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ABSTRACT

This paper studies how demand for labor reacts to financial technology (fintech) shocks based on comprehensive databases of fintech patents and firm job postings in the U.S. during the past decade. We first develop a measure of fintech exposure at the occupation level by intersecting the textual information in job task descriptions and fintech patents. We then document a significant decline of job postings in the most exposed occupations, and an increase in industry as well as geographical concentration of these occupations. Firms resort to an upskilling strategy in face of the fintech disruption, requiring "combo" (finance and software) skills, higher education attainments, and longer work experiences in the hiring of fintech-exposed jobs. Financial firms and those with high innovation outputs are able to offset the disruptive effect from the fintech shock. Among innovating firms, however, only inventors (but not acquisition-driven innovators) experience growth in hiring, sales, investment, and enjoy better returns on assets.

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1. Introduction

Advances in financial technology (fintech) are reshaping the landscape of financial services in the United States and globally. The term "fintech" refers to technology and innovation that aim to compete with traditional methods and channels for the delivery of financial services. Telecommunications and information technology have been adopted by financial service providers to create new options and to ease access by consumers (households and businesses) to navigate the complexity and constraints they face. Although the term has gained its prominence in the recent decade as an external disruptor, we are reminded that the evolution of finance has always worked in tandem with the adoption of new technologies, from wire transfer as a long-distance payment technology in the late 1800s to credit cards and automated teller machines (ATMs) during the 1950s and 1960s. Post-financial crisis has marked a dramatic shift toward decentralization (e.g., blockchains and crypto-asset) and disintermediation (e.g., peer-to-peer lending platforms), imposing disruption on the established financial institutions (Brainard, 2016; Agarwal and Chua, 2020; Hikida et al., 2020).

Economists have also long debated the trade-off between the new opportunities for businesses and consumers from technological advancement and the labor force displacements caused by them. The common empirical challenge to quantify the effect of technologies on jobs and firm's outcomes is due to the general lack of ex ante measures for exposure to technology at the micro-level. Our study focuses on such relationship in the context of fintech innovations, and our first objective is to overcome the challenge by developing a novel measure of occupation exposure to fintech innovations. Such a measure is constructed by cross-analyzing and extracting the similarity in the textual information in job task descriptions and that in recent fintech patent filings.[1] The procedure results in time-varying fintech exposure scores for the universe of 772 occupations as classified by the six-digit O*NET Standard Occupation

[1] Specifically, our fintech exposure measure captures both the cosine similarity between the two text corpuses (i.e., job task descriptions and fintech patent filings) and the intensity of fintech innovations (e.g., the amount of fintech patent filings). Intuitively, it measures the amount of "shadow" that a cloud of fintech innovations casts on the job tasks of a given occupation.

Code (SOC), which can also be aggregated to the firm or industry level.[2] As an overview, we discover non-monotonic relations in that the occupations paying middle-ranged salaries and requiring intermediate education attainments are the most exposed to fintech innovations. Both ends of the spectrum, especially people with advanced degrees, tend to be the least affected. Fintech exposure, while mostly gender neutral, also affects the prime-aged (between 35 and 50) workers the most.

The second, and main objective of our study is to characterize and quantify how demand for talent shifts in response to fintech shocks. To this end, we link job postings by firms (and the states they reside in) from Burning Glass Technology (BGT) to individual occupations, and then to our measure of exposure to recent fintech innovations. The resulting panel consists of about 300,000 cohorts at occupation × state × year level, aggregated from the original 161.6 million BGT-listed vacancies during 2007, and 2010-2018. We find that the job posting of occupations in the top quartile of fintech exposure ("the most exposed" hereafter) experienced significant drops (as a share of all job postings in a given state and year) during the sample period. After controlling for state by year fixed effects and competing technology exposures (from AI and software), we find that the most exposed occupations experienced a 5 percent loss of job posting shares from 2007 to 2018, confirming a disruptive effect of the technology on jobs. Among all subfields of fintech innovations, data analysis, blockchain, and robo-advising have the greatest effects.

The loss of jobs exposed to fintech is not evenly borne across industries, firms, and geography. Three industries most exposed to fintech innovations, including finance, professional, management and administrative services (PMA), and information, accounted for 40% of all job postings in the U.S. in 2007 but have lost nearly 13 percentage points by 2018. Likewise, traditional financial hubs, such as New York metro, Boston (MA), Washington metro (DC, MD and VA), Charlotte (NC), Atlanta (GA), Chicago (IL), San Francisco (CA), Seattle

[2]Since a burgeoning literature has studied the relation between technologies and labor market due to AI and software, we compare our fintech exposure measure with the existing occupational measures developed by Webb (2019) and find little resemblance and correlation between the two, confirming that our measure captures different technological shocks from those explored by the literature.

(WA) and state of Texas have suffered the steepest losses of jobs that are most exposed to fintech. Also, we find that fintech innovations are concentrated in four industries: finance, information, manufacturing, and PMA. This pattern is confirmed by further finding that the financial industry is both the target of disruption and a leader in the fintech innovation effort, and that financial firms are both inventing and acquiring fintech patents more than others. This is contrary to a conventional belief that fintech innovation is primarily sourced outside the finance and related industries.

Firms are not expected to be passive players in a wave of disruption. We examine one aspect of their response, namely, the change in their recruiting strategies for jobs that have been overall downsized in relation to fintech exposure. Firms resort to upskilling in hiring of fintech-disrupted jobs, requiring more education attainments and longer work experiences. The demand for "finance + software" skills and "software-only" skills rises as fintech exposure increases, but that for "finance-only" skills goes in the reverse direction.[3] However, firms' human resource adjustments are limited by local market conditions. Ample supply of quality labor and light labor protection regulations help firms weather the disruption better. Based on the Herfindahl-Hirschman Index (HHI) constructed at occupation level, we also find that jobs exposed to fintech become more concentrated across industries and states, suggesting that workers associated the peripheral players (in terms of both industries and regions) are the most vulnerable to the technology shock.

A disruptive force on jobs due to technology does not speak to its impact on the operating outcomes of firms, e.g., in terms of sales growth and returns to capital. Therefore, the last main objective of the paper is to shed light on how firms fare when facing fintech exposure. Though the most exposed firms indeed experience significantly lower employment growth relative to other firms, confirming the relation at the occupation level, they do not suffer in sales growth and return on assets (ROA), nor in research and development (R&D) investment.

[3] While the impact along the skill/experience/education spectrum is similar to that of AI, it is in contrast to the impact from software innovations which seem to disproportionately disrupt highly educated workers with long work experience and from industrial robots that mainly affect manufacturing sector and in the low-skilled and less-educated workers (e.g., Graetz and Michaels, 2018; Webb, 2019).

In fact, inventor firms (i.e., firms that are the original developers of the fintech patents), but not acquisition-driven innovating firms (i.e., firms that acquire fintech patents), are the bright spots on the landscape: they hire more, invest more in R&D, and enjoy higher sales growth and return on assets. In sum, fintech constitutes a disruptive force for workers but not for (shareholders of) firms, and there is a win-win situation at firms that are originators of new technology.

Our paper is related to a growing literature on the impact of technological changes, especially on jobs. This literature begins with studies that investigate the broad trends in terms of wages and employment polarization and inequality in the U.S. labor market over the last 30 years (e.g., Autor et al., 2003; Autor and Dorn, 2013; Goos et al., 2014; Gregory et al., 2016). Several papers make the case that a primary driver of these trends is routine-biased technological change, resulting in firms' substitution of technology for labor. While most technological changes are a gradual, secular phenomenon, the adjustments to technological change are more episodic with more rapid substitutions occurring during and immediately after economic recessions and in the depressed local markets (Jaimovich and Siu, 2020; Hershbein and Kahn, 2018). Later work in this area has turned to estimating the impact of major waves in technology advancement, from automation to AI, on employment and wages. Acemoglu and Restrepo (2018) find significant negative effects of adopting industrial robots on employment and wages, as well as blue-collar occupations, in local labor markets exposed to robots. Graetz and Michaels (2018) show an increasing productivity in industries adopting more robots, but no clear employment patterns. More recently, Alekseeva et al. (2020) and Acemoglu et al. (2020) document a dramatic increase in the demand for AI skills in online job postings over the period 2010-2018, and significant changes in skill requirements by firms that are AI-exposed. Babina et al. (2020) develop measures for firm-level AI investment and find that AI-investing firms enjoy high growth as well as contribute to higher industry concentration.

Our paper aims to be the first to study the effect of fintech on jobs and demand for skills. While industrial robots are almost exclusively adopted by manufacturing firms and AI is widely adopted by service sectors (Acemoglu et al., 2020), fintech is a technological disruption primarily targeted at the financial services industry. The impact of fintech disruption cannot be deduced from the earlier research. Our paper also contributes to the literature on the impact of technological innovations on incumbent firms. There is an extensive literature that has modeled how innovation from outside of an industry can harm or benefit incumbent firms (Arrow, 1962; Henderson and Cockburn, 1996; Christensen, 1997; Ellison and Ellison, 2011; Adner, 2013) and how incumbents use their own innovations to defend themselves from outside threats (Dasgupta and Stiglitz, 1980; Gilbert and Newbery, 1982; Aghion et al., 2001). Our analyses not only uncover the disruptive effects of fintech, but also explore how firms, especially those in the financial industry and those that are innovative, adapt to the change.

Our paper naturally belongs to the literature on fintech. Some papers in this field explore design of specific fintech such as blockchain while others examine the fintech entry in various consumer credit markets.[4] For instance, Buchak et al. (2018) and Fuster et al. (2019) study whether there is substitution or complementarity between fintech lenders and traditional banks in the mortgage market. Vallee and Zeng (2019) examines how information provision to investors by a marketplace lender affects investors' performance. In addition, a related study by Chen et al. (2019b) uses machine-learning algorithms to identify fintech patents and then estimates the value of fintech patents to innovators and the overall financial sector.[5] Different from all of these papers, ours focuses on the demand for talent by firms as they become exposed to fintech innovations. Since we exploit the connections between finance and other industries, our paper also shed some light on the spillover effect of fintech adoption.

The remainder of the paper is structured as follows. We describe various data sources in Section 2. In Section 3, we explain the construction of the occupational fintech exposure measures and describe sample construction and summary statistics. Our main baseline analysis is

[4] Chen et al. (2019a) survey economic research on blockchains and its recent advances. Papers that study fintech lenders in the unsecured personal loan market include, among others, Iyer et al. (2016), Havrylchyk et al. (2019), Balyuk (2016), Cornaggia et al. (2017), Balyuk and Davydenko (2018), Danisewicz and Elard (2018), De Roure et al. (2018), Hertzberg et al. (2018), Balyuk (2019), Chava et al. (Forthcoming), Tang (2019), and Di Maggio and Yao (Forthcoming).

[5] Chen et al. (2019b) adopt a methodology of anticipation-adjusted stock market reactions, similar to Kogan et al. (2017), to quantify the value of innovations. In a more recent paper, Lerner et al. (2021) study the evolution of financial innovation over the past two decades using patents from traditional financial firms and information technology and other non-financial firms.

presented in Section 4 while Section 5 presents additional heterogeneity analysis of different industries and firms. In Section 6, we explore the empirical relation between fintech exposure and firm-level outcomes obtained from Compustat. Section 7 concludes.

2. Data Sources

2.1. Fintech Patents and Inventors

The first key data input is a comprehensive sample of fintech-related patent filings from 2003 to 2017 retrieved from the U.S. Patent and Trademark Office (USPTO), following the procedure developed by Chen et al. (2019b). In the first step, the full set of Class G (Physics) & H (Electricity) patent filings were narrowed down to a subset that are plausibly related to financial services by a text-based filtering against a list of financial terms. Second, several supervised machine-learning algorithms (including neural networks and support vector machines) are applied to the textual data of the filtered patent filings to train and classify those related to fintech.[6] The two-step procedure results in a total of 6,511 fintech patent filings which fall into one of seven categories: cybersecurity, mobile transactions, data analytics, blockchain, peer-to-peer (P2P), robo-advising, and internet of things (IoT).[7] Textual information from the title and abstract of each fintech patent allows us to perform a text corpus on the scope and content of the underlying innovations, which could then be matched to occupations.

The objective of our study requires an accurate identification of inventors and assignees behind the fintech patents. Each patent may provide information on its applicant, inventor, and assignee. The applicant is the party responsible for managing the patent application; the inventor has the exclusive right to their discoveries (before any transfers), and the assignee is the recipient of the transfer of the legal rights (entire or a percentage) to the invention. For

[6] This process involves three steps: (i) text preprocessing, (ii) creating a training sample, and (iii) training the algorithms to produce a classification (Chen et al., 2019b). In particular, a training sample of 1,800 filings is created through manual classification of the filings into nine different categories: seven fintech categories, non-fintech financial filings, and filings unrelated to financial services.

[7] Note that our sample covers the same set of fintech patent filings identified by Chen et al. (2019b).

this reason, we track each patent over its life cycle from the filing date, the publication date, to the grant date, and post-granting. In addition to information from the patent data, the supplemental assignments data available at USPTO helps to track down assignees for patents that went through transfers.

2.2. O*NET Occupation Data

The second data inputs key to our research is the O*NET database[8] maintained by the U.S. Department of Labor, which outlines the specific tasks performed by individual occupations. There are 967 occupations in O*NET, each identified by a SOC, and comes with a set of tasks listed in natural language. For example, tasks associated with the occupation "accountants" (SOC 13-2011) entail "review accounts for discrepancies and reconcile differences," "establish tables of accounts and assign entries to proper accounts and assign entries to proper accounts," and "examine inventory to verify journal and ledger entries." An average occupation has 20 tasks, with a full range from 5 to 40. Each task is also given numerical values that indicate its importance, relevance, and frequency within the occupation. These values become the natural weights when we aggregate tasks to the occupation level.

2.3. Burning Glass Job Postings Data

The third, and the most critical, input is a proprietary dataset covering over 180 million job postings in the United States in 2007 and 2010–2018. The dataset, provided by BGT, gathers job postings from more than 40,000 online job boards and company websites with a sophisticated de-duplication algorithm. The BGT dataset captures a near universe of online jobs posting and covers between 60–70% of jobs posted in the U.S., either online or offline (Carnevale et al., 2014). More importantly, online job ads exhibit similar trends and are closely correlated with employer surveys over time as well as across industries and occupations (Templin and Hirsch 2013). Therefore, BGT data provides a robust representation of job

[8]Studies that use O*NET database include, among others, Howell and Wolff (1991), Autor et al. (2003), Deming (2017), and Webb (2019).

openings in the U.S. (Hershbein and Kahn, 2018).

The BGT dataset contains detailed occupation information at six-digit SOC level that can be matched to occupational data, and location of job posting at the state level. It contains information on employer identity and skill requirements scraped from the text of the vacancy. For example, we are able to identify job openings that require different skills (e.g., finance, software and other skill), different years of experience (e.g., 1-4 and more than 4 years) and different educational attainment (e.g., high school, bachelor's and master's degrees). The dataset allows us to construct several measures of job postings as labor market outcomes variables following Modestino et al. (2019). These variables include changes in the fraction of a occupation-state cohort's job postings relative to the state total postings and changes in the fraction of job postings requiring certain skills, educational attainment, and years of experiences.

2.4. Other Data

Several other databases enrich our set-up. First, the American Community Survey (ACS) is provided by IPUMS which samples 1% of the U.S. population since 2005 (except for the census bureau year 2010 when IPUMS samples 10% of the U.S. population). Our IPUMS sample represents 150.8 million individuals (age between 16 and 64) in a single year on average in 2007-2018. We have access to individual-level demographic information including gender, age, occupation (SOC 6-digit), location, education category (e.g., less than high school, completed high school, college and above), and degree major (e.g., business, technology, etc.), which could be collapsed into occupation $\times$ state $\times$ year-level variables, with weights commensurate with those in the IPUMS surveys. Second, we obtain the annual employment and average wage at occupation level from Occupational Employment Statistics (QES) released by U.S. Bureau of Labor Statistics (BLS). The state union membership data is provided and updated by Hirsch et al. (2001). Finally, the financial information and stock returns of public firms in our sample are retrieved from Compustat and CRSP, respectively.

3. Research Design and Sample Overview

3.1. Measuring Fintech Exposure

3.1.1. Methodology

The premise to studying firm response to fintech shock is a measure that characterizes fintech exposure at the occupation level. Because there exists no such measure in the literature, we develop it by exploiting the overlap between the textual information of fintech patent filings from USPTO and that of job descriptions from O*NET. Note that the text of fintech patents contains key information about what the technological inventions do, and that of job descriptions contains specific tasks that define each occupation. Thus an analysis over these two text corpuses can inform whether and how much a body of fintech patents over a specific period of time has been directed at the tasks of each occupation.

Figure 1 illustrates the process we use to quantify the occupational exposure to fintech innovations, similar to the one adopted by Webb (2019) for AI technology. We begin with the text of fintech patent filings to capture the scope and the intensity of fintech innovations. Specifically, we compile a list of fintech-related keywords by extracting the text from the titles and abstracts of the patent filings, where the most critical and concise information about the innovation is deposited. We tokenize the titles and abstracts of fintech patent filings by removing punctuation and stop words. As an illustration, Figure 2 plots the clouds of the most frequent keywords in fintech patents in three periods: 2003-2006 (early years), 2017 (latest) and 2003-2017 (all years). While transaction is among the frequent keywords in all three panels, frequencies of other keywords such as card, information, device, and payment vary over time. Next, we obtain detailed job task descriptions from O*NET database. We tokenize the text of each task description and remove punctuation and stop words to create task-specific keywords.

[Insert Figure 1 Here.]

[Insert Figure 2 Here.]

The overlap of the resulting two sets of the text captures the exposure of each occupation to fintech innovations. We track the frequency of the unique keywords in the individual job tasks and the fintech patent filings separately using two numerical vectors. The first vector, $a_{i,j}$, records the frequencies of keywords in the job task description j of occupation i. The second vector, b_t, captures the frequencies of keywords in the fintech patents filed during the five-year period ending in year t. Then a given task's fintech exposure, $FT_{i,j,t}$, is the scalar projection of the fintech vector b_t onto the vector of a given task $a_{i,j}$:

$$FT_{i,j,t} = \cos(\theta)\|b_t\| = \frac{a_{i,j} \cdot b_t}{\|a_{i,j}\|}, \tag{1}$$

where $\cdot$ denotes the inner product and $||\cdot||$ is the Euclidean norm or the length of the vector, *cos* is the cosine similarity function, and θ is the angle between the two vectors. Numerically, scalar projection calculates the length of the vector projection of vector b_t onto vector $a_{i,j}$. We multiply the cosine similarity by the length of b_t to consider the intensity of fintech innovations over time. Intuitively, the scalar projection measures the amount of "shadow" that a cloud of fintech innovations casts on a given job task. Moreover, the exposure measure is always weakly increasing if we expand the time period for the set of fintech patents.

Based on equation (1), exposure to fintech is an increasing function of the following two factors: (i) the cosine similarity (i.e., $\cos(\theta)$) between the task and fintech vectors, and (ii) the amount/intensity of fintech innovations as captured by the norm of the fintech vector (i.e., $\|b_t\|$). In a situation where there are a large amount of fintech patent applications and where a job task has high overlap with those patent filings, this task is deemed as having a high exposure to fintech innovations.

Fintech exposure at the task level could be aggregated into the occupation level, $FT_{i,t}$, for a given occupation i, by averaging over task-level scores:

$$FT_{i,t} = \sum_{j \in K_i} w_{i,j} \times FT_{i,j,t}/10^7, \tag{2}$$

where K_i is the set of tasks in occupation i, and $w_{i,j}$ is the weight of individual task j in occupation i assigned in the O*NET database. Finally, the scalar 10^7 merely puts the typical values of the measure on a reasonable scale.

Because of the five-year moving window for patent filings, the fintech exposure scores for tasks and occupations are time varying but slow moving. Note that our method is readily adaptable to forming alternative measures for robustness checks. For example, disaggregated measures of exposure to each of the seven subsets of fintech innovations (including cybersecurity, mobile transactions, data analytics, blockchain, P2P, robo-advising, and IoT) could be constructed analogously. An all-time exposure measures using fintech patent applications from the full sample period of 2003 to 2017 is an alternative, and so is a measure based on granted (rather than filed) fintech patents during the previous five years.

Table 1 features two occupations with high fintech exposure (credit analysts and information security analysts) and low fintech exposure (mathematical science teachers and orthodontists), respectively, based on the all-time exposure measure using fintech patent filings from 2003 to 2017. For the economy of space, the table only shows the top three job tasks for each occupation and the top five keywords for each task that overlap with the keywords of fintech patents. We observe that a credit analyst's job is exposed to fintech innovations in that the latter involve part of the tasks related to data, financial, transactions, and credit. Information security analysts are exposed to the technologies that intersect tasks involving systems, computer, data, information and security. In contrast, almost none of the keywords underlying the tasks for mathematical science teachers and orthodontists have a meaningful exposure to fintech patents.

[Insert Table 1 Here.]

Since patents vary greatly in their technical and economic significance, and hence their disruptive force, we quantify the economic impact of individual patents on the financial industry using the method proposed by Chen et al. (2019b). More specifically, we first estimate the disruptive impact of patents based on the stock market reactions of financial firms to patent publication, and then classify the top 25% fintech patents with the most *negative* value as the most disruptive. Applying the textual analysis method described above on the most disruptive subset of fintech patents and its complement subset, we produce two separate fintech exposure measures - exposure to the most-disruptive and less-disruptive innovations, respectively.

3.1.2. Overview of Fintech Exposure

Based on the procedure outlined in the previous sections, we are able to construct the fintech exposure scores for all 772 occupations at six-digit SOC level for the full sample period of 2003-2017. Most occupations have a raw fintech exposure score between 0 and 1 though there is no natural limit to the upper bound.[9] Table 2 lists the ten occupations with highest and ten with the lowest fintech exposure scores. It turns out that on the top of the list are information security analysts, credit analysts, software developers (applications), travel agents, and electronics engineers; while at the bottom there are carpenters, slaughters, police and detectives, orthodontists, and dancers. In addition, our measure shows that personal financial advisors have the highest exposure to innovations in robo-advising, as one would expect. Thus, the scoring system mostly confirms casual observations.

[Insert Table 2 Here.]

To explore the time-varying nature of fintech exposure, Panel A of Figure 3 plots time series of three fintech exposure scores constructed based on (i) cumulative fintech patent applications since 2003 (i.e., 2003 to t); (ii) fintech patent applications during the five-year period ending in a given year (i.e., $t-5$ to t) and (iii) granted fintech patents during the five-year period. Series (i) steadily increases over time as it reflects a cumulative effect of fintech innovations over time. Series (ii) reveals more time-varying trends, where fintech exposure grew during most of the sample period but peaked in 2016. Finally, series (iii) has a similar shape as (ii) but in a smaller magnitude since only a fraction (about 48%) of fintech patent filings are granted.

[9] Figure A.1 plots the histogram of fintech exposure scores.

[Insert Figure 3 Here.]

Panel B of Figure 3 disaggregates fintech exposure into the seven fintech sub-categories, based on filed patents during the more recent five-year period. The figure features staggered waves over time. Cybersecurity led innovations in other fields and has posed the largest shock to occupations. Mobile transaction kicked off around 2010 following the financial crisis and grew exponentially after 2012. Data analytics has also gained momentum after the financial crisis. P2P and blockchain were invented around 2012 and 2015, respectively; robo-advising and IoT each has maintained a stable share of exposure since 2001.

3.1.3. Relation with Other Occupational Exposure

A burgeoning literature explores impact of various technological breakthroughs on the demand for labor and employment. It is thus necessary for us to relate to as well as to differentiate from the tech shocks analyzed in other studies. In particular, we compare with the two occupational measures developed by Webb (2019) regarding AI and Software, as they represent the current focuses in the discussions of technology. Our measure bears some similarities to the Webb (2019) measures as they are all based on textual analyses of patents and O*NET occupation descriptions. However, patents used in the matching procedures are different and they capture different technological discovery. There are also methodological differences in that we process the entire texts of both titles and abstracts of the patents, instead of using only verb-noun pairs extracted from titles of patents, allowing the matching to build on richer information. Finally, we incorporate time-series variation with a moving time window for fintech patents. As a comparison, Figure 4 plots the average of fintech exposure (in percentile rank) against each of the two occupational measures developed by Webb (2019). Overall, there is no apparent correlation between fintech exposure and the AI or software series, suggesting that the impact of fintech is likely to be distinct from the development in the other two areas.

[Insert Figure 4 Here.]

3.1.4. The Demographics of Fintech Exposure

Though occupations are the focal subjects of our study, the fintech shocks are ultimately borne by people who work in the affected occupations. We are thus interested in gaining a glimpse into the demographics sorted by fintech exposure, with the help of the individual-level data from the 2007 IPUMS. Specifically, we consider the following four demographic characteristics: occupation average hourly wage (in percentiles), educational attainments (broken down into five levels: less than high school; high school; some college; college; master and above), percent of female workers in an occupation, and individual age. Figure 5 plots the percentile of cumulative fintech exposure from 2003 to 2017, at the occupation level, in relation to these variables. When the demographic variables are recorded at the individual level (e.g., education and age), the fintech exposure is averaged over all the workers in a given demographic group.

[Insert Figure 5 Here.]

Panel A of Figure 5 uncovers an inverse U-shaped curve between fintech exposure and occupational wage in that the occupations paying middle-ranged salaries are most exposed to fintech innovations, and both ends of the wage spectrum tend to be the least affected. A similar pattern prevails in Panel B in that individuals with intermediate education attainments (high school and some college) are more exposed to fintech than their less (no high school) or more (college and above) educated peers. Interestingly, people with advanced degrees (master and above) are the least affected. Panel C shows that fintech exposure is most likely gender neutral, with a flat relation between fintech exposure and share of female workers. Finally, Panel D shows that fintech innovations affect the prime-aged workers (between 35 and 50) the most, while the exposure drops steeply for workers with age above 50.

3.2. Linking Fintech Exposure to Job Postings

3.2.1. Sample Construction and Summary Statistics

Given the objective of our study to trace out how demand for talent responds to fintech shocks, a key component of our empirical strategy is to link firm- or establishment-level job postings to the occupational exposure to fintech innovations. Job posting variables are constructed using data from BGT, including number of postings, share of postings in a local market as well as job requirements for skills, education and work experience. Our default fintech exposure measure is based on fintech patents filed during a five-year moving time window.

Corresponding to fintech exposure measures at occupation $\times$ year level, the main variables from BGT posting data are aggregated at occupation $\times$ state $\times$ year level to allow for cross-sectional variations in local labor market conditions.[10] We exclude postings without adequate information to classify occupation, state or time from the sample. The base of our sample consists 161.6 million vacancies during 2007, and 2010-2018. For the ease of interpretation, we transform the fintech exposure raw score to percentiles or broader ranges such as quartiles within each year. We follow Modestino et al. (2019) to construct two measures capturing the relative change in the volume intensity of job postings. The first measure is the percentage-point change (year over year) in the share of job postings by an occupation $\times$ state $\times$ year in all postings in the same state $\times$ year. The second is the percentage-point change (year over year) in the share of job postings requiring certain skill levels, educational attainments, and years of experiences.[11]

Table 3 presents the summary statistics of the variables in the main sample at the occupation $\times$ state $\times$ year level, with about 300,000 cohorts and 772 occupations. There are 440 postings on average at cohort level, greater than the 75^{th} percentile value of 275, suggesting

[10]We also constructed alternative samples at occupation $\times$ year, occupation $\times$ industry $\times$ year and occupation $\times$ firm $\times$ year level and repeated our baseline analysis as robustness tests.

[11]As an overview, Figure A.2 in Appendix plots the time series of number of job postings by four quartiles of occupational fintech exposure. Panel A suggests that the most exposed occupations contain most job postings than others, but also recovered the slowest from the financial crisis. Panel B confirms that share of the most exposed job postings have declined steadily since 2012, which is complemented by relative growth in occupations in the second and third quartiles.

a right skewed distribution. An average cohort accounts for 15.7 basis points of total postings within each state. While the full sample percentile scores are calibrated to a uniform distribution, among the sub-categories, blockchain has a much lower average percentile (18.1) than others, reflecting a relatively short-lived wave of blockchain innovation that disrupts existing occupations. To ensure reliability of the measure, we drop observation cells with fewer than three postings, about 0.025% of the original sample. To further mitigate the influence of outliers, following Modestino et al. (2019), we conduct weighted regressions as our main specification where weights are the number of postings underlying each observation.[12]

[Insert Table 3 Here.]

By parsing the skill keywords contained in the posting, we identify that on average 86% of the job postings have some skill requirements. The shares are 12% and 21% when we break the skill requirements to finance and software, respectively. Table 3 further reports shares of job postings with three mutually exclusive skill requirements – both finance and software skills (5.1%), finance but not software (6.6%), software but not finance (15.5%) – to analyze the specialized demand for talent by firms in face of fintech disruption. Similarly, we also construct share of job postings that require different educational attainment and years of experience. About 43% of job postings require minimum level of education, evenly split between high school diploma and bachelor's degree and above (BA+). About 37% of job postings require experience: 27% 1-4 years; 10% 4-plus years of experience. The last six rows of Table 3 reports summary statistics of local socio-demographic characteristics from IPUMS. The variables are first averaged at state by year level and then matched to our main sample. The average median age is 40, and women on average account for 47% of the workforce. On average, 32% of workers have a BA+ while 6.3% have a business major degree and 2.4% have an IT related degree (i.e., a communication technology, computer or information science degree).

[12]As robustness check, we also report the unweighted regression results in Table A.1 in Appendix, which are consistent with those using the main specification.

Finally, Figure 6 shows that the cumulative posting share change from 2007 to 2018 at the occupation level stays flat initially as fintech exposure increases but exhibits steep decline above the 75^{th} percentile of exposure, the total loss of 7 basis point loss of job postings (as a share in the state) during the 2007-2018 period represents an 8 percent relative to the average weighted posting share (90.2 basis point).

[Insert Figure 6 Here.]

3.2.2. Identifying Fintech Innovators

We hypothesize that the firms' responses in their hiring strategies in exposure to the fintech shock are likely to be quite different between those that are innovative themselves and the rest. Hence this section outlines how we identify the fintech innovators.

To identify innovators, we follow the life cycle of patents to locate information on both inventors (who file the patents) and assignees (who currently own the patents, possibly via transfers).[13] We match the innovator firm's name to BGT data. We then classify firms that are active innovators from otherwise based on whether a firm files fintech patents. In our sample, 70.8% of patent filing firms file only one fintech patent application during the whole sample period. These "one-time" inventors, in large numbers, may just have enjoyed occasional discoveries that are not part of their core innovative competence. For this reason, we classify firms with two or more fintech patent filings as fintech inventors. Among firms not classified as inventors, we identify those who innovate primarily through acquiring fintech patents as non-inventor innovators if they acquire at least one fintech patent. Large financial firms engaged in more fintech patent acquisitions since 2001, as shown in Figure 7, catching up with the fintech wave that started earlier.[14]

[13] The inventor identity may also change after the initial filing under several scenarios. First, while some patents are filed under individual inventor names, they are actually sponsored by their employers. The information is usually updated before publication or grant date by the filing attorney. In this case, we treat employer firms as inventors. Second, consistent with the evidence documented by Cohen et al. (2016, 2019), Non-Practicing Entities (NPEs) actively acquire fintech patents, e.g., one of the largest NPEs in fintech domain is III Holdings 1, LLC, which holds 121 fintech patents acquired from American Express.

[14] Panel A of Table A.2 in the Appendix lists the top ten firms in each of the two categories (inventors and acquisition innovators), and the number of fintech patents they own. Mastercard, Visa, American Express

[Insert Figure 7 Here.]

Among firms covered by the BGT data, there are 367 fintech inventors, 320 acquisition-driven innovators, and more than 2 million other, non-innovating firms by our criteria. Not surprisingly, fintech innovators tend to be large firms, with an average of 1,179 and 916 job postings annually for inventors and acquisition innovators, respectively, compared to only 27 for non-innovators. On the other hand, NPEs have very few postings.

Fintech innovations are concentrated in four industries: finance (NAICS 52), information (NAICS 51), manufacturing (NAICS 31-33) and PMA (NAICS 54-56). Some inventors in manufacturing, such as GE Capital and GM Financial, are financial subsidiaries of parent companies that are rooted in manufacturing.[15] Such an industry allocation is somewhat at odds with a conventional belief that fintech innovation represents an external shock on the financial industry. Data indicates that the financial industry is actually leading the innovation effort in fintech. Financial industry is also a net buyer of fintech patents. Figure 7 shows that over the period of 2003 to 2017, financial firms have acquired 369 and sold 216 fintech patents based on USPTO assignment data, their activities accounting for more than a quarter of all the fintech patent transactions.[16] Acquisitions by financial firms have intensified since 2011 and continued until 2016 when Bank of America and Visa were on a shopping spree for fintech patents from private firms and individuals. These transfers/acquisitions support the contention that both original and acquired innovations are important ways for financial firms to remain competitive facing the potential disruption from fintech.

and Bank of America lead other firms as the most prolific inventors in the fintech domain. And the rest of the top ten are mostly large, publicly traded firms in payment-related businesses. The list of top non-inventor innovators, however, is a mixture of large inventors such as Paypal and American Express and NPEs like Liberty Peak Ventures, III Holdings 1, and Intellectual Ventures II.

[15] See more details in Panel B of Table A.2 in the Appendix. Among all industries, finance accounts for 32.11% of the fintech patents, followed by information with 12.4% and PMA with 4.15%.

[16] Two largest deals from finance to other industries are Xatra Fund MX LLC's acquisition of 44 fintech patents from American Express; and III Holdings 1 LLC's purchase of 121 fintech patents from American Express. Both acquirers are NPEs. See https://www.richardsonoliver.com/2014/07/16/intellectual-ventures-is-buying-again/.

3.2.3. Distributions of Fintech Exposure and Jobs

A. Distribution across Industries

Table 4 summarizes the distributions of fintech exposure and demand for jobs across different industries (at the NAICS two-digit level).[17] Industries most exposed to fintech innovations include finance, PMA, and information, all with fintech exposure well above the 70^{th} percentile. Within the financial industry, firms in the banking and brokerage subsectors have higher exposure than their peers in the asset management, payment and insurance subsectors. The opposite end of the spectrum are accommodation and food services, educational services and arts, entertainment and recreation. The three most exposed industries account for 40% of the total postings at the beginning of our sample (2007), while the three least exposed industries account for only 12%. However, the three most exposed industries also experienced the largest loss in shares of postings from 2007 to 2018 (-12.8% combined); while the three least exposed industries have gained 6.2% (combined) in their posting shares. If we take the perspective at the occupation level, the most fintech-exposed occupations account for 71% of all losses in the three most exposed industries. Overall, the coefficient of correlation between cumulative change in job posting share and fintech exposure at occupation level is -0.51, signaling that fintech has been a strong disruptive force on jobs.

[Insert Table 4 Here.]

We present evidence of heterogeneity across industries in Table 4. 74% (column (3) divided by column (2)) of all jobs in finance are among the most exposed occupations, and that share is 50% for information and 55% for PMA, respectively. In contrast, finance has only lost 38% (columns (5) divided by column (3)) of its most exposed jobs, and that share is 50% for information and 34% for PMA, respectively. These numbers suggest that even facing similar fintech disruption, industries have fared differently. Notably finance, the most exposed

[17] The industry fintech exposure is defined as the job posting-weighted average of occupations' fintech exposure in the industry. Because the most fintech exposed occupations (top quartile) accounts for approximately 40% of the total job postings, this job posting-weighted average exposure is right-skewed and all industries are above the 39^{th} percentile.

industry, retains healthy demand for labor relative to its two peer industries with closest fintech exposure.[18]

B. Distribution across Geography

A parallel distributional analysis applies to geography. Panel A of Figure 8 plots the average fintech exposure, weighted by postings, at the state level in 2007. It shows an uneven geographic distribution of the impact from fintech. Traditional financial hubs, such as the New York metro (e.g., NY, NJ and CT), Boston (MA), The Washington D.C. metro (e.g., MD and VA), Charlotte (NC), Atlanta (GA), Chicago (IL), San Francisco (CA), Seattle (WA) and state of Texas, are most exposed to fintech innovations. States in Mountain and rest of South are the least exposed. Panel B further shows that the most exposed occupations in NY, NJ and CA also suffer the steepest job losses, followed by FL, PA, WA, WI and IL.

[Insert Figure 8 Here.]

4. Fintech Shock, Job Postings, and Employment: Empirical Results

4.1. Empirical specification

The goal of this section is to estimate how firms adjust their hiring strategies and how employment responds post fintech shock. Our baseline analysis, at the occupation × state × year level, is as follows:

$$\Delta Y_{o,s,t-1->t} \quad = \quad \beta_1 \cdot FT_{o,t-1} + \beta_2 \cdot X_o + \gamma_{s,t} + \varepsilon_{o,s,t}. \tag{3}$$

[18] In our sensitivity checks, we find that job posting share in finance is overall stable across the spectrum of fintech exposure; but PMA and information industries are significantly affected by fintech innovations with a similar pattern to that in Figure 6. Details are reported in Figure A.3 in the Appendix, which maps the cumulative change of posting shares to fintech exposure percentiles for each of the seven industries that include finance and a few related sectors.

In the equation above, occupation, state, and year are indexed by o, s, and t, respectively. The key independent variable, $FT_{o,t-1}$, is fintech exposure (expressed in percentiles or in top quartile classification) at the occupation level based on five-year moving time window of fintech patents (as described in Section 3.1). The outcome variable, $\Delta Y_{o,s,t-1->t}$, is change in job posting shares in basis points, from year $t-1$ to t, of postings in occupation o located in state s and year t as a share of all postings in in state s and year t.[19] X_o is a vector of control variables, notably, the occupation-level software and AI exposure measures developed by Webb (2019). The regression incorporates fixed effects at the state × year level ($\gamma_{s,t}$) to absorb any confounding factors that would affect the supply and demand conditions of the local labor market each year. Unless otherwise stated, all potentially unbounded variables are winsorized at the 1% extremes. Standard errors are clustered at the state level.

4.2. Fintech Exposure and Job Posting

Table 5 reports the estimation results of Equation (3). In the first four columns, the key independent variable, fintech exposure at the occupation-year level lagged by one year, is measured in continuous percentiles; and in the last four columns, it is coded as a dummy variable that equals one if the exposure falls into the top quartile in a given year (based on the evidence in Figure 6, which we term as the "most exposed" occupations). We control for the two competing cross-sectional occupation exposure measures in columns (3), (4), (7) and (8), and also alternate specifications with different fixed effects: (i) year fixed effects in columns (1) and (5), (ii) state and year fixed effects in columns (2)-(3) and (6)-(7), and (iii) state × year fixed effects in columns (4) and (8).

[Insert Table 5 Here.]

In Panel A, estimates of the coefficient associated with fintech exposure are very similar across specifications, and are uniformly statistically significant at 1% level. Moreover, the

[19] The change in posting shares across all occupations within a state sum up to zero by construction. Given the large number of observations within a state-year cohort (772 occupations), there is minimal compromise on the degree of freedom due to this add-up constraint.

estimates are qualitatively similar but slightly larger after the inclusion of other occupational exposure measures, suggesting that the impact from fintech exposure is distinct from that from AI and software. Given the consistency of the results, we will designate the full-control specifications in columns (4) and (8) as our default. Result in column (4) suggests that when fintech exposure moves up by one percentile, occupation-level job posting share decreases by 0.084 basis point. Column (8) shows that relative to other occupations, those in the highest exposed quartile see a 4.6 basis point decrease in job posting share. Relative to the average job posting share (90 basis points as shown in Table 1), this represents about 5 percent decrease. Both effects are within the same state-by-year so that macroeconomics or regional conditions are not driving the disparity.

We conduct a slew of robustness tests using alternative specifications of both dependent and independent variables. First, we explore how the impact of fintech exposure is distributed among different subfields, such as cybersecurity and blockchain. In Panel B Table 5, exposure to individual components of fintech replaces the aggregate exposure. It turns out that exposure to all subfields of fintech innovations have significant (at 1% level) and negative effects on job postings. Among them, robo-advising, data analysis and blockchain have the greatest effect, with one percentile increase in the exposure being associated with 5.7, 5.6 and 5.1 basis points decrease of posting share, respectively. In contrast, the exposure to the other four technologies brings about more modest effect, from 2.6 basis points for IoT to 4.5 basis points in cybersecurity.

Second, we cross-check job posting with actual employment. The main outcome variables in our study are based on job postings, which reflect firms' desire to hire. While such information captures firms' active strategies, it remains interesting to see if the relation shown in Table 5 also holds for actual employment. Using the IPUMS data covering the 2009-2018 period, the coefficient estimate of fintech exposure, equivalent to that in column (1) of Table 5, suggests that a one-percentile increase of fintech exposure is associated with a 0.27 basis point decrease in the employment share.[20] It is not surprising that the impact is multiple times higher in job

[20]For full results, please see columns (1) of Table A.1 in the Appendix.

postings than in employment as the former represents the extensive margin where adjustment takes place.

Third, we validate the results using first-time job postings only. In our main set-up, we include all job postings in our analysis. About 62% of job postings are likely repeated ones, presumably because many positions remain vacant after a previous effort. While the total number of postings is a reasonable proxy for the intensity of demand for talent, we also consider unique, first postings as a measure for distinct new positions. Following Cen et al. (2018), we classify a job posting as a re-posting if there is a previous posting with the same job title and job hours by the same firm in the same county location within a year. We find that an one-percentile increase in fintech exposure is associated with a 1.8 basis point decrease in the posting share, about 40 percent of the estimated effect in Table 5.[21] The effects are significant and proportional relative to those estimated using all job postings.

Finally, we experiment with alternative measures of fintech exposure as well as job posting outcomes to ensure robustness. The alternative specifications including (i) replacing the first difference model in Equation (3) with an occupation fixed effect, (ii) using unweighted observations, (iii) relying on only granted (instead of filed) fintech patents, and (iv) adopting all-time fintech measures or raw exposure scores. The coefficient estimates associated with fintech exposure remain negative and significant at 1% level in all specifications, suggesting robustness of our baseline result.[22]

4.3. Downskilling versus Upskilling

So far we have established the overall negative effect of fintech exposure on firm hiring. In this section, we further investigate whether the recruiting strategies of the exposed firms exhibit upskilling or downskilling in the overall downsizing trend.

We formalize the analysis with a regression of change in job posting shares that require different types of skills or levels of education/experience on fintech exposure measured by the

[21]For full results, please see columns (2) of Table A.1 in the Appendix.
[22]For full results, please see columns (3)-(8) of Table A.1 in the Appendix.

most exposed quartile dummy, controlling for exposures to AI and software innovations and state × year fixed effects. Table 6 reports the results. Columns (1)-(3) show "finance & software" skills and "software-only" skills are in significantly higher demand as fintech exposure increases, and a reverse negative relation prevails in "finance-only" skills. This suggests that while fintech innovations disrupt existing occupations, they also create job opportunities for people who are well-versed in software language, and even more so for talents that are bilingual in both finance and technology.

[Insert Table 6 Here.]

Columns (4)-(5) show a monotonic relation between fintech exposure and the length of work experience or the level of education required. For example, the share of postings for jobs that require 0-4 years of experience increases by 13.5 basis points for the most exposed occupations; the same coefficient is more than twice as big, at 36.3 basis points for postings requiring four-more years of experience. Such a pattern is echoed in education requirement. For the most exposed jobs, the posting share of jobs that require high school education decreases by 12.0 basis points, but that for jobs requiring college degree and above increases by 50.6 basis points. Each of the two effects are significant at the 1% level, and so is their difference.

Thus, Table 6 shows strong evidence that firms resort to an upskilling recruiting strategy after facing fintech disruption. While the impact along the skill/experience/education spectrum is similar to that of AI, it is in contrast to the impact from software innovations which see to disproportionately disrupt highly educated workers with long work experience (e.g., Webb, 2019). It also contrasts the impact of industrial robots which is concentrated in manufacturing sector and in the low-skilled and less-educated workers (e.g., Graetz and Michaels, 2018).

4.4. Local Labor Market Frictions

Local market frictions such as lack of quality labor available in the existing pool and strong labor protection regulations could limit firms' ability to adjust their labor force in response to an external shock such as fintech disruption. We formally test this hypothesis using data on state-level skilled labor supply from the U.S. Census and data on unionization from Hirsch et al. (2001). Specifically, we add to our baseline regressions interaction terms of the most exposed quartile dummy and state-level labor force circumstances including the percent of people with a BA+, with a business degree and with an information technology degree, respectively, and that of union members in the non-agricultural sectors. Table 7 reports the results, in which the dependent variable is change in job posting share in columns (1)-(4) and change in employment share in columns (5)-(8).

Coefficients on the interaction terms with local supply of business and IT talents are positive and significant at the 10% and 5% level, respectively, suggesting that states with more educated workers (with business or IT degrees) adjust better to the fintech exposure and endure fewer employment loss in the most exposed occupations. Not surprisingly, the supply of IT degree holders is about twice as important as that of business degree holders in offsetting the disruption of fintech.

The union status of the labor force in the state (as measured by percentage of labor force that are unionized) has no discernible effect on firms' desire to hire (job posting shares), but does affect employment. Based on the result in column (8), a one-standard deviation increase in union membership (5.3 percentage points) offsets 11.2 basis points in the loss of employment share among the most exposed occupation (significant at the 10% level).

[Insert Table 7 Here.]

4.5. Occupation Redistribution and Concentration

Aside from new hirings, the fintech shock also reshapes the distribution of occupations (and hence talents) across different industries and geographies. Figure 9 plots the HHI of occupations calculated based on the posting shares across states (Panel A) and industries (Panel B) over occupational fintech exposure percentile. Both Panels show that occupations become more concentrated with increasing fintech exposure. In Table 8, we run regressions of changes in HHI, both year over year (YOY) and cumulative change from 2007 to 2018, on the indicator variable for the highest fintech exposure quartile at the occupation-year level. Results confirm that occupations that are most exposed to fintech became significantly more concentrated in terms of both industry and geography, where the HHI indices rose by 6.7 and 5.7, respectively. In contrast, we find that occupations that are more exposed to AI became less (more) concentrated across states (industries) over time, though the effects are small relative to that of fintech exposure.

[Insert Figure 9 Here.]

[Insert Table 8 Here.]

5. Cross-Sectional Heterogeneity

In this section, we further explore the differential impact of the fintech exposure on financial firms as well as innovative firms. Such analyses aim to provide insights into the redistributional effects of the fintech shocks.

5.1. Finance versus Other Sectors

The term fintech already suggests that the disruption is aiming at the traditional financial sector. Therefore, the financial industry warrants a separate analysis vis-a-vis other sectors. Table 9 presents the regressions of change in job posting share on the two fintech exposure measures that capture occupations' exposure separately to the most disruptive and less disruptive fintech innovations (as defined in Section 3.1.1). Column (1) shows that when both fintech exposures are included as the explanatory variables, only the coefficient on the less disruptive fintech exposure is negative and significant while the exposure to the most-disruptive fintech is not associated with any significant job posting change.

Such a result is intriguing as fintech that is expected to disrupt traditional finance the most is not causing job losses overall. Once we separate finance sectors from the others, results become more intuitive. Column (2) shows that finance sector jobs are indeed vulnerable to disruptive technology while other sectors are not. On the other hand, technologies that have lower disruptive power toward financial sector are associated with more job losses in other sectors than in finance. The last two columns of the table confirm similar findings within each sector by controlling the industry fixed effects.

[Insert Table 9 Here.]

How can firms in the financial sector survive the fintech innovations that are created to disrupt the *modus operandi* of financial services? One hypothesis is that financial firms respond to the disruptions by innovating and reinventing themselves. The incumbent may succeed with their existing advantages such as capital, talents and platforms. We test this hypothesis by analyzing financial firms' innovation in relation to fintech disruption and report the results in Table 10. In this analysis, the dependent variable is the number of patents (all and ones that fall into the most disruptive category, in logarithm) invented or acquired, respectively, at the firm-year level. The main explanatory variables are firm's fintech exposure to the most or less disruptive innovations, lagged by one year. The sample includes all firms but we interact the key independent variables with the financial firm dummy. Finally, all regressions incorporate both firm and year fixed effects.

Columns (1) and (2) show that firms in all sectors generally change very little in their innovation activities in relation to fintech exposure. However, column (3) shows that firms in financial industry are inventing significantly more relative to other firms when they become highly exposed to the most disruptive fintech. Among all firms that fall into the top quartile of exposure to the most disruptive fintech patents, financial firms file 48.4 basis points more fintech patents themselves compared to non-financial firms, and the difference is significant at the 1% level. Moreover, column (4) further shows that financial firms themselves are filing more disruptive fintech patents when they face high disruption. Columns (5)-(8) suggest a similar pattern when it comes to fintech patent acquisition. That is, financial firms are significantly more likely to acquire fintech patents (especially the more disruptive ones) when they become highly exposed to disruptive technology. The notable difference between acquisition-driven innovation (last four columns) and invention fintech (first four columns) is that even when the exposure comes from less disruptive fintech patents, it still motivates financial firms to engage in more (though with less intensity) acquisition-based innovation.

[Insert Table 10 Here.]

5.2. Differential Responses between Innovator and Non-Innovator Firms

Previous analyses already suggest that firms respond to the fintech disruption differently depending on whether they are innovating themselves. This section explores such heterogeneity in more detail. For this purpose, we aggregate the BGT job posting data to three groups of firms (inventor, acquisition-driven innovator, and non-innovator). Table 11 reports job posting regressions at the firm type $\times$ occupation $\times$ state $\times$ year level. Among the independent variables, fintech exposure ("FT Quartile 4") also interacts with the two types of innovators. Columns (1)-(3) show that innovating firms see an increase in hiring in the most exposed occupations relative to non-innovators. Moreover, acquisition-driven innovators completely offset the negative impact of fintech exposure on job postings.

[Insert Table 11 Here.]

Columns (4)-(6) show that fintech inventors significantly increase job postings that require software skills with and without being combined with finance skills. The emphases on skills turns out to be different between the two types of innovators. Acquisition-driven innovators favor talents with finance skills while inventors demand more people with both finance and software skills. Overall, results in this section indicate that jobs in innovating firms have not suffered due to fintech exposure. Moreover, software (finance) skill is more valued by inventor (acquisition-driven innovator) firms.

6. Firm Outcomes

While our main analysis estimates firm's adjustments in hiring and innovative activities in relation to fintech exposure, a natural question to explore next is whether such adjustments translate to real outcomes including operating performance and employment. More specifically, we estimate the firm outcomes in relation to fintech exposure at the firm × year level using the following specification:

$$\begin{aligned} \Delta Y_{i,\ t-1->t} \ &= \beta_1 \cdot FT_{i,t} + \beta_2 \cdot (FT_{i,t} \times Inno\_Type_{i,t}) + \beta_3 \cdot Inno\_Type_{i,t} \\ &\quad + X_{i,t-1} + \gamma_j + \gamma_t + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where $\Delta Y_{i,\ t-1->t}$ refers to the change in logarithm of employment, sales revenue and R&D expenditure, and ROA; $FT_{i,t}$ is the firm-level percentage of job postings that fall into the top quartile fintech-exposed occupations; $Inno\_Type_{i,t}$ is a set of indicator variables for inventor and non-inventor innovators, respectively; $X_{i,t-1}$ include standard firm-year control variables (e.g., total assets, firm age, cash holding, cash flow, capital expenditure, R&D dummy, and industry fixed effects). Thus β_1 captures the difference in firm outcomes between the most exposed firms and other firms. β_2 captures the incremental effect to innovators (relative to non-innovator firms) when they are among the most exposed firms. Standard errors are clustered at industry level.

Table 12 reports the regression results. First, the most exposed firms show significant lower employment growth relative to other firms, which confirms findings in the previous sections. However, the most exposed firms do not exhibit any statistically significant differences in sales growth or R&D investment as well as ROA. Second, relative to other firms that are highly exposed to fintech innovations, inventors in fact experience higher growth employment growth, which is consistent with Table 11. The same firms also have higher growth of sales and R&D investment, and increases of ROA. In contrast, there is no statistically significant difference in any of these firm outcomes between the acquisition-driven innovator and non-innovator firms.

[Insert Table 12 Here.]

In summary, though fintech is a disruptive force for jobs overall, it is nevertheless neutral for firms operating performance as firms adjust hiring and innovation strategies. Moreover, both jobs and operating metrics gain at firms that are innovating themselves relative to others, but even within this subset of firms the incremental demand for labor do not offset the overall loss the fintech shock causes. Finally and perhaps most importantly, firms at the cutting edge of innovation (i.e., inventors) experience boom for both labor and return to capital, but innovator firms that do not develop original technology (but only obtain technology via purchasing patents) still do not escape the fintech disruption.

7. Conclusion

This paper aims to inform the ongoing debate in whether and how fintech constitutes disruptions and/or presents the growth opportunities, especially with respect to labor demand and employment. Building on a novel measure of fintech exposure at the occupation level by conducting cross-textual analysis of job tasks and fintech patents, we discover that job postings in the most exposed occupations suffer a significant decline both in absolute magnitude and relative to other occupations. The exposed firms resort to upskilling (in terms of the requirement of skills, experience and educational attainments) in hiring albeit among overall downsizing. Fintech-exposed jobs also become more concentrated across industries and states. Nevertheless, innovative firms and finance sector manage to offset the economy-wide negative impact to different degrees. Finally, firms producing original fintech innovations themselves gain in both employment and operating performance.

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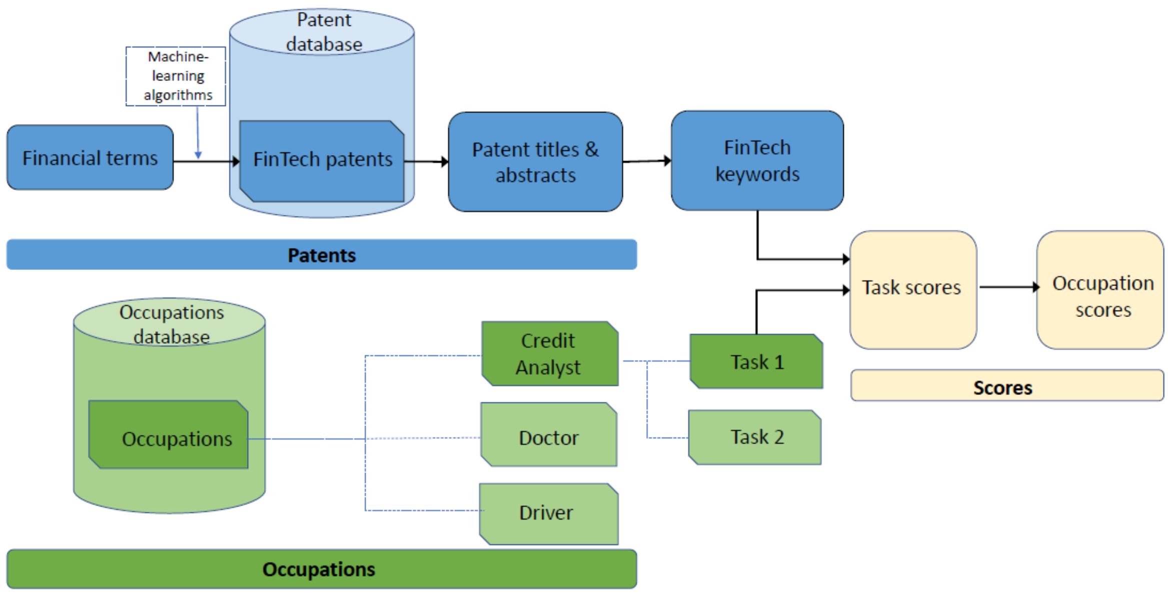
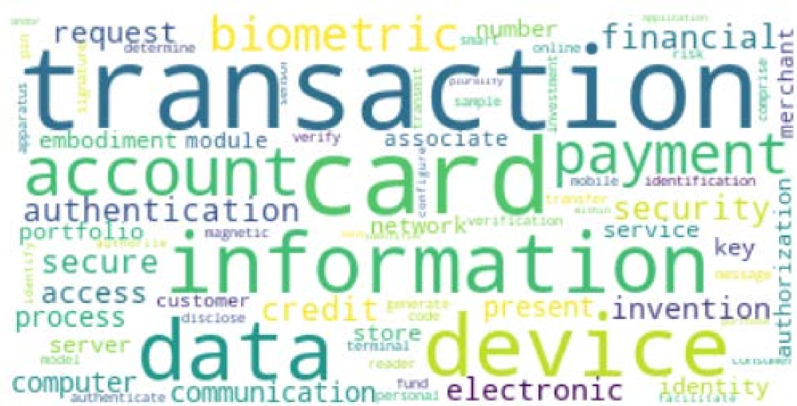
Figure 1. Process of Constructing Fintech Exposure Measure at Occupation Level



This diagram illustrates the process of how we construct the fintech exposure at occupation level. We extract a list of keywords in the titles and abstracts of fintech patent filings and another list of keywords in the description of each job task in O*NET occupation data. We then analyze the overlap between the two using the textual analysis. The fintech exposure measure captures both the cosine similarity between the two text corpuses and the intensity of fintech innovations (i.e., the amount of fintech innovations). The task-level score is aggregated to occupation level using the weights based on task importance, relevance, and frequency in O*NET occupation data.

Figure 2. Most Frequent Keywords in Fintech Patents

A: 2003-2006 Fintech Patent Applications



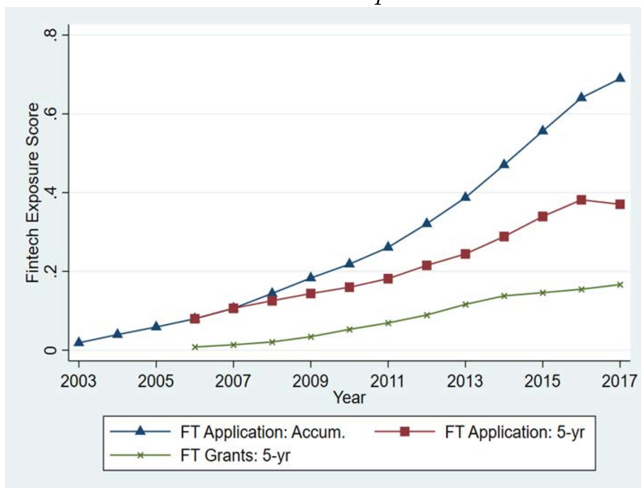
B: 2017 Fintech Patent Applications

C: 2003-2017 Fintech Patent Applications

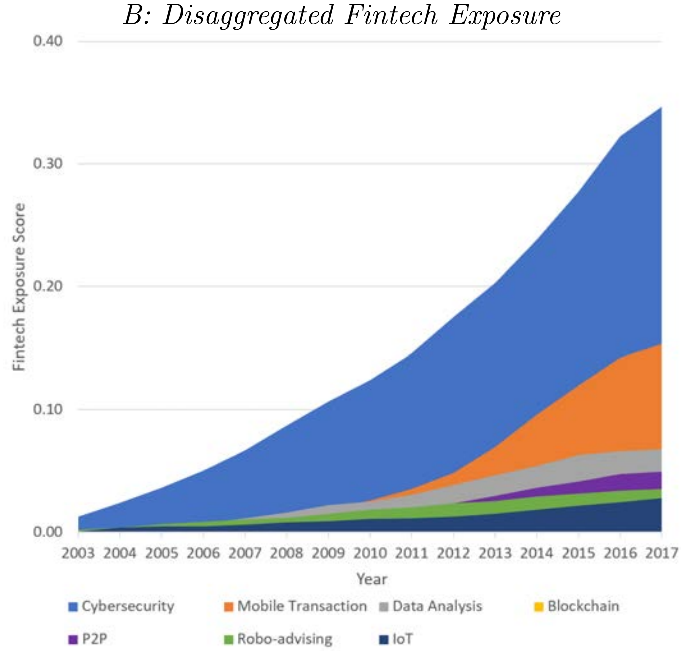
This figure presents the clouds of keywords in the fintech patents filed in 2003-2006 (Panel A), 2017 (Panel B) and 2003-2017 (Panel C), respectively. Font size indicates the frequency of the keywords. We only display top 75 keywords in each panel.

Figure 3. Fintech Exposure Measures

A: Fintech Exposure



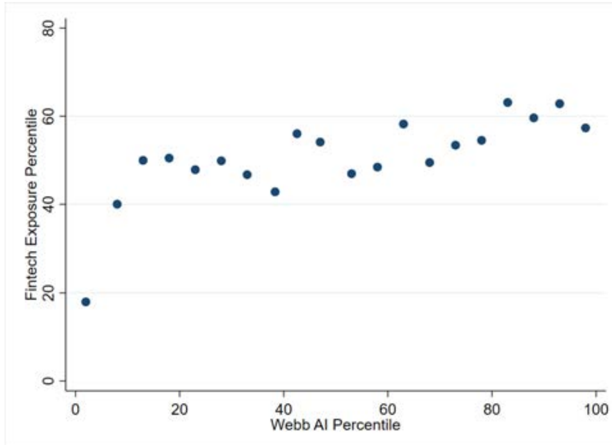
B: Disaggregated Fintech Exposure



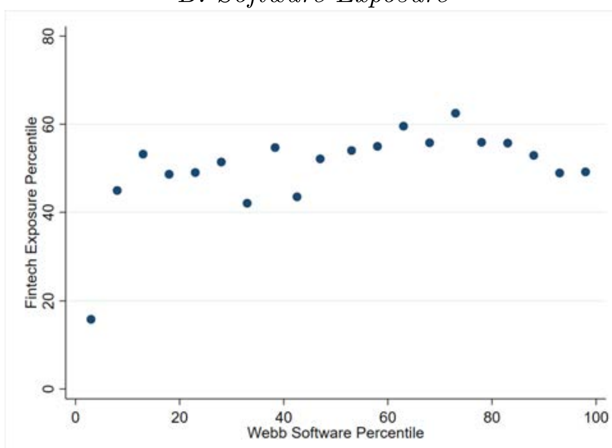
The figure plots the time trend of average fintech exposure measures over time. Panel A plots three overall fintech exposure measures: (i) one constructed using all fintech patent applications ending in a given year (blue line), (ii) one constructed using fintech patent applications in the five-year period ending in a given year (red, the default used in our analysis), and (iii) one constructed using granted fintech patents in the five-year period ending in a given year (green). Panel B plots time series of average disaggregated fintech exposure measures constructed using the subset of fintech patent in each of the seven fintech subcategories filed in the five-year period ending in a given year.

Figure 4. Correlation with Other Occupational Exposure Measures

A: AI Exposure

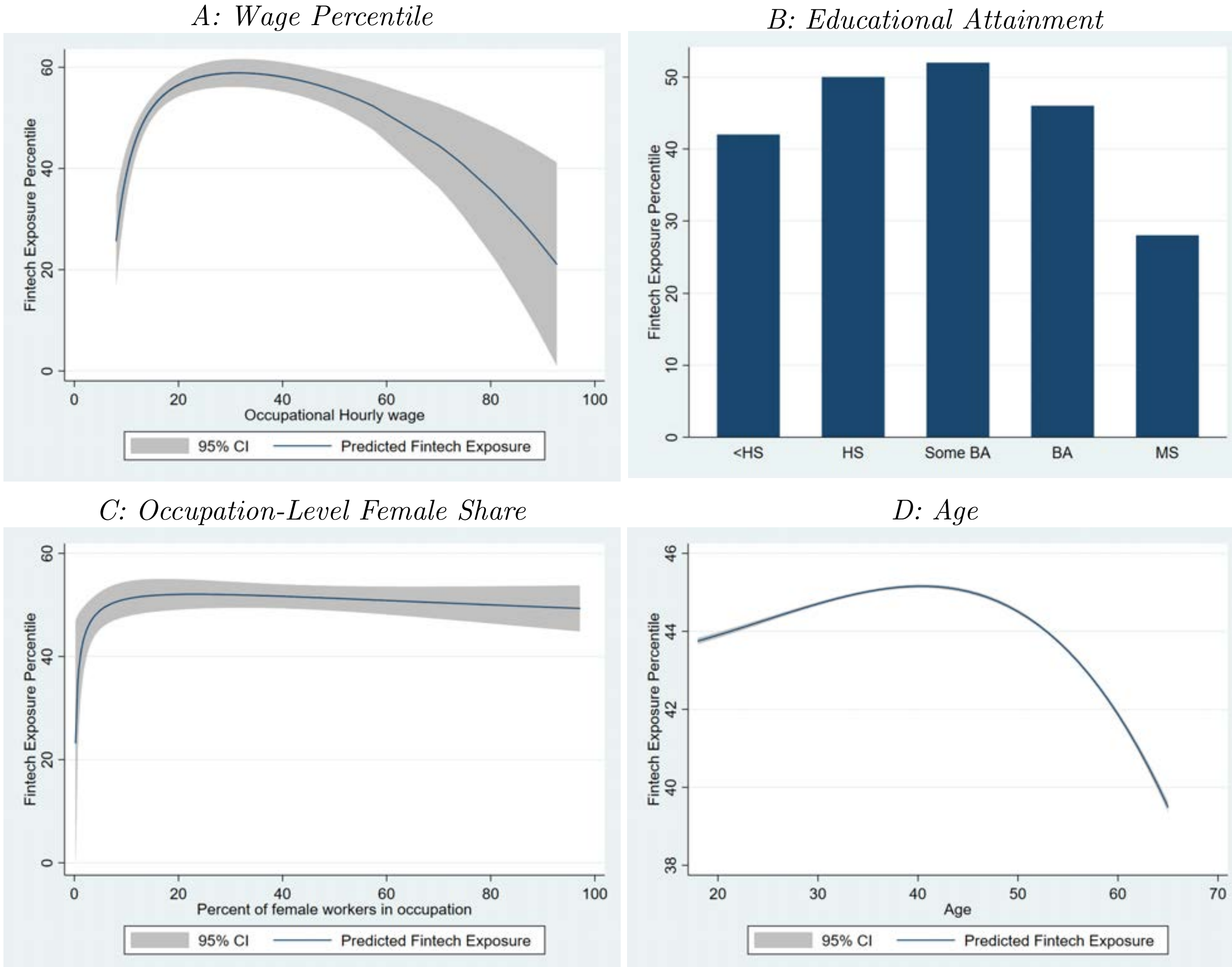


B: Software Exposure



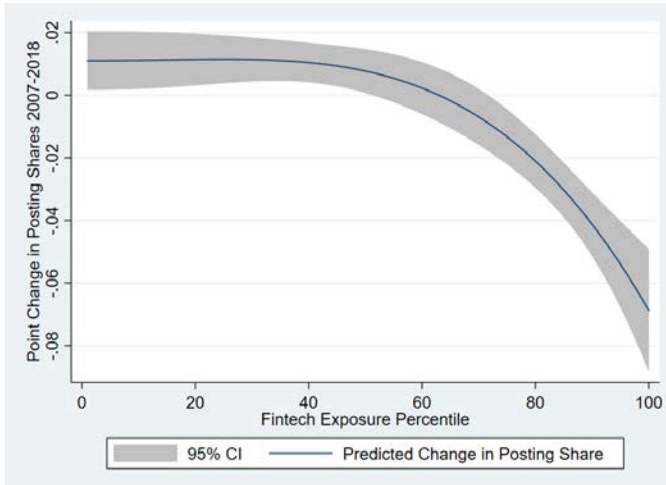
The figure presents the correlation between occupational fintech exposure and two occupational exposure measures constructed by Webb (2019): AI and software. We transform the fintech exposure scores to percentiles at 6-digit SOC level and plot the average fintech exposure percentile over the AI and software exposure measures. All the data series are at occupation level. The fintech exposure measure is constructed by the authors based on fintech patent filings from 2003 to 2017.

Figure 5. Fintech Exposure by Demographic Characteristics



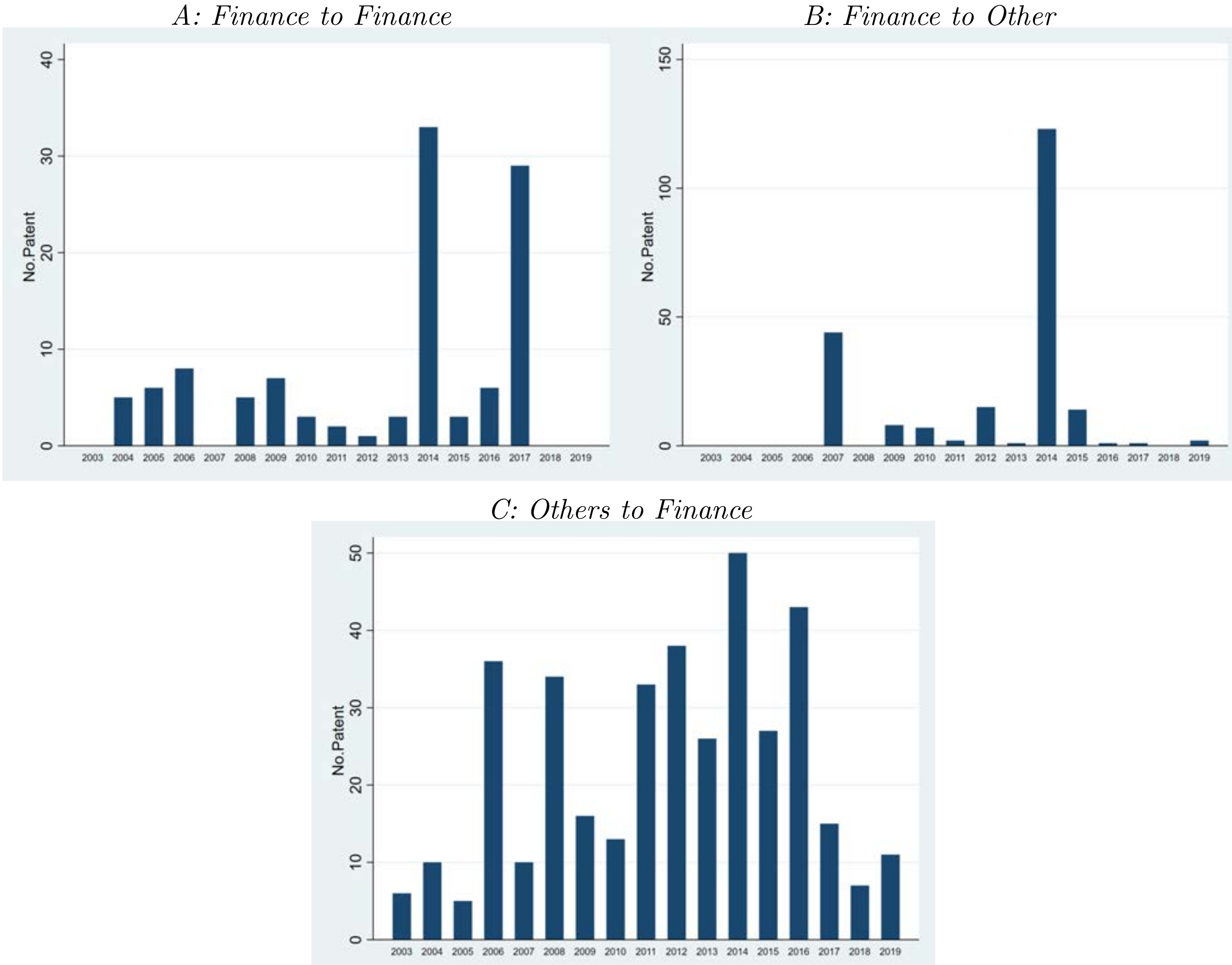
The figure plots demographic characteristics of occupations with different fintech exposure. Panel A shows the fractional-polynomial prediction of the average occupation-level fintech exposure percentiles by occupational wage (measured as an occupation's mean hourly wage from OES data released in May 2007). Panel B plots the fintech exposure percentiles averaged across all workers in each educational category in the 2007 IPUMS. Panel C plots the prediction of the average fintech exposure percentiles by the percent of female workers in each occupation in the 2007 IPUMS. Panel D plots the predicted average fintech exposure percentiles by the age cohort of all workers in the 2007 IPUMS. The fintech exposure measure is constructed by the authors based on fintech patent filings from 2003 to 2017.

Figure 6. Cumulative Change in Posting Share



The figure plots the relation between occupation-level fintech exposure and cumulative change in job posting shares. The y-axis is the cumulative change in job posting shares from 2007 to 2018 based on BGT data, and the x-axis is the time-invariant occupation-level fintech exposure percentiles. The fintech exposure measure is constructed by the authors.

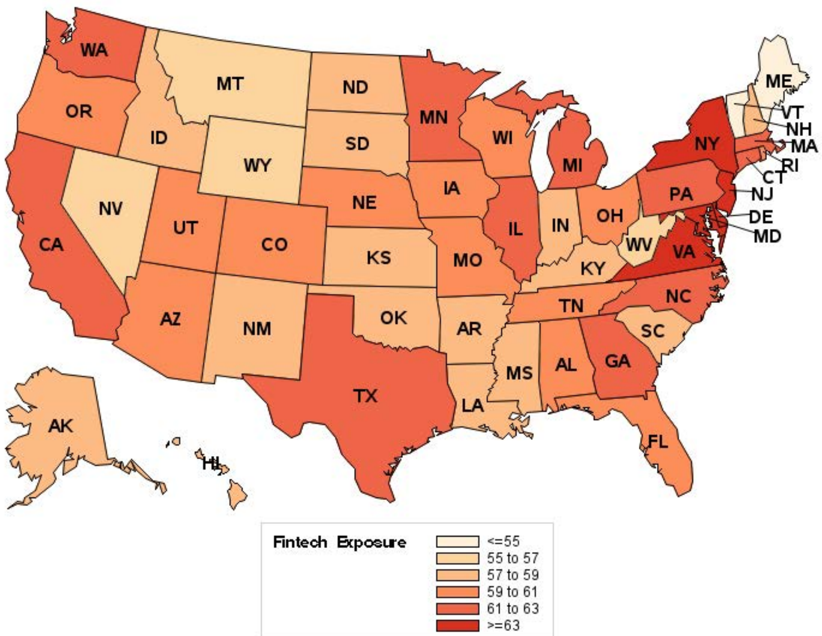
Figure 7. Fintech Patent Assignments In and Out of Finance Sector



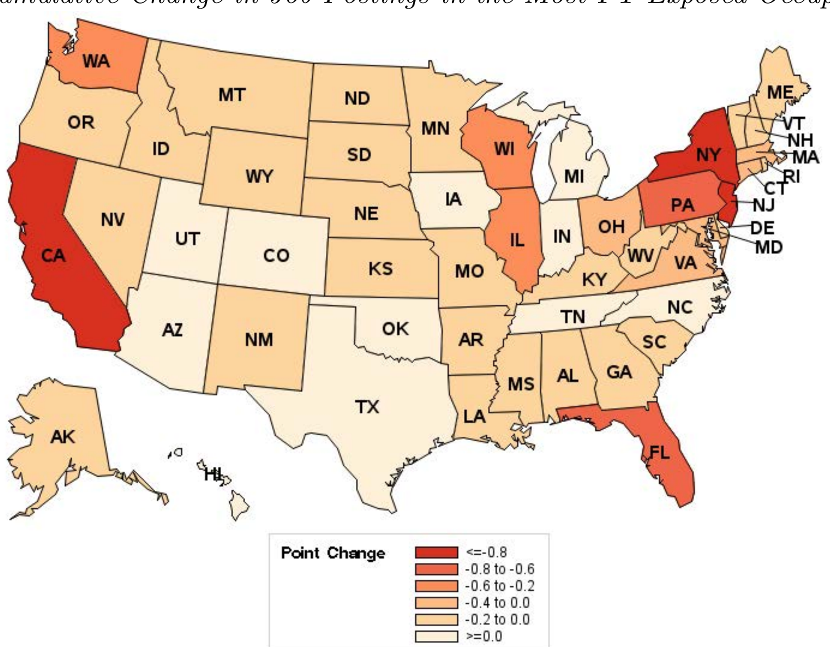
This figure plots the time trend of fintech patent assignments transacted in 2003-2019. We aggregate the assignments into three flows: Panel A shows flows from finance to finance, Panel B shows those from finance to other industries, and Panel C shows those from other industries to finance. Most fintech patents are transferred to finance from other industries, in particular between 2012-2016. Two jumps in Panel B are results of purchases by NPEs from financial firms. In 2007, Xatra Fund MX LLC, an intellectual venture, acquired 44 fintech patents from American Express. In 2014, III Holdings 1, LLC purchased a 121 fintech patents from American Express. In 2016, Bank of America and Visa acquired more than 10 fintech patents. This analysis is based on patent assignment data available at USPTO.

Figure 8. Geographic Distribution of Fintech Exposure

A: Fintech Exposure



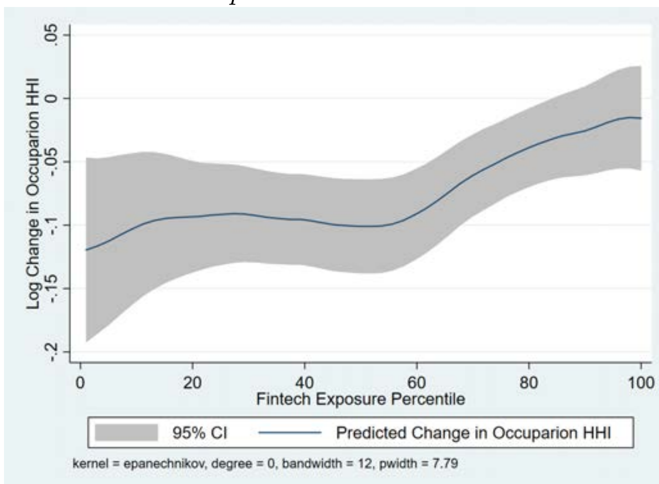
B: Δ Cumulative Change in Job Postings in the Most FT-Exposed Occupations



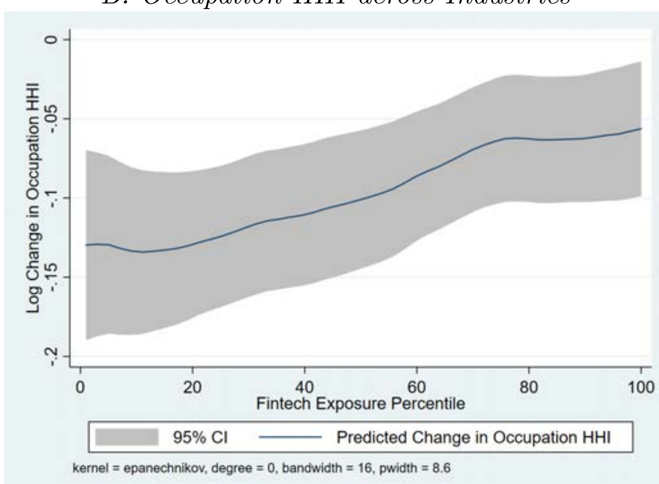
The figure plots the relation between fintech exposure and cumulative change in job posting shares at state level. Panel A plots state-level average of occupational fintech exposure percentiles weighted by job postings in 2007. Panel B plots the accumulative change of job posting shares in the most FT exposed occupations (top quartile) from 2007 to 2018 at state level. The change in job postings are calculated using BGT job postings in 2007 and 2018. The fintech exposure measure is constructed by the authors based on fintech patent filings from 2003 to 2017.

Figure 9. Changes in Occupation Concentration

A: Occupation HHI across States



B: Occupation HHI across Industries



This figure plots the relation between occupation-level fintech exposure and cumulative change in concentration of occupations across states (Panel A) and industries (Panel B), respectively, using a locally weighted smoothing regression following Acemoglu and Autor (2011). Bandwidth is set to 1.2 with 100 observations for Panel A and 1.6 for Panel B. The y-axis is the accumulative change from 2007 to 2018 in the natural logarithm of occupational HHI index across states in Panel A and across NAICS two-digit industry in Panel B. The x-axis is the time-invariant occupation-level fintech exposure percentiles. The fintech exposure measures are constructed by the authors based on fintech patent filings from 2003 to 2017.

Table 1: Measuring Occupation-Level Fintech Exposure: An Illustration

Occupation Title	Job Task	Weight in Occupation	Top 5 Keywords (frequency)	FT Exposure
Credit Analysts	◇ Analyze credit data and financial statements to determine the degree of risk involved in extending credit or lending money.	0.114	data (7142), financial (3606), credit (2023), risk (1421), determine (681)	0.144
	◇ Consult with customers to resolve complaints and verify financial and credit transactions.	0.112	financial (3606), transactions (2773), credit (2023), verify (252), customers (235)	0.100
	◇ Generate financial ratios, using computer programs, to evaluate customers' financial status.	0.105	financial (3606), using (3243), computer (2271), generate (556), customers (235)	0.126
Information Security Analysts	◇ Monitor current reports of computer viruses to determine when to update virus protection systems.	0.096	systems (2662), computer (2271), determine (681), current (324), protection (80)	0.060
	◇ Monitor use of data files and regulate access to safeguard information in computer files.	0.093	data (7142), information (6333), computer (2271), access (1590), use (1474)	0.180
	◇ Confer with users to discuss issues such as computer data access needs, security violations, and programming changes.	0.091	data (7142), computer (2271), security (1616), access (1590), users (463)	0.117
Mathematical Science	◇ Maintain regularly scheduled office hours to advise and assist students.	0.066	maintain (50), assist (37), office (18), scheduled (5), advise (1)	0.001
Teachers, Post-	◇ Maintain student attendance records, grades, and other required records.	0.064	required (183), records (163), maintain (50), grades (3), attendance (2)	0.006
secondary	◇ Prepare and deliver lectures to undergraduate or graduate students on topics such as linear algebra, differential equations, and discrete mathematics.	0.063	deliver (26), discrete (22), differential (12), prepare (6), linear (3)	0.001
Orthodontists	◇ Adjust dental appliances to produce and maintain normal function.	0.114	function (249), produce (58), maintain (50), normal (31), adjust (23)	0.005
	◇ Fit dental appliances in patients' mouths to alter the position and relationship of teeth and jaws or to realign teeth.	0.108	position (110), relationship (83), fit (30), alter (6), appliances (5)	0.002
	◇ Study diagnostic records, such as medical or dental histories, plaster models of the teeth, photos of a patient's face and teeth, and X-rays, to develop patient treatment plans.	0.106	models (179), records (163), medical (37), face (37), treatment (37)	0.004

This table presents information about four occupations selected to illustrate the process of constructing the occupational fintech exposure measure. In particular, we show top three tasks along with their weights and most frequent keywords matched with those in fintech patents for each of the four occupations. The two occupations on the top (i.e., credit analysts and information security analysts) have high exposure to fintech while the two in the bottom (i.e., mathematical science teachers and orthodontists) have low exposure to fintech.

Table 2: Occupations with Highest and Lowest Fintech Exposure Scores

O*NET SOC	Occupation Title	FT Exposure	FT Percentile
	Top 10 Occupations with the Highest FT Exposure		
15-1122	Information Security Analysts	3.25	100
13-2041	Credit Analysts	3.07	100
15-1132	Software Developers, Applications	2.74	100
41-3041	Travel Agents	2.73	100
17-2072	Electronics Engineers, Except Computer	2.52	100
15-1121	Computer Systems Analysts	2.47	100
15-1133	Software Developers, Systems Software	2.43	100
15-1142	Network and Computer Systems Administrators	2.40	99
43-9111	Statistical Assistants	2.37	99
15-2041	Statisticians	2.26	99
	Bottom 10 Occupations with the Lowest FT Exposure		
35-9011	Dining Room and Cafeteria Attendants ...	0.18	2
25-1054	Physics Teachers, Postsecondary	0.18	2
35-3011	Bartenders	0.18	1
47-3014	Helpers–Painters, Paperhangers, Plasterers ...	0.17	1
27-2031	Dancers	0.17	1
53-3011	Ambulance Drivers and Attendants ...	0.16	1
29-1023	Orthodontists	0.16	1
33-1012	First-Line Supervisors of Police and Detectives	0.16	1
51-3023	Slaughterers and Meat Packers	0.15	1
47-3012	Helpers–Carpenters	0.11	1

This table lists top 10 and bottom 10 occupations based on their exposure to fintech innovations. Fintech exposure is the time-invariant fintech exposure score based on all fintech patent applications filed in 2003-2017. Fintech percentile is the percentile rank based on the fintech exposure measure.

Table 3: Summary Statistics

Variables	N	Mean	SD	P25	P50	P75	Min	Max
Occupational Exposure Measures								
Fintech Score (5-Year Application)	290,895	0.27	0.20	0.14	0.22	0.33	0.02	1.74
Fintech Percentile	290,895	51.95	28.81	27	53	77	1	100
Fintech Quartile 4 Dummy	290,896	0.27	0.44	0	0	1	0	1
Fintech Percentile - Cybersecurity	290,895	51.83	28.90	27	53	77	1	100
Fintech Percentile - Mobile Transaction	290,895	51.72	28.82	27	52	77	1	100
Fintech Percentile - Data Analysis	290,895	52.43	28.64	28	53	78	1	100
Fintech Percentile - Blockchain	290,895	18.10	29.14	1	1	28	1	100
Fintech Percentile - P2P	290,895	51.50	28.85	27	52	77	1	100
Fintech Percentile - Robo-advising	290,895	53.04	28.68	28	54	78	1	100
Fintech Percentile - IoT	290,895	51.43	28.88	27	52	77	1	100
AI Percentile	324,892	51.01	28.29	27	51	75	1	100
Software Percentile	324,892	49.86	28.16	26	49	74	1	100
Robot Percentile	324,892	48.89	28.23	25	47	73	1	100
Job Posting Variables								
No of Postings	324,892	440	1,205	15	60	275	3	12,483
Unweighted Posting Shares (Basis Point)	324,892	15.70	40.19	0.83	3.17	13.25	0.01	1,975
- Most Exposed Occupations	87,305	20.75	39.86	1.49	5.60	20.86	0.021	648
Weighted Posting Shares (Basis Point)	324,892	90.20						
- Most Exposed Occupations	87,305	86.71						
Finance & Software Skills (%)	324,892	5.09	9.31	0	0.30	6.39	0	52.80
Finance No Software Skills (%)	324,892	6.57	10.90	0	1.90	8.33	0	66.10
Software No Finance Skills (%)	324,892	15.50	18.30	0.97	8.74	23.40	0	84.60
High School (%)	324,892	21.80	22.20	0	16.20	35.70	0	95.70
Bachelor's Degree and above (%)	324,892	21.50	26.50	0	8.33	38.70	0	100
1-4 Years Experiences (%)	324,892	27.44	18.99	13.04	26.21	39.22	0.00	81.84
4+ Years Experiences (%)	324,892	9.82	13.10	0	3.96	14.90	0	61.70
Local Socio-Demographic Variables								
Median Age	324,892	40.34	0.79	39.96	40.35	40.77	37.17	42.63
Female (%)	324,892	47.30	1.35	46.40	47.50	48.10	43.70	52.00
Bachelor's Degree and Above (%)	324,892	32.11	5.75	28.14	30.79	35.58	20.59	63.76
Business Major Degree (%)	324,892	6.34	2.01	6.00	6.71	7.47	0.00	9.92
Tech Major Degree (%)	324,892	2.37	0.94	1.96	2.38	3.02	0.00	5.81
Union Membership (%)	324,892	10.60	5.32	5.80	10.20	14.50	1.60	25.20

The table reports the summary statistics of the main sample at occupation $\times$ state $\times$ year level. Posting share is the fraction of job postings at cohort level to the state totals in a given year. The occupation-level fintech exposure measures are calculated by the authors (as described in Section 3.1.1). Occupational exposure to AI and software are from Webb (2019). All job posting variables, including number and share of postings as well as fraction of job postings that require different skills, experience, and educational attainment, are calculated using BGT data in 2007 and 2010-2018. State-level demographic characteristics are from IPUMS and CPS datasets in 2007-2018.

Table 4: Industry Distribution of Fintech Exposure

NAICS Code	Industry Title	FT Percentile	Post Share$_0$ All Occupations	Post Share$_0$ Most FT-Exposed	Δ Posting Share All Occupations	Δ Posting Share Most FT-Exposed
		(1)	(2)	(3)	(4)	(5)
11	Agriculture	60.48	0.09	0.04	0.01	0.00
21	Mining	66.24	0.50	0.24	-0.19	-0.10
22	Utilities	67.61	0.50	0.27	-0.13	-0.09
23	Construction	59.86	1.44	0.67	0.17	-0.13
31-33	Manufacturing	66.60	8.64	4.37	-2.24	-1.66
42-45	Wholesale and Retail Trade	62.13	7.04	1.88	6.20	1.18
48-49	Transportation and Warehousing	65.49	2.53	0.61	4.61	0.07
51	Information	70.31	6.28	3.10	-2.73	-1.56
52	Finance and Insurance	79.77	12.93	9.53	-4.38	-3.63
53	Real Estate Rental and Leasing	55.32	1.96	0.53	0.24	0.00
54-56	Professional, Management and Admin	71.72	21.08	11.53	-5.72	-3.93
61	Educational Services	43.81	5.41	1.77	1.37	-0.09
62	Health Care and Social Assistance	51.74	18.93	4.84	-2.30	-0.99
71	Arts, Entertainment, and Recreation	48.71	0.51	0.14	0.67	0.10
72	Accommodation and Food Services	39.95	6.23	0.93	4.28	0.05
81	Other Services	53.94	2.06	0.47	0.28	0.04
92	Public Administration	59.73	3.82	1.41	-0.11	-0.06
All Industries		63.00	100	42.35	0.00	-10.73
Correlation with FT		1.00	0.23	0.52	-0.51	-0.59

This table reports industry distribution of fintech exposure and changes in job posting shares. Fintech percentile is the industry average of occupational fintech exposure percentiles weighted by job postings in 2007. All the job posting variables are calculated using BGT data in 2007 and 2010-2018.

Table 5: Fintech Exposure and Job Posting Change

Panel A: Baseline Specification

Dep Var	Basis Point Change in Posting Shares							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FT Percentile	-0.067***	-0.064***	-0.085***	-0.084***				
	(-10.163)	(-11.408)	(-7.502)	(-7.580)				
FT Quartile 4					-4.378***	-4.047***	-4.661***	-4.592***
					(-8.391)	(-9.099)	(-7.548)	(-7.601)
AI Percentile			-0.028***	-0.028***			-0.028***	-0.029***
			(-3.728)	(-3.930)			(-3.831)	(-4.043)
Software Percentile			0.053***	0.054***			0.055***	0.055***
			(8.094)	(8.178)			(7.883)	(7.955)
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
State FE	No	Yes	Yes	No	No	Yes	Yes	No
State × Year FE	No	No	No	Yes	No	No	No	Yes
N	277,075	277,075	277,075	277,075	277,075	277,075	277,075	277,075
R^2	0.012	0.026	0.031	0.090	0.013	0.026	0.031	0.089

Panel B: Dis-aggregated FT Exposure

Dep Var	Basis Point Change in Posting Shares						
Indep Var	Cyber-security	Mobile Transaction	Data Analysis	Block-chain	P2P	Robo-advising	IoT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FT Quartile 4	-4.537***	-4.128***	-5.613***	-5.156***	-3.507***	-5.725***	-2.634***
	(-7.69)	(-7.45)	(-6.93)	(-6.15)	(-6.32)	(-6.47)	(-6.60)
AI Percentile	-0.031***	-0.035***	-0.025***	-0.036***	-0.045***	-0.021**	-0.032***
	(-4.25)	(-5.19)	(-3.33)	(-5.20)	(-6.97)	(-2.58)	(-4.56)
Software Percentile	0.055***	0.056***	0.050***	0.048***	0.050***	0.042***	0.054***
	(7.99)	(7.88)	(7.69)	(7.96)	(7.96)	(7.14)	(8.16)
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	277,075	277,075	277,075	277,075	277,075	277,075	277,075
R^2	0.089	0.089	0.092	0.087	0.087	0.093	0.086

The table reports the baseline regressions that estimate the effect of fintech exposure on changes in job postings at occupation × state × year level. The dependent variable is the year-over-year change of job posting share. The posting share is calculated as the share of job posting in each cell relative to the state total in that year using the BGT data. The main explanatory variable is the lagged occupational fintech exposure percentile (SOC 6-digit) that varies over time and is constructed using fintech patent applications in 5-year rolling window ending in a given year. FT Quartile 4 dummy equals one if an occupation's fintech exposure is in the top quartile, and zero otherwise. In Panel B, fintech exposure measures are constructed using a subset of fintech patent applications: cybersecurity, mobile transactions, data analytics, blockchain, P2P, robo-advising, and IoT. AI percentile and software percentile are the percentile ranks of occupation-level AI exposure and software exposure scores, respectively, developed by Webb (2019). We also control for the cohort-level initial posting share in columns (3)-(4) and (7)-(8) of Panel A and all columns of Panel B. All regressions are weighted by the number of job postings. Sample is constructed using BGT data in 2007 and 2010-2018. Standard errors are clustered at state level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 6: Changes in Skill and Education Requirements

Dep Var	Basis Point Change in Posting Shares that Require						
	Different Skills			Years of Experience		Minimum Degree	
	Finance & Software	Finance No Software	Software No Finance	0-4 Years	4+ Years	HS & Below	BA & Above
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FT Quartile 4	29.584***	-16.819***	19.721***	13.548***	36.319***	-11.980***	50.567***
	(18.78)	(-10.23)	(10.36)	(10.21)	(13.94)	(-5.81)	(21.41)
AI Percentile	0.338***	0.077***	0.338***	0.166***	0.732***	-0.860***	1.513***
	(17.44)	(2.70)	(9.12)	(5.15)	(17.24)	(-15.20)	(25.81)
Software Percentile	-0.470***	0.076**	-0.082***	-0.084***	-0.286***	0.685***	-1.310***
	(-21.93)	(2.09)	(-2.95)	(-3.01)	(-7.85)	(14.52)	(-27.88)
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	277,075	277,075	277,075	277,075	277,075	277,075	277,075
R^2	0.156	0.056	0.209	0.106	0.213	0.143	0.222

The table reports the regression results examining the effect of occupational fintech exposure on skill requirements of the postings at occupation × state × year level. The dependent variable is the year-over-year change in job posting shares that require skills specified in the column title in columns (1)-(3), require experiences specified in the column title in columns (4)-(5) and educational attainment specified in the column title in columns (6)-(7). The main explanatory variable, FT Quartile 4 dummy, equals one if the lagged occupation's fintech exposure percentile (SOC 6-digit) constructed using fintech patent applications in 5-year rolling window is in the top quartile, and zero otherwise. AI percentile and software percentile are the percentile ranks of occupation-level AI exposure and software exposure scores, respectively, developed by Webb (2019). We also control for the cohort-level initial posting shares and state × year fixed effects. All the regressions are weighted by the number of job postings. Sample is constructed using BGT data in 2007 and 2010-2018. Standard errors are clustered at state level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 7: Effect of Labor Force Characteristics (State Level)

Dep Var	Basis Point Change in							
	Posting Shares				Employment Shares			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FT Quartile 4	-6.698***	-6.827***	-6.135***	-4.947***	-0.474***	-0.499***	-0.415***	-0.401**
	(-8.90)	(-9.15)	(-8.86)	(-4.96)	(-3.58)	(-3.77)	(-3.32)	(-2.22)
× % BA+	0.003				0.050***			
	(0.06)				(3.39)			
× % Business Degree		0.649*				0.150**		
		(1.72)				(2.01)		
× % IT Degree			1.095**				0.451***	
			(2.47)				(3.80)	
× % Union Membership				0.032				0.021*
				(0.40)				(1.72)
AI Percentile	-0.029***	-0.029***	-0.029***	-0.029***	0.004**	0.004**	0.004**	0.004**
	(-4.04)	(-4.05)	(-4.05)	(-4.04)	(2.11)	(2.10)	(2.10)	(2.14)
Software Percentile	0.056***	0.056***	0.056***	0.055***	0.001	0.001	0.001	0.001
	(8.09)	(8.10)	(8.08)	(7.95)	(0.79)	(0.79)	(0.79)	(0.81)
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	277,075	277,075	277,075	277,075	184,861	184,861	184,861	184,861
R^2	0.090	0.090	0.090	0.089	0.085	0.085	0.085	0.085

The table reports the regression results examining the effect of state-level labor force characteristics on the labor market responses to fintech exposure at occupation × state × year level. The dependent variable is the year-over-year change in job posting shares in columns (1)-(4) and change in employment shares in columns (5)-(8). The main explanatory variables are the interaction of FT Quartile 4 dummy, which equals one if the lagged occupation's fintech exposure percentile (SOC 6-digit) constructed using fintech patent applications in 5-year rolling window is in the top quartile, and zero otherwise, and four state-level labor market variables in the prior year. The four state-level variables are the percentages of state labor force with a BA+ degree, with a business degree, and with an information technology degree, respectively, and the percentage of union members in the non-agricultural sectors. The union membership data is provided and updated by Hirsch et al. (2001). AI percentile and software percentile are the percentile ranks of occupation-level AI exposure and software exposure scores, respectively, developed by Webb (2019). We also control for the cohort-level initial posting shares and state × year fixed effects. All the regressions are weighted by the number of job postings in columns (1)-(4) and employment in 2009-2018 in columns (5)-(8). Sample is constructed using BGT job posting data in 2007 and 2010-2018 in columns (1)-(4) and IPUMS employment data in 2009-2018 in columns (5)-(8). Standard errors are clustered at state level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 8: Occupational Concentration

Dep Var	ΔLog(Occupational HHI)			
	Across State		Across Industry	
	YoY	2007-2018	YoY	2007-2018
	(1)	(2)	(3)	(4)
FT Quartile 4	0.011***	0.067***	0.001	0.057***
	(3.69)	(6.46)	(0.75)	(3.10)
AI Percentile	-0.000	-0.001***	-0.000*	0.002***
	(-0.11)	(-3.39)	(-1.72)	(3.42)
Software Percentile	-0.000	0.000	0.000	-0.001**
	(-0.57)	(0.77)	(0.16)	(-1.98)
Year FE	Yes	Yes	Yes	Yes
N	6,911	767	6,867	761
R^2	0.086	0.064	0.004	0.030

The table reports the regressions that examine the change in concentration of occupations across states and industries in response to occupational fintech exposure. We measure concentration using the HHI. The dependent variable is the change in the natural logarithm of a given occupations' HHI across states in columns (1)-(2) and industries in columns (3)-(4). The dependent variable in columns (1) and (3) is year-to-year change while that in columns (2) and (4) is the log difference between 2007 and 2018. The main explanatory variable is FT Quartile 4 dummy that equals one if occupation's fintech exposure percentile (SOC 6 digit) constructed using fintech patent applications in 5-year rolling window is in the top quartile, and zero otherwise in columns (1) and (3). In columns (2) and (4), it is constructed based on all fintech patent applications in 2003-2017. AI percentile and software percentile are the percentile ranks of occupation-level AI exposure and software exposure scores, respectively, developed by Webb (2019). We also control for year fixed effects in all regressions. All the regressions are weighted by the number of job postings of a given occupation and standard errors are clustered at occupation level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 9: Labor Market Response of Financial Sector vs. Others

Dep Var	Basis Point Change in Posting Shares			
	(1)	(2)	(3)	(4)
FT Quartile 4 - Most Disruptive	0.195	0.316	0.353	0.471*
	(0.768)	(1.179)	(1.335)	(1.693)
× Financial Sector		-1.233***		-1.317***
		(-3.545)		(-3.721)
FT Quartile 4 - Less Disruptive	-0.965***	-1.130***	-0.934***	-1.104***
	(-3.320)	(-3.618)	(-3.226)	(-3.543)
× Financial Sector		1.985***		1.842***
		(4.855)		(4.630)
Financial Sector		-0.690***		
		(-6.478)		
AI Percentile	-0.009***	-0.008***	-0.004***	-0.004***
	(-6.593)	(-6.409)	(-2.805)	(-3.000)
Software Percentile	0.007***	0.007***	0.005***	0.005***
	(6.650)	(6.215)	(4.537)	(4.597)
State × Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
N	1,010,853	1,010,853	1,010,853	1,010,853
R^2	0.048	0.048	0.052	0.052

The table reports the regressions that examine the heterogeneity in labor market adjustments by the financial sector vs. others in response to fintech exposure at occupation × state × industry (NAICS 2-digit) × year level. The dependent variable is the year-over-year change of job posting share. The posting share is calculated as the share of job posting at cohort level relative to the state totals in that year using the BGT data. The main explanatory variables are the two fintech exposure measures—indicators for the most exposed occupations to the most and less disruptive fintech innovations, respectively. Both fintech exposure measures are constructed at SOC 6-digit level using the most and less disruptive fintech patent applications to the finance industry in 5-year rolling window, respectively. We interact the fintech exposure measures with the the financial sector dummy (NAICS 52). AI percentile and software percentile are the percentile ranks of occupation-level AI exposure and software exposure scores, respectively, developed by Webb (2019). We control for the cohort-level initial posting shares and state by year fixed effects. We additionally control for two-digit NAICS industry fixed effects in columns (3)-(4). All the regressions are weighted by the number of job postings. Standard errors are clustered at state level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 10: Innovation Response of Financial Firms vs. Others

Dep Var	Log(Invented Fintech Patents) × 100				Log(Acquired Fintech Patents) × 100			
	All Patents	Most Disruptive	All Patents	Most Disruptive	All Patents	Most Disruptive	All Patents	Most Disruptive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FT Quartile 4 - Most Disruptive	-0.098	-0.045	-0.143	-0.064	-0.001	0.005	-0.035	-0.021
	(-1.21)	(-1.09)	(-1.54)	(-1.40)	(-0.04)	(0.29)	(-1.01)	(-1.23)
× Financial Firm			0.484***	0.200***			0.345***	0.272***
			(3.85)	(2.87)			(11.87)	(16.89)
FT Quartile 4 - Less Disruptive	0.095	0.045	0.099	0.047	0.035	0.019	0.022	0.011
	(1.61)	(1.25)	(1.58)	(1.16)	(0.76)	(0.94)	(0.54)	(0.91)
× Financial Firm			-0.067	-0.034			0.151***	0.091***
			(-0.79)	(-0.56)			(4.82)	(6.39)
Log(Annual Job Postings)	-0.002	0.005	-0.002	0.005	0.006	-0.004	0.007	-0.004
	(-0.21)	(1.09)	(-0.18)	(1.10)	(0.49)	(-1.18)	(0.53)	(-1.18)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	107,959	107,959	107,959	107,959	107,959	107,959	107,959	107,959
R^2	0.681	0.690	0.681	0.690	0.200	0.147	0.200	0.147

The table reports the regressions that examine the change in innovation activities by financial firms vs. others in response to fintech exposure based on the firm × year sample that includes both public and private firms. The sample contains 26,031 unique firms in 2007 and 2010-2018 covered by the BGT data. The dependent variable is the logarithm of the number of fintech patents invented (× 100) in columns (1) and (3), the logarithm of the number of most disruptive fintech patents invented (× 100) in columns (2) and (4), the logarithm of the number of fintech patents acquired (× 100) in columns (5) and (7), and the logarithm of the number of most disruptive fintech patents acquired (× 100) in columns (6) and (8). The main explanatory variables are the two fintech exposure measures—indicators for the most exposed occupations to the most and less disruptive fintech innovations, respectively. Both fintech exposure measures are constructed at SOC 6-digit level using the most and less disruptive fintech patent applications to the financial industry in 5-year rolling window, respectively. We interact the fintech exposure measures with the financial firm dummy (NAICS 52). We control for firm and year fixed effects. Standard errors are clustered at NAICS two-digit and year level. Patent application and assignment data are obtained from USPTO. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 11: Differences between Innovator and Non-Innovator Firms

Dep Var	Basis Point Change in Posting Shares					
				Different Skills		
	All			financial + Software	Finance No Software	Software No Finance
	(1)	(2)	(3)	(4)	(5)	(6)
FT Quartile 4	-2.267***	-2.190***	-2.288***	28.727***	-9.545***	14.344***
	(-7.26)	(-7.33)	(-7.32)	(15.99)	(-4.13)	(7.46)
× Inventor	1.554***		1.575***	19.766***	19.082	4.734
	(4.71)		(4.78)	(2.92)	(1.37)	(0.40)
× Acquisition Innovator		2.321***	2.422***	-17.875	148.258***	-4.778
		(3.09)	(3.20)	(-0.79)	(3.99)	(-0.10)
AI Percentile	-0.043***	-0.043***	-0.043***	0.216***	-0.038	0.309***
	(-9.72)	(-9.73)	(-9.72)	(10.24)	(-0.92)	(6.97)
Software Percentile	0.053***	0.053***	0.053***	-0.349***	0.184***	0.062*
	(6.83)	(6.83)	(6.82)	(-19.26)	(3.22)	(1.99)
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Innovator FE	Yes	Yes	Yes	Yes	Yes	Yes
N	314,533	314,533	314,533	314,533	314,533	314,533
R^2	0.075	0.075	0.075	0.075	0.040	0.109

The table reports the regressions that examine the heterogeneity in labor market adjustments by fintech innovator and non-innovator firms in response to occupational fintech exposure. We define three types of firms based on inventor and assignee names of fintech patents: inventors, acquisition innovators (assignee), and non-innovators (reference group). All the regressions are based on firm type × occupation × state × year-level data in 2007 and 2010-2018. The dependent variable is the year-over-year change of job posting share in columns (1)-(3) and the year-over-year change of job posting share that require skills specified in the column title in columns (4)-(6). The posting share is calculated as the share of job posting at cohort level relative to the state total in that year using the BGT data. The main explanatory variable, FT Quartile 4 dummy, equals one if the lagged occupation's fintech exposure percentile (SOC 6-digit) constructed using fintech patent applications in 5-year rolling window is in the top quartile, and zero otherwise. We include the interaction terms of the fintech exposure measure with two fintech innovators dummy variables, and also control for AI and software percentiles developed by Webb (2019), cohort-level initial posting shares, and state by year fixed effects. All the regressions are weighted by the number of job postings. Standard errors are clustered at state level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

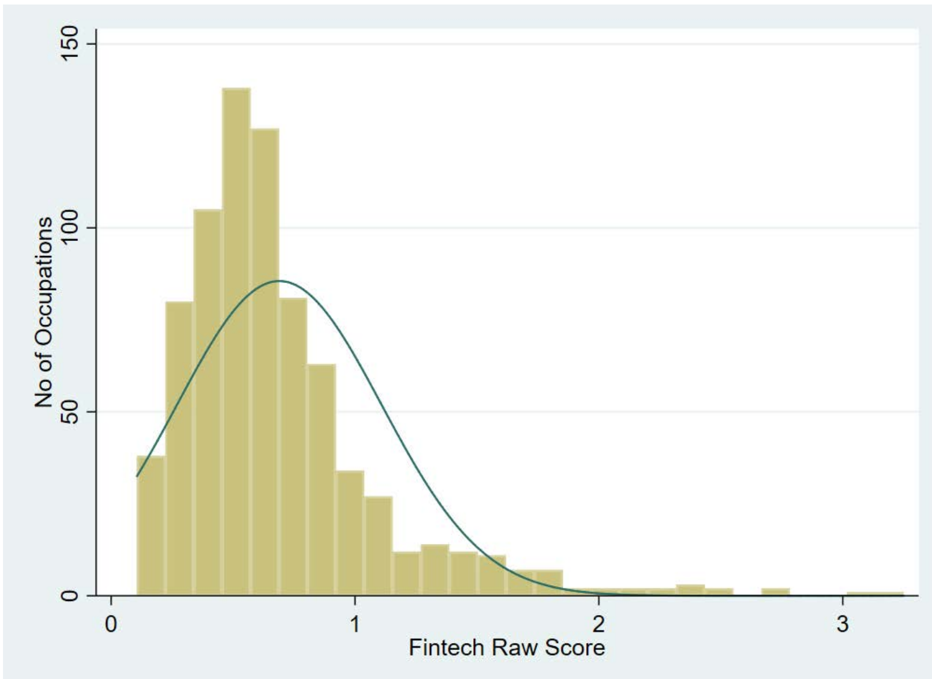
Table 12: Firm Outcomes

Dep Var	ΔLog(Employ) × 100		ΔLog(Sales) × 100		ΔLog(R&D) × 100		ROA × 100	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FT Quartile 4	-0.010**	-0.010**	-0.005	-0.006	0.018	0.018	-0.034	-0.038
	(-2.20)	(-2.30)	(-0.41)	(-0.44)	(1.61)	(1.62)	(-0.57)	(-0.64)
× Inventor		0.035**		0.056**		0.074*		0.202*
		(1.99)		(2.21)		(1.87)		(1.78)
× Non-Inventor Innovator		0.018		-0.026		-0.189		0.224
		(0.38)		(-0.46)		(-1.61)		(1.29)
Inventor		-0.027*		-0.044**		-0.041*		-0.266***
		(-1.90)		(-2.42)		(-1.84)		(-2.74)
Non-Inventor Innovator		-0.030		0.013		0.079		-0.274**
		(-1.09)		(0.37)		(1.63)		(-2.41)
Firm Attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16,746	16,746	17,007	17,007	14,157	14,157	14,836	14,836
R^2	0.054	0.054	0.055	0.055	0.047	0.047	0.143	0.144

The table reports the regressions that examine the relation between firm outcomes and fintech exposure based on the firm × year sample in 2007 and 2010-2018. The sample contains 2,243 firms. The dependent variable is the year-over-year change of firm outcomes: the number of employees in columns (1)-(2), annual sales in 2003 dollar in columns (3)-(4), R&D expenditure in columns (5)-(6) and ROA defined as annual net income over assets in columns (7)-(8) . Firm FT Quartile 4 is the lagged firm-level percentage of job postings that fall into the top quartile fintech-exposed occupations. We define two types of fintech innovators based on inventor and assignee names of the patent: inventor and non-inventor innovators (assignee). Control variables are lagged firm time varying attributes, including the natural logarithm of total assets in 2003 dollar, R&D expenditure in 2003 dollar, firm age, capital expenditure scaled by assets and cash scaled by assets. Additional controls include the market-to-book ratio defined as market capitalization scaled by assets in columns (1)-(2) and the net working capital scaled by assets in columns (3)-(4). We also control for NAICS four-digit industry and year fixed effects. Standard errors are clustered at NAICS four-digit level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Appendix

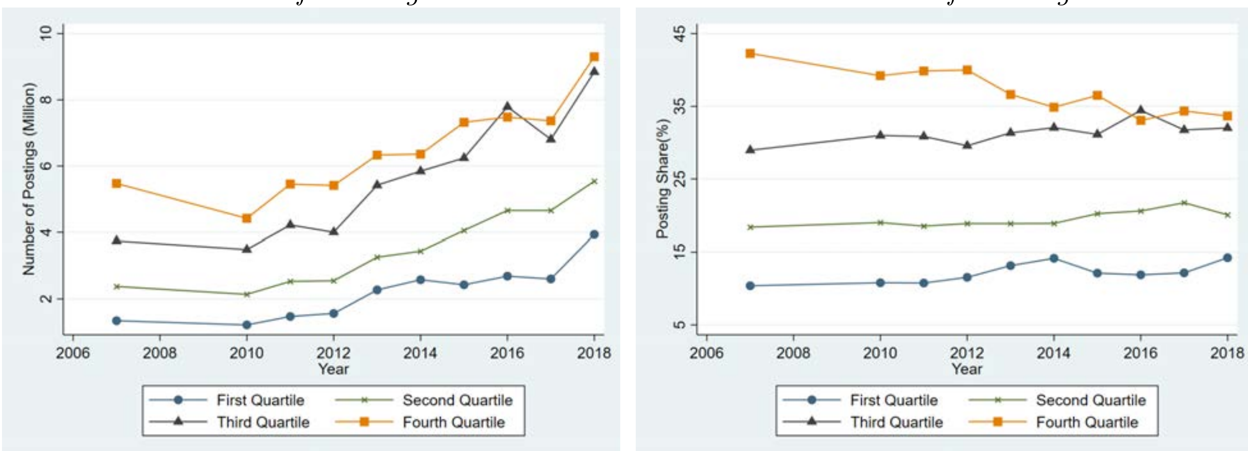
Figure A.1. Distribution of Occupational Fintech Exposure



The figure displays the distribution across six-digit SOC occupations of fintech exposure scores based on all fintech patent applications in 2003-2017.

Figure A.2. Job Postings by Fintech Exposure Quartile

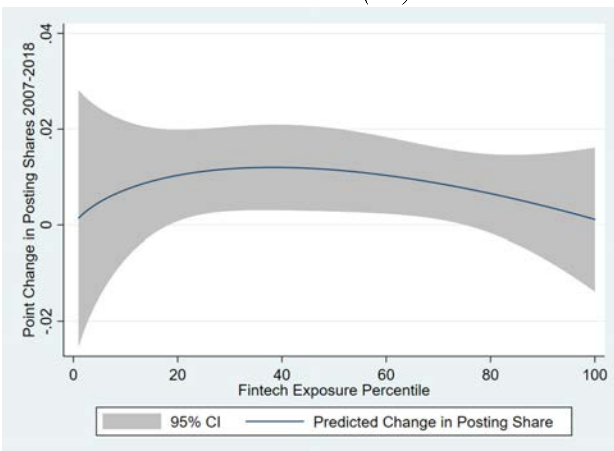
A: No of Postings *B: Share of Postings*



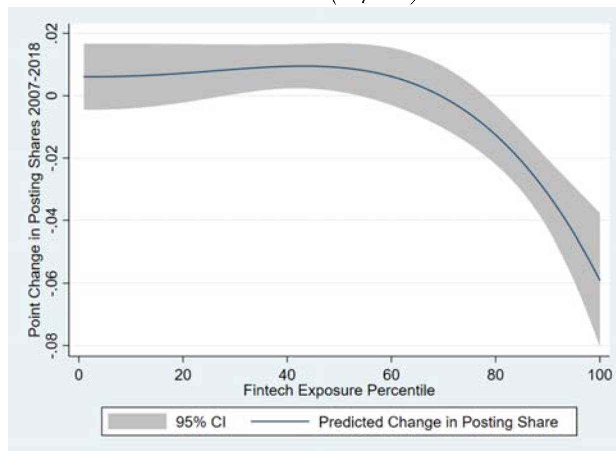
The figure plots the time trends of annual job postings in Panel A and posting shares in Panel B by fintech exposure quartiles. The job posting variables is calculated using BGT data in 2007 and 2010-2018. The fintech exposure measures are constructed by the authors.

Figure A.3. Cumulative Change in Posting Share by Industry

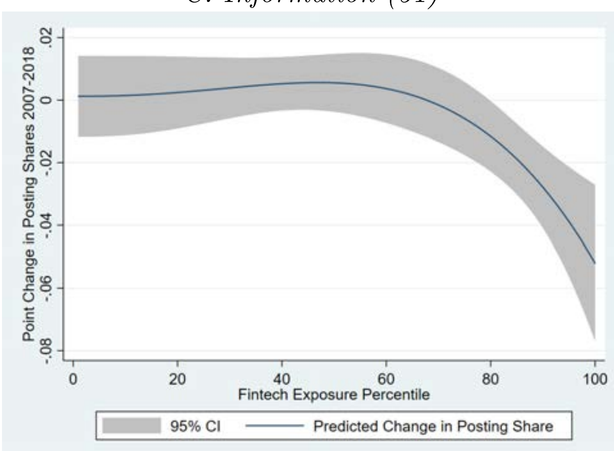
A: Finance (52)



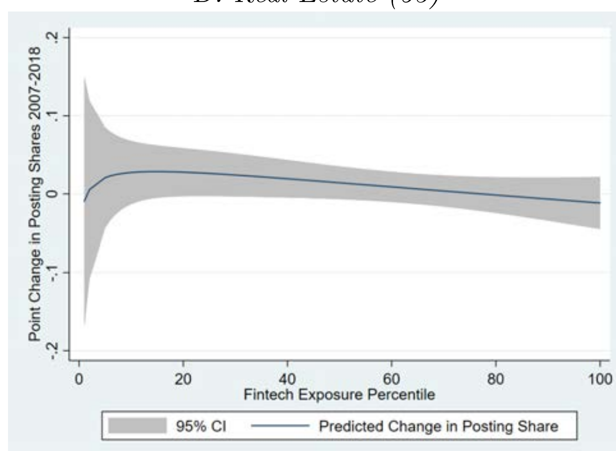
B: PMA (54-56)



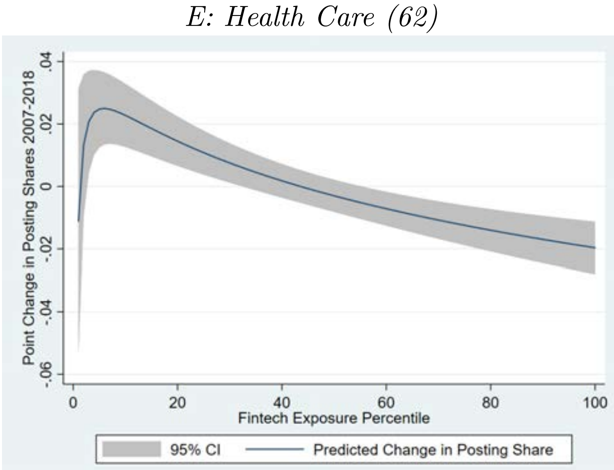
C: Information (51)



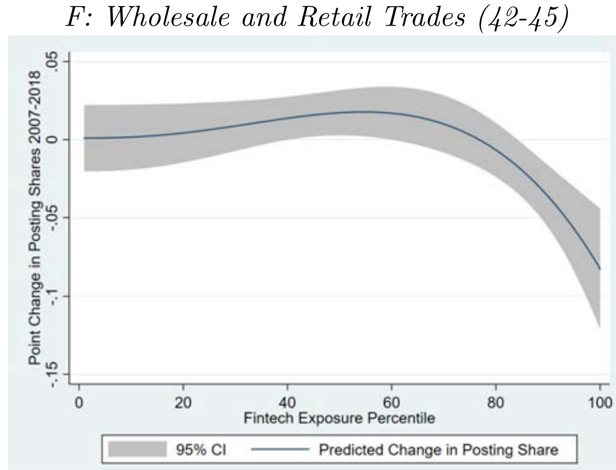
D: Real Estate (53)



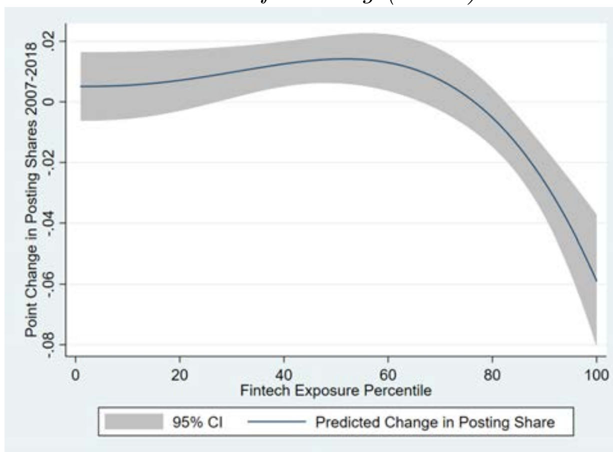
E: Health Care (62)



F: Wholesale and Retail Trades (42-45)



G: Manufacturing (31-33)



The figure plots the relation between fintech exposure and cumulative change in job posting shares at industry level. The y-axis is the cumulative change in job posting share in an industry from 2007 to 2018 and the x-axis is the time-invariant occupation-level fintech exposure percentile. Panels A-G plot the relation for finance, PMA, information, real estate, health care, wholesale and retail trades, and manufacturing, respectively. The selected industries are closely related to financial sector based on the supply and use table. The change in job posting share is calculated using BGT data in 2007 and 2010-2018. The fintech exposure measures are constructed by the authors.

Table A.1: Additional Robustness Tests

Dep Var	Basis Point Change in Shares of							
	Employment	First Posting	Posting					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FT Quartile 4	-0.168*	-1.796**	-0.673***					
	(-1.89)	(-2.607)	(-14.33)					
FT Quartile 4 - Granted				-4.959***				
				(-7.64)				
FT Quartile 4 - EW					-4.676***			
					(-7.43)			
FT Quartile 4 - Accum.						-4.551***		
						(-7.79)		
FT Raw Score							-8.529***	
							(-6.95)	
FT Percentile								-0.965***
								(-5.84)
AI Percentile	0.004**	-0.056***	-0.004***	-0.032***	-0.031***	-0.032***	-0.027***	
	(2.15)	(-5.240)	(-3.47)	(-4.54)	(-4.27)	(-4.51)	(-3.55)	
Software Percentile	0.001	0.064***	0.003***	0.056***	0.052***	0.056***	0.051***	
	(0.82)	(2.738)	(3.74)	(7.93)	(7.62)	(7.97)	(7.95)	
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	184,861	241,420	277,075	277,075	277,075	277,075	277,075	277,074
R^2	0.085	0.054	0.001	0.090	0.089	0.089	0.088	0.121

The table reports the regression results of additional robustness check of the effect of fintech exposure on employment and job postings at occupation × state × year level. It aims to validate that the findings from Table 5 is not driven by the unsatisfied demand of labor and any possible measurement errors. The employment share is the fraction of a cell's employment to the state totals in a given year. The posting share is the fraction of a cell's job postings to the state totals in a given year. The dependent variable is the basis point change in employment and first posting shares, respectively, in columns (1) and (2) and the basis point change in all job posting shares in columns (3)-(8). The main explanatory variable, FT Quartile 4 dummy, equals one if the lagged occupational fintech exposure percentile is in the top quartile, and zero otherwise. Fintech exposure measure is constructed using patent applications in 5-year rolling window in columns (1)-(3), (5), (7) and (8), using patents granted in 5-year rolling window in column (4), and using all patent applications in 2003-2017 in column (6). Regression in column (3) is not weighted. FT Quartile 4 in column (5) equals one if the lagged occupational employment-weighted fintech exposure percentile is in the top quartile, and zero otherwise. We use the fintech exposure raw score instead of Quarter 4 dummy in column (7) and control for occupation fixed effects in column (8). AI percentile and software percentile are the percentile ranks of occupation-level AI exposure sores and software exposure scores, respectively, from Webb (2019). We also control for cohort-level initial employment share in column (1) and cohort-level initial job posting share in columns (2)-(8). Standard errors are clustered at state level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table A.2: Distribution of Fintech Patents

Panel A: Top Innovator Firms

Inventor			Acquisition Innovator		
Firm	# Patent	# Postings	Firm	# Patent	# Postings
Mastercard	393	7,686	Paypal	243	9,828
Visa	316	381,930	Liberty Peak Ventures	196	0
American Express	313	121,462	III Holdings 1	121	0
Bank of America	144	37,557	Intellectual Ventures II	60	172
Ebay	140	271,214	Capital One	48	117,998
IBM	120	29,103	Xatra Fund MX	44	0
First Data Corporation	118	30,550	American Express	43	121,462
Square	88	6,028	Visa	32	381,930
Paypal	87	9,828	Verifone	31	3,104
Capital One	80	117,998	Western Union	28	4,084

Panel B: Industry Distribution

		No of Fintech Patent				% Fintech Patent			
NAICS Code	Industry Title	Filing Date	Publication Date	Grant Date	1 Year After	Filing Date	Publication Date	Grant Date	1 Year After
11	Agriculture	0	0	0	0	0.00	0.00	0.00	0.00
21	Mining	7	7	4	4	0.11	0.11	0.13	0.13
22	Utilities	0	0	0	0	0.00	0.00	0.00	0.00
23	Construction	1	1	1	1	0.02	0.02	0.03	0.03
31-33	Manufacturing	254	260	144	144	3.90	3.99	4.65	4.84
42-45	Wholesale and Retail Trade	46	48	37	35	0.71	0.74	1.19	1.18
48-49	Transportation and Warehousing	11	11	5	5	0.17	0.17	0.16	0.17
51	Information	807	840	468	463	12.39	12.90	15.11	15.56
52	Finance and Insurance	2,091	2,091	1,014	950	32.11	32.11	32.73	31.92
53	Real Estate Rental and Leasing	2	2	2	2	0.03	0.03	0.06	0.07
54-56	PMA	270	260	121	113	4.15	3.99	3.91	3.80
61	Educational Services	4	4	3	3	0.06	0.06	0.10	0.10
62	Health Care and Social Assistance	0	1	0	0	0.00	0.02	0.00	0.00
71	Arts, Entertainment and Recreation	4	2	2	1	0.06	0.03	0.06	0.03
72	Accommodation and Food Services	4	3	1	2	0.06	0.05	0.03	0.07
81	Other Services	6	2	0	0	0.09	0.03	0.00	0.00
92	Public Administration	0	0	0	0	0.00	0.00	0.00	0.00
Other		3,004	2,979	1,296	1,253	46.15	45.76	41.83	42.10
Total		6,511	6,511	3,098	2,976	100	100	100	100

The table reports the industry and firm distributions of fintech patent applications. We identify the innovator firms based on inventor and assignee's name obtained from patent application and assignment databases available at USPTO. We match these firms to BGT data to obtain their industry information. Panel A reports top 10 innovators based on USPTO patent application and assignment datasets and BGT dataset, and Panel B reports the industry distribution of fintech patent applications in 2003-2017. There are two types of innovators: inventors are the inventors of fintech patents and acquisition innovators are the assignees (but not the inventors) of fintech patents.