Surviving the Fintech Disruption*

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Abstract

This paper studies how demand for labor reacts to financial technology (fintech) shocks based on comprehensive databases of U.S. fintech patents and firm job postings in the US in 2007 and 2010-2018. 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 the industry as well as geographical concentration of these occupations. Firms resort to an upskilling recruiting strategy in face of the fintech disruption, requiring more fintech skills, higher education attainments, and longer work experiences in the hiring of fintech-exposed jobs. We further explore the heterogeneity across firms, industries and geography. Firms with high innovation outputs are able to offset the disruptive effect from the fintech shock. Among innovating firms, 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 the technology and innovation that aims to compete with traditional financial methods in the delivery of financial services. Telecommunications and information technology have been adopted by financial service providers to create new options and ease of access to help consumers (households and businesses) 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 cyptoassets) 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 long debated between the new opportunities for businesses and consumers from, and the labor force displacements caused by, technological advancement. The common empirical challenge to quantify the effect of technologies on jobs is due to the general lack of firm-level data on the use of or impact from technologies. 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 exposure to fintech innovations. Such a measure, at the occupation-year level, is constructed by cross-analyzing the textual information in job task descriptions and that in recent fintech patent filings to capture the cosine similarity between the two as well as the intensity of fintech innovations. The procedure results in time-varying fintech exposure scores for the universe of 772 occupations as classified by 6-digit O*NET Standard Occupation Code (SOC), which can also be aggregated to the firm or industry level.[1] We discover an inverse U-shaped relation between fintech exposure and occupational wage in that the occupations paying middle-ranged salaries and possessing intermediate education attainments are the most exposed to fintech innovations. Both ends of the spectrum, especially people with advanced degrees (master and above), tend to be the least affected. Fintech exposure is mostly gender neutral and affect 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 firm- or establishment-

[1]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.

year level job postings from Burning Glass Technology (BGT) to occupations, and then to our occupational measure of exposure to fintech innovations during the past five years. The resulting panel consists of about 300,000 cohorts at occupation × state × year level, aggregated from the original 161.6 million vacancies during 2007, 2010-2018. We find that the job posting shares (out of all job postings in a given state × year) of occupations in the top quartile of fintecn exposure ("the most exposed" here after) experienced significant drops. After controlling for state and year fixed effects and competing technology exposures (from AI and software), we find that the most exposed occupations experienced an annual decreases of 4.6 basis points in job posting shares (slightly over 20 percent of the average share). From 2007 to 2018, the decline amounted to a 44 percent loss of job posting shares in these most exposed occupations, confirming a disruptive effect of the technology on jobs. Among all subfields of fintech innovations, data analysis, blockchain and Robot-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 US in 2007 and 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 (WA) and state of Texas have suffered the steepest losses of jobs that are most exposed to fintech. Fintech innovations are concentrated in four industries: finance, information, manufacturing, and PMA. This pattern shows that the finance industry is leading the innovation effort in fintech by inventing and/or acquiring fintech patents, contrary to a conventional belief that fintech innovation primarily sourced outside the finance and related industries. In fact, innovators (including those in the most exposed industries including finance) are able to offset the negative impact of fintech shock on jobs.

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 by fintech. 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.[2] 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

[2]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 seems to disproportionately disrupt highly educated workers with long work experience.

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 growth and efficiency. 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, R&D investment, and return on assets (ROA), nor in research and development (R&D) investment. 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 constitute a disruption 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 US 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 automation technologies on employment and wages.[3] For example, Alekseeva et al. (2020) document a dramatic increase in the demand for AI skills in online job postings over the period 2010-2019. Babina et al. (2020) find that at firm and industry level, AI investment is stronger among firms with higher cash reserves, higher mark-ups and higher R&D intensity. Acemoglu et al. (2020) study the impact of AI on labor markets and document rapid and broad growth in AI-related vacancies over 2010-2018.

Unlike the automation technologies explored in these studies, our paper aims to be the first to study the effect of fintech on labor via firms' recruiting. There are several differences between fintech and the previously studied technologies. First, while industrial robots are exclusively adopted by manufacturing firms and AI is mostly adopted by service sectors (Acemoglu et al., 2020), fintech is a technological disruption primarily to financial services. As an

[3] 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) estimate an increasing productivity in industries adopting more robots, but no clear employment patterns.

essential intermediary, financial institutions hold almost all the savings in the society, implying their efficiency and risk are systemic. Second, earlier research already indicated that the disruptive impact of robots, software, and AI interfere with different segments of the workers (in terms of education, skill, and experience), therefore a separate analysis on the impact of fintech disruption is warranted as it 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). Recently, Chen et al. (2019b) identify a comprehensive sample of all fintech patents using machine-learning algorithm and estimate that most fintech innovations yield instantaneous positive value to innovators but negative value to industries, especially the disruptive technologies that originate from non-financial startups.[4] Cunningham et al. (Forthcoming) develop a model to illustrate so called "killer acquisitions" – a strategy taken by incumbent firms to acquire innovative targets solely to preempt future competition. Our analysis extends the literature by focusing on the relationship between fintech innovations and responses in firm recruiting over a long period of time and across different firms, industries and geographically. Such analyses integrate financial markets and labor market dynamics over a long period of time. Our results suggest that the most exposed occupations suffer a significant loss of both new hiring and employment stock. However, finance industry, to which the technological disruption is towards, actually fends off disruption by acquiring and adopting the changes quickly, making them the primary provider and the least victims of fintech innovations.

Finally, 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.[5] 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. Differentiated

[4] They adopt a methodology of anticipation-adjusted stock market reactions, similar to Kogan et al. (2017), to quantify the value of innovations. In a related 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.

[5] Chen et al. (2019a) survey economic research on blockchains and its recent advances. Papers that study the unsecured personal loans 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. (2019), Tang (2019), and Di Maggio and Yao (Forthcoming).

from these papers, ours is focused 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 measure and an overview of their properties. The section also describes sample construction, summary statistics, and correlation analysis of fintech exposure and labor market outcomes. Our main baseline analysis is 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 patent filings from 2003 to 2017 retrieved from the US Patent and Trademark Office (USPTO), following the procedure developed by Chen et al. (2019b) to classify patents as fintech-related. 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, and the assignee is the recipient of

[6] This process involves three steps: text preprocessing, creating a training sample, and 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).

the transfer of the legal rights (entire or a percentage) to the invention.For 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." Occupations have 20 tasks each on average, 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 within each occupation.

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 Burning Glass Technologies (BGT), gathers job postings from more than 40,000 online job boards and company websites with a sophisticated de-duplication algorithm. The BGT data captures a near universe of online jobs posting and covers between 60–70% of jobs posted in the US, 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; Ganong 2014). Therefore, BGT data provides a robust representation of job 45 openings in the US (Hershbein and Kahn, 2018).

The BGT data 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. The data contains information on employer identity and skill requirements scraped from the text of the vacancy. For example, we are able to identity job openings that require different skills (e.g., finance, software and other skill), different years of experience (e.g., 1-2, 3-4 and more than 4 years) and different educational attainment (e.g., high school, bachelor's and master degrees).

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

The data allows us to construct several measures of job postings following Modestino et al. (2019) as labor market outcomes variables, including changes in the faction of a occupation-state cell'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)provided by IPUMS (Ruggles et al., 2019) samples 1% of the US population since 2005 except for the census bureau year 2010 when IPUMS samples 10% of the US population. Our IPUMS sample represents 150.82 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 × state × year-level employment 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 (OES) released by U.S. Bureau of Labor Statistics (BLS) every year. Finally, the financial information of public firms is retrieved from WARDS especially the Compustat.

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 (and industry) level. Because there is not such an existing measure, we develop it by exploiting the overlap between the text 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 financial technologies do, and that of job descriptions contains specific tasks that define each occupation. Thus a textual analysis over these two text corpuses can inform whether and how much fintech patenting 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). 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.

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 each with high fintech exposure (credit analysts and information security analysts) and low fintech exposure (mathematical science teachers and orthodontists) 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 substitute part of the tasks involving data, financial, transactions, and credit. Information security analysts are exposed to the technologies that substitute 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.]

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 in . It turns out that on the top of the list are information security analysts, credit analysts, software developers (applications), travel

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

agents and electronics engineers; while at the bottom there are carpenters, slaughters, police and detectives, orthodontists and dancers. 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 (i.e., t-5 to t). Series (i) steadily increases over time as it reflects a cumulative effect from fintech innovations over time. The 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.

[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, the differences are significant. First, patents used in the matching procedures are different and measure different technological discovery. Second, instead of using only verb-noun pairs extracted from titles of patents, we process the entire texts of both titles and abstracts of the patents, offering richer information in the matching process. Third, we incorporate time-series variation in the exposure measure by adopting a moving time window for fintech patents. As a comparison, Figure 4 plots average of fintech exposure (in percentile rank) over the full percentile ranks of each of the two occupational measures developed by Webb (2019). Overall there is no apparent correlation between fintech exposure and the other series. The average of fintech exposure remains mostly flat as the other occupational measures moves from the lowest to the highest values, suggesting that exposure to fintech is distinctly from that to AI and Software.

[Insert Figure 4 Here.]

3.1.4. The Demographics of Fintech Exposure

Though occupations are the direct 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 (between 35 and 50) workers the most, while the exposure drops steeply above age of 50.

3.2. Linking Fintech Exposure to Job Postings

3.2.1. Sample Design and Summary Statistics

Given the objective of our study to trace out how demand for talent respond 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 with data from Burning Glass Technology (BGT), including number of postings, share of postings in a local market as well as job requirements for skills, education and work experience. For the fintech exposure measure, we adopt the default five-year moving time window for filed patents.

Corresponding to fintech exposure measures that are constructed 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 geographic 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. We follow Modestino et al. (2019) to construct two measures capturing the relative change in the intensity of job postings. The first measure is the percentage-point change (i.e., 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 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 is 275, suggesting a right skewed distribution. Each cohort accounts for 16 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 observations with fewer than three postings, about 0.025% of the sample. To further mitigate the influence of outliers, we also conduct weighted regressions where weights are the number of postings underlying each

[10] We also constructed alternative samples at occupation $\times$ year, occupation $\times$ industry $\times$ year and occupation $\times$ firm $\times$ year level and repeated baseline analysis on these samples 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 quartile.

observation following Modestino et al. (2019).[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 requirement. The share is 12%, 21% and 59% when we break the skill requirement to finance, software and other skills, respectively. Table 3 further reports shares of job postings with four mutually exclusive skill requirements – both finance and software skills, finance but not software, software but not finance, and others – to analyze the specialized demand for talent within each sector. Similarly, we also construct share of job postings that require different educational attainment and years of experience. 43% of job postings require some level of education, evenly split between high school diploma and bachelor's degree and above. About 38% of job postings require experience: 19% 0-2 years; 8% 2-4 years; 10% 4+ years of experience. The last two rows of Table 3 reports summary statistics of demographic characteristics of US population from IPUMS. The variables are first averaged within each occupation using the SOC code and then matched to our main sample. The median (average) age is 40 (41), and women on average account for 47% of the workforce.

Finally, Figure 6 shows that posting share remains stable or even increases as fintech exposure increases but suffers steep decline above the 75^{th} percentile of exposure, where the total loss of 7 basis point loss of job postings (as a share in the state) from 2007 to 2017 represents a 44% relative to the average posting share (16 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 these industries.

Fintech exposure should have quite different implications for firms that are fintech innovators themselves versus those that do not contribute to innovations in this area. 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] Second, as shown by Cohen et al. (2016, 2019), NPEs actively acquire fintech patents, e.g., one of the

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

[13] The inventor identifier 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.

largest NPE in fintech domain is III Holdings 1, LLC which holds 121 fintech patents acquired from American Express. We can 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, many just have enjoyed accidental discoveries that are not part of their core innovative competence. For this reason, we set the classification filter for "inventor" to be two or more patents.[14] 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 started earlier.[15]

[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 firms by our criteria. Not surprisingly, fintech innovators tend to be large firms with annual job postings of 1,179 and 916 for inventors and acquisitional 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, information, manufacturing and PMA. Some inventors in manufacturing, such as GE Capital and GM Financial, are financial subsidiaries of parent companies that are rooted in manufacturing.[16] Such an industry allocation is somewhat at odds with a conventional belief that fintech innovation represents an external shock on the finance industry. Data indicates that the finance industry is actually leading the innovation effort in fintech. Finance industry is also a net buyer of fintech patents. Figure 7 shows that over the period of 2003 to 2018, finance firms have acquired 369 and sold 216 fintech patents based on USPTO assignment data.[17] Acquisitions by finance firms have intensified since 2011 and continued until 2016 when Bank of America and

[14] A sensitivity check indicates qualitatively similar, but weaker results, if we classify firms with any number of patents to be innovators.

[15] Panel A of Table A.2 in the Appendix lists the top ten firms in each of the two categories, and the number of fintech patents they own. Mastercard, Visa, American Express 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 largest non-inventor innovators, however, is s mixture of the large inventors such as Paypal and American Express and NPEs like Liberty Peak Ventures, III Holdings 1 and Intellectual Ventures II.

[16] 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%.

[17] Two largest deals from finance to other industries are that Xatra Fund MX LLC (non-finance firm)'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/.

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 finance firms to remain competitive facing the potential disruption from fintech.

3.2.3. Distributions of Fintech Exposure and Jobs

A. Distribution of Impact across Industries

Table 4 summarizes the distributions of fintech exposure and demand for jobs across different industries (at the NAICS two-digit level).[18] Industries most exposed to fintech innovations include finance (NAICS = 52), PMA (54-56) and information (51), all with fintech exposure percentiles well above the 70^{th} percentile. The opposite end of the spectrum are accommodation and food services (72), educational services (61) and arts, entertainment and recreation (71), where the fintech exposure percentiles are all below 50^{th} percentile. 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%. The distributional statistics suggest that fintech affects larger sectors more than smaller ones with the coefficient of correlation at 0.23. The three most exposed industries also experienced the largest loss in shares of postings from 2007 to 2018 (-12.8% combined). In contrast, 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.]

Simple correlations might mask the non-linear relations among the variables as well as heterogeneity across industries. Table 4 further suggests that 74% 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) / (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, and finance, as the most exposed industry, has survived well in labor market relative to

[18] 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.

its two most important peers. In our sensitivity checks,[19] we find that job posting share in finance is overall stable across the spectrum of fintech exposure; but PMA and information are significantly affected by fintech innovations with a similar pattern to that in Figure 6. The two industries that heavily rely on financial services, real estate and health care, exhibit overall negative relation between job posting and fintech exposure. Finally, two large industries, trades and manufacturing, also see significant drop in job posting shares when fintech exposure reaches the highest quartile.

B. Distribution of Impact 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 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 after being exposed to the fintech shock. Our baseline analysis, set at the occupation × state × year level, is as follows:

$$\Delta Y_{o,s,t-1->t} \quad = \quad \beta_1 \cdot FT_{o,t-1} + \beta_2 \cdot X_o + \gamma_{s,t} + \varepsilon_{o,s,t-t0}, \tag{3}$$

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 postings shares in percentage points, from $t-1$ to t, of postings in occupation o located

[19] 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 state s and year t as a share of all postings in in state s and year t.[20] X_o is a vector of control variables, notably, the occupation-level software and AI exposure measures developed by Webb (2019). The regression incorporates a slew of fixed effects at the state $\times$ year level ($\gamma_{s,t}$) to absorb any confounding factors that would affect the supply and demand conditions of the local labor market. 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 results from 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 percentiles; and in the last four columns, it is coded as a dummy variable equal to one if the exposure falls into the top quartile during the year (based on the evidence in Figure 6. We control for the three cross-sectional alternative occupation exposure measures in columns (3), (4), (7) and (8), and also alternative between year fixed effects (in columns (1) and (5)) and state $\times$ 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 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 softwares. 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 exposed quartile see a 4.6 basis point decrease in job posting share. Relative to the average job posting share (20.75 basis points), this represents about 22 percent decrease. Both effects are conditional on the same state-by-year so that macroeconomics or regional conditions are not driving the disparity.

We conduct a slew of robustness tests on alternative specifications of both dependent and independent variables to ensure the robustness of the estimates and inferences. 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

[20] 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.

innovations have significant (at 1% level) and negative effects on job postings. Among them, Robot-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 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 0.268 basis point decrease in the employment share.[21] It is not surprising that the impact is multiple times higher in job posting than in employment as adjustments 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 count all job-postings about 62% of which are repeated postings, presumably because the position remains vacant after the previous effort. While the total number of postings is a reasonable proxy for the intensity of demand for talent, we also consider the unique, or first, postings as a measure for distinct new positions. Following Cen et al. (2020), 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.[22] Overall, 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 replacing the first difference model in Equation (3) with an occupation fixed effect, using unweighted observations, relying on only granted (instead of filed) patents, adopting all-time fintech measures or raw exposure scores. The coefficient estimates associated with fintech exposure remain negative and significant at 1% level, suggesting robustness of the relation.[23]

4.3. Downskilling versus Upskilling

So far we have established the overall negative effect of fintech exposure on firm hiring, as well as the effects sorted by requirements for skill, experience and education contained in job

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

postings at the extensive margin. This section goes further to address 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 onto fintech exposure (as measured in percentiles), controlling for exposures to AI and software innovations and year $\times$ state fixed effects. Table 6 reports the results. Panel A shows "finance & software" skills and "software-only" skills are in higher demand as fintech exposure increases, and a reverse negative relation prevails in other combinations of skills (including "finance-only" skills).[24] Demand for talents with software skills increases with fintech exposure. Moreover, talents with dual skills (finance + software) are in particularly high demand (a 29.5 basis point increase in posting shares) compared to jobs requiring software skills along (19.5 basis points). The combined results suggest 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.]

Panel B of Table 6 presents an analogous analysis regarding required experience levels and educational attainments. It shows a monotonic relation between fintech exposure and the length of work experience or the level of education required. For example, the share of postings decrease by 6.8 basis points (significant at the 5% level) for jobs that require 0-2 years of experience, for a one-percentile increase of fintech exposure; the same coefficient switches sign to an increase of 36.1 basis points (significant at the 1% level) for four-or-more years of experience. Such a pattern is echoed in education requirement. For every percentile increase in fintech exposure, posting shares of jobs that require high school education decreases by 12.0 basis point, but that for college and above is an increase of 50.1 basis points. Each of the two effects are significant at the 1% level, and so is their difference.

Thus, results in Table 6 are strong evidence that firms resort to 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.

[24] The residual category to the skill combination possibilities in (2) to (5), "no skill requirement," is not tabulated because the sum of coefficients across an exhaustive list of categories should be equal to the negative of the coefficient in column (1).

4.4. Occupation Redistribution and Concentration

Aside from new hirings, the fintech shock also reshapes the distribution of occupations (and hence talents) across industries and geographies. Figure 9 plots the variation in the HHI of occupations across industries (Panel A) and states (Panel B) over occupational fintech exposure percentile. Both Panels show that occupations become more concentrated with the fintech exposure. In Table 7, we run regressions of changes in HHI, both year over year (YOY) and cumulative from 2007 to 2017, on the indicator variable for the highest fintech exposure quartile, using the data at occupation level while controlling occupation exposures for AI and software. Results confirm that occupations that are most exposed to fintech became significantly more concentrated in terms of both industry and geography.

[Insert Figure 9 Here.]
[Insert Table 7 Here.]

5. Heterogeneity Analyses

In this section, we trace out the impact of fintech exposure from suppliers to users of innovation, and further explore the differential impact of the exposure on firms that are innovators themselves versus the others. Such analyses aim to provide insights about the re-distributional effects of the fintech shocks.

5.1. Fintech Providers

We first explore gains or losses of jobs by the top three industries that provide fintech patents (finance, information and PMA), relative to other industries. Table 8 presents the analysis in which we interact the fintech exposure with three industries individually (Columns (1)-(3)). Results are consistent across all specifications that job postings in these sectors were not impacted by fintech exposure as the positive coefficients on the industry interaction terms mostly neutralize the negative coefficient on fintech exposure unconditionally. Taking column (4) as an example: while the broad economy suffer significant job losses associated with fintech exposure (0.87 basis point), the finance industry gains 0.83 basis points relative to the whole economy. The information and PMA industries offset the economy-wide negative impact by about half way. Combined evidence suggests that jobs in the industries who are providers of fintech innovations do sustain the disruptions from the fintech shock.

[Insert Table 8 Here.]

As in the previous analyses, we further examine to what extent these industries are up-skilling or downskilling their new hires. In Columns (5)-(8) of Panel A, coefficients on the interaction terms highlight the results. Compared to other industries, finance industry significantly increases the job postings that require “finance but not software” skills, but significantly decreases their job postings that require “software but not finance” skill. Information industry only marginally increases their job postings that require “finance but not software” skills. Finally, the PMA industry desires talents with both skills, and decrease demand for purely finance talents. The results suggest that finance industry is re-aligning its hiring to strict finance skills to strengthen its core competence while other industries expand their skills to include finance skills.

Panel B presents an sorted analyses on requirements of experience and education, and an analogous contrast between finance and the other two industries emerges. Overall, new hirings in finance tend to concentrate more on the low end of work experience and education as fintech exposure increases; and the reverse is true for information and PMA. In other words, finance industry responds to fintech shock by relative downskilling in hiring; while information and PMA respond with relative upskilling.

How can finance industry retreat to finance hiring only while it has managed to maintain a leading role in fintech innovations thus far? Lerner et al. (2021) attribute two important factors to the sharp increase in the number of financial patents and applications since 2001. First, the July 1998 appellate decision in State Street v. Signature and subsequent rulings by the Supreme Court (i.e., Bilski v. Kappos in 2010 and Alice Corp. v. CLS Bank in 2014) established that business methods were statutory subject matter on an equal playing field with more traditional technologies. Thus many of the fintech patents are not softwares that require such skills. Second, they also find that banks and payments firms have increasingly focused on their core areas (i.e., banking, capital markets and payment), while IT firms and other financial firms have continued to patent widely in finance via process patents.

5.2. Innovator versus Non-Innovator Firms

To differentiate the two types of innovating firms, we aggregate the BGT data to three groups (inventor, non-inventor or acquisition-driven innovator, and non-innovator) at the occupation $\times$ state $\times$ year level. Table 9 reports the job posting regression with interactions terms between fintech exposure and each of the two innovator types. Columns (1)-(3) in Panel A show that innovating firms see relative increase in hiring, relative to non-innovators, when facing higher fintech exposure. Acquisition-driven innovators completely offset the negative impact of fintech on job posting associated with fintech exposure, while the inventors offset about half of the unconditional negative impact.

[Insert Table 9 Here.]

Columns (4)-(7) in Panel A show that fintech inventors significantly increase job postings that require software skills with and without being combined with finance skills. Acquisition-driven innovators, in contrast, favor talents with finance skills and in fact decrease demand for software skills. Panel B suggests that inventors significantly increase their hiring of junior-level jobs with well-educated candidates; while the acquisition-driven innovators skew their hiring toward the low-end of both education and experience. The coefficients in the first row indicate that hiring by non-innovators exhibit clear upskilling in both experience and education.

6. Firm Outcomes

While our main analysis is to estimate the effect of fintech innovation on firm's adjustments in hiring, a natural question to explore next is whether firm's innovation and hiring activities will be translated to tangible outcomes including those directly or indirectly related to employment. We construct a firm × year-level sample that contains fintech exposure and firms' financial data from Compustat and estimate the firm outcomes due to fintech exposure at firm level in the following specification:

$$\Delta Y_{i,\ t-1->t} \;\; = \;\; \beta_1 \cdot FT_i + \beta_2 \cdot (FT_i \times T_i) + \beta_3 \cdot T_i + X_{i,t-1} + \gamma_j + \gamma_t + \varepsilon_{i,t}, \qquad (4)$$

where $\Delta Y_{i,\ t-1->t}$ include the change in logarithm of employment and sales revenue, change in R&D investment scaled by lagged firm assets and ROA; FT_i is firm-level percent of job postings in the most fintech-exposed quartile; T_i indicate whether firms are inventor and non-inventor innovators, respectively; $X_{i,t-1}$ include standard firm-year control variables (e.g., assets, firm age, cash holding, cash flow, capital expenditure and R&D dummy and industry at NAICS 4-digit level). Thus β_1 captures the difference in firm outcomes between the most exposed firms and other firms; β_3 captures the difference between innovator and non-innovator firms; β_2 captures the incremental difference between innovator and non-innovator firms while both are among the most exposed. Standard errors are also clustered at industry level.

Table 10 reports the regression results. First, the most exposed firms show significant lower employment growth relative to other firms. However, these firms do not have any statistically significant differences in sales growth and change of ROA as well as R&D investment. Second, relative to other firms that are most exposed to fintech innovations, inventors see higher employment growth, which is consistent with Table 9. The inventors most exposed to fintech innovations also have higher growth of sales and increases of ROA as well as R&D investment. In contrast, there is no statistically significant difference in any of these firm outcomes between the non-inventor innovator and non-innovator firms when both are in the most exposed category. Third, when firms are not among the most exposed quartile, inventors have lower growth of employment and sales, but their changes in ROA and R&D are not statistically different from the non-innovator firms. Non-inventor innovator firms differ slightly from inventor firms in that while they also see higher employment growth than non-innovator firms, the estimate is not statistically significant. Also while inventor firms have higher but not significant change in R&D compared to non-innovator firms, non-inventor innovator firms have significantly (at 5% level) higher change of R&D investment than the non-innovator firms.

[Insert Table 10 Here.]

How to interpret these firm-level results? Since the fintech exposure is identified at occupation level, the employment results confirm the negative relation between fintech exposure and demand for jobs at firm level. Facing the technological disruption to certain labor skills, firms that actively invent are able to sustain their employment growth relative to other firms. These firms also tend to have higher growth of sales, R&D investment and ROA. On the other hand, there is no significant difference in most firm outcomes between non-inventor innovator and non-innovator firms.

In summary, fintech shock is bad news for jobs overall, but not for firms (whose operating performance remains neutral to the exposure). Both jobs and operating metrics gain at firms that are driving the fintech innovation but the incremental demand for labor by these firms do not offset the overall loss the technology shock causes. Finally, innovator firms that do not develop original technology (but only obtain technology via purchasing patents) do not escape the disruption faced by non-innovator firms.

7. Conclusion

There has been much debate about the growth opportunities and the job displacement brought about by technological advancement. In this paper, we explore the relationship between fintech innovations and job outcomes, built on a novel measure of fintech exposure at the occupation level by conducting 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 industries manage to offset the economy-wide negative impact to different degree. Especially, inventor firms gain in both employment and operating performance.

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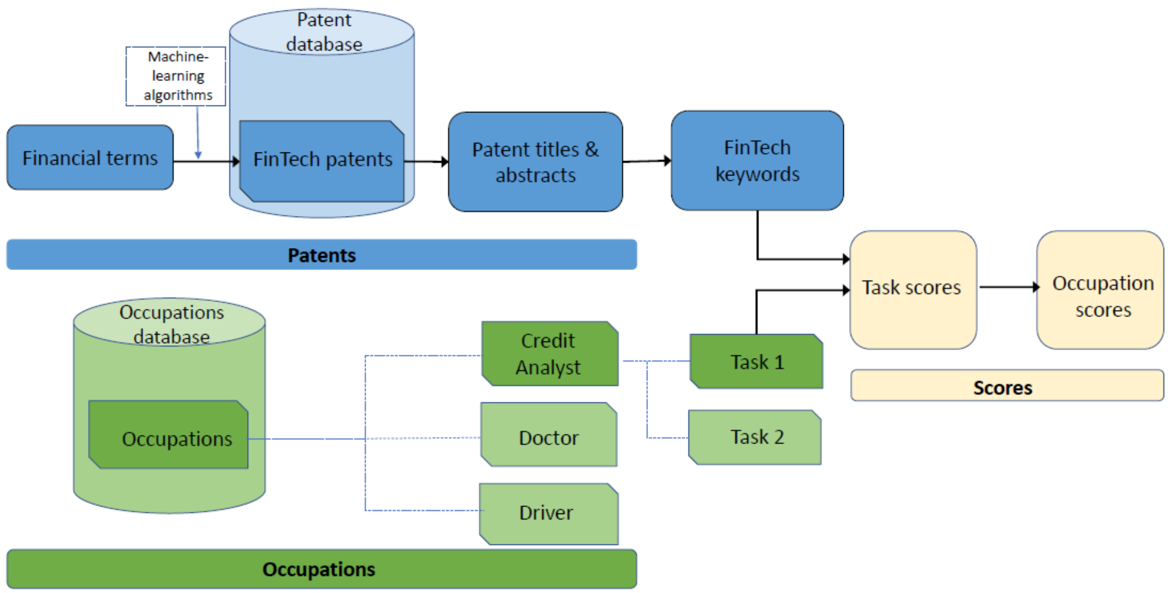
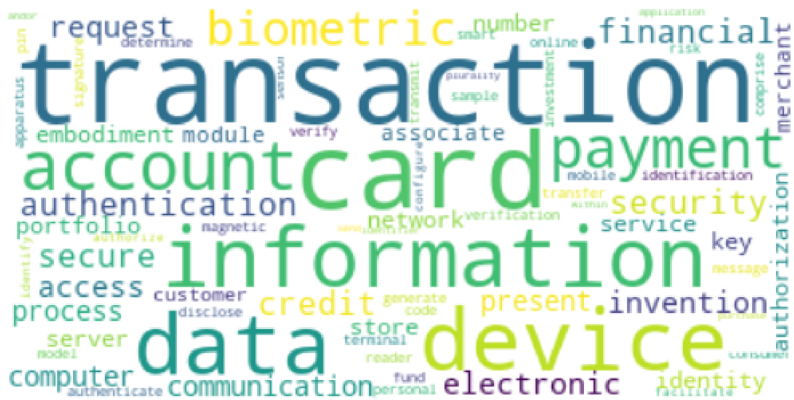
Figure 1. Process of Constructing Fintech Exposure Measure at Occupation Level



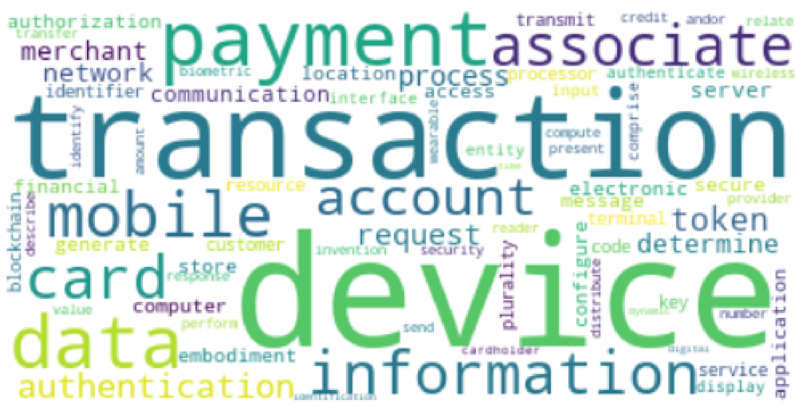
This diagram illustrates the process of how we construct the fintech exposure at occupation level. We extract a list of keywords in the titles and abstracts of fintech patents and another list of keywords in the job task description in O*NET occupation data. We then analyze the overlap between the two using the textual analysis. The matching is summarized as the cosine similarity between the two vectors. The task-level similarity score is aggregated to occupation level using the weights in O*NET occupation data.

Figure 2. Most Frequent Keywords in Fintech Patents

A: 2003-2006 Fintech Patent Applications



B: 2017 Fintech Patent Applications

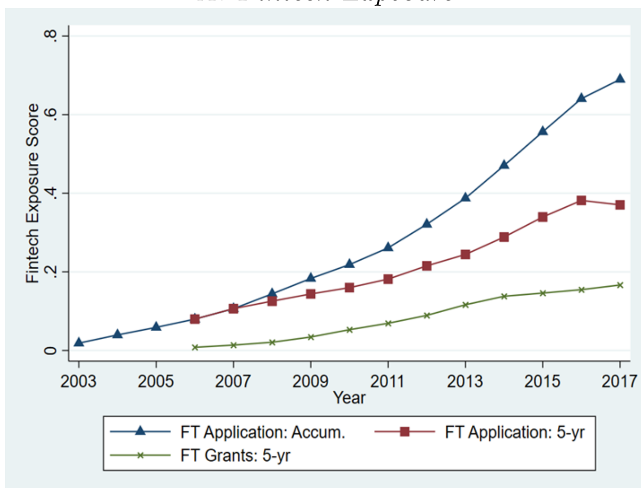


C: 2003-2017 Fintech Patent Applications

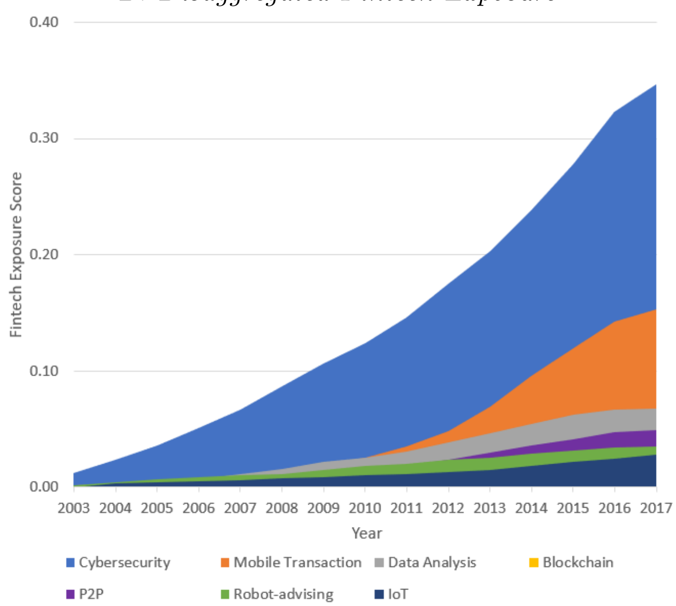
This figure plots the clouds of keywords in the fintech patents filed in 2003-2006 (Panel A), 2017 (Panel B) and 2003-2018 (Panel C), respectively. Font size indicates the frequency of the keywords. We only display top 75 keywords.

Figure 3. Fintech Exposure Measures

A: Fintech Exposure



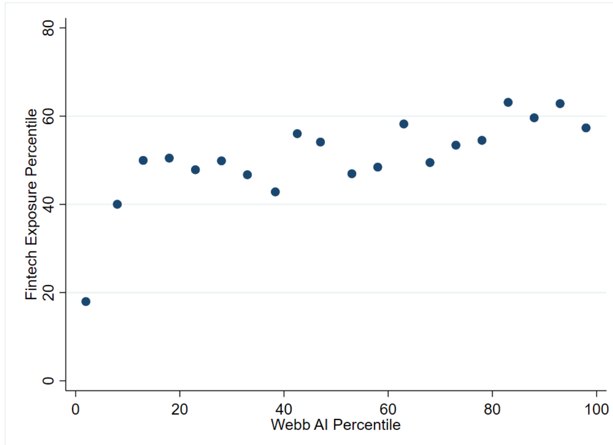
B: Disaggregated Fintech Exposure



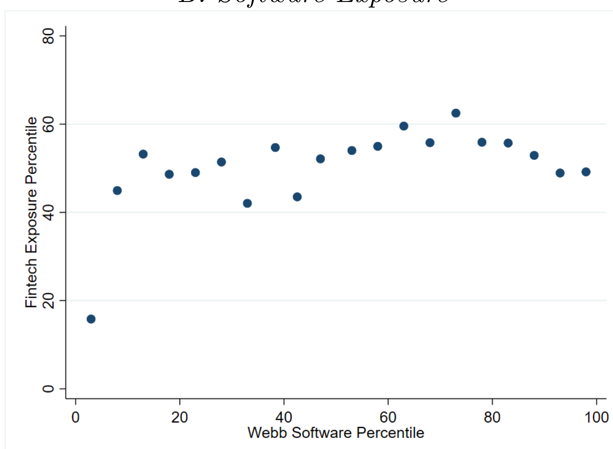
The figure plots the time trend of average Fintech exposure measures over time. Panel A plots three overall fintech exposure measures: one constructed using all fintech patent applications before each year (blue line), one constructed using fintech patent applications in the five years before each year (red, the default used in our analysis) and one constructed using granted fintech patents filed in the five years before each 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 categories filed in the five years before each year.

Figure 4. Correlation with Other Occupational Exposure Measures

A: AI Exposure

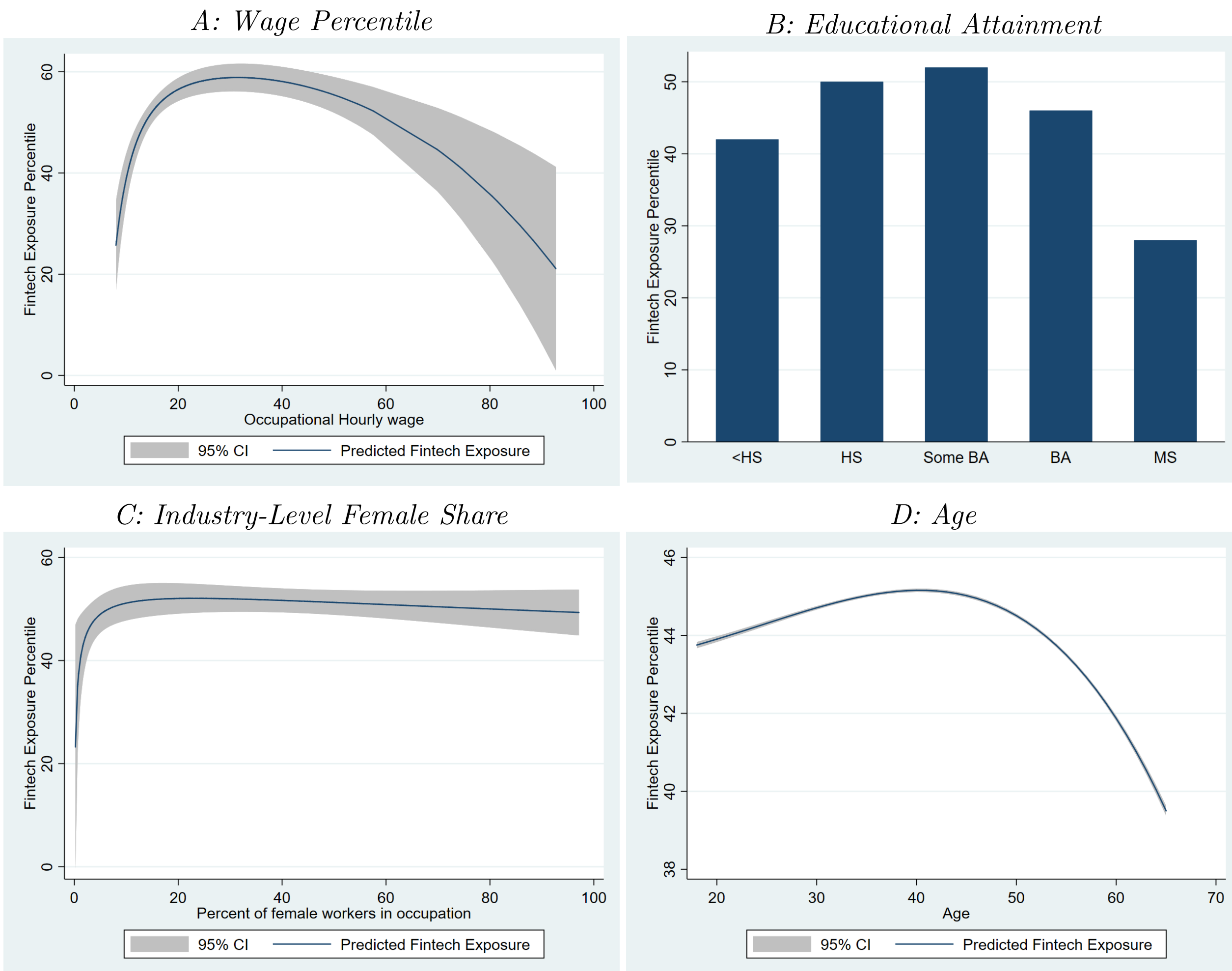


B: Software Exposure



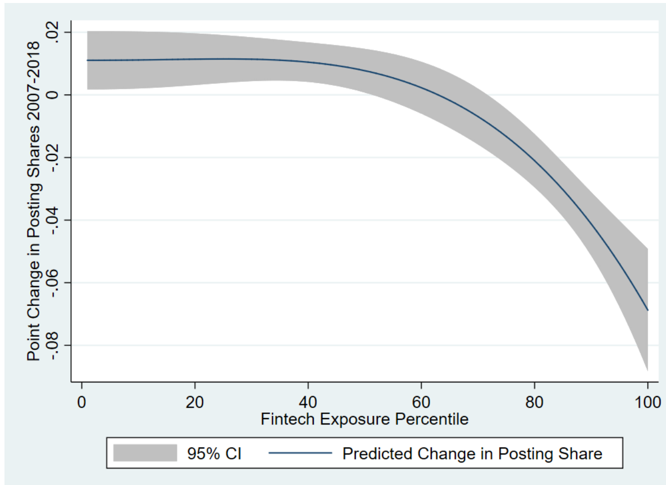
The figures present the correlation between occupational Fintech exposure and two occupational exposure measures constructed by Webb (2019): AI and software. We transform the fintech exposure scores to percentiles at 6-digit SOC level and plot the average fintech exposure percentile over each of three alternative exposure measures. All the data series are at occupation level. The fintech exposure measures are constructed by the author.

Figure 5. Fintech Exposure by Demographic Characteristics



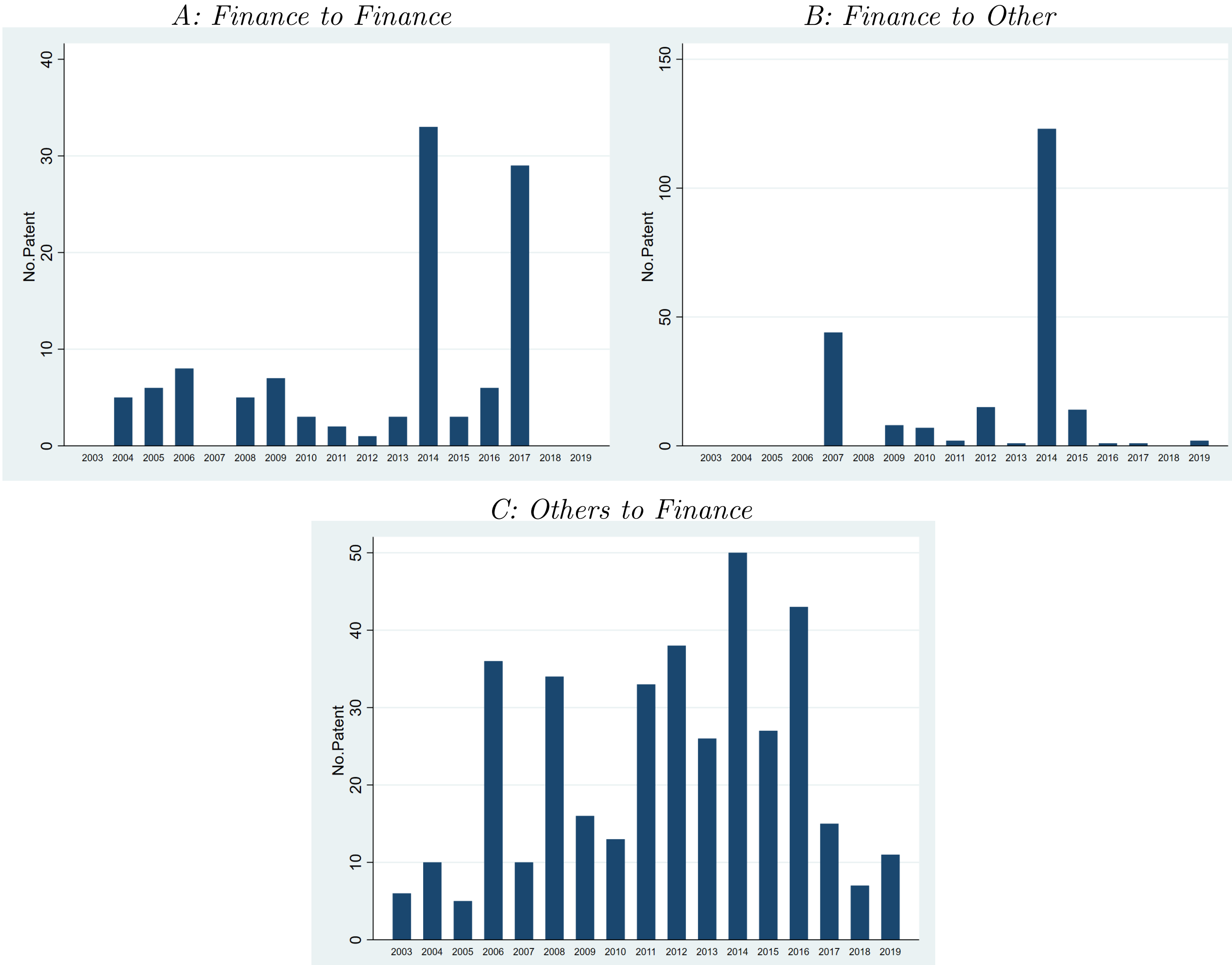
The figure plots demographic characteristics of fintech exposure. Panel A shows the fractional-polynomial prediction of the average occupation-level fintech exposure percentiles by occupational wage which is measured as an occupation's mean hourly wage from OES data released in May 2007. Panel B plots 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 measures are constructed by the author.

Figure 6. Cumulative Change in Posting Share



The figure plots the relation between fintech exposure and cumulative change in job postings. The y-axis is the cumulative change in job postings from 2007 to 2018 and x-axis is the time-invariant occupation-level fintech exposure percentiles. The change in job postings are calculated using job postings in 2007 and 2018 from BGT. The fintech exposure measures are constructed by the author.

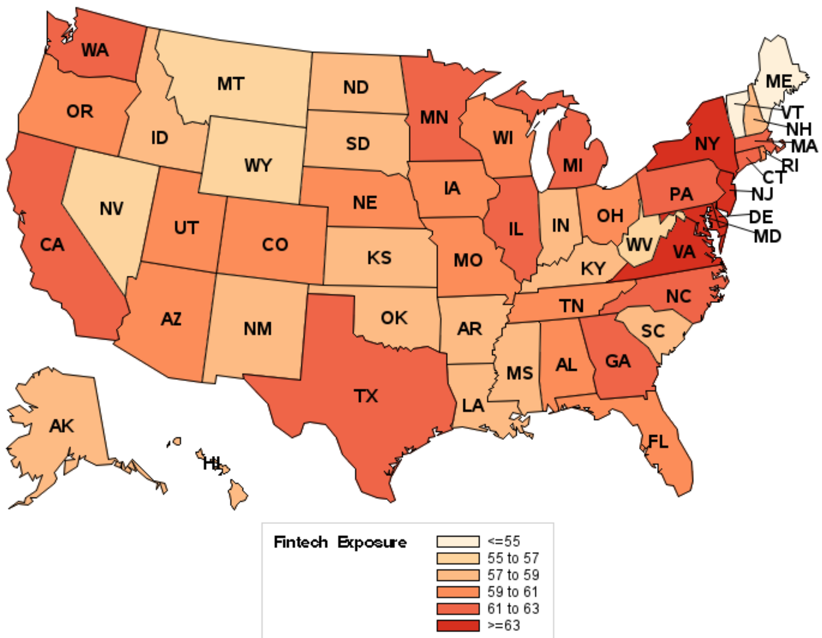
Figure 7. Fintech Patent Assignments In and Out of Finance Sector



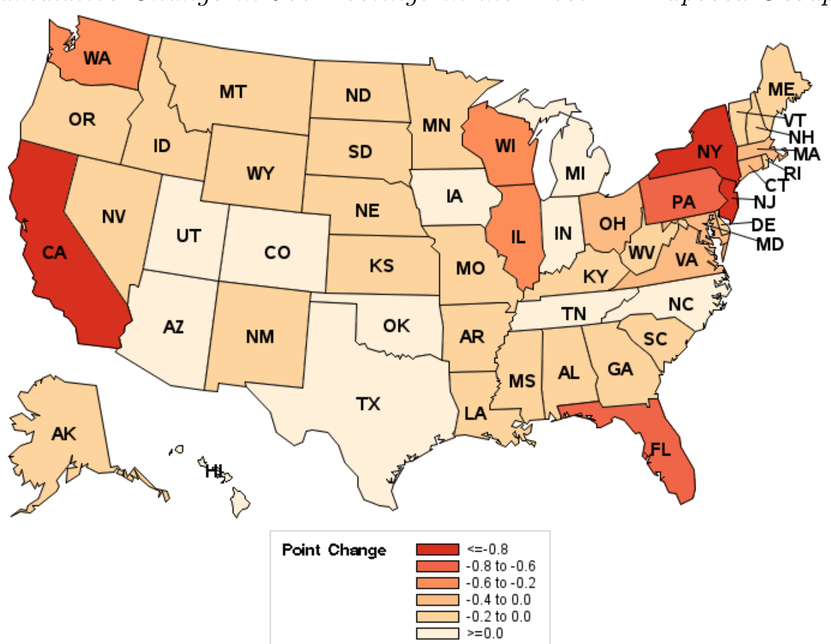
This figure plots the time trend of fintech patent assignments in 2003-2018. We aggregate the assignments into three flows: Panel A shows finance to finance, Panel B shows finance to other industries and Panel C shows other industries to finance. Most fintech patents are transferred to finance from other industries in particular between 2012-2016. Two jumps in Panel B are results of NPEs purchase from finance 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. Data used is based on patent assignment data available at USPTO.

Figure 8. Geographic Distribution of Fintech Exposure

A: Fintech Exposure



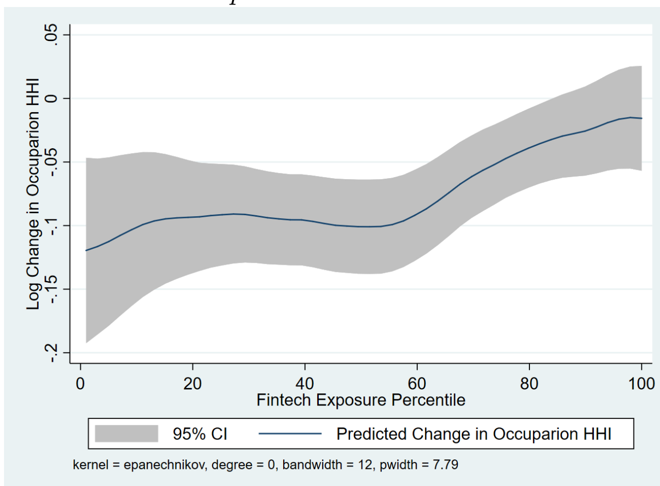
B: Δ Cumulative Change in Job Postings in the Most FT-Exposed Occupations



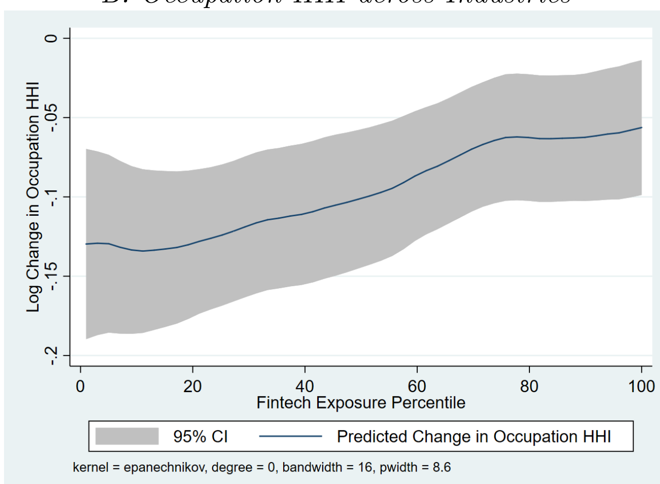
The figure plots the relation between fintech exposure and cumulative change in job postings at state level. Panel (A) plots state-level average of occupational fintech exposure percentiles weighted by job postings in 2007. Panel (B) plots the accumulative change of job postings in the most FT exposed occupations (top quartile) from 2007 to 2018 at state level. The change in job postings are calculated using job postings in 2007 and 2018 from BGT. The fintech exposure measures are constructed by the author.

Figure 9. Changes in Occupation Concentration

A: Occupation HHI across States



B: Occupation HHI across Industries



This figure plots the relation between fintech exposure and cumulative change in concentration of occupations using a locally weighted smoothing regression (bandwidth 1.2 with 100 observations in plot (a) and 1.6 in plot (b)), following Acemoglu and Autor (2011). The y-axis is the accumulative change in the natural logarithm of occupational HHI index across states in plot(a) and across NAICS two-digit industry in plot(b) from 2007 to 2018. x-axis is the time-invariant occupation-level fintech exposure percentiles. The fintech exposure measures are constructed by the author.

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 top three tasks along with their weights and most frequent keywords matched with those in fintech patents for four occupations. Two occupations on the top have high exposure to fintech while the other have low exposure to fintech. The information in the table is used to illustrate the matching process of constructing occupational fintech exposure.

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 of the time-invariant score.

Table 3: Summary Statistics

Variables	N	Mean	SD	P25	P50	P75	Min	Max
				Occupational Exposure				
Fintech Score (5-Year Application)	290,895	0.265	0.195	0.135	0.216	0.333	0.0217	1.739
Fintech Percentile	290,895	51.95	28.81	27	53	77	1	100
Fintech Quartile 4 Dummy	290,896	0.269	0.443	0	0	1	0	1
Fintech Percentile - Cybersecurity	290,895	51.83	28.9	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	18.1	29.14	1	1	28	1	100
Fintech Percentile - P2P	290,895	51.5	28.85	27	52	77	1	100
Fintech Percentile - Robot-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
No of Occupations	772							
				Number/Share of Posting				
No of Postings	324,892	440	1,205	15	60	275	3	12,483
First Posting (%)	219,979	38.26	16.35	26.56	36.84	48.60	0.53	100.00
Posting Shares (Basis Point)	324,892	15.70	40.19	0.83	3.17	13.25	0.014	1,9750.00
- Most Exposed Occupations	324,892	20.75	39.86	1.49	5.60	20.86	0.021	648.50
				Skill Required				
Finance & Software Skills (%)	324,892	5.09	9.31	0.00	0.30	6.39	0.00	52.80
Finance No Software Skills (%)	324,892	6.57	10.90	0.00	1.90	8.33	0.00	66.10
Software No Finance Skills (%)	324,892	15.50	18.30	0.97	8.74	23.40	0.00	84.60
Other Skills (%)	324,892	58.80	26.40	39.70	62.40	80.00	0.00	100.00
				Education Required				
High School (%)	324,892	21.80	22.20	0.00	16.20	35.70	0.00	95.70
Bachelor's Degree and above (%)	324,892	21.50	26.50	0.00	8.33	38.70	0.00	100.00
				Experience Required				
0-2 Years Experiences (%)	324,892	18.80	16.00	6.72	16.10	27.00	0.00	81.80
2-4 Years Experiences (%)	324,892	8.48	9.79	0.00	5.43	13.70	0.00	51.60
4+ Years Experiences (%)	324,892	9.82	13.10	0.00	3.96	14.90	0.00	61.70
				Demographic Variables from IPUMS				
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

The table reports the summary statistics of the main sample at occupation (SOC 6-digit) by state by year in Panel A and public firm by year sample in Panel B. In Panel A, posting shares 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 author. Occupational exposure to AI and software are from Webb (2019). All job posting data including number and share of postings as well as fraction of job postings that require different skills, experience and educational attainment are calculated using data from BGT. State level demographic characteristics are from IPUMS and ACS.

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 postings. 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***	-0.084***	-0.084***				
	(-10.262)	(-11.514)	(-7.567)	(-7.646)				
FT Quartile 4					-4.375***	-4.045***	-4.654***	-4.585***
					(-8.397)	(-9.107)	(-7.534)	(-7.587)
AI Percentile			-0.028***	-0.028***			-0.028***	-0.029***
			(-3.715)	(-3.921)			(-3.776)	(-3.992)
Software Percentile			0.054***	0.054***			0.055***	0.055***
			(8.107)	(8.192)			(7.873)	(7.946)
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
Observations	287,567	287,567	287,567	279,765	287,567	287,567	287,567	287,567
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	Robot-advising	IoT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FT Quartile 4	-4.529***	-4.121***	-5.608***	-5.148***	-3.496***	-5.722***	-2.628***
	(-7.68)	(-7.44)	(-6.92)	(-6.14)	(-6.30)	(-6.47)	(-6.59)
AI Percentile	-0.030***	-0.035***	-0.025***	-0.036***	-0.044***	-0.021**	-0.032***
	(-4.20)	(-5.15)	(-3.25)	(-5.20)	(-6.91)	(-2.57)	(-4.56)
Software Percentile	0.055***	0.056***	0.050***	0.048***	0.050***	0.042***	0.054***
	(7.98)	(7.88)	(7.67)	(7.97)	(7.95)	(7.14)	(8.15)
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	287,567	287,567	287,567	287,567	287,567	287,567	287,567
R^2	0.089	0.088	0.092	0.087	0.087	0.092	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 in Panel A is the lagged occupational fintech exposure percentile (SOC 6 digit) that varies over time constructed using fintech patent applications in 5-year rolling window. FT Quartile 4 dummy equals one if the occupation's fintech exposure percentile is in the quartile 4 and 0 otherwise. The main explanatory variable n Panel B is the lagged disaggregated fintech exposure measures: cybersecurity, mobile transactions, data analytics, blockchain, P2P, robo-advising and IoT. AI percentile and software percentile is the percentile rank 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 Panel A Columns (3)-(4) and (7)-(8) and Panel B. All regressions are weighted by the number of job postings. Sample is constructed using BGT data in 2007 and 2010-2019. Standard errors are clustered at state level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 6: Changes in Skill and Education Requirements

Panel A: Skill Requirement

Dep Var	Basis Point Change in Posting Shares that Require			
	Finance + Software	Finance No Software	Software No Finance	Other Skills
	(1)	(2)	(3)	(4)
FT Quartile 4	29.501***	-16.853***	19.452***	-62.350***
	(18.74)	(-10.23)	(10.26)	(-16.05)
AI Percentile	0.337***	0.069**	0.339***	-1.649***
	(17.45)	(2.50)	(9.21)	(-20.90)
Software Percentile	-0.470***	0.080**	-0.079***	1.653***
	(-21.85)	(2.23)	(-2.88)	(19.83)
State × Year FE	Yes	Yes	Yes	Yes
N	287,567	287,567	287,567	287,567
R^2	0.155	0.055	0.207	0.074

Panel B: Experience and Education

Dep Var	Basis Point Change in Posting Shares that Require				
	Year of Experiences			Minimum Degree	
	0-2 Years	2-4 Years	4+ Years	HS	BA+
	(1)	(2)	(3)	(4)	(5)
FT Quartile 4	-6.763**	13.471***	36.119***	-11.964***	50.128***
	(-2.62)	(10.16)	(13.91)	(-5.77)	(21.35)
AI Percentile	-0.105*	0.164***	0.733***	-0.878***	1.519***
	(-1.71)	(5.02)	(17.23)	(-15.38)	(25.68)
Software Percentile	0.256***	-0.082***	-0.288***	0.706***	-1.318***
	(5.41)	(-2.91)	(-7.84)	(15.02)	(-27.95)
State × Year FE	Yes	Yes	Yes	Yes	Yes
N	287,567	287,567	287,567	287,567	287,567
R^2	0.141	0.105	0.211	0.141	0.220

The table reports the regression results examining the effect of occupational fintech exposure on skill requirement of the postings. The dependent variable is the year-over-year change in job posting shares that require skills specified in the column title in Panel A and the year-over-year change in job posting shares that require experience and educational attainment specified in the column title in Panel B. The main explanatory variable, FT Quartile 4 dummy, equals one if the occupation's fintech exposure percentile (SOC 6 digit) constructed using fintech patent applications in 5-year rolling window is in the quartile 4 and 0 otherwise. AI percentile and software percentile is the percentile rank 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 by year fixed effect. All the regressions are weighted by the number of job postings. Sample is constructed using BGT data in 2007 and 2010-2019. Standard errors are clustered at state level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 7: 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 in response to occupational fintech exposure. We measure concentration using the Herfindahl-Hirschman Index (HHI). The dependent variable is the change in the natural logarithm of a given occupations' HHI across states in Column (1)-(2) and industry in Column (3)-(4). The dependent variable in Column (1) and (3) is year-to-year change while that in Column (2) and (4) is the long difference between year 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 quartile 4 and 0 otherwise in Column (1) and (3). In Column (2) and (4) it is constructed based on all fintech patent applications in 2003-2017. AI percentile and software percentile is the percentile rank 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 8: Differences of Selected Industries

Panel A: Job Postings and Skill Requirement

Dep Var	Basis Point Change in Posting Shares							
	All Postings				Finance + Software	Finance No Software	Software No Finance	Other Skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FT Quartile 4	-0.829***	-0.791***	-0.809***	-0.869***	23.669***	-17.366***	11.562***	-35.179***
	(-7.632)	(-7.807)	(-7.818)	(-7.440)	(11.34)	(-10.51)	(3.87)	(-9.21)
× Finance	0.808***			0.833***	0.529	48.171***	-46.261***	48.104***
	(5.568)			(5.378)	(0.09)	(9.37)	(-6.49)	(5.36)
× Information		0.560***		0.624***	6.118	47.768***	22.863***	-71.020***
		(4.950)		(5.175)	(0.99)	(8.14)	(3.12)	(-5.69)
× PMA			0.349***	0.408***	-0.896	-17.716***	10.405**	-11.200**
			(3.204)	(3.305)	(-0.38)	(-4.12)	(2.14)	(-2.03)
Finance	-0.708***			-0.857***	32.164***	-11.505***	12.643*	-41.743***
	(-6.490)			(-6.889)	(7.66)	(-3.14)	(1.84)	(-5.37)
Information		-0.937***		-1.078***	-13.165**	-38.595***	-18.407*	33.332***
		(-6.377)		(-6.706)	(-2.62)	(-8.61)	(-1.69)	(2.81)
PMA			-0.599***	-0.701***	5.860***	1.703	2.297	-43.174***
			(-5.264)	(-5.735)	(3.62)	(0.61)	(0.87)	(-10.53)
AI Percentile	-0.009***	-0.009***	-0.008***	-0.008***	0.373***	-0.226***	0.333***	-1.437***
	(-6.885)	(-6.983)	(-6.715)	(-6.065)	(11.83)	(-6.23)	(7.55)	(-17.48)
Software Percentile	0.007***	0.007***	0.007***	0.007***	-0.374***	0.293***	-0.071*	1.303***
	(6.461)	(6.698)	(6.885)	(6.130)	(-14.42)	(7.83)	(-1.89)	(17.47)
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,140,912	1,140,912	1,140,912	1,140,912	1,140,912	1,140,912	1,140,912	1,140,912
R^2	0.047	0.048	0.048	0.048	0.031	0.014	0.042	0.017

Panel B: Experience and Education

Dep Var	Basis Point Change in Posting Shares that Require				
	Year of Experiences			Minimum Degree	
	0-2 Years	2-4 Years	4+ Years	HS	BA +
	(1)	(2)	(3)	(4)	(5)
FT Quartile 4	-4.878**	16.225***	19.813***	-3.207	30.042***
	(-2.03)	(8.30)	(7.18)	(-0.70)	(9.13)
× Finance	59.669***	-20.876***	-50.703***	49.454***	-46.158***
	(8.90)	(-3.96)	(-6.89)	(7.69)	(-5.96)
× Information	-1.900	-31.696***	34.105***	-16.126*	93.587***
	(-0.20)	(-5.05)	(3.90)	(-1.69)	(9.02)
× PMA	7.419*	-1.953	35.611***	-16.830***	40.438***
	(1.90)	(-0.51)	(8.42)	(-3.47)	(7.28)
Finance	-51.074***	17.674***	80.063***	-44.933***	98.787***
	(-7.55)	(4.97)	(14.00)	(-8.32)	(11.21)
Information	-88.883***	13.052**	6.224	-51.319***	-57.811***
	(-10.91)	(2.44)	(0.76)	(-5.78)	(-4.21)
PMA	-74.460***	2.949	9.137**	-10.571**	-22.005***
	(-11.32)	(1.18)	(2.12)	(-2.63)	(-4.55)
AI Percentile	-0.470***	0.244***	0.691***	-0.812***	1.729***
	(-8.84)	(6.46)	(17.17)	(-11.96)	(25.94)
Software Percentile	0.754***	-0.129***	-0.046	0.348***	-0.994***
	(11.53)	(-3.77)	(-1.14)	(4.08)	(-18.04)
State × Year FE	Yes	Yes	Yes	Yes	Yes
N	1,140,912	1,140,912	1,140,912	1,140,912	1,140,912
R^2	0.034	0.016	0.046	0.038	0.069

The table reports the regressions that examine the heterogeneity in labor market adjustments by fintech provider industries in response to occupational fintech exposure. We identify the fintech provider industry based on the industry of the firms who are the inventor or assignee of any fintech patent and they are finance (NAICS 51), information (NAICS 51) and PMA (NAICS 54-56). The dependent variable in Panel A Column (1)-(4) is the year-over-year change of job posting share. The dependent variable in Panel A Column Column (5)-(8) and Panels B is the year-over-year change of job posting share that require skills, experience and education specified in the column title. The posting share is calculated as the share of job posting at occupation × state × year 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 occupation's fintech exposure percentile (SOC 6 digit) constructed using fintech patent applications in 5-year rolling window is in the quartile 4 and 0 otherwise. We also include the interaction of the fintech exposure measure with the dummy variables of three fintech provider industries. AI percentile and software percentile is the percentile rank 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 by year fixed effect. 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 9: Differences between Innovators and Non-Innovators

Panel A: Job Postings and Skill Requirement

Dep Var	Basis Point Change in Posting Shares						
	All Postings			Finance + Software	Finance No Software	Software No Finance	Other Skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FT Quartile 4	-2.256***	-2.192***	-2.283***	28.711***	-9.516***	13.967***	-45.600***
	(-7.25)	(-7.33)	(-7.33)	(15.93)	(-4.13)	(7.27)	(-16.41)
× Inventor	1.418***		1.445***	18.369***	22.219*	9.343	-10.606
	(4.56)		(4.63)	(2.75)	(1.69)	(0.75)	(-0.78)
× Acquisition Innovator		2.801***	2.894***	-21.312	137.517***	-28.815	99.611***
		(4.07)	(4.16)	(-1.17)	(3.63)	(-0.61)	(3.73)
AI Percentile	-0.044***	-0.043***	-0.044***	0.217***	-0.041	0.324***	-1.274***
	(-9.75)	(-9.75)	(-9.75)	(10.32)	(-0.99)	(7.43)	(-16.01)
Software Percentile	0.053***	0.053***	0.053***	-0.348***	0.184***	0.050	1.218***
	(6.84)	(6.84)	(6.83)	(-19.32)	(3.24)	(1.58)	(15.68)
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Innovator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	339,561	339,561	339,561	339,561	339,561	339,561	339,561
R^2	0.071	0.071	0.071	0.072	0.038	0.105	0.044

Panel B: Experience and Education

Dep Var	Basis Point Change in Posting Shares that Require				
	Year of Experiences			Minimum Degree	
	0-2 Years	2-4 Years	4+ Years	HS	BA+
	(1)	(2)	(3)	(4)	(5)
FT Quartile 4	-8.470***	8.518***	29.621***	-17.608***	24.160***
	(-3.59)	(5.42)	(11.83)	(-8.39)	(8.83)
× Inventor	130.612***	8.880*	-52.808***	-35.001**	119.486***
	(15.30)	(1.88)	(-6.06)	(-2.51)	(8.54)
× Acquisition Innovator	-35.068	79.831***	-170.573***	349.751***	-282.678***
	(-1.10)	(3.89)	(-7.73)	(10.37)	(-6.85)
AI Percentile	-0.011	0.145***	0.536***	-0.235***	1.091***
	(-0.20)	(4.22)	(12.71)	(-3.08)	(14.02)
Software Percentile	0.132**	0.016	-0.106***	0.065	-0.686***
	(2.13)	(0.49)	(-2.82)	(1.01)	(-13.94)
State × Year FE	Yes	Yes	Yes	Yes	Yes
Innovator FE	Yes	Yes	Yes	Yes	Yes
N	339,561	339,561	339,561	339,561	339,561
R^2	0.101	0.052	0.133	0.115	0.161

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 two types of fintech innovators based on inventor and assignee names of the patent: inventors and acquisition innovators (assignee). The dependent variable in Panel A Column (1)-(3) is the year-over-year change of job posting share and that in Panel A Column (4)-(7) and Panel B is the year-over-year change of job posting share that require skills, experience and education specified in the column title. The posting share is calculated as the share of job posting at occupation × state × year 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 occupation's fintech exposure percentile (SOC 6 digit) constructed using fintech patent applications in 5-year rolling window is in the quartile 4 and 0 otherwise. We also include the interaction of the fintech exposure measure with two fintech innovators dummy variables, AI and software percentiles developed by Webb (2019), cohort-level initial posting shares and state by year fixed effect. 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%).

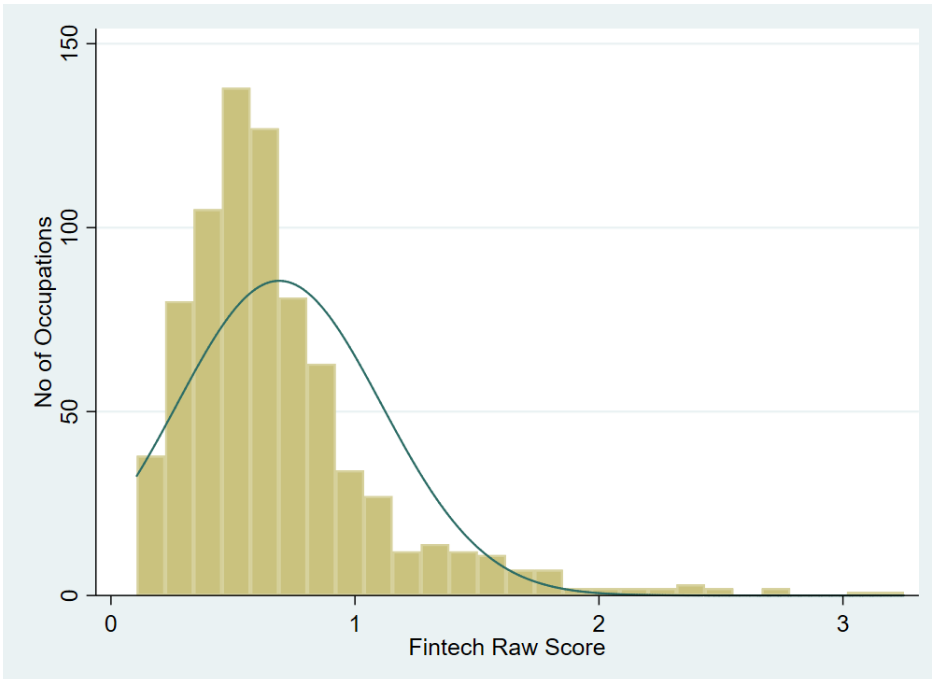
Table 10: Firm Outcomes

Dep Var	ΔLog(Employment)		ΔLog(Sales)		ΔROA		ΔR&D/Assets	
	(1)	(2)	(3)	(4)	(3)	(4)	(7)	(8)
Firm FT Quartile 4	-0.009*	-0.009*	-0.006	-0.007	-0.115	0.000	0.020	0.020
	(-2.13)	(-2.14)	(-0.29)	(0.00)	(-0.98)	(-0.99)	(0.96)	(0.00)
× Inventor		0.038**		0.045**		0.155*		0.080*
		(3.26)		(2.32)		(2.19)		(1.98)
× Non-Inventor Innovator		-0.005		-0.033		-0.151		-0.070
		(-0.11)		(-0.42)		(-0.39)		(-1.74)
Inventor		-0.035***		-0.045**		-0.064		0.012
		(-3.71)		(-2.44)		(-0.75)		(0.32)
Non-Inventor Innovator		-0.012		0.038		0.155		0.110**
		(-0.33)		(0.80)		(0.57)		(3.25)
Firm Time 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	13,959	13,959	14,250	14,250	14,255	14,255	14,251	14,251
R^2	0.056	0.056	0.073	0.073	0.180	0.180	0.050	0.050

The table reports the regressions that examine the heterogeneity in firm operations by fintech innovator and non-innovator firms at firm × year level in 2007-2018. The final firm sample contains 2,243 firms. Firm FT Quartile 4 is the lagged firm average of occupational FT quartile 4 exposure weighted by job postings. We exclude year 2008-2009 when the BGT posting data is unavailable. We define two types of fintech innovators based on inventor and assignee names of the patent: inventor and non-inventor innovators (assignee). The dependent variable is the change in firm outcomes specified by the first row. It is the number of firm employees in Column (1)-(2), firm annual sales in 2003 dollar in Column (3)-(4) and firm ROA defined as annual sales over assets in column (5)-(6) and firm R&D expenses over assets in column (7)-(8) . Control variables include the natural logarithm of lagged total assets in 2003 dollar, firm age, capital expenditure scaled by assets, cash scaled by assets, the cash flow scaled by assets. We additionally control for the lagged R&D dummy which equals one if the firm has R&D expenses and 0 otherwise in Column (1)-(3). We also control for NAICS four-digit fixed effects and year fixed effects. Standard errors are clustered at NAICS four-digit and year level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Appendix

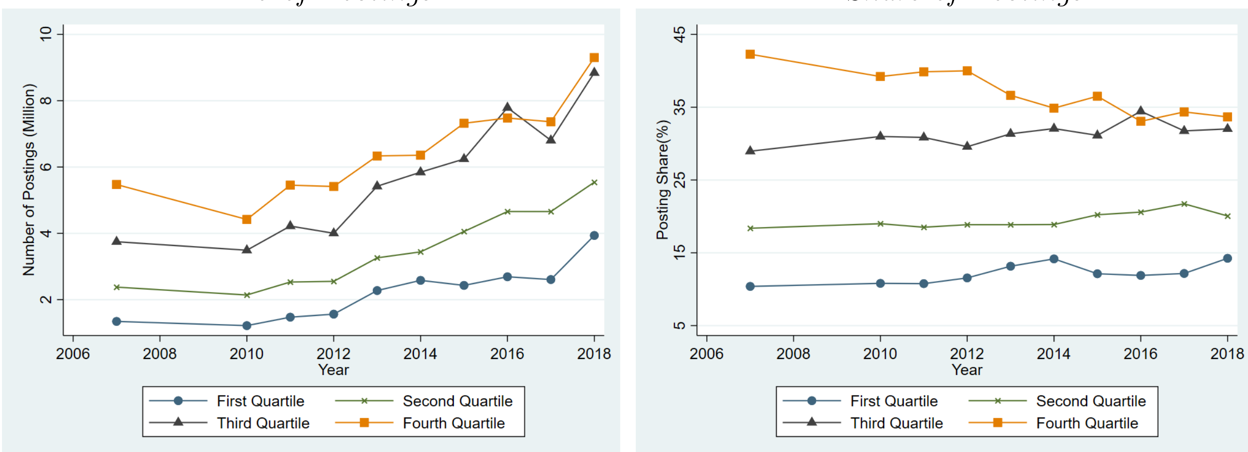
Figure A.1. Distribution of Occupational Fintech Exposure



Note: Figure displays the distribution across six-digit SOC occupations of fintech exposure scores based on all Fintech patent applications in 2003-2017.

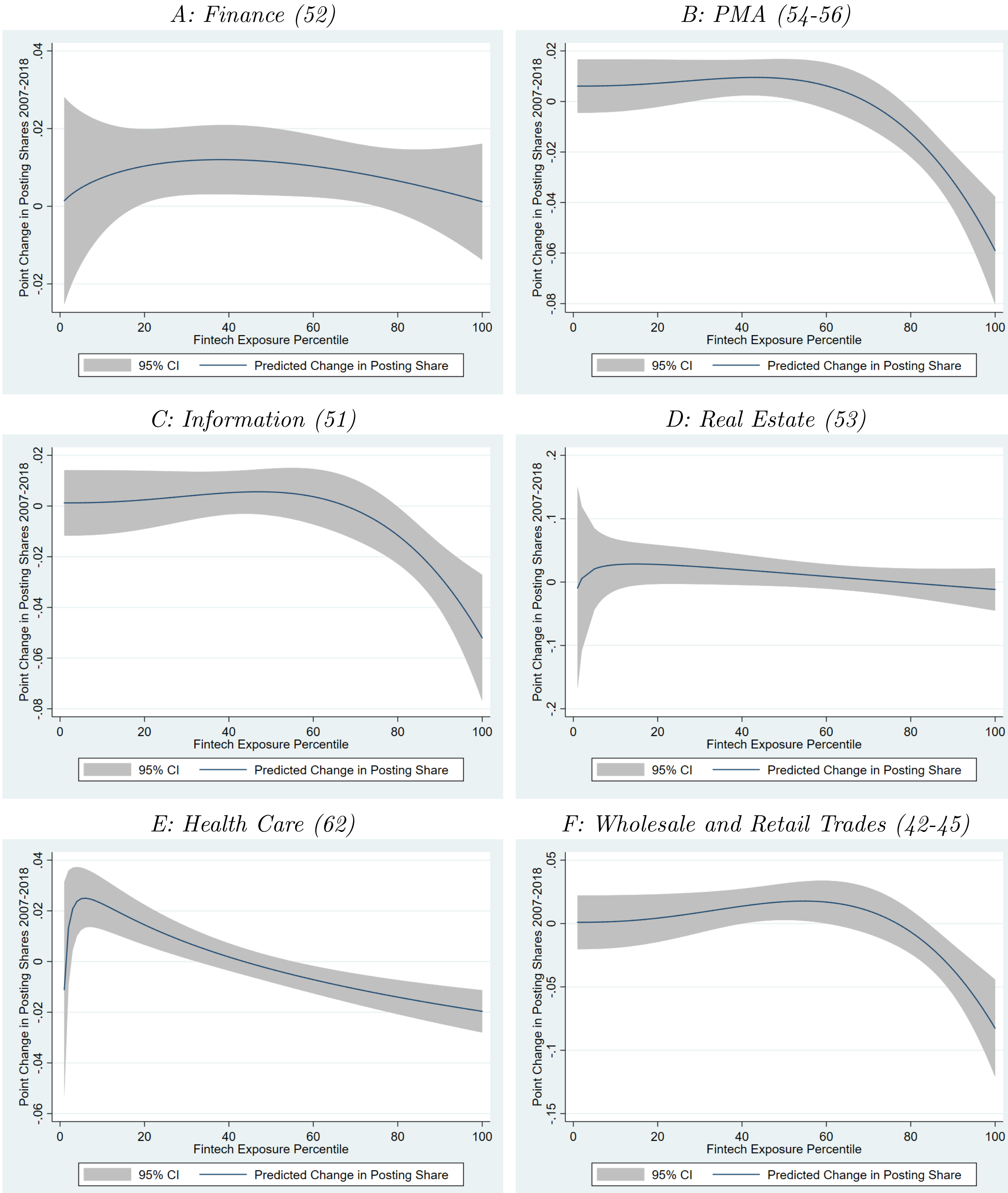
Figure A.2. Job Postings by Fintech Exposure Quartile

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

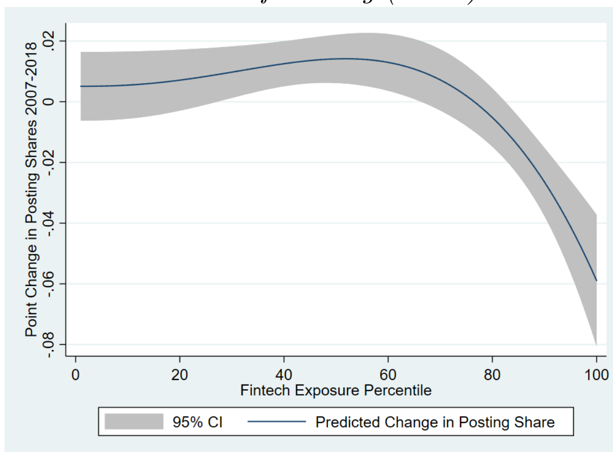


The figures plot xxx.

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



G: Manufacturing (31-33)



The figure plots the relation between fintech exposure and cumulative change in job postings at industry level. The y-axis is the cumulative change in job postings in an industry from 2007 to 2017 and x-axis is the time-invariant occupation-level fintech exposure percentiles. Panel A plots the relation for all industries. Panels B-H 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 finance based on the supply and use table. The change in job postings are calculated using job postings in 2007 and 2018 from BGT. The fintech exposure measures are constructed by the author.

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	-0.268***	-1.84***	-0.656***					
	(-3.17)	(-9.031)	(-14.47)					
FT Quartile 4- Granted				-4.964***				
				(-7.64)				
FT Quartile 4- EW					-4.671***			
					(-7.42)			
FT Quartile 4 -Accum.						-0.080***		
						(-7.44)		
FT Raw Score							-8.520***	
							(-6.94)	
FT Percentile								-0.822***
								(-6.58)
AI Percentile	0.004	-0.056***	-0.004***	-0.032***	-0.031***	-0.029***	-0.027***	
	(1.62)	(-12.960)	(-3.35)	(-4.50)	(-4.24)	(-3.96)	(-3.54)	
Software Percentile	0.005***	0.066***	0.003***	0.056***	0.052***	0.054***	0.051***	
	(2.75)	(7.786)	(3.65)	(7.93)	(7.62)	(8.22)	(7.95)	
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	164,891	197,457	287,567	287,567	287,567	287,567	287,567	287,567
R^2	0.090	0.056	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 occupational employment and job postings. It validates that The main findings of Fintech exposure's disruptive impact on labor market affects the actual employment, and is not driven by the unsatisfied demand of labor and measures used in our baseline analysis are not affected by any possible measurement errors. The regressions are based on 6 digit SOC occupation by state by year IPUMS employment data in 2009-2018 and BGT job posting data in 2007, and 2010-2018. The employment share is the fraction of a cell's employment to the total state employment in a given year.The posting share is the fraction of a cell's job postings to the total state postings in a given year. The dependent variable in Column (1) and (2) is the basis point change in employment shares and first posting shares, respectively. The dependent variable in Column (3)-(8) is the basis point change in all job posting shares. FT Quartile 4 dummy equals one if the occupation's fintech exposure percentile (SOC 6 digit) is in the quartile 4 and 0 otherwise. In Column (1)-(3), FT Quartile 4 is based on the percentile rank of the lagged occupational Fintech exposure sores based on patent applications in 5-year rolling window, but we do not weight the observations in column (3). In Column (4), FT Quartile 4 is based on the percentile rank of the lagged occupational Fintech exposure sores based on patent granted in 5-year rolling window. In Column (5), FT Quartile 4 is based on the percentile rank of the lagged occupational Fintech exposure sores based on patent applications in 5-year rolling window and weighted by lagged occupational employment. In Column (6), FT Quartile 4 is based on the percentile rank of the lagged occupational Fintech exposure sores based on all patent applications in 2003-2017. In Column (7), FT raw score is is the lagged raw score of occupational Fintech exposure based on based on patent applications in 5-year rolling window. In Column (8), FT percentile is the lagged raw score of occupational Fintech exposure based on based on patent applications in 5-year rolling window and we control for occupation fixed effects. AI percentile and software percentile is the percentile rank of occupation-level AI exposure sores and software exposure scores, respectively, from Webb (2019). In Column (1), We control for a cell's initial employment share, and weight the observations by the number of employment. Column (2) -(8), We control for a cell's initial job posting share, and weight the observations by the number of job postings. 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			Not Inventor		
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		3,005	2,980	1,296	1,253	46.15	45.76	41.83	42.10
Total		6,512	6,512	3,098	2,976	100	100	100	100

The table reports the industry and firm distribution 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 then match these firms to BGT data to get 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 2003-2018. There are two types of innovators: inventors are the inventor of any fintech patent and acquisition innovators are the assignee of any fintech patent. The third column is a subset of acquisition innovators who are not the inventor of any fintech patent. # Patent is the total number of fintech patent invented or acquired in 2003-2018. # Job posting is the number of job postings in 2007, 2010-2018 in BGT. # Job posting is zero if the firm is not covered by BGT.

Table A.3: Top 15 Fintech-exposed Public Firms

Public Firm	Firm FT Quartile 4	Assets (2003 Dollar)	Headquarter
Astoria Financial Corp	1	14,720.93	Lake Success, NY
Pinnacle Finl Partners Inc	1	8,317.34	Nashville, TN
Centerstate Bank Corp	1	6,093.84	Winter Haven, FL
Homestreet Inc	1	4,192.11	Seattle, WA
Open Text Corp	1	3,248.55	Waterloo, ON
City Holding	1	2,540.86	Charleston, WV
German American Bancorp	1	2,059.02	Jasper, IN
Farmers & Merchants Bancorp	1	2,010.73	Lodi, CA
Cowen Inc	1	1,947.03	New York, NY
Bar Harbor Bankshares	1	1,874.70	Bar Harbo , ME
First Long Island Corp	1	1,819.73	Glen Head, NY
Two River Bancorp	1	712.68	Tinton Falls, NJ
Patriot National Bancorp	1	510.25	Stamford, CT
Elmira Svgs Bank New York	1	424.46	Elmira, NY
River Valley Bancorp	1	372.23	Madison, IN

The table presents the top 15 US public firms with the highest Fintech exposure defined as the mean of job-posting weighted average occupational Fintech quartile 4 exposure in 2007-2018 and the largest mean assets in 2003 dollars.