petitions filed by sample firms with USCIS. The prevailing wage rate is petition-specific and is conceptually defined as the average wage paid to similarly employed workers in the requested occupation in the area of intended employment.[18]

We estimate the following specification:

$$\begin{aligned} \mathit{Wage\ Premium}_{j,i,k,l,d} = \alpha &+ \beta_1 \times \mathit{EAWA}_{i,d} + \beta_2 \times \mathit{EAWA}_{i,d} \times \mathit{Treated}_i + \beta_3 \times \mathit{Post}_{i,d} \\ &+ \beta_4 \times \mathit{Post}_{i,d} \times \mathit{Treated}_i + X' \times \beta_5 + \eta_k + \eta_l + \eta_i + \eta_t + \epsilon_{j,i,d}, \end{aligned} \tag{7.1}$$

where $\mathit{Wage\ Premium}_{j,i,k,l,d}$ is the wage proposed by the bank i normalized by the prevailing wage for job k in city l reported in the bank's the H1B visa petition submitted on day d. X' includes the logarithm of contract duration and the logarithm of number of proposed workers in each petition. The other variables are defined as above.

Table 8 presents the estimates. In columns (1)-(2) we detect a pattern consistent with the arguments discussed above in the multivariate difference-in-differences specification. STEM-

[18]This wage rate is usually obtained by contacting the State Workforce Agency (SWA) having jurisdiction over the geographic are of intended employment or from other legitimate sources of information.

dependent banks did pay higher wage premia to existing foreign STEM workers during the EAWA period and wage premium were still higher in the period after the EAWA ban was lifted relative to before the financial crisis.

In columns (3)-(4) of Table 8 we repeat the analysis for non-STEM workers. We find a substantially smaller and statistically insignificant difference in wage premia during and after the EAWA period, which is consistent with financial institutions finding the hiring of STEM foreign workers more valuable than the hiring of non-STEM foreign workers. This result is not surprising because high-skilled immigration, as discussed in the opening of the paper, often provides high-skilled talent that cannot be found domestically, whereas qualified less skilled employees are easier to find domestically.

Finally, in Figure 4 we assess the dynamics of the estimated coefficients over time when splitting the post-EAWA period into several periods. Consistent with the results in Table 8, we find that the wage premium to STEM foreign workers increased during the EAWA period and stayed higher relative to the pre-crisis period thereafter. No differential premium is detected for non-STEM foreign workers either during or after the EAWA period.

7.1 An Anatomy of STEM Jobs' Skill and Knowledge Sets

Our results in terms of patenting activities and labor-market implications suggest that STEM immigrants might be a more important driver of the innovation produced by financial institutions than non-STEM immigrants. To check this possibility more directly, we compare skill and knowledge profiles of STEM jobs with those of non-STEM jobs, both of which in the US are sponsored under the H1B visa program that was subject to the EAWA restrictions.

To this aim we resort to the O*NET Program, the primary source of occupational information in the US. For each occupation under the Standard Occupational Classification (SOC) System, the O*NET rating indicates the degree to which a specific skill component is peculiar to the occupation. Skill components include basic skills (e.g., reading, facilitate the acquisition of new knowledge) and cross-functional skills (e.g., problem solving, extend across several domains of activities), which are assessed in the areas of business and management, manufacturing and production, engineering and technology, mathematics and science, health services, and others.[19]

Based on these occupation-level ratings, we measure skill and knowledge differences between STEM and non-STEM occupations. Specifically, we use numerical ratings to quantify the level of a descriptor (a skill or knowledge component) h to N STEM occupations relative to the of level of the same descriptor to M non-STEM occupations.

To have a comparison within bank, we require that both types of occupations are sponsored by bank i during the period of 2004-2006 and compute the following:

$$Difference_{h,i} = \frac{\frac{\sum_{k=1}^{N}\sum_{1}^{n} Rating_{h,k}}{\sum_{N}\sum_{n} 1}}{\frac{\sum_{k=1}^{M}\sum_{m} Rating_{h,k}}{\sum_{M}\sum_{m} 1}} - 1, \tag{7.2}$$

where $Rating_{h,k}$ is the rating on the level of a descriptor h to occupation k. For each STEM occupation, bank i sponsors n individual visas; for each non-STEM occupation, bank i sponsors m individual visas. Based on equation 7.2, we average $Difference_{h,i}$ across J banks to calculate the level of descriptor h to STEM occupations relative to non-STEM occupations as follows:

$$Difference_{h} = \frac{\sum_{J} Difference_{h,i}}{J}, \tag{7.3}$$

where J is the number of banks sponsoring H1B jobs in our sample. Our null hypothesis is that ratings on the skill component h are equal across different occupations and that $Difference_{h}$ in equation (7.2) is zero.

Panel A of Figure 5 plots $Difference_{h}$ calculated using skill ratings against 20 skill elements. "Science," "repairing," "installation," "equipment maintenance," and "program-

[19]To match with the timing of STEM-dependence that we measure, we download O*NET version 11.0 as of December, 2006 from .

ming" are among the most advantageous skill sets owned by an average STEM occupation.

Panel B of Figure 5 plots t-statistics for the mean calculated according to equation 7.3, and the results suggest that most skill differences between STEM and non-STEM occupations are statistically different from zero.

Panel C of Figure 5 plots $Difference_h$ calculated using knowledge ratings against 20 elements. "Science," "repairing," "installation," "equipment maintenance," and "programming" are among the most advantageous skill sets owned by an average STEM occupation.

Panel D of Figure 5 plots $Difference_h$ constructed by using knowledge ratings against 33 elements. STEM occupations outperform non-STEM occupations by more than 200% in the several knowledge areas, including"biology," "physics," "chemistry," "fine arts," and "design" but the differences are barely statistically significant.

Overall, our evidence seems to suggest that indeed STEM and non-STEM workers provide substantially different sets of skills to the financial institutions that hire them and hence workers cannot be easily substituted for the scope of innovation production across the two categories.

8 Conclusions

Since the 2008 financial crisis, billions of dollars in venture capital are raised around the globe to "disintermediate" the financial services industry. One important question is to what extent banks, which, contrary to FinTech companies, bear most of the burden of regulatory compliance, are able to adopt up-to-date financial technologies to improve the security of customers' data and compete with FinTech companies.

In this paper, we show that nationalistic labor policies—restrictions in the ability of domestic companies to hire specialized foreign workers—can be a detrimental force in traditional financial institutions' possibility to compete with FinTech companies. Specifically, we show that financial firms that rely substantially on foreign workers reduce and worsen their innovation activity following a ban on the hiring of new foreign workers, which was an ancillary provision required to access TARP funds during the 2008-2009 Financial Crisis.

Our paper suggests a set of paths for future research. First, what are the competitive forces that shape the ability of financial companies to hire foreign STEM workers vis-à-vis other non-financial industrial companies and competing technological companies? Moreover, what are the implications of worse patenting activities by financial companies that cannot hire specialized foreign STEM workers in terms of investment and profitability in the long-run? And, ultimately, what are the welfare effects of the lower and worse innovation activities by financial companies? The increasing global threat of cyberattacks against financial corporations emphasizes the national-security scope of these innovation activities: Losing the edge on such cutting-edge technology might have negative implications above and beyond the short- and medium-run economic effects on firms 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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Figure 1: **Aggregated Patents and Top 20 Innovative Banks**

This figure presents the aggregated number of patents filed by our sample banks over time (Panel A), the top 20 banks that filed the most patents from January 2007 through December 2014 (Panel B), the number of inventors over time (Panel C), and the top 20 banks that hired the most inventors from January 2007 through December 2014 (Panel D).

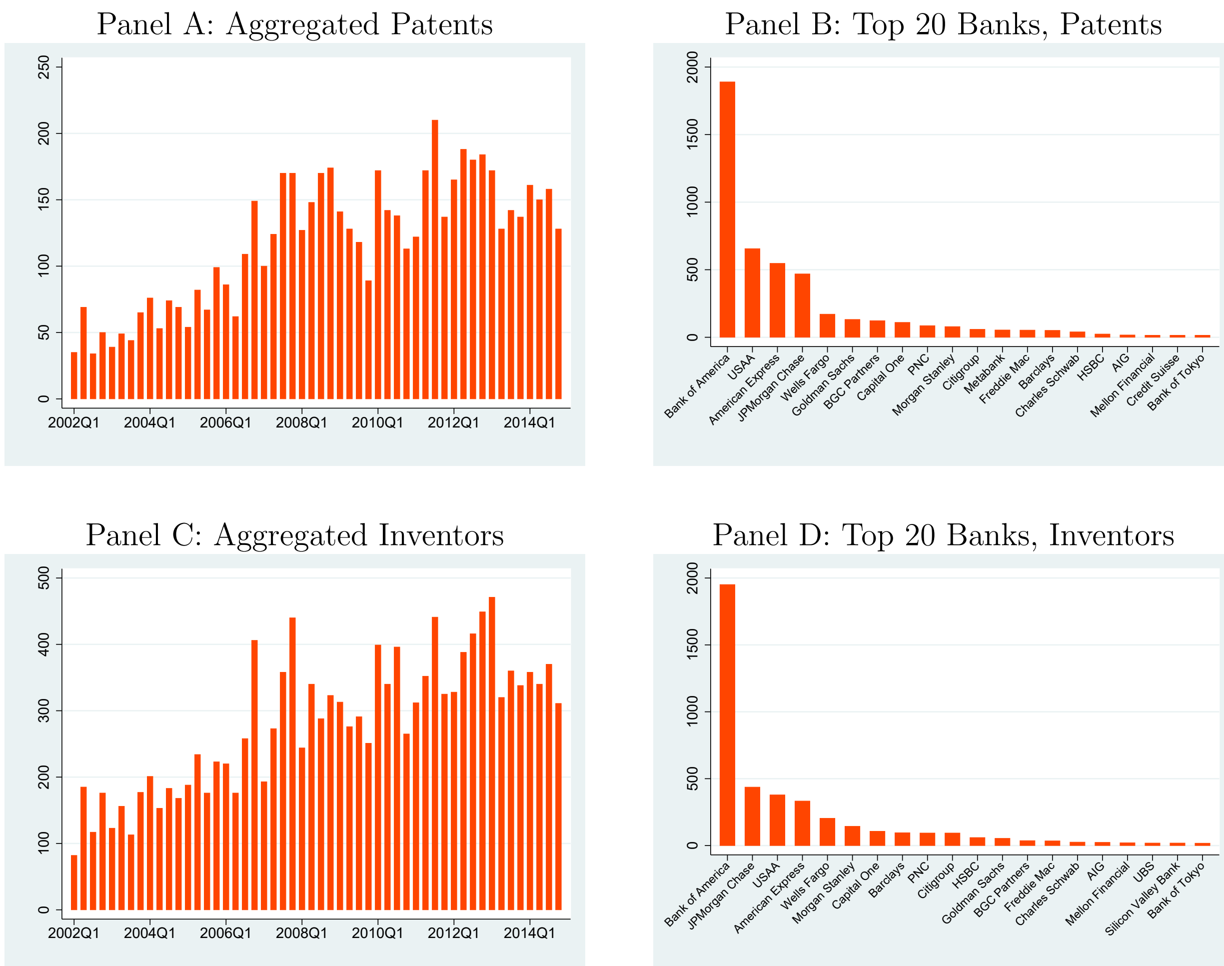

Figure 2: **Aggregated STEM/Non-STEM Workers and Top 20 Financial Institutions Ranked by Hired H1-B Employees**

This figure presents the aggregated number of STEM workers hired by our sample banks through the H1B visa program over time (Panel A), the top 20 banks that hired the most STEM workers from January 2004 through December 2006 (Panel B), the aggregated number of non-STEM workers hired by our sample bans through the H1B visa program over time (Panel C), and the top 20 banks that hired the most non-STEM workers from January 2004 through December 2006 (Panel D).

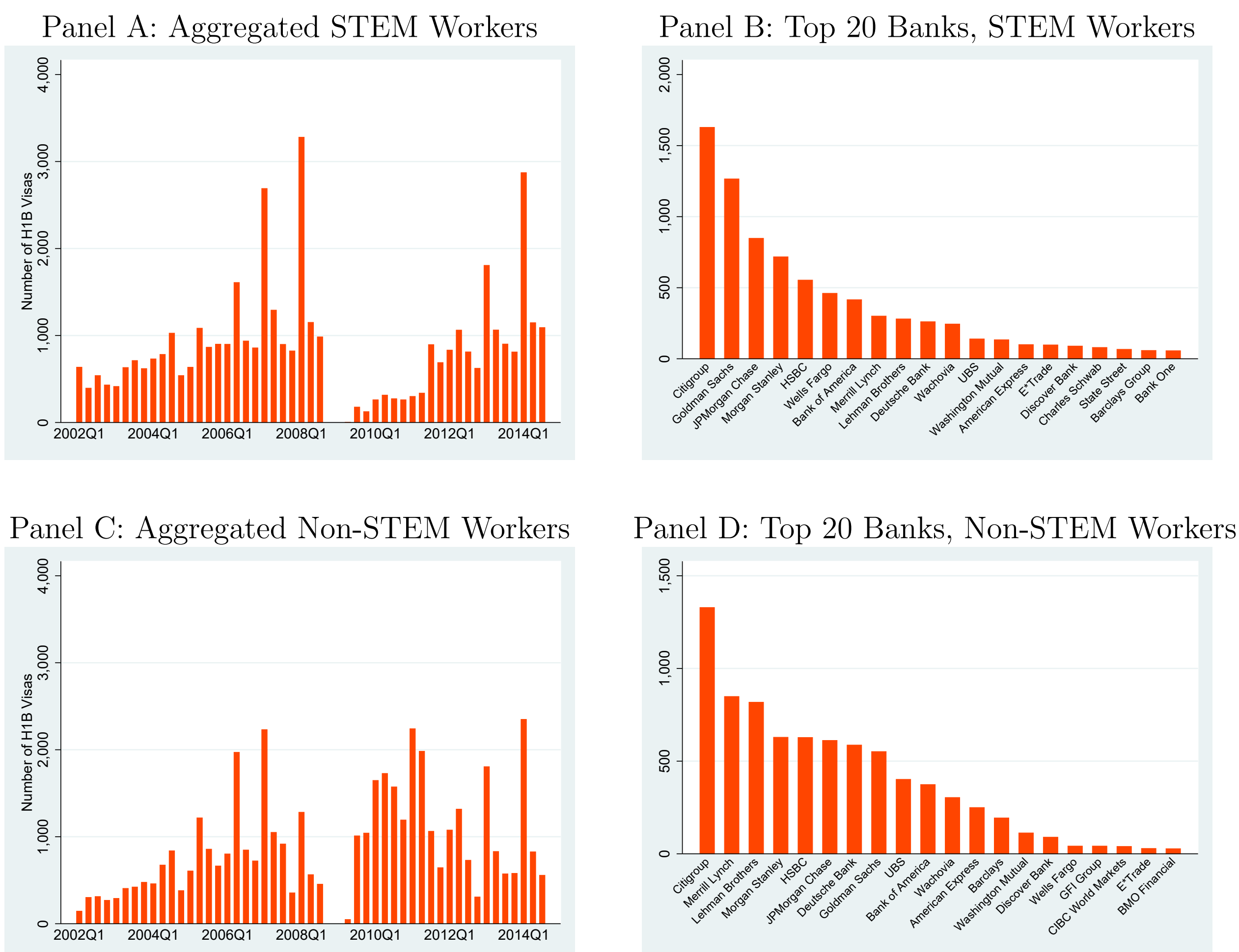

Figure 3: **Parallel Trends Assumption: H1B-sponsored STEM Employment**

This figure plots the estimated coefficients $\hat{\beta}_t$ and the 95% confidence intervals from the following linear equation:

$$Ln(\#STEM + 1)_{i,s} = \alpha + \sum_{t=-5}^{5} \beta_t \times Period_{i,t} \times Treated_i + \sum_{t=-5}^{5} \gamma_t \times Period_{i,t} + X_i' \times \theta + \eta_i + \eta_s + \epsilon_{i,s}.$$

The dependent variable is the logarithm of number of H1B-sponsored STEM workers hired by bank i as of month t (#STEM) plus 1. $Period_t$ is a dummy variable that equals 1 if bank i is in its t^{th} period (180 days) relative to the event period in which it is subject to the Employ American Workers Act (EAWA). The excluded period is t=-1. Treated is $STEM\%_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. X' includes $H1B_{i,-3} > 0$ and $STEM_{i,-3} > 0$. $H1B_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored worker over the last three years, and zero otherwise. $STEM_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored, STEM worker over the last three years, and zero otherwise. Standard errors are clustered at the level of the bank (i).

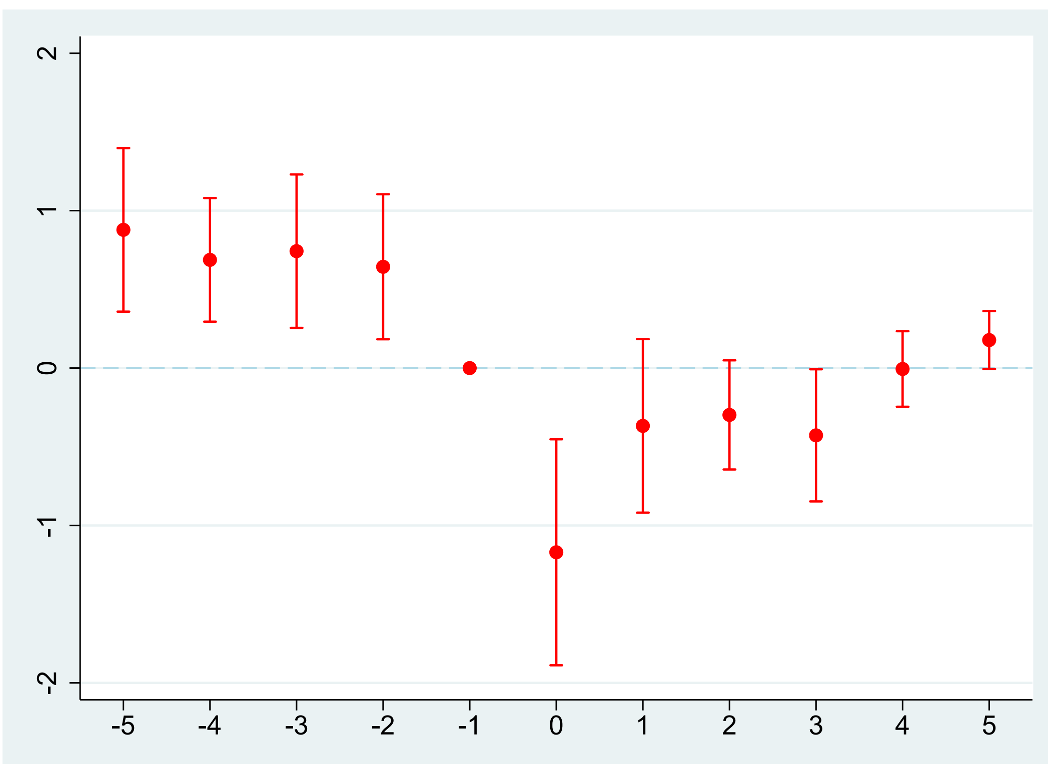

Figure 4: **Wage Premium of H1-B Employees**

This table reports estimates from the following linear specification:

$$Wage\ Premium_{j,i,k,l,s} = \alpha + \sum_{t=-8}^{10} \beta_t \times Period_{i,t} \times Treated_i + \sum_{t=-8}^{10} \gamma_t \times Period_{i,t} +$$
$$X' \times \gamma + \eta_j + \eta_i + \eta_k + \eta_l + \eta_s + \epsilon_{j,i,k,l,s}$$

where Wage Premium$_{j,i,k,l,s}$ is the wage offered to foreign hires divided by the prevailing wage for visa j filed by bank i in city k for job l as of calender year s. Period$_{i,t}$ is a dummy variable that equals 1 if bank i is in its t^{th} period (180 days) relative to the event period in which it is subject to the Employ American Workers Act (EAWA). The excluded period is t=-1. Treated is STEM%$_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 - 2006. X' includes the logarithm of employment duration (in months) and the logarithm of number of proposed employees in each visa. The sample period is from January 2007 through December 2014. The sample unit is at the visa level. Standard errors are clustered at the level of the bank (i).

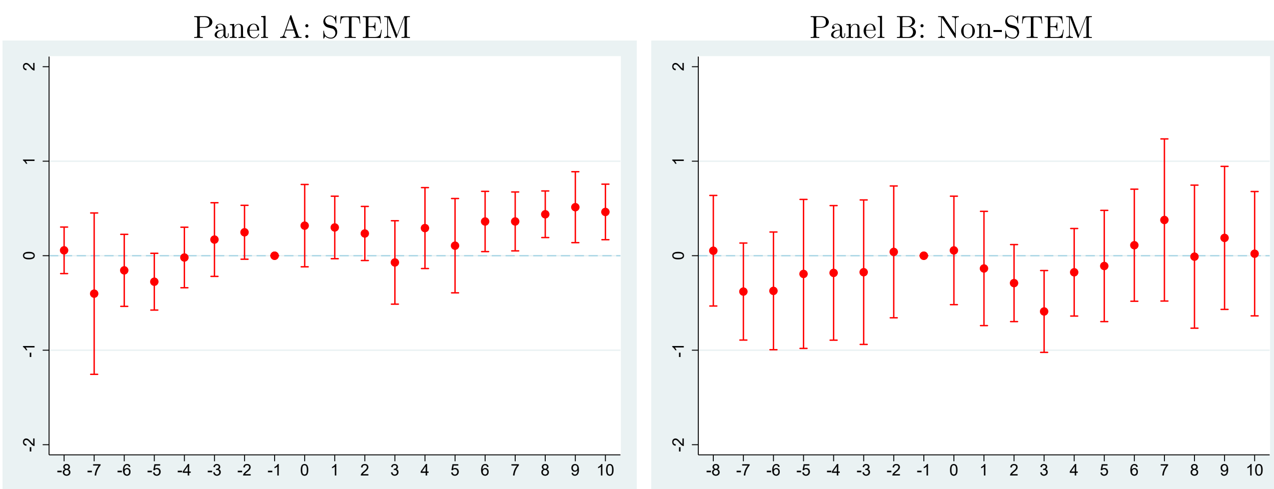

Figure 5: **STEM Skills**

*This figure plots the difference of O*NET ratings for the level of each skill or knowledge element of STEM occupations relative to non-STEM occupations sponsored by our sample banks via the H1B program over the period of 2004 – 2006. For each skill, or knowledge, element h corresponding to bank i sponsoring N STEM occupations and M non-STEM occupations, the "Difference" score is calculated as follows:*

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

*where $Rating_{h,k}$ is the mean of ratings across all individuals rated by O*NET for element h of occupation k. For each STEM or non-STEM occupation, bank i sponsors n and m individual visas, respectively. The mean of difference for an 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 banks is provided in the figure.

Table 1: **Bank Patents**

Panel A of this table reports the top 20 classifications for patents filed by our sample banks to the United States Patent and Trademark Office (USPTO). These patents were eventually granted. Panel B of this table reports the top 20 patents by citations that were filed by our sample banks in 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:	231
709	multi-computer data transferring	
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 the bank-month sample in our main analysis. The sample unit is at the level of bank i as of month s. Patent is a dummy variable that equals 1 if bank i files at least one patent in month s that is granted in the future, and zero otherwise. Ln(#STEM+1) the logarithm of the number of H1B-sponsored STEM workers (#STEM) plus one. STEM is a dummy variable that equals 1 if bank i in month s hires at least 1 H1B-sponsored STEM worker, and zero otherwise. Biz-Meth is a dummy variable that equals 1 if bank i files at least one business-methods patent (USPTO classification 705) in month s that is granted in the future, and zero otherwise. Non-Biz-Meth is a dummy variable that equals 1 if bank i files at least one non-business-method patent in month s that is granted in the future, and zero otherwise. FinTech is a dummy variable that equals 1 if bank i files at least one FinTech patent in month s that is granted in the future, and zero otherwise. First Filer is a dummy variable that equals 1 if at least one inventor files at least one patent for bank i for the first time in month s, and zero otherwise. First Filer & Inventor is a dummy variable that equals 1 if at least one first filer is listed as the first inventor in patents where inventor names are non-alphabetically ordered, and zero otherwise. $STEM\%_{0406}$ *is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 - 2006.* $STEM\%_{0406} > 0$ *is a dummy variable that equals 1 if bank i hires at least one H1B-sponsored STEM worker over the period of 2004 – 2006, and zero otherwise. EAWA is a dummy variable that equals 1 if an employer is subject to the Employ American Workers Act (EAWA), and zero otherwise. Post is a dummy variable that equals 1 for all months after the EAWA became ineffective, and zero otherwise.* $H1B_{i,-3} > 0$ *is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored worker over the last three years, and zero otherwise.* $STEM_{i,-3} > 0$ *is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored, STEM worker over the last three years, and zero otherwise. The sample period for patent related variables is from January 2007 through December 2014.*

	N	Mean	Std	Min	P10	P25	P50	P75	P90	Max
Ln(#STEM)	11,808	0.229	0.753	0.000	0.000	0.000	0.000	0.000	0.693	5.974
STEM	11,808	0.111	0.314	0.000	0.000	0.000	0.000	0.000	1.000	1.000
Patent	11,808	0.083	0.276	0.000	0.000	0.000	0.000	0.000	0.000	1.000
Biz-Meth	11,808	0.056	0.230	0.000	0.000	0.000	0.000	0.000	0.000	1.000
Non-Biz-Meth	11,808	0.057	0.231	0.000	0.000	0.000	0.000	0.000	0.000	1.000
FinTech	11,808	0.040	0.196	0.000	0.000	0.000	0.000	0.000	0.000	1.000
First Filer	11,808	0.054	0.226	0.000	0.000	0.000	0.000	0.000	0.000	1.000
First Filer & Inventor	11,808	0.029	0.169	0.000	0.000	0.000	0.000	0.000	0.000	1.000
$STEM\%_{0406}$	11,808	0.208	0.318	0.000	0.000	0.000	0.000	0.344	0.750	1.000
$STEM\%_{0406} > 0$	11,808	0.382	0.486	0.000	0.000	0.000	0.000	1.000	1.000	1.000
EAWA	11,808	0.039	0.193	0.000	0.000	0.000	0.000	0.000	0.000	1.000
Post	11,808	0.139	0.346	0.000	0.000	0.000	0.000	0.000	1.000	1.000
$H1B_{-3} > 0$	11,808	0.289	0.453	0.000	0.000	0.000	0.000	1.000	1.000	1.000
$STEM_{-3} > 0$	11,808	0.132	0.339	0.000	0.000	0.000	0.000	0.000	1.000	1.000

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

This table reports estimates from the following linear specification:

$$Ln(\#STEM + 1)_{i,s} = \alpha + \beta_1 \times EAWA_{i,s} + \beta_2 \times EAWA_{i,s} \times Treated_i + \beta_3 \times Post_{i,s} + \beta_4 \times Post_{i,s} \times Treated_i + X_i' \times \theta + \eta_i + \eta_t + \epsilon_{i,s}.$$

The dependent variable is the logarithm of the number of H1B-sponsored STEM workers (#STEM) plus one. In columns (1)-(4), Treated is $STEM_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. In columns (5)-(8), Treated is a dummy variable that equals 1 if the number of STEM jobs hired by bank i over the period of 2004 – 2006 is greater than zero, and zero otherwise. $EAWA_{i,s}$ is a dummy variable that equals 1 if firm i is subject to the Employ American Workers Act (EAWA) in month s, and zero otherwise. $Post_{i,s}$ is a dummy variable that equals 1 if, in month s, EAWA does not apply to firm i that previously complied with EAWA, and zero otherwise. $H1B_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored worker over the last three years, and zero otherwise. $STEM_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored, STEM worker over the last three years, and zero otherwise. The sample period is from January 2007 through December 2014. Standard errors are clustered at the level of bank (i).

	Continuous Treatment				Discrete Treatment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA	0.0400	0.0773	0.1109	0.1001	0.1238***	0.1381***	0.1771***	0.1660***
	(0.55)	(0.92)	(1.28)	(1.13)	(4.57)	(3.57)	(4.15)	(3.91)
EAWA × Treated	-1.3450***	-1.5180***	-1.5731***	-1.5739***	-0.8137***	-0.8612***	-0.8987***	-0.8981***
	(-3.34)	(-3.57)	(-3.68)	(-3.67)	(-3.67)	(-3.75)	(-3.86)	(-3.82)
Post		0.0586	0.0895	0.0783		0.0229	0.0868**	0.0758**
		(0.90)	(1.32)	(1.14)		(0.59)	(2.32)	(2.03)
Post × Treated		-0.2579	-0.4143**	-0.4123**		-0.0719	-0.2067	-0.2061
		(-1.29)	(-2.03)	(-2.01)		(-0.49)	(-1.41)	(-1.39)
$H1B_{-3} > 0$			0.2580***	0.2578***			0.2522***	0.2520***
			(3.72)	(3.70)			(3.66)	(3.64)
$STEM_{-3} > 0$			-0.2069**	-0.2078**			-0.2032**	-0.2041**
			(-2.17)	(-2.16)			(-2.12)	(-2.11)
Constant	0.2417***	0.2454***	0.2002***	0.2023***	0.2417***	0.2452***	0.2012***	0.2033***
	(55.85)	(15.73)	(7.49)	(7.46)	(54.18)	(15.48)	(7.45)	(7.42)
N	11,808	11,808	11,808	11,808	11,808	11,808	11,808	11,808
adj. R^2	0.66	0.66	0.67	0.68	0.67	0.67	0.67	0.68
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Year-Month FE	No	No	No	Yes	No	No	No	Yes

t-statistics in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

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

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

$$\textit{Patent Filed}_{i,s} = \alpha + \beta_1 \times EAWA_{i,s} + \beta_2 \times EAWA_{i,s} \times Treated_i + \beta_3 \times Post_{i,s} + \beta_4 \times Post_{i,s} \times Treated_i + X_i' \times \theta + \eta_i + \eta_t + \epsilon_{i,s}.$$

The dependent variable ($Patent_{i,s}$) is a dummy variable that equals 1 if firm i files at least one patent in month s that is granted in the future, and zero otherwise. In columns (1)-(4), Treated is $STEM\%_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. In columns (5)-(8), Treated is a dummy variable that equals 1 if the number of STEM jobs hired by bank i over the period of 2004 – 2006 is greater than zero, and zero otherwise. $EAWA_{i,s}$ is a dummy variable that equals 1 if firm i is subject to the Employ American Workers Act (EAWA) in month s, and zero otherwise. $Post_{i,s}$ is a dummy variable that equals 1 if, in month s, EAWA does not apply to firm i that previously complied with EAWA, and zero otherwise. $H1B_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored worker over the last three years, and zero otherwise. $STEM_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored, STEM worker over the last three years, and zero otherwise. The sample period is from January 2007 through December 2014. Standard errors are clustered at the bank level (i).

	Continuous Treatment				Discrete Treatment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA	0.0178	0.0192	0.0182	0.0157	0.0220	0.0274	0.0251	0.0225
	(0.93)	(1.06)	(1.01)	(0.87)	(1.03)	(1.43)	(1.31)	(1.19)
EAWA × Treated	-0.1700***	-0.1877***	-0.1849***	-0.1877***	-0.0914**	-0.1069***	-0.1035***	-0.1045***
	(-2.83)	(-3.13)	(-3.05)	(-3.07)	(-2.43)	(-3.19)	(-3.05)	(-3.06)
Post		0.0024	0.0004	-0.0010		0.0085	0.0024	0.0011
		(0.20)	(0.03)	(-0.08)		(0.95)	(0.28)	(0.12)
Post × Treated		-0.0262	-0.0067	-0.0062		-0.0235	-0.0066	-0.0064
		(-0.49)	(-0.13)	(-0.12)		(-0.88)	(-0.27)	(-0.26)
$H1B_{-3} > 0$			-0.0103	-0.0105			-0.0112	-0.0113
			(-1.20)	(-1.21)			(-1.38)	(-1.39)
$STEM_{-3} > 0$			0.0257*	0.0258*			0.0260*	0.0261*
			(1.70)	(1.70)			(1.74)	(1.74)
Constant	0.0842***	0.0851***	0.0841***	0.0844***	0.0842***	0.0851***	0.0843***	0.0847***
	(116.16)	(33.57)	(26.41)	(26.74)	(113.11)	(33.67)	(25.84)	(26.12)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Year-Month FE	No	No	No	Yes	No	No	No	Yes
N	11,808	11,808	11,808	11,808	11,808	11,808	11,808	11,808
adj. R^2	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57

Table 5: **Employ American Workers Act (EAWA) and First Patent Filers**

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

$$\begin{aligned} \textit{First Filer}_{i,s} = \alpha + \beta_1 \times \textit{EAWA}_{i,s} + \beta_2 \times \textit{EAWA}_{i,s} \times \textit{Treated}_i + \beta_3 \times \textit{Post}_{i,s} \\ + \beta_4 \times \textit{Post}_{i,s} \times \textit{Treated}_i + X_i' \times \theta + \eta_i + \eta_t + \epsilon_{i,s}. \end{aligned}$$

In Panel A, the dependent variable (First Filer$_{i,s}$) is a dummy variable that equals 1 if at least one inventor files patents for bank i for the first time in month s, and zero otherwise. In Panel B, the dependent variable (First Filer& Inventor$_{i,s}$) is a dummy variable that equals 1 if at least one first filer (defined in Panel A) is listed as the first inventor in patents where inventor names are non-alphabetically ordered, and zero otherwise. In columns (1)-(2), Treated is $STEM_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. In columns (3)-(4), Treated is a dummy variable that equals 1 if the number of STEM jobs hired by bank i over the period of 2004 – 2006 is greater than zero, and zero otherwise. $EAWA_{i,s}$ is a dummy variable that equals 1 if bank i is subject to the Employ American Workers Act (EAWA) in month s, and zero otherwise. $Post_{i,s}$ is a dummy variable that equals 1 if, in month s, EAWA does not apply to firm i which previously complied with EAWA, and zero otherwise. $H1B_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored worker over the last three years, and zero otherwise. $STEM_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored, STEM worker over the last three years, and zero otherwise. The sample period is from January 2007 through December 2014. Standard errors are clustered at the bank level (i).

	Continuous Treatment		Discrete Treatment	
	Panel A. First Filer			
	(1)	(2)	(3)	(4)
EAWA × Treated	-0.1565***	-0.1583***	-0.0976***	-0.0985***
	(-3.14)	(-3.18)	(-3.51)	(-3.51)
N	11,808	11,808	11,808	11,808
adj. R^2	0.48	0.48	0.48	0.48
	Panel B. First Filer & First-Ranked Inventor			
	(1)	(2)	(3)	(4)
EAWA × Treated	-0.1275*	-0.1294*	-0.0668**	-0.0678**
	(-1.86)	(-1.89)	(-2.36)	(-2.39)
N	11,808	11,808	11,808	11,808
adj. R^2	0.40	0.40	0.40	0.40
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Year-Month FE	No	Yes	No	Yes

t-statistics in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 6: **Employ American Workers Act (EAWA) and Patenting Activities: Breakdown of Categories**

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

$$\textit{Biz-Meth}_{i,s},\ \textit{Non-Biz-Meth}_{i,s},\ \textit{or}\ \textit{FinTech}_{i,s}, = \alpha + \beta_1 \times EAWA_{i,s} + \beta_2 \times EAWA_{i,s} \times Treated_i + \beta_3 \times Post_{i,s} + \beta_4 \times Post_{i,s} \times Treated_i + X_i' \times \theta + \eta_i + \eta_t + \epsilon_{i,s}.$$

The dependent variable is a dummy variable that equals 1 if firm i files at least business-method patent, non-business-method patent, or FinTech patent in month s that is granted in the future, and zero otherwise. In columns (1)-(4), Treated is $STEM_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 - 2006. In columns (5)-(8), Treated is a dummy variable that equals 1 if the number of STEM jobs hired by bank i over the period of 2004 - 2006 is greater than zero, and zero otherwise. $EAWA_{i,s}$ is a dummy variable that equals 1 if firm i is subject to the Employ American Workers Act (EAWA) in month s, and zero otherwise. $Post_{i,s}$ is a dummy variable that equals 1 if, in month s, EAWA does not apply to firm i that previously complied with EAWA, and zero otherwise. $H1B_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored worker over the last three years, and zero otherwise. $STEM_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored, STEM worker over the last three years, and zero otherwise. The sample period is from January 2007 through December 2014. Standard errors are clustered at the bank level (i).

	Continuous Treatment			Discrete Treatment		
	Biz-Meth	Non-Biz-Meth	FinTech	Biz-Meth	Non-Biz-Meth	FinTech
	(1)	(2)	(3)	(4)	(5)	(6)
EAWA	-0.0108	0.0401*	0.0108	-0.0228*	0.0538**	0.0166
	(-0.46)	(1.73)	(1.06)	(-1.67)	(2.11)	(1.58)
EAWA × Treated	-0.1645	-0.1151	-0.0562	-0.0609	-0.0802**	-0.0368
	(-1.28)	(-1.52)	(-1.19)	(-1.54)	(-2.19)	(-1.64)
Post	-0.0141	0.0142	0.0037	-0.0181	0.0188*	0.0072
	(-0.69)	(1.04)	(0.41)	(-1.27)	(1.78)	(1.21)
Post × Treated	-0.1173	0.0818*	0.0984**	-0.0539	0.0348	0.0452**
	(-1.29)	(1.94)	(2.05)	(-1.46)	(1.54)	(2.05)
$H1B_{-3} > 0$	-0.0317***	0.0148	0.0156*	-0.0316***	0.0135	0.0145*
	(-3.07)	(1.53)	(1.96)	(-3.05)	(1.51)	(1.91)
$STEM_{-3} > 0$	0.0628***	-0.0249*	-0.0199*	0.0615***	-0.0235*	-0.0188
	(3.05)	(-1.96)	(-1.69)	(3.03)	(-1.88)	(-1.58)
Constant	0.0703***	0.0579***	0.0336***	0.0705***	0.0581***	0.0338***
	(15.48)	(18.62)	(12.03)	(15.10)	(18.69)	(12.29)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11,808	11,808	11,808	11,808	11,808	11,808
adj. R^2	0.46	0.59	0.50	0.46	0.59	0.50

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

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

$$\overline{PR\ Adj.\ Cites}_{i,s} = \alpha + \beta_1 \times EAWA_{i,s} + \beta_2 \times EAWA_{i,s} \times Treated_i + \beta_3 \times Post_{i,s} + \beta_4 \times Post_{i,s} \times Treated_i + X' \times \beta_5 + \eta_i + \eta_t + \epsilon_{i,s},$$

For each patent category, $\overline{PR\ Adj.\ Cites}$ is the averaged Adj. Cites of (granted) patents filed by bank i in month s. Adj. Cites 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). PR Adj. Cites is the percentile rank of Adj. Cites in our sample. The end of observation period for patent citation is January, 2022. In columns (1)-(2), Treated is $STEM\%_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. In columns (3)-(4), Treated is a dummy variable that equals 1 if the number of STEM jobs hired by bank i over the period of 2004 – 2006 is greater than zero, and zero otherwise. $EAWA_{i,s}$ is a dummy variable that equals 1 if bank i is subject to the Employ American Workers Act (EAWA) in month s, and zero otherwise. $Post_{i,s}$ is a dummy variable that equals 1 if, in month s, EAWA does not apply to bank i which previously complied with EAWA, and zero otherwise. The sample period is from January 2007 through December 2014. Standard errors are clustered at the bank level (i).

	Panel A. All Patents			
	(1)	(2)	(3)	(4)
EAWA × Treated	-0.0907	-0.1179	0.0409	-0.0041
	(-0.82)	(-0.97)	(0.76)	(-0.05)
N	981	981	981	981
adj. R^2	0.21	0.22	0.20	0.21
	Panel B. Business Method			
	(1)	(2)	(3)	(4)
EAWA × Treated	0.3019*	0.2873	0.1797***	0.1784**
	(1.85)	(1.60)	(3.08)	(2.24)
N	662	662	662	662
adj. R^2	0.30	0.31	0.30	0.31
	Panel C. Non-Business Method			
	(1)	(2)	(3)	(4)
EAWA × Treated	-0.3940***	-0.4223***	-0.1814**	-0.1824**
	(-3.42)	(-3.56)	(-2.55)	(-2.68)
N	670	670	670	670
adj. R^2	0.20	0.20	0.19	0.20
	Panel D. FinTech			
	(1)	(2)	(3)	(4)
EAWA × Treated	-0.7965***	-0.8085***	-0.5332***	-0.6773***
	(-4.70)	(-5.87)	(-6.44)	(-4.95)
N	475	475	475	475
adj. R^2	0.16	0.19	0.15	0.18
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Year-Month FE	No	Yes	No	Yes

Table 8: **Wage Premium of H1-B Employees**

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

$$\begin{aligned} \textit{Wage Premium}_{j,i,k,l,d} = \alpha + \beta_1 \times \textit{EAWA}_{i,d} + \beta_2 \times \textit{EAWA}_{i,d} \times \textit{Treated}_i + \beta_3 \times \textit{Post}_{i,d} + \\ \beta_4 \times \textit{Post}_{i,d} \times \textit{Treated}_i + \beta_5 \times X' + \eta_k + \eta_l + \eta_i + \eta_t + \epsilon_{j,i,k,l,d}, \end{aligned}$$

where Wage Premium$_{j,i,k,l,d}$ is the wage proposed by the firm i over prevailing wage of the same job k in city l as of day d. Treated is STEM%$_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. EAWA$_{i,d}$ is a dummy variable that equals 1 if firm i is subject to the Employ American Workers Act (EAWA) in day d, and zero otherwise. Post$_{i,d}$ is a dummy variable that equals 1 if, in day d, EAWA does not apply to firm i which previously complied with EAWA, and zero otherwise. X' includes the logarithm of employment duration (in months) and the logarithm of number of proposed employees in each visa. The sample period is from January 2007 through December 2014. Standard errors are clustered at the level of bank (i).

	STEM		Non-STEM	
	(1)	(2)	(3)	(4)
EAWA	-0.0946	-0.0840	-0.0915	-0.0807
	(-1.53)	(-1.31)	(-1.33)	(-1.05)
EAWA × Treated	0.3094**	0.2909**	0.2290	0.2034
	(2.51)	(2.22)	(1.45)	(1.09)
Post	-0.0728	-0.0758	-0.0000	-0.0041
	(-1.51)	(-1.56)	(-0.00)	(-0.07)
Post × Treated	0.2809***	0.2924***	0.0460	0.0585
	(3.35)	(3.15)	(0.35)	(0.48)
Ln(Duration)	-0.0290**	-0.0287**	-0.0196	-0.0197
	(-2.15)	(-2.13)	(-1.41)	(-1.42)
Ln(# Immigrants)	0.0083	0.0125	0.0136	0.0164
	(0.51)	(0.78)	(1.17)	(1.41)
Constant	1.4430***	1.4406***	1.3988***	1.3995***
	(15.36)	(15.38)	(15.26)	(15.30)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes
Year-Month FE	No	Yes	No	No
City FE	Yes	Yes	Yes	Yes
Job FE	Yes	Yes	Yes	Yes
N	26,583	26,583	26,439	26,439
adj.R^2	0.20	0.20	0.12	0.13

Online Appendix: Nationalistic Labor Policies Hinder Innovation

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Not for Publication

A.1 Examples of Patent Abstracts

Patent Application Number: 11617847

A system, computer product and method for profiling consumers to recommend a financial transaction instrument having benefits tailored to psychographic characteristics of the consumer. A set of questions is presented to a consumer, in order to determine the psychographic characteristics of the consumer. At least one subset of questions is presented, based on answers to the set of questions, the at least one subset of questions relating more specifically to available benefits. A tailored financial transaction instrument is recommended, having benefits which are based on answers to the at least one subset of questions.

Patent Application Number: 16119428

Systems and methods for mobile wallet payments are disclosed. In one embodiment, in an information processing apparatus comprising at least one computer processor, a method for conducting a payment using an electronic wallet may include: (1) a mobile application receiving a selection of an alternate payment currency; the mobile application receiving a payment payload from an issuer; the mobile application providing the selection of the alternate payment currency and an identifier to the issuer; and the mobile application providing the payment payload and the identifier to a merchant host. The merchant host may communicate the identifier to the issuer, and the issuer may identify selection of the alternate payment currency based on the identifier.

Patent Application Number: 10710611

Methods and apparatus for a smartcard system are provided which securely and conveniently provides for secure transaction completion in a contact or contactless environment. The invention utilizes selection of processing applications based on the account issuer parameters and risk factors (stored on a smartcard) and merchant system parameters and risk factors (stored on a merchant system database). The invention permits a merchant system and smartcard to exchange information useful for determining if particular transactions should be completed online or offline.

Patent Application Number: 11619110

An account reconciliation system having a particular usefulness in the reconciliation of centrally billed accounts and more specifically, in the reconciliation of centrally billed accounts in the travel industry is provided. The system and methods of the present invention expand on the traditional match/non-match techniques and provide complete transaction management for every item on a client's account. In another sense, reconciliation is redefined to include each and every transaction on an account regardless of it's reconciliation status, i.e., matched, unresolved, pending, etc. Consequently, the present invention reconcile the client's account to the account balance.

Patent Application Number: 10588811

Processes (200, 400) for reducing fraud risk in credit transactions, particularly those involving airline ticket purchases, includes collecting the following additional transaction variables and their use in real-time authorization decisions: credit card holder name, reservation code, passenger name, origin city, destination city, travel date, routing description, class of service, e-ticket indicator, number of passengers traveling and carrier code. The additional transaction variables received during a transaction involving the purchase of airline tickets are passed, in addition to the transaction variables traditionally included in a real-time authorizations request, to a fraud risk evaluation model maintained by a financial institution (106) or other entity responsible for authorizing a payment for the transaction. The fraud-risk models use historical behavior and optimal risk decision-making factors to authorize or reject the transaction in real time, without slowing standard authorization processing times.

Patent Application Number: 10710317

The present invention discloses a system and methods for biometric security using signature recognition biometrics in a smartcard-reader system. The biometric security system also includes a signature scan sensor that detects biometric samples and a device for verifying biometric samples. In one embodiment, the biometric security system includes a smartcard configured with a signature scan sensor. In another embodiment, the system includes a reader configured with a signature scan sensor. In yet another embodiment, the present invention discloses methods for proffering and processing signature samples to facilitate authorization of transactions.

Patent Application Number: 11461356

A computer-implemented method and system to facilitate a purchase. A request for payment for a charge by a provider to a customer having a plurality of accounts is received at a host computer. At least one of the accounts qualifies for pre-tax treatment and at least one account does not qualify for pre-tax treatment. A hold is placed on funds in one or more of the plurality of accounts sufficient to cover the charge. The host determines whether the charge qualifies for pre-tax treatment. If the charge qualifies for pre-tax treatment, then at least the account qualifying for pre-tax treatment is debited for some or all of the charge.

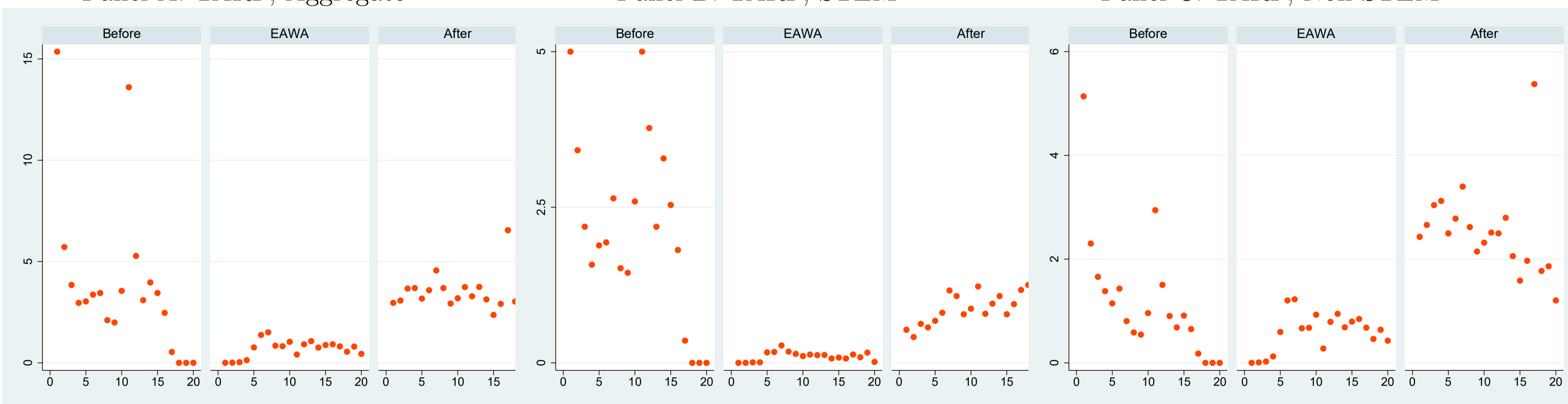
Patent Application Number: 13280938

A coordination server of a contactless payment system may receive a total bill of purchases for a customer from a merchant POS terminal, associate the total bill of purchases with a unique identifier of an RFID tag of a check presenter, and receive notification that payment of the total bill of purchases is authorized. The coordination server may receive the unique identifier and payment information from a contactless-enabled device, and transmit the payment information and the total bill to the merchant POS terminal for transmittal to a merchant acquirer for completion of the transaction under business as usual standards. In one embodiment, the coordination server transmits the payment information and the total bill to a merchant acquirer, which then routes the payment request to an appropriate payment network. In another embodiment, the coordination server transmits the payment information and the total bill directly to the appropriate payment network.

Figure A.1: **H1B Employment around EAWA: Financial Institutions**

This figure plots binscatter plots mapping event days relative to the beginning and end of the Employ American Workers Act (EAWA) into the average number of H1B-sponsored employees hired by firms conditioning on TARP status and proposed job categories. "Before," "EAWA," and "After" are 730-event-day periods before, during, and after institutions' compliance to EAWA, respectively. Each period is divided into 20 equal-sized bins. We first calculate the average number of hired workers across institutions within an event day and then aggregate numbers across event days within each bin. For TARP participants, an EAWA period is institution-specific (see Table A.1 for detailed descriptions). For non-TARP participants, an EAWA period is from February 17, 2009 through February 17, 2011.

Panel A: TARP, Aggregate | Panel B: TARP, STEM | Panel C: TARP, Non-STEM



Panel D: Non-TARP, Aggregate | Panel E: Non-TARP, STEM | Panel F: Non-TARP, Non-STEM

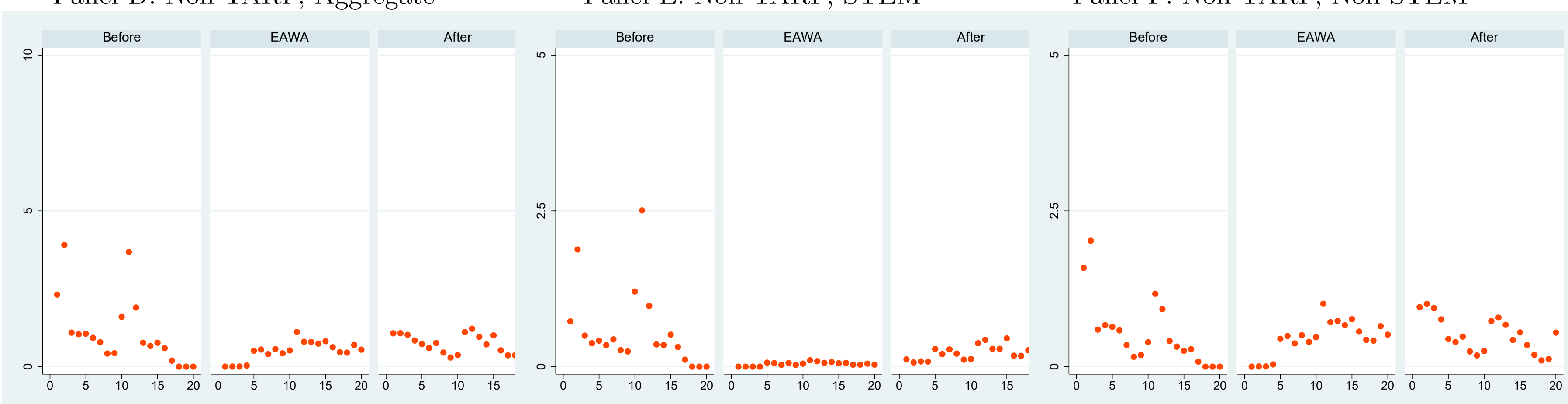


Figure A.2: **Top 20 Financial Institutions Ranked by FinTech Patents**

This figure presents the name of banks (and their corresponding numbers) that filed the most number of patents from January 2007 through June 2015.

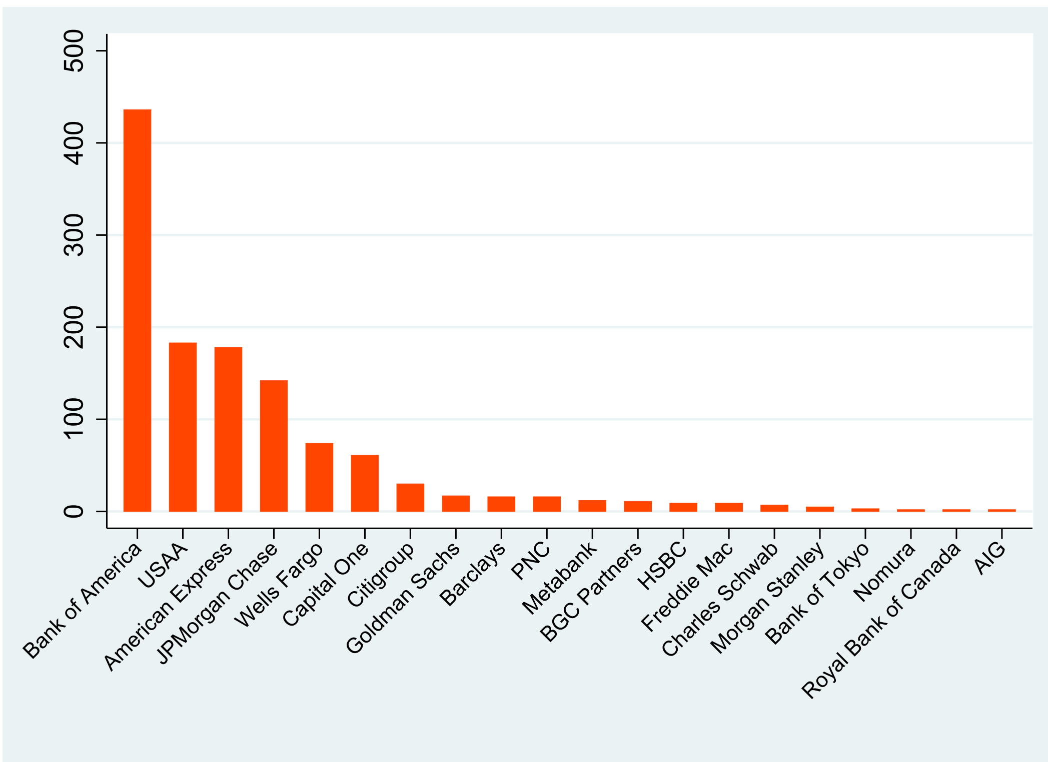


Table A.1: **Event Dates**

This table presents events dates for TARP paricipants. "TARP begin" refers to the date in which a financial institution agrees to receive funds from the Treasury. "TARP end" refers to the date in which a financial institution fully pays off the funds. "EAWA begin" refers to the latter date between "TARP begin" and February, 17, 2009. "EAWA end" refers to the earlier date between "TARP end" and February, 17, 2011. Length is the number of days for which a participant has been subject to EAWA.

	TARP begin	TARP end	EAWA begin	EAWA end	Length
American Express	Jan 9, 2009	July 29, 2009	Feb 17, 2009	Jul 29, 2009	162
Bank One	Oct 28, 2008	Dec 16, 2009	Feb 17, 2009	Dec 16, 2009	302
Bank of America	Oct 28, 2008	Mar 9, 2010	Feb 17, 2009	Mar 9, 2010	385
Bank of New York Mellon	Oct 28, 2008	Aug 5, 2009	Feb 17, 2009	Aug 5, 2009	169
Branch Banking & Trust Co	Nov 14, 2008	Jul 22, 2009	Feb 17, 2009	Jul 22, 2009	155
C1 Bank	Dec 12, 2008	Nov 24, 2009	Feb 17, 2009	Nov 24, 2009	280
Capital One, FSB	Nov 14, 2008	Dec 9, 2009	Feb 17, 2009	Dec 9, 2009	295
Chase Manhattan Bank	Oct 28, 2008	Dec 16, 2009	Feb 17, 2009	Dec 16, 2009	302
Citigroup Inc	Oct 28, 2008	Jan 31, 2011	Feb 17, 2009	Jan 31, 2011	713
Citizens Bank	Oct 28, 2008	Jan 31, 2011	Feb 17, 2009	Feb 17, 2011	730
Discover Financial Services	Mar 13, 2009	Jul 7, 2010	Mar 13, 2009	Jul 7, 2010	481
Fifth Third Bank	Dec 31, 2008	Mar 16, 2011	Feb 17, 2009	Feb 17, 2011	730
First American Corp	Jul 24, 2009	Dec 11, 2012	Jul 24, 2009	Feb 17, 2011	573
First American Financial Corp	Jul 24, 2009	Dec 11, 2012	Jul 24, 2009	Dec 9, 2009	138
GE Capital	Nov 12, 2008	Jul 22, 2009	Feb 17, 2009	Jul 22, 2009	155
Goldman Sachs	Oct 28, 2008	Jul 22, 2009	Feb 17, 2009	Jul 22, 2009	155
Horizon Bank	Dec 19, 2008	Nov 23, 2011	Feb 17, 2009	Feb 17, 2011	730
Huntington Bancshares	Nov 14, 2008	Jan 19, 2011	Feb 17, 2009	Jan 19, 2011	701
Independence Bank NA	Jan 9, 2009	Oct 16, 2013	Feb 17, 2009	Feb 17, 2011	730
JPMorgan Chase	Oct 28, 2008	Dec 16, 2009	Feb 17, 2009	Dec 16, 2009	302
KeyCorp	Nov 14, 2008	Apr, 20 2011	Feb 17, 2009	Feb 17, 2011	730
Merrill Lynch	Oct 28, 2008	Mar 9, 2010	Feb 17, 2009	Mar 9, 2010	385
Morgan Stanley	Oct 28, 2008	Aug 12, 2009	Feb 17, 2009	Aug 12, 2009	176
PNC Financial Services Group	Dec 31, 2008	May 5, 2010	Feb 17, 2009	May 5, 2010	442
Silicon Valley Bank	Dec 12, 2008	Jun 16, 2010	Feb 17, 2009	Jun 16, 2010	484
TCF Financial Corp	Nov 14, 2008	Dec 21, 2009	Feb 17, 2009	Dec 21, 2009	307
US Bancorp	Nov 14, 2008	Jul 15, 2009	Feb 17, 2009	Jul 15, 2009	148
Wells Fargo & Co	Oct 28, 2008	May 26, 2010	Feb 17, 2009	May 26, 2010	463
Zions Bancorporation	Nov 14, 2008	Dec 5, 2012	Feb 17, 2009	Feb 17, 2011	730
American International Group	Sep 16, 2008	Dec 11, 2012	Feb 17, 2009	Feb 17, 2011	730
Ford Motor	Dec, 2008	After Feb 17, 2011	Jun 23, 2009	Feb 17, 2011	730
Chrysler	Dec, 2008	May 24, 2011	Feb 17, 2009	Feb 17, 2011	730
General Motors	Dec, 2008	Dec 9, 2013	Feb 17, 2009	Feb 17, 2011	730
GMAC (Ally)	Dec, 2008	Dec 18, 2014	Feb 17, 2009	Feb 17, 2011	730

Table A.2: **Employ American Workers Act (EAWA) and Hiring of Foreign STEM Workers**

This table reports estimates from the following linear specification:

$$STEM_{i,s} = \alpha + \beta_1 \times EAWA_{i,s} + \beta_2 \times EAWA_{i,s} \times Treated_i + \beta_3 \times Post_{i,s} + \beta_4 \times Post_{i,s} \times Treated_i + X_i' \times \theta + \eta_i + \eta_t + \epsilon_{i,s}.$$

the dependent variable is a dummy equal to 1 if firm i in month s hires at least 1 H1B-sponsored STEM worker, and zero otherwise. In columns (1)-(4), Treated is $STEM_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. In columns (5)-(8), Treated is a dummy variable that equals 1 if the number of STEM jobs hired by bank i over the period of 2004 – 2006 is greater than zero, and zero otherwise. $EAWA_{i,s}$ is a dummy variable that equals 1 if firm i is subject to the Employ American Workers Act (EAWA) in month s, and zero otherwise. $Post_{i,s}$ is a dummy variable that equals 1 if, in month s, EAWA does not apply to firm i that previously complied with EAWA, and zero otherwise. $H1B_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored worker over the last three years, and zero otherwise. $STEM_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored, STEM worker over the last three years, and zero otherwise. The sample period is from January 2007 through December 2014. Standard errors are clustered at the level of bank (i).

	Continuous Treatment				Discrete Treatment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EAWA	0.0260	0.0393	0.0600*	0.0548*	0.0516***	0.0620***	0.0818***	0.0764***
	(0.88)	(1.31)	(1.88)	(1.66)	(4.24)	(3.05)	(3.75)	(3.34)
EAWA × Treated	-0.3419***	-0.3790***	-0.4078***	-0.4022***	-0.2145***	-0.2282***	-0.2408***	-0.2376***
	(-3.21)	(-3.25)	(-3.53)	(-3.47)	(-3.38)	(-3.78)	(-3.90)	(-3.84)
Post		0.0205	0.0345	0.0299		0.0160	0.0360*	0.0314
		(0.63)	(1.05)	(0.89)		(0.83)	(1.88)	(1.62)
Post × Treated		-0.0557	-0.0788	-0.0786		-0.0209	-0.0424	-0.0424
		(-0.48)	(-0.77)	(-0.77)		(-0.28)	(-0.62)	(-0.62)
$H1B_{-3} > 0$			0.1483***	0.1483***			0.1467***	0.1466***
			(4.46)	(4.44)			(4.47)	(4.45)
$STEM_{-3} > 0$			-0.0311	-0.0317			-0.0299	-0.0306
			(-0.88)	(-0.89)			(-0.86)	(-0.88)
Constant	0.1134***	0.1129***	0.0728***	0.0737***	0.1134***	0.1129***	0.0731***	0.0740***
	(83.96)	(15.26)	(5.97)	(6.00)	(82.05)	(15.27)	(5.94)	(5.97)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Year-Month FE	No	No	No	Yes	No	No	No	Yes
N	11,808	11,808	11,808	11,808	11,808	11,808	11,808	11,808
adj. R^2	0.57	0.57	0.59	0.60	0.58	0.58	0.59	0.60

t-statistics in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

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

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

$$\begin{aligned} \textit{First Filer}_{i,s} = \alpha + \beta_1 \times \textit{EAWA}_{i,s} + \beta_2 \times \textit{EAWA}_{i,s} \times \textit{Treated}_i + \beta_3 \times \textit{Post}_{i,s} \\ + \beta_4 \times \textit{Post}_{i,s} \times \textit{Treated}_i + X_i' \times \theta + \eta_i + \eta_t + \epsilon_{i,s}. \end{aligned}$$

In Panel A, the dependent variable (First Filer$_{i,s}$) is a dummy variable that equals 1 if at least one inventor files patents for bank i for the first time in month s, and zero otherwise. In Panel B, the dependent variable (First Filer& Inventor$_{i,s}$) is a dummy variable that equals 1 if at least one first filer (defined in Panel A) is listed as the first inventor in patents where inventor names are non-alphabetically ordered, and zero otherwise. In columns (1)-(2), Treated is STEM$_{0406}$, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. In columns (3)-(4), Treated is a dummy variable that equals 1 if the number of STEM jobs hired by bank i over the period of 2004 – 2006 is greater than zero, and zero otherwise. $EAWA_{i,s}$ is a dummy variable that equals 1 if bank i is subject to the Employ American Workers Act (EAWA) in month s, and zero otherwise. Post$_{i,s}$ is a dummy variable that equals 1 if, in month s, EAWA does not apply to firm i which previously complied with EAWA, and zero otherwise. $H1B_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored worker over the last three years, and zero otherwise. $STEM_{i,-3} > 0$ is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored, STEM worker over the last three years, and zero otherwise. The sample period is from January 2007 through December 2014. Standard errors are clustered at the bank level (i).

	Continuous Treatment		Discrete Treatment	
	Panel A. First Filer			
	(1)	(2)	(3)	(4)
EAWA	0.0096	0.0091	0.0205	0.0200
	(0.58)	(0.57)	(1.43)	(1.42)
EAWA × Treated	-0.1565***	-0.1583***	-0.0976***	-0.0985***
	(-3.14)	(-3.18)	(-3.51)	(-3.51)
Post	-0.0072	-0.0080	-0.0092	-0.0100
	(-0.36)	(-0.40)	(-0.48)	(-0.51)
Post × Treated	-0.0735	-0.0733	-0.0342	-0.0341
	(-1.02)	(-1.01)	(-0.99)	(-0.98)
$H1B_{-3} > 0$	0.0045	0.0045	0.0040	0.0039
	(0.58)	(0.58)	(0.55)	(0.55)
$STEM_{-3} > 0$	-0.0040	-0.0040	-0.0032	-0.0032
	(-0.32)	(-0.32)	(-0.27)	(-0.27)
Constant	0.0587***	0.0589***	0.0587***	0.0589***
	(16.17)	(16.08)	(16.03)	(15.94)
N	11,808	11,808	11,808	11,808
adj. R^2	0.48	0.48	0.48	0.48
	Panel B. First Filer & First-Ranked Inventor			
	(1)	(2)	(3)	(4)
EAWA	0.0032	0.0020	0.0047	0.0036
	(0.21)	(0.13)	(0.47)	(0.34)
EAWA × Treated	-0.1275*	-0.1294*	-0.0668**	-0.0678**
	(-1.86)	(-1.89)	(-2.36)	(-2.39)
Post	-0.0030	-0.0036	-0.0093	-0.0098
	(-0.22)	(-0.26)	(-0.72)	(-0.76)
Post × Treated	-0.0864*	-0.0862*	-0.0338	-0.0336
	(-1.71)	(-1.70)	(-1.46)	(-1.45)
$H1B_{-3} > 0$	0.0002	0.0001	-0.0003	-0.0004
	(0.03)	(0.02)	(-0.05)	(-0.06)
$STEM_{-3} > 0$	0.0109	0.0110	0.0119	0.0120
	(1.03)	(1.04)	(1.17)	(1.17)
Constant	0.0334***	0.0335***	0.0333***	0.0335***
	(12.44)	(12.50)	(11.87)	(11.92)
N	11,808	11,808	11,808	11,808
adj. R^2	0.40	0.40	0.40	0.40
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Year-Month FE	No	Yes	No	Yes

t-statistics in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.4: **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.5: **Sample Descriptive Statistics: Patent Citations**

This table presents descriptive statistics for averaged quality of (granted) patents filed by sample banks from January 2007 through December 2014. The sample unit is at the level of bank i as of month s in which at least one patent is filed. Adj. Cites 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). PR Adj. Cites is the percentile rank of Adj. Cites in our sample. $\overline{\text{PR Adj. Cites}}$ *is the averaged Adj. Cites of all (granted) patents filed by bank i in month s.* $\overline{\text{Adj. Cites}} > 1$ *is a dummy variable that equals 1 if adjusted citations, averaged across patents filed by bank i in month s, is above 1, and zero otherwise. The end of observation period for patent citation is January, 2022.* $STEM\%_{0406}$ *is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006.* $STEM\%_{0406} > 0$ *is a dummy variable that equals 1 if bank i hires at least one H1B-sponsored STEM worker over the period of 2004 – 2006, and zero otherwise. EAWA is a dummy variable that equals 1 if an employer is subject to the Employ American Workers Act (EAWA), and zero otherwise. Post is a dummy variable that equals 1 for all months after the EAWA became ineffective, and zero otherwise.* $H1B_{i,-3} > 0$ *is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored worker over the last three years, and zero otherwise.* $STEM_{i,-3} > 0$ *is a dummy variable that equals 1 if bank i hired at least one H1B-sponsored, STEM worker over the last three years, and zero otherwise.*

	N	Mean	Std	Min	P10	P25	P50	P75	P90	Max
$\overline{\text{PR Adj. Cites}}$	981	0.511	0.266	0.000	0.149	0.320	0.500	0.722	0.894	0.999
$\overline{\text{PR Adj. Cites}}$ (Biz-Meth)	662	0.478	0.261	0.000	0.141	0.271	0.458	0.690	0.855	0.995
$\overline{\text{PR Adj. Cites}}$ (Non-Biz-Meth)	670	0.527	0.280	0.000	0.142	0.328	0.513	0.745	0.937	0.998
$\overline{\text{PR Adj. Cites}}$ (FinTech)	475	0.534	0.274	0.000	0.153	0.348	0.525	0.770	0.909	0.999
$\overline{\text{Adj. Cites}} > 1$	981	0.350	0.477	0.000	0.000	0.000	0.000	1.000	1.000	1.000
$\overline{\text{Adj. Cites}} > 1$ (Biz-Meth)	662	0.337	0.473	0.000	0.000	0.000	0.000	1.000	1.000	1.000
$\overline{\text{Adj. Cites}} > 1$ (Non-Biz-Meth)	670	0.349	0.477	0.000	0.000	0.000	0.000	1.000	1.000	1.000
$\overline{\text{Adj. Cites}} > 1$ (FinTech)	475	0.404	0.491	0.000	0.000	0.000	0.000	1.000	1.000	1.000
$\text{STEM\%}_{0406}$	981	0.375	0.304	0.000	0.000	0.000	0.350	0.581	0.792	1.000
$\text{STEM\%}_{0406} > 0$	981	0.688	0.464	0.000	0.000	0.000	1.000	1.000	1.000	1.000
EAWA	981	0.0730	0.261	0.000	0.000	0.000	0.000	0.000	0.000	1.000
Post	981	0.410	0.492	0.000	0.000	0.000	0.000	1.000	1.000	1.000
$\text{H1B}_{-3} > 0$	981	0.708	0.455	0.000	0.000	0.000	1.000	1.000	1.000	1.000
$\text{STEM}_{-3} > 0$	981	0.365	0.482	0.000	0.000	0.000	0.000	1.000	1.000	1.000

Table A.6: **Employ American Workers Act (EAWA) and Patent Citations: Full Table**

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

$$\begin{aligned}\overline{PR\ Adj.\ Cites}_{i,s} &= \alpha + \beta_1 \times EAWA_{i,s} + \beta_2 \times EAWA_{i,s} \times Treated_i + \beta_3 \times Post_{i,s} \\ &+ \beta_4 \times Post_{i,s} \times Treated_i + X' \times \beta_5 + \eta_i + \eta_t + \epsilon_{i,s},\end{aligned}$$

For each patent category, $\overline{PR\ Adj.\ Cites}$ *is the averaged Adj. Cites of (granted) patents filed by bank i in month s. Adj. Cites 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). PR Adj. Cites is the percentile rank of Adj. Cites in our sample. The end of observation period for patent citation is January, 2022. In columns (1)-(2), Treated is* $STEM\%_{0406}$*, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. In columns (3)-(4), Treated is a dummy variable that equals 1 if the number of STEM jobs hired by bank i over the period of 2004 – 2006 is greater than zero, and zero otherwise.* $EAWA_{i,s}$ *is a dummy variable that equals 1 if bank i is subject to the Employ American Workers Act (EAWA) in month s, and zero otherwise.* $Post_{i,s}$ *is a dummy variable that equals 1 if, in month s, EAWA does not apply to bank i which previously complied with EAWA, and zero otherwise. The sample period is from January 2007 through December 2014. Standard errors are clustered at the bank level (i).*

	Panel A. All Patents			
	(1)	(2)	(3)	(4)
EAWA	0.0409	0.0594	-0.0355	0.0074
	(0.51)	(0.72)	(-0.56)	(0.09)
EAWA × Treated	-0.0907	-0.1179	0.0409	-0.0041
	(-0.82)	(-0.97)	(0.76)	(-0.05)
Post	-0.0205	-0.0127	-0.0072	0.0062
	(-0.55)	(-0.32)	(-0.15)	(0.13)
Post × Treated	0.1095*	0.1113*	0.0388	0.0348
	(1.99)	(1.92)	(0.78)	(0.64)
$H1B_{-3} > 0$	-0.0316	-0.0114	-0.0300	-0.0124
	(-0.49)	(-0.20)	(-0.43)	(-0.19)
$STEM_{-3} > 0$	0.0536	0.0658*	0.0362	0.0496
	(1.47)	(1.87)	(0.92)	(1.27)
Constant	0.5004***	0.4776***	0.5079***	0.4860***
	(10.11)	(10.26)	(9.77)	(10.03)
N	981	981	981	981
adj. R^2	0.21	0.22	0.20	0.21
	Panel B. Business Method			
	(1)	(2)	(3)	(4)
EAWA	-0.0535	-0.0731	-0.0685	-0.0935
	(-0.74)	(-0.86)	(-1.32)	(-1.24)
EAWA × Treated	0.3019*	0.2873	0.1797***	0.1784**
	(1.85)	(1.60)	(3.08)	(2.24)
Post	-0.0105	-0.0366	-0.0007	-0.0478
	(-0.15)	(-0.44)	(-0.01)	(-0.67)
Post × Treated	0.1582	0.2178	0.0731	0.1307
	(1.30)	(1.49)	(1.19)	(1.63)
$H1B_{-3} > 0$	-0.0576	-0.0947	-0.0400	-0.0891
	(-0.67)	(-1.18)	(-0.49)	(-1.16)
$STEM_{-3} > 0$	0.0229	0.0412	0.0218	0.0459
	(0.60)	(1.11)	(0.58)	(1.20)
Constant	0.4795***	0.4991***	0.4669***	0.4916***
	(7.20)	(7.99)	(7.09)	(8.20)
N	662	662	662	662
adj. R^2	0.30	0.31	0.30	0.31
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Year-Month FE	No	Yes	No	Yes

	Panel C. Non-Business Method			
	(1)	(2)	(3)	(4)
EAWA	0.0959	0.1158	0.0630	0.0698
	(1.21)	(1.43)	(1.12)	(1.12)
EAWA × Treated	-0.3940***	-0.4223***	-0.1814**	-0.1824**
	(-3.42)	(-3.56)	(-2.55)	(-2.68)
Post	-0.0116	-0.0275	0.0495	0.0416
	(-0.15)	(-0.38)	(1.52)	(0.83)
Post × Treated	-0.0235	-0.0033	-0.0874	-0.0874
	(-0.20)	(-0.03)	(-1.68)	(-1.18)
$H1B_{-3} > 0$	-0.1385	-0.0622	-0.1505	-0.0927
	(-0.69)	(-0.62)	(-0.69)	(-0.79)
$STEM_{-3} > 0$	0.1338***	0.1338**	0.1052**	0.0998*
	(2.91)	(2.71)	(2.24)	(1.94)
Constant	0.6029***	0.5495***	0.6245***	0.5873***
	(4.11)	(7.42)	(3.99)	(6.97)
N	670	670	670	670
adj. R^2	0.20	0.20	0.19	0.20
	Panel D. FinTech			
	(1)	(2)	(3)	(4)
EAWA	0.3357***	0.3155***	0.4191***	0.5265***
	(3.02)	(3.05)	(6.61)	(4.23)
EAWA × Treated	-0.7965***	-0.8085***	-0.5332***	-0.6773***
	(-4.70)	(-5.87)	(-6.44)	(-4.95)
Post	0.0920	0.0603	0.3565***	0.4169***
	(0.61)	(0.39)	(7.53)	(6.80)
Post × Treated	-0.1683	-0.1308	-0.3757***	-0.4534***
	(-0.64)	(-0.57)	(-4.05)	(-5.86)
$H1B_{-3} > 0$	-0.3228***	-0.2747	-0.3608***	-0.3586**
	(-3.51)	(-1.56)	(-2.80)	(-2.08)
$STEM_{-3} > 0$	0.2213**	0.2508**	0.1787**	0.2061**
	(2.54)	(2.45)	(2.24)	(2.28)
Constant	0.7116***	0.6742***	0.7590***	0.7575***
	(10.49)	(6.27)	(8.68)	(7.54)
N	475	475	475	475
adj. R^2	0.16	0.19	0.15	0.18
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Year-Month FE	No	Yes	No	Yes

Table A.7: **Employ American Workers Act (EAWA) and Patent Quality: Alternative Measure of Quality**

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

$$\overline{\textit{Adj. Cites}_{i,s}} > 1 = \alpha + \beta_1 \times EAWA_{i,s} + \beta_2 \times EAWA_{i,s} \times Treated_i + \beta_3 \times Post_{i,s} \\ + \beta_4 \times Post_{i,s} \times Treated_i + X' \times \beta_5 + \eta_i + \eta_t + \epsilon_{i,s},$$

For each patent category, $\overline{\textit{Adj. Cites}_{i,s}} > 1$ *is a dummy variable that equals 1 if adjusted citations, averaged across patents filed by bank i in month s, is above 1, and zero otherwise. Adj. Cites 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). The end of observation period for patent citation is January, 2022. In columns (1)-(2), Treated is* $STEM\%_{0406}$*, which is the number of H1B-sponsored STEM workers as a fraction of the total number of H1B-sponsored workers hired by bank i over the period of 2004 – 2006. In columns (3)-(4), Treated is a dummy variable that equals 1 if the number of STEM jobs hired by bank i over the period of 2004 – 2006 is greater than zero, and zero otherwise.* $EAWA_{i,s}$ *is a dummy variable that equals 1 if bank i is subject to the Employ American Workers Act (EAWA) in month s, and zero otherwise.* $Post_{i,s}$ *is a dummy variable that equals 1 if, in month s, EAWA does not apply to bank i which previously complied with EAWA, and zero otherwise. The sample period is from January 2007 through December 2014. Standard errors are clustered at the bank level (i).*

	(1)	(2)	(3)	(4)
Panel A. All Patents				
EAWA × Treated	-0.2174*	-0.2090	-0.0322	-0.0499
	(-1.73)	(-1.42)	(-0.44)	(-0.58)
N	981	981	981	981
adj. R^2	0.19	0.20	0.19	0.20
Panel B. Business Method				
EAWA × Treated	0.3781*	0.5430***	0.2175**	0.3491***
	(1.91)	(2.95)	(2.38)	(4.57)
N	662	662	662	662
adj. R^2	0.27	0.28	0.27	0.28
Panel C. Non-Business Method				
EAWA × Treated	-0.5595***	-0.5218***	-0.3145***	-0.3275***
	(-3.39)	(-3.17)	(-4.96)	(-3.88)
N	670	670	670	670
adj. R^2	0.13	0.12	0.12	0.11
Panel D. FinTech				
EAWA × Treated	-0.8235***	-0.7635***	-0.5334***	-0.7567***
	(-3.34)	(-3.38)	(-6.32)	(-3.45)
N	475	475	475	475
adj. R^2	0.09	0.12	0.08	0.11
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Year-Month FE	No	Yes	No	Yes