Banks, Fintech Disruptions, and Labor Consequences

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Abstract

I examine how traditional depository banks respond to increased competition from fintech firms. My identification strategy exploits the staggered adoption of the regulatory sandbox legislation in some US states. I first show that the adoption of regulatory sandboxes leads to an 8% increase in the number of fintech startups. Using bank-level employment data collected from LinkedIn, I find that the rise in fintech firms leads banks to increase wages and employment of high-skilled workers. At the same time, banks close more branches. Overall, my results suggest that banks boost high-skilled employment and close costly branches in a bid to be more responsive to the potential disruptions from fintech firms.

Keywords: Fintech, banks, Regulatory Sandbox

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1 Introduction

Over the past few decades, there have been significant advancements in financial technology which include mobile banking and online lending. The number of fintech firms that disrupt traditional ways of banking has been on the rise (Chen, Wu, and Yang, 2019). Although traditional banks offer higher quality products, they have lost market share to fintech firms, mainly because of complex regulatory requirements and costs (Buchak, Matvos, Piskorski, and Seru, 2018). Fintech firms bring about new automated technologies such as tools that simplify and speed up each step of the mortgage origination process, replacing traditional mortgage specialists (Fuster, Plosser, Schnabl, and Vickery, 2019). The impact of fintech firms on traditional banks has therefore been an important topic to policy makers [1]. This impact, however, is not fully understood due to insufficient empirical evidence.

Researchers face several empirical challenges in identifying the impact of disruptive technology brought about by fintech firms. At the heart of these concerns is the possibility that there could be confounding variables, such as macroeconomic shocks, that affect the developments of both fintech firms and traditional depository banks at the same time. I alleviate this challenge by exploiting the staggered adoption of regulatory sandboxes among US states. A regulatory sandbox is a legislation set up by state regulators that allows fintech startups to conduct live experiments on their products and services in a controlled environment. The regulatory sandbox program is designed specifically to not only help new fintech firms to ease regulatory burdens and costs but also foster financial innovation.

First introduced in the UK in 2015, regulatory sandboxes are now present in more than 20 countries worldwide, including the US, China, Australia and Canada. Arizona is the

[1] See for example OECD's discussion on digital banking disruptions

first state in the US that introduced the sandbox program that aims to lift regulations requirements and allow innovative financial products and services to be tested to a restricted number of consumers. The program has seen initial success over the past five years in operation. In 2019, Verdigris Holdings, Inc. entered the Arizona sandbox with a plan to develop solutions that cater customized financial services at low costs to underbanked segment of the population. Verdigris Holdings now owns BrightFi, a fintech platform that provides banking solutions for those who have no access to traditional banks. Following Arizona, nine other states have introduced their sandbox programs. US states that adopted the regulatory sandbox program are documented in Figure 1 and the signing dates are presented in Figure 2.

Using a stacked data, my difference- in-differences identification strategy exploits the staggered adoption of the regulatory sandboxes among US states. It helps overcome endogeneity concerns by exploiting the fact that not all US states have adopted regulatory sandboxes; in addition, among those states that have adopted the program, not all of them did so at the same time. I can thus construct a time-varying control group that provides a counterfactual for how fintech firms and banks would have evolved in the treated states in the absence of sandboxes.

My review of the political economy shows that the passage of the regulatory sandbox program was mainly motivated by legislators who wish to reap the benefits of regulatory sandboxes in their states. For example, Arizona Attorney General Mark Brnovich was the first to make the case for stateside regulatory sandboxes, advocating the program's various benefits that include not only cost savings to new fintech startups but also tax revenue, innovation, and job growth to the state.[2] He later worked with Arizona Representative Jeff Weninger to establish the state's regulatory sandbox legislation. Overall, lobbying does not seem to play a role in the decision, especially since the main beneficiaries of the sandbox programs are fintech startups, which often have limited financial resources and are unlikely to spend much on lobbying. This fact alleviates concerns that my results may be driven by reverse causality or by some unobservable shocks affecting both the growth opportunities and lobbying efforts of fintech startups.

I first show that the adoption of regulatory sandbox increases new entrants of fintech firms. My sample period is from the first quarter of 2016 (8 quarters before the first sandbox adoption) to the last quarter of 2021. I find that the adoption of regulatory sandbox legislation in a state leads to an 8% significant increase in fintech entry in the state. This result is consistent with the expectation that regulatory sandbox programs attract fintech firms by reducing their regulatory burdens and providing them with a valuable testing ground for their products. My analysis controls for standard state-level macroeconomic variables: state-level real gross state product (GSP) growth, per-capita income and unemployment. These macroeconomic variables are in addition to the state and year-quarter fixed effects that I include in all specifications, which account for time-invariant differences across states and time-varying shocks affecting all states, respectively.

In addition, I find that the adoption of fintech sandbox increases employment in newly founded financial firms. I obtain state-level employment data from the Census Bureau's Quarterly Workforce Indicators (QWI) database. I select firms that are 0 to 3 years old and in the financial industry to capture young financial firms. I find that the adoption of fintech

[2] Arizona Attorney General Mark Brnovich op-ed

sandbox leads to an average of 5% increase in employment and 7.9% increase in job growth in young financial firms.

Overall, my results show that the staggered adoption of fintech sandbox is an appropriate mechanism to study the impact of the rise in fintech firms on traditional banks. I hypothesize that traditional banks will respond to increased competition by demanding more skilled employees. As a result, I hypothesize that they will hire more employees, especially employees with fintech experience and skills, and offer them higher wages. Finally, I hypothesize that banks will close more physical branches in a bid to be more efficient following the increased entrants from fintech firms.

Using data from LinkedIn to assemble bank-level data of workers with relevant fintech skills and experiences, I find that the increase in fintech entrant leads to significant increase of 7.1% in employees with these fintech backgrounds. Furthermore, I find this advancement of fintech firms leads to 11.5% and 15.2% increase in total bank employment and bank wages, respectively. Finally, I find that banks close costly branches to reduce costs following the increased competition from fintech firms. In the analysis at the bank level, I include bank-state fixed effects, which control for time-invariant characteristics at the bank and states levels, for example, the overall reputation or the initial popularity of banks in a certain state. I also include bank-year-quarter fixed effects, which control for time-variant changes at the bank level, for example, bank's balance sheet information that changes over time.

Together, my results suggest that banks on average boost recruitment, offer high wages, and close costly branches in a bid to be more efficient and responsive to the potential disruptions from fintech firms. To the best of my knowledge, my paper provides the first empirical evidence on the labor impact of increased competition from fintech firms on traditional depository banks. It provides support to theoretical models which show that digital disruption has the potential to bring in new players and increase competition in the banking industry (Philippon, 2019; Vives et al., 2019; Tian, 2022).

My paper contributes to the growing literature that studies the various impacts of fintech adoption. Previous literature shows that there have been significant advancements of fintech firms and they are replacing banks in various capacities (Buchak, Matvos, Piskorski, and Seru, 2018; Tang, 2019; Xiao, 2020; Irani, Iyer, Meisenzahl, and Peydro, 2021). In addition, digital divide can be caused by higher access costs (Jack and Suri, 2014; Bachas, Gertler, Higgins, and Seira, 2018; Jiang, Yu, and Zhang, 2021) and the availability of advanced infrastructures (Saka, Eichengreen, and Aksoy, 2021; Lee, Morduch, Ravindran, Shonchoy, and Zaman, 2021). My paper studies the social consequences of technology growth by analyzing labor impacts created by how banks respond to the increased competition from fintech firms.

This paper also contributes to the literature on banking competition (Cetorelli and Strahan, 2006; Garmaise and Moskowitz, 2006; Cornaggia, Mao, Tian, and Wolfe, 2015; Drechsler, Savov, and Schnabl, 2017; Jiang, 2019; Buchak and Jørring, 2021).Most of the existing papers focus on banks' price competition (Egan, Hortaçsu, and Matvos, 2017; Xiao, 2020). My paper adds to this literature by showing how banks' branching and labor decisions interact with banks' responses to increased competition.

Finally, my paper adds to the rich literature of the relationship between finance and labor. Several papers have analyzed how frictions in the capital markets affect firm employment growth (Chodorow-Reich, 2014; Adelino, Ma, and Robinson, 2017; Giroud and Mueller, 2017; Antoni, Maug, and Obernberger, 2019; Benmelech, Frydman, and Papanikolaou, 2019; Appel, Farre-Mensa, and Simintzi, 2019). My paper focuses on a different type of friction, showing that increased competition affects banks' hiring decisions.

The remaining sections of the paper are organized as follows. Section 2 discusses the institutional background of the regulatory sandbox. Section 3 summarizes the data and Section 4 describes the methodology. Sections 5 documents the impacts of regulatory sandboxes on fintech firms. Section 6 presents banks' reactions. Section 7 concludes.

2 Institutional Background

Current development

The regulatory sandbox program enables businesses to obtain limited access to test innovative financial products or services without meeting all regulatory requirements. It is first introduced by the Financial Conduct Authority in the UK in 2015. Regulators in China, Singapore, Australia, Canada, and more than 20 other countries have followed suit and initiated their own sandbox programs. In the US, there are 10 states with regulatory sandboxes. The main purpose the regulatory sandbox is to foster innovations in financial technology.

Launched in 2018, Arizona's first-in-the-nation fintech sandbox provides relief for entrepreneurs by lifting regulation requirements and allowing innovative products and services to be tested to a restricted number of consumers. The Arizona Attorney General Office supervises the program to ensure compliance with consumer protection laws. The program has seen initial success over the past five years in operation. In 2019, Verdigris Holdings, Inc. entered the Arizona sandbox with a plan to develop solutions that cater customized financial services at low costs to underbanked segment of the population. Verdigris Holdings now owns BrightFi, a fintech platform that provides banking solutions for those who have no access to traditional banks. According to Michael Coghlan, CEO of BrightFi, the sandbox program gives his company a great foundation for success: "It gave us a degree of latitude that allowed us to test things and test approaches and develop operations that perhaps would be more difficult had we not been participating in the Sandbox." [3] . Past fintech firms that partcipated in the Arizona sandbox are listed in Figure 2A and the current participants are listed in Figure 3A in the Appendix.

Following Arizona, nine other states have introduced their sandbox programs. The US states that adopted regulatory sandbox are documented in Figure 1. Figure 2 provides the signing dates.

[Figure 1 and Figure 2 here]

Sandbox heterogeneity

There is heterogeneity in how sandboxes are adopted in different states. While Arizona sandbox excludes cryptocurrency, the regulatory sandbox in Hawaii includes an innovation lab that supports digital currency innovation. For the first two-year duration of the innovation lab, Hawaii will allow the participating digital currency issuers to establish businesses in Hawaii without obtaining a state money transmitter license. The two-year initiative selected 19 participants that include Robinhood Crypto and and BlockFi Trading.

Utah, on the other hand, has taken significant step forward by expanding its regulatory sandbox to allow more innovators to take advantage of a controlled regulatory environment. From its first introduction in 2019, Utah's program now includes legal sandbox that foster legal services innovation.

Heterogeneity in sandbox timing is addressed by using stacked regressions. A stacked regression is an alternative approach developed by applied re- searchers for circumventing

[3] azag.gov: Arizona attorney general's office highlights successes of fintech sandbox

the issues with TWFE DiD estimators as demonstrated in Gormley and Matsa (2011) and Baker, Larcker, and Wang (2022) .

Why states adopt regulatory sandboxes

State-by-state regulation of fintech firms has become increasingly more complex. Today, each state has enacted a different combination of laws regulating a variety of statutorily defined financial activities, including issuing loans (from consumer and payday loans to automobile debt and mortgages), servicing debts, and transmitting money.

The main component of this state-by-state approach to regulating fintech firms is licensing. Each state requires fintech firms to obtain a license from the state financial regulator before offering specified services within the state. This type of regulation is known as "activities-based" as opposed to "entity-based": regulation is based on the type of financial activities the firm performs. The process of applying for a license is costly and time-consuming, with firms spending over $1 million and waiting two years for a final decision (McQuinn and Castro, 2019). Failing to obtain a license can result in serious penalties, ranging from civil liability to criminal punishment. Once licensed, non-banks are subject to oversight by the state's financial regulator and must file annual financial reports, pay fees, and submit to regular examinations. The examination process is described as time-consuming and document-heavy for the firms.

State governments are willing to extend regulatory exceptions because the startups that emerge from such experiments could bring about new jobs, tax revenue and expanded access to financial services. According to the National Law Review, regulatory sandboxes often reduce the barriers to entry for entrepreneurs and enable them to safely test and iterate on a solution before they invest considerable resources to scale their product and service offerings.[4]. In exchange, regulators are able to gather empirical data about new business models and use an evidence-based approach for future policy decisions. This approach can validate or dispel regulatory concerns about an innovation's impact and assist regulators in delivering beneficial services to end users.

In a 2017 op-ed in the American Banker, Arizona Attorney General Mark Brnovich (R) was the first to make the case for stateside regulatory sandboxes.[5] He stated that fintech startups are burdened with a fractured and redundant regulatory system. "Not only can it take several months to obtain regulatory approval to operate a fintech startup in just one state, but it can cost a startup thousands of dollars in fees, compliance costs and legal work. Launching a product nationwide is harder still. Entrepreneurs navigating our 50-state licensing regime commonly expect two years of frustration and expenses in the millions." With this vision, Attorney General Brnovich worked with Arizona Representative Jeff Weninger to introduce regulatory sandbox legislation. Governor Doug Ducey ultimately signed the bill into law on March 23, 2018, making Arizona the first state in the U.S. with a regulatory sandbox. Overall, Arizona's regulatory sandbox program is mainly pushed forward by state legislators thanks to the various benefits that it promises.

Likewise, Hawaii's Digital Currency Innovation Lab (partnership between the Department of Commerce and Consumer Affairs, Division of Financial Institutions and Hawaii Technology Development Corporation) played a key role in helping pass regulatory sandbox legislation in that state. Overall, my investigation of the political economy suggests that the legislation was mainly initiated by legislators who wish to reap the benefits of regulatory sandboxes in their states. Lobbying does not seem to play a role in the decisions, especially

[4] States' motivations behind sandbox legislations
[5] Arizona Attorney General Mark Brnovich op-ed

since the main beneficiaries of the sandbox programs are fintech startups, which often have limited financial resources and are unlikely to spend much on lobbying. This fact alleviates concerns that my results may be driven by reverse causality or by some unobservable shocks affecting both the growth opportunities and lobbying efforts of fintech startups.

However, sandboxes have attracted plenty of scrutiny from consumer groups and even other regulators, who fear that the regulatory relief would be used to offer untested and thus harmful products. In 2019, a group of New York State Attorneys General form a coalition to urge the Consumer Financial Protection Bureau (CFPB) not to adopt regulatory sandbox. They argued that the proposed policies would erode critical consumer protections under the guise of fostering innovation in the consumer financial marketplace. California has been debating the adoption of regulatory sandbox for years. The state created a special task force that recommended exploration of the development of a regulatory sandbox. The work has been paused due to lawmakers questioned whether the agency has strayed from its core mission of public protection.

To further understand the drivers of the passage of regulatory sandboxes among states, Table 1 investigates whether a state's macroeconomic and legal conditions predict the introduction of regulatory sandbox program.

[Table 1 here]

In Table 1, Column 1 and Column 2 show that a state's income per capita, unemployment rate and GSP growth rate are not significantly correlated with the passage of sandbox program. The results suggest that the adoption of regulatory sandbox is driven by persistent characteristics of the states rather than changes in their economic conditions.

I reach a similar conclusion in columns 3 and 4 when I control for the party that has political control of the state. I find that the adoption of regulatory sandbox is not significantly different between states where the Republican party controls both chambers of the state legislature and the governor is Republican than in states where Democrats control both the legislative and executive branches (Democratic state) or in states with split political control.

Columns 5 examine whether these conclusions are robust to including the macroeconomic and political economy all at once. I continue to find that, when state fixed effects are included, all the state-level controls again become insignificant when we include state-level fixed effects. The fact that all the analyses where we estimate the effects of anti-troll laws include state fixed effects implies that the persistent state characteristics that Table 1 shows are correlated with the adoption of regulatory sandbox do not pose a threat to my identification strategy.

3 Data

3.1 Data

I collect data on fintech startup firms from Crunchbase. Crunchbase obtains data directly from its network of executives, entrepreneurs, and investors of the covering companies. By using machine learning algorithms, Crunchbase performs data validation to maintain an accurate and high-quality database. In addition, Crunchbase covers the most comprehensive set of startup firms, including fintech startups. It is widely used in academic research (Kaplan and Lerner, 2016; Davis, Morse, and Wang, 2020).

Next, I obtain state-level employment data from the Census Bureau's Quarterly Workforce Indicators (QWI) database. Employment is measured at the end of each quarter. For each state-quarter, the QWI reports employment data aggregated by firm age and four-digit North American Industry Classification System (NAICS) industry. The QWI reports data for firm age categories in which I chose 0-2 years to capture employment at young financial firms.

I obtain bank employment, wages and establishments data at the state-level from Quarterly Census of Employment and Wages (QCEW) of the Bureau of Labor Statstics (BLS). The QCEW program publishes a quarterly count of employment and wages reported by employers covering more than 95 percent of U.S. jobs, available at state level by industry. The industry data was organized by NAICS number. To get the data for banks, I select NAICS 52211 that designates commercial banks.

Finally, information on bank branches is collected from the from the Federal Deposit Insurance Corporation (FDIC), which is the annual survey of branch offices as of June 30 each year for all FDIC-insured institutions. I merged this data with FDIC daily database on bank branches openings and closing to get the quarterly data on bank branches. Note that FDIC only insures deposits in banks and excludes FDIC-insured entities, such as credit unions.

I present my results controlling for the following state-level macroeconomic variables: state quarterly real GSP growth rate and income per capita (log-transformed), from the Bureau of Economic Analysis; state-level quarterly unemployment rate, from the BLS.

[Table 2 here]

3.2 LinkedIn Data

The lack of employer-employee matched data has been a significant hurdle in studying the labor effects of fintech advancements on banks. The US Census Bureau houses employee data at individual level. However, the information about employee is restricted and can take years to apply for, making it difficult to track bank employees longitudinally. I overcome this challenge by assembling data from LinkedIn. LinkedIn is the world's largest online professional networking platform, which began in 2003 and has since grown to over 740 million users worldwide. LinkedIn is a professional networking platform that allows users to create online profiles that serve as virtual resumes. These profiles typically include information about a user's education and employment history, including details about the schools they attended, the programs they participated in, their work experience and the positions they held at different companies.

LinkedIn data offer two benefits for this study: First, professionals with experience and skillsets consistent for fintech initiatives, the main target for this paper, are more likely to have LinkedIn profiles. Second, LinkedIn profiles are public to all users, making it difficult for individuals to make false claims about their employment. As LinkedIn users back-fill their complete user educational and employment history when creating their profile, I obtain a large and consistent during my sample period (2016–2021). It also provides users ample time to update their employment history, minimizing concerns about data completeness.

First, I obtained the main data of commercial employees at the bank level by assembling all profiles who have ever worked at a commercial bank during my sample period. From the main dataset, I filter out the subset of employees with skills and experiences that would be useful for a fintech initiative - *the fintech employment sample* - from my main data in three steps. First, I include all employees with finance, IT and computer related degrees and/or majors. Second, I include all employees who have experiences working in finance or technology related companies and projects in their working history. Third, I include employees who have listed their skills with technology related, such as having skills in programming languages that include Artificial Intelligence, Python, Java, SQL, Scala and C++.

Large commercial banks such as Bank of America, JPMorgan Chase, Citi and Wells Fargo are the primary employers in both the main sample and the fintech employment sample.

3.3 Summary Statistics

Table 2, Panel A reports summary statistics for my sample at the state level. My sample period is from the first quarter of 2016 (8 quarters before the first sandbox adoption) to the last quarter of 2021. The average state has approximately 1.48 newly established fintech firms in a given quarter. Average total employment in financial service firms that are between zero and three years old is just over 1,800. The average number of job growth for firms in the same category is just above 230. Panel A also provides summary statistics for banks at the state level. The average number of bank establishment at a state is 1,584, while the average bank employment at a given quarter is just below 26,500.

Summary statistics for my macroeconomic controls are as follows: the mean state-level quarterly GSP growth rate is 2.1%; income per capita averages $53,400; and the unemployment rate during my sample period averages 4.52%.

Panel B compares the mean values of the outcome and control variables for states with and without regulatory sandbox prior to the adoption of the first regulatory sandbox legislation in Arizona. Specifically, column 1 reports the mean of each variable over 2016Q1–2016Q4 for those states that pass regulation sandbox program at some point during my sample period, while column 2 reports the mean for those states that pass no such program. The p -values corresponding to the differences between these means (clustered at the state level) are reported in column 3.

While fintech entry in treated states tends to be lower than in never-treated states, this difference is not statistically significant. There is also an economically large (but statistically insignificant) difference between financial service firm employment (0 to 3 years old) and bank wages for the two groups, mainly due to the presence of California and Massachusetts in the never-treated group. The differences in these two categories shrink when I exclude these two states. In addition, my results also hold after excluding California and Massachusetts from my sample, suggesting that these two states do not drive my conclusions.

[Table 3 here]

Table 3 reports summary statistics for my sample at the bank level. A bank has an average of 0.45 branch in a given quarter in a state, with the standard deviation of 8.4. Average bank closure is 0.005.

4 Methodology

I construct a stacked sample following Gormley and Matsa (2011) and Baker, Larcker, and Wang (2022) based on each state's sandbox adoption in years 2018 to 2021. To identify the effect of regulation sandbox on outcome variables, such as fintech entries and bank employment, I estimate the following difference-in-differences specification:

$$y_{st} = \delta RegBox_{st} + \beta X_{st-1} + \theta \text{Other state initiatives}_{st} + \sigma_s + \alpha_t + \epsilon_{st}.$$

where s denotes states and t denotes year-quarters. RegBox is the dummy variable equals to one if sandbox is passed on or after t. X_{st-1} is the vector of state-level control variables (GSP growth rate, income, unemployment rate). State-level control variables also include other state initiatives, which is an indicator set equal to one if state s has adopted one of the initiatives aimed at promoting or easing fintech regulations in or before quarter t , and zero otherwise. σ_s : state fixed effects and α_t: year-quarter fixed effects.

Table 1 shows that changes to macroeconomic conditions do not predict the adoption of regulatory sandbox, I include these variables as controls, as they may be related to broader employment trend. σ_s is a state fixed effect, which controls for state characteristics that do not vary over my sample period, such as the fact that California is larger and attracts more fintech startups, and more democratic than Alabama; and σ_t is a year-quarter fixed effect, which absorbs aggregate shocks affecting all states. In all specifications, I report robust standard errors clustered at the state level (Bertrand, Duflo, and Mullainathan, 2004).

Similarly, to identify the effect of increased fintech entrants the bank level, I estimate the following difference-in-differences specification:

$$y_{bst} = \delta RegBox_{st} + \beta X_{bst-1} + \theta \text{Other state initiatives}_{st} + \sigma_{bs} + \alpha_{bt} + \epsilon_{st}.$$

where b denotes banks, s denotes states and t denotes year-quarters. RegBox is the dummy variable equals to one if sandbox is passed on or after t. X_{bst-1} is the vector of bank control variables. State-level control variables also include other state initiatives, which is an indicator set equal to one if state s has adopted one of the initiatives aimed at promoting or easing fintech regulations in or before quarter t , and zero otherwise. σ_{bs} : bank-state fixed effects and α_{bt}: bank-year-quarter fixed effects.

In this analysis, I include σ_{bs} as bank-state fixed effects, which control for time-invariant characteristics at the bank and states levels, for example, the overall reputation or the initial popularity of banks in a certain state. I also include σ_{bs} as bank-year-quarter fixed effects, which control for time-variant changes at the bank level, for example, bank's balance sheet information that changes over time.

In both specifications, my empirical setting allows for the same state to be part of the treatment and control groups at different time points. In other words, at any year-quarter t , the control group includes both states that adopt a regulatory sandbox program after year-quarter t (but before the end of my sample period) and so eventually are treated, and states that are never treated (either because they have yet to pass a regulatory sandbox program or do so after the end of the sample period). Figure 3 illustrates my research design.

[Figure 3 here]

5 Impacts of regulatory sandbox

5.1 Regulatory sandbox increases new entrants from fintech firms

In Table 4, I use Crunchbase to get data on fintech firms' inception date and location. The dependent variable is an indicator equal to one if a state has adopted the sandbox legislation program in that quarter. The treatment states are those who adopted the sandbox legislation program at some points in the sample, while the control states do not. By including state fixed effects and year-quarter fixed effects in the specification, I effectively control for any underlying state characteristics and aggregate shocks that could affect the results. The research design allows the same state to be part of the treatment and control groups at different time points. This dynamic helps to address potential concerns about omitted variable bias and other confounding factors.

Table 4 shows that the adoption of regulatory sandbox legislation in a state leads to an 8% average increase in fintech entry in the state. The result is statistically significant. This result is consistent with the expectation that regulatory sandbox programs attract more fintech firms by reducing their regulatory burdens and providing them with a valuable testing ground for their products. In addition, this result shows that the staggered adoption of fintech sandbox is an appropriate mechanism to study the impact of the increased competition from fintech firm on traditional banks.

[Table 4 here]

Recent methodology papers in empirical corporate finance have pointed out the deficiency of the log1plus regression approach. Therefore, I conduct two robustness tests to validate my results without using the log1plus approach. First, I run the regression with the number of fintech entry as the dependent variable. Second, I follow Cohn, Liu, and Wardlaw (2022) to use Poisson regression to estimate the effect of fintech entry following the state adoption of regulatory sandbox. Results of the robustness tests are consistent with result in Table 4. Details of the tests are reported in Table A3 in the Appendix.

5.2 Young financial service firms obtain more employment

In Table 5, I obtain state-level employment data from the Census Bureau's Quarterly Workforce Indicators (QWI) database. Employment is measured at the end of each quarter (EmpEnd). For each state-quarter, the QWI reports employment data aggregated by firm age and industry. I select firms that are 0 to 3 years old and in the financial industry to capture young financial firms. I find that adoption of fintech sandbox leads to an average of 5% increase employment and 7.9% increase in the average number of job growth in young financial firms. The results suggest that regulatory sandbox programs facilitate young financial firms to focus their resources into business growth and talent recruitment.

[Table 5 here]

5.3 Identification

Reverse causality and omitted variables pose a potential problem to the parallel-trends assumption of my identification strategy. In this section, I will present several pieces of evidence that are consistent with the parallel-trends assumption.

Table 4 previously shows that there is an increase in fintech entry following the adoption of regulatory sandbox. To drive my findings, an omitted variable would not only need to be correlated with the staggered adoption of regulatory sandbox program among states but also differentially affect fintech start-ups. In addition, young fintech firms are unlikely to be able to spend much on lobbying, alleviating concerns that my results may be driven by reverse causality.

Next, Figure 4 shows how the number of fintech entry changes around the adoption of regulatory sandbox legislation. The figure plots the estimated average difference in number of fintech entry at treated states relative to control states from quarter $t-4$ to quarter $t+3$, where for each treated state, quarter t is the quarter when state adopted sandbox legislation. Consistent with the parallel-trends assumption, I find no significant difference in the evolution of at treated and control states prior to the passage of regulatory sandbox legislation.

[Figure 4 here]

Table 6 and Table 7 report a series of tests aimed at further alleviating identification concerns. In Table 6, column 1 estimates the effect of regulatory sandboxes on fintech entry after I match treated and control states; the matching metric is a linear combination of the geographical distance between the states' population centroids (one-third of the weight) and the absolute value of the difference between each of the three macroeconomic controls included in my regressions, measured at the beginning of my sample period (two-thirds of the weight combined). The results of this test are similar to those in Table 4, which suggests that my findings are not confounded by the possibility that employment dynamics in Alabama may be more similar to those in Kentucky than to those in New York.

In Column 2 of Table 6, I exclude California and Massachusetts out of the sample. These two states are known to have a high concentration of fintech start-ups. My results also hold after excluding California and Massachusetts from my sample, suggesting that these two states do not drive my conclusions.

[Table 6 here]

Table 7 reports a placebo test where I change the timing of passage of the regulatory sandbox legislation. Specifically, I falsely assume that each state that passed a sandbox legislation did so two years before the law was actually passed in the state. For example, I assume that Nevada passed its regulatory sandbox legislation in January 2018 instead of in January 2020 (the actual date). The placebo sample goes from first quarter of 2016 to fourth quarter of 2019, consistent with the actual sample of analysis. Consistent with my identification assumption, this placebo treatment effect is neither economically nor statistically significant.

[Table 7 here]

6 Banks' reactions to increased competition

6.1 Banks increase total employment hire more employees with fintech skills

In Table 8, I obtain bank employment data from LinkedIn. First, I assemble profiles of all individuals who have ever worked at a commercial bank during my sample period to arrive at comprehensive employment data at the bank level. I then construct the fintech employment data by focusing on employees with finance and technology-related educational background. I also include employees who listed skills in AI and programming language skills, and who previous working experience in fintech or technology and software companies. These steps ensure that my fintech employment sample includes employees that are desirable for a fintech initiative, such as a project that offers banking services digitally instead of in-person only via physical branches. I hypothesize that with the advancements of financial technology firms, banks would be more likely to respond by transforming their own service offerings towards more technology-friendly settings. To facilitate this transformation, commercial banks need to boost their hiring, particularly in employees with the right skill sets.

I find that adoption of fintech sandbox leads to 7.1% increase in employment of employees with fintech skills and backgrounds. The results are significant in specification (1) where I control for bank-state fixed effects and specification (2) where I control for both bank-state FE and bank-year-quarter fixed effects. Bank-state fixed effects control for differences across banks and states that are constant over time, such as the overall reputation of the bank in a certain state. Bank-year-quarter fixed effects, on the other hand, control for differences across banks and time, such as changes in the bank's balance sheet information.

[Table 8 here]

In Table A1 and A2 in the Appendix, I report the impacts of sandbox legislation on commercial banks employment and wages at the state level. I obtain state-level bank employment and wages data from Quarterly Census of Employment and Wages (QCEW). The QCEW program publishes a quarterly count of employment and wages reported by employers covering more than 95 percent of U.S. jobs, available at state level by industry. To get the data for banks, I select NAICS 52211 that designates commercial banks. I find that increased fintech entrant leads to 11.5% and 15.2% increase in the average bank employment and bank wages respectively at the state-level. The results are significant in specification (1) and (3) where I don't include state controls and in (2) and (4) where I do. The results suggest that banks boost recruitment activities and offer more attractive remuneration to new talents in a bid to counter the potential disruptive impacts caused by fintech firms.

To address parallel trend assumption, Figure 5 and Figure 6 shows the changes around the adoption of regulatory sandbox legislation of bank employment and bank wages respectively at the state-level. The figure plots the estimated average difference in number of fintech entry at treated states relative to control states from quarter $t-4$ to quarter $t+3$, where for each treated state, quarter t is the quarter when state adopted sandbox legislation. Consistent with the parallel-trends assumption, I find no significant difference in the evolution of at treated and control states prior to the passage of regulatory sandbox legislation.

[Figure 5 here]

[Figure 6 here]

6.2 Banks reduce the number of establishments

[Table 9 here]

I obtain state-level bank establishments data from Quarterly Census of Employment and Wages (QCEW). I find that fintech's increased entrants lead to a 10% decrease in the average number of bank establishments at the state-level. This result stands in contrast with the increase in wages and employment. Although banks boost recruitment activities, they close costly physical branches to become more efficient. Together, the results suggest that banks close physical branches and hire more talents to facilitate the process of being more digital. This would help them to respond more effectively to the potential disruptions by increased competition from fintech firms.

6.3 Banks close branches

Before fintech disruptions, consumers rely on bank branches. Opening new branches would generally imply that banks are growing and serving new segment of the market. However, bank branches incur significant operating costs such as rental, maintenance and security costs. Financial technology, on the other hand, provides banking services without the customers ever have to leave their home. When there is more competition, especially from disruptive fintech firms, I predict that banks would expand their digital services and thus are more likely to close costly branches to improve their operating margin and be more flexible.

[Table 10 here]

In Table 10, I analyzed the impact on bank branches following the increased competition from fintech firms at the bank level. Information on bank branches is collected from the FDIC. I adopt two outcome variables: the natural log of total number of branches and the number of branch closures scaled by last quarter's total branch numbers. Using the same difference-in-differences regression at the bank level, I find that following the increased competition from fintech firms, banks close on average 0.4% of branches.

7 Conclusions

Due to fintech firms' growing prominence in the economy, there has been increasing interest in studying their impacts in academic and policy circles alike. Fintech firms are fundamentally changing the way we bank by introducing breakthrough technology and innovative approaches. The impact of fintech firms on traditional banks has therefore been an important topic. This impact, however, is not fully understood as there is insufficient empirical evidence on this topic. This paper attempts to bridge this gap in the literature by studying how banks react to the increased competition from fintech firms.

Using the staggered adoption of regulatory sandboxes among US states as an identification strategy, I first show that the adoption of regulatory sandbox legislation in a state leads to an 8% significant increase in fintech entry in the state. This increase in competition from fintech firms leads banks to significantly increase employment of high-skilled workers with relevant fintech backgrounds and experiences. I also find that bank increase and employment and wages at the state-level. The results suggest that traditional depository banks respond to increased competition by boosting recruitment and offering them better wages.

In addition, I find that banks reduce the number of branches following the increased competition from fintech firms. Together, my results suggest that banks recruit more skilled workers and close costly branches in a bid to be more efficient and responsive to the potential disruptions from fintech firms.

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Figure 1: States that adopted regulatory sandbox during my sample period (lighter blue)

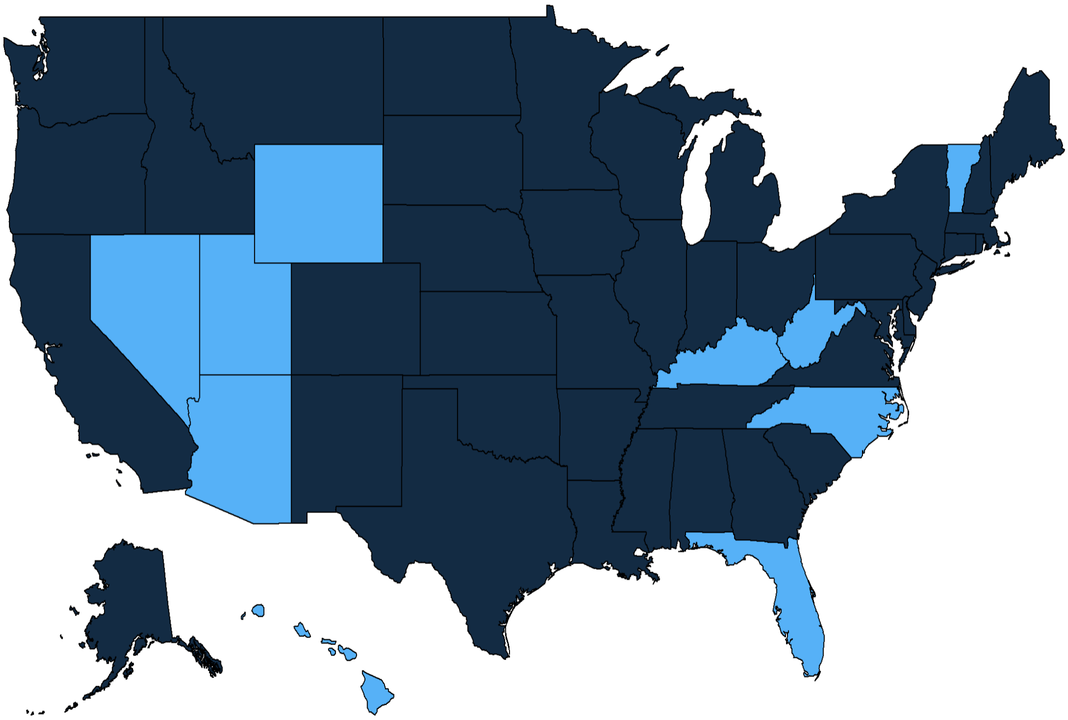


Figure 2: Signing dates of states that adopted regulatory sandbox

State	Signing Date
Arizona	March 23, 2018
Wyoming	February 29, 2019
Utah	March 25, 2019
Kentucky	June 27, 2019
Vermont	January 01, 2020
Nevada	January 17, 2020
Hawaii	March 17, 2020
West Virginia	July 01, 2020
Florida	January 01, 2021
North Carolina	October 15, 2021

Figure 3: Research Design

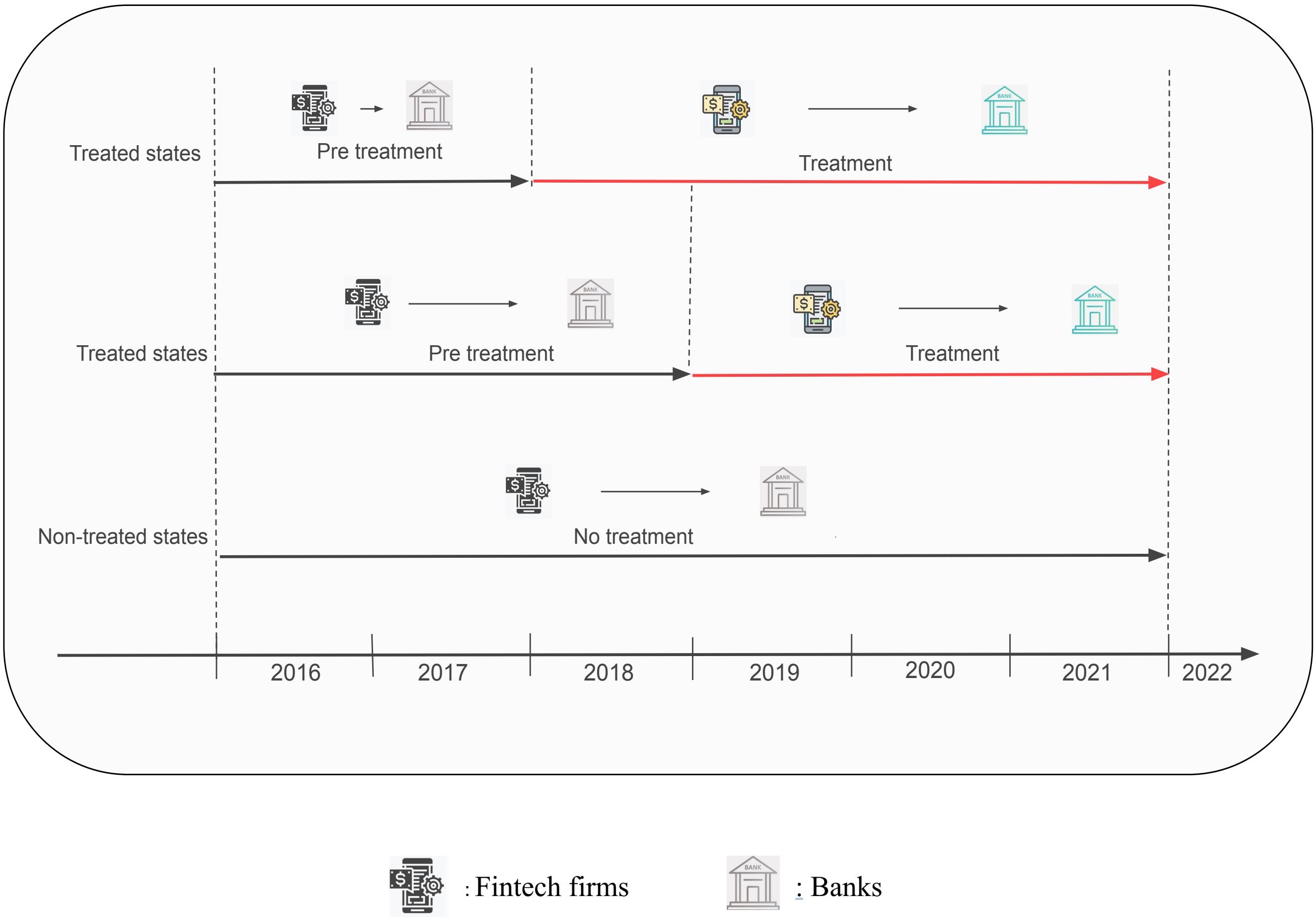
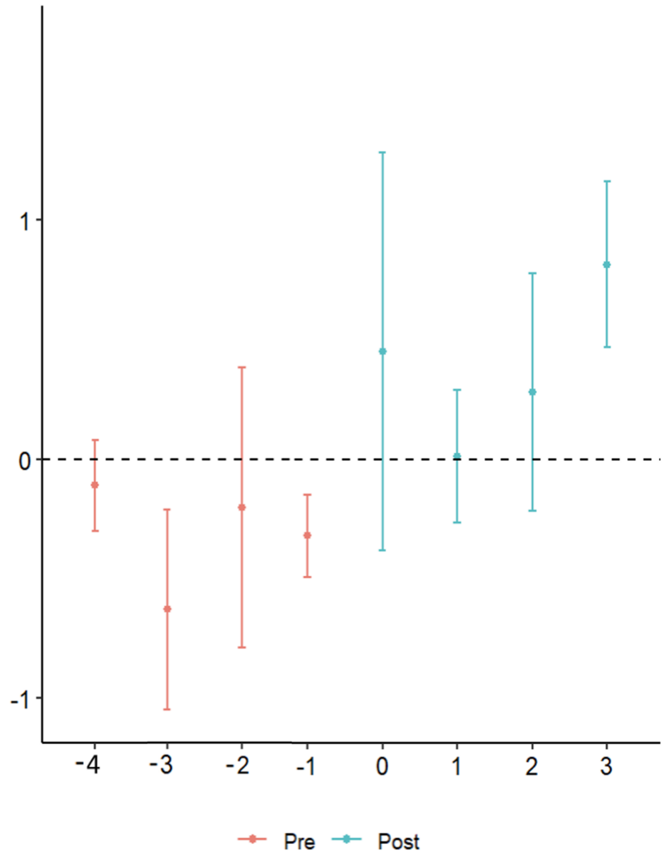
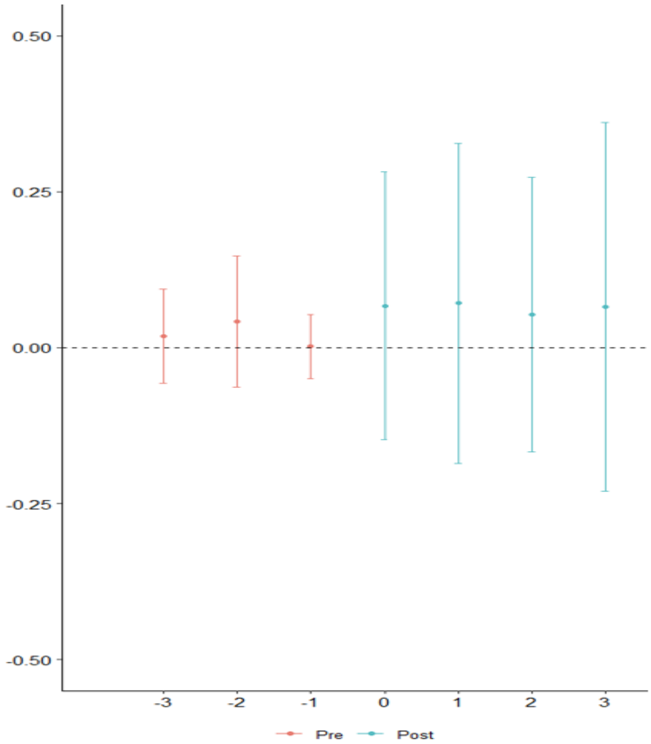


Figure 4: Fintech start-ups entry coefficient trend



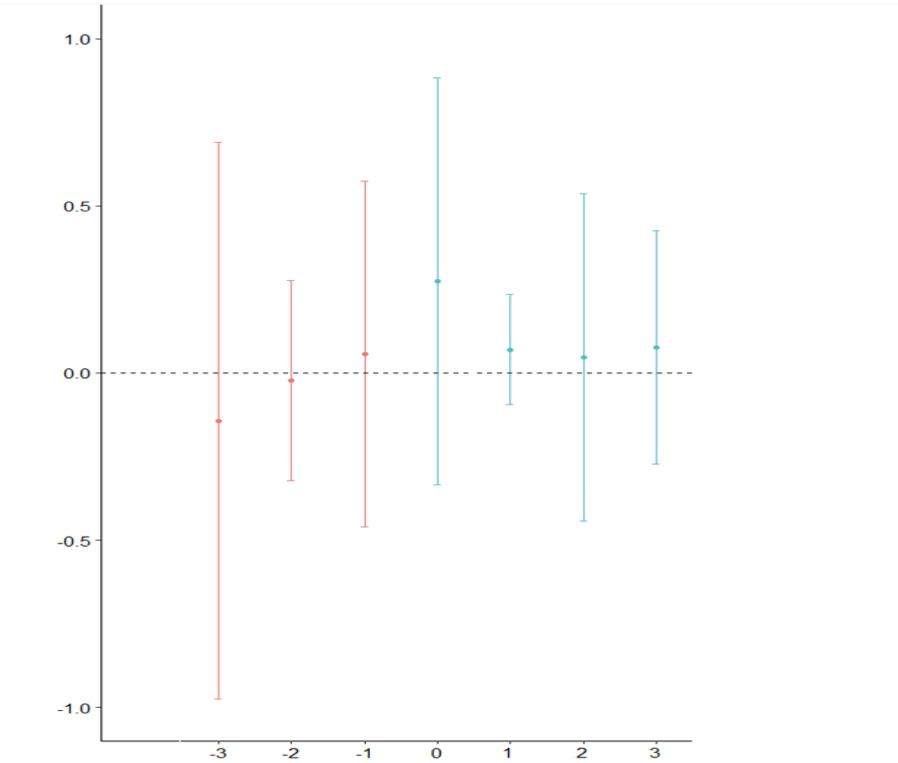
This figure shows the evolution of fintech entry (average effect by length of exposure) in treated states with regulatory sandbox legislation relative to control states without such laws following the methodology in Callaway and Sant'Anna (2021).

Figure 5: Bank employment coefficient trend



This figure shows the evolution of average bank employment (average effect by length of exposure) in treated states with regulatory sandbox legislation relative to control states without such laws following the methodology in Callaway and Sant'Anna (2021).

Figure 6: Bank wages entry coefficient trend



This figure shows the evolution of bank wages (average effect by length of exposure) in treated states with regulatory sandbox legislation relative to control states without such laws following the methodology in Callaway and Sant'Anna (2021).

Table 1: Predictive regressions

This table examines whether a state's macroeconomic conditions predict the adoption of regulatory sandbox. The dependent variable is an indicator equal to one if a state has adopted regulatory sandbox in that quarter. The controls in columns 1 and 2 are state-level macroeconomic controls: GSP growth rate, the natural logarithm of income per capita and unemployment rate. The controls in columns 3 and 4 are indicators for whether the state is controlled by Republicans or Democrats (i.e., a single party controls both the legislative and executive branches); the excluded group are states where the legislative and executive branches are controlled by different parties. The specification in columns 5 includes all the control variables from columns 1 through 4. All control variables are lagged one quarter. Each observation is a state-quarter. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	Adoption of regulatory sandbox				
	(1)	(2)	(3)	(4)	(5)
State gdp growth	0.0026	0.0014			0.0015
	(0.88)	(0.31)			(0.42)
ln(income per capita)	-0.1195	1.0434			1.324
	(-0.73)	(0.64)			(0.77)
Unemployment rate	0.0229	0.0327			0.0112
	(1.00)	(1.40)			(1.22)
Dem. state			0.003	0.004	0.002
			(0.32)	(0.08)	(0.02)
Rep. state			0.0205	0.076	0.018
			(0.42)	(0.12)	(0.09)
State FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	No	Yes	No	Yes	Yes
No. of observations	1,200	1,200	960	960	960
R^2	1.73	2.91	3.32	2.44	2.65

Table 2: State-level summary statistics

Panel A reports summary statistics for the full sample. All variables are quarterly . Panel B compares the characteristics of states with and without regulatory sandbox prior to the adoption of the first adoption. Column 1 reports the mean of each variable over 2016Q1–2016Q4 for states that pass regulatory sandbox at some point during the sample (i.e., the eventually treated group). Column 2 reports the analogous means for states that do not adopt regulatory sandbox at any point during the sample (i.e., the never-treated group). The p -values of the differences (clustered by state) between these groups are reported in column 3.

	Observations	Mean	Median	SD
	(1)	(2)	(3)	(4)
Panel A				
Unemployment rate	1200.00	4.52	4.2	1.9
GSP growth rate	1200.00	2.10	2.30	10.34
State income	1200.00	53400.43	52227.50	8868.82
Fintech entry	1200.00	1.48	0.00	4.37
Employment (0-3 years, financial service)	1150.00	1866.02	1095.50	2564.64
Job growth (0-3 years, financial service)	1150.00	232.23	116.00	359.63
Bank establishments	1200.00	1583.88	1227.00	1496.25
Bank employment	1200.00	26451.34	16738.00	28011.24
Bank wages	1200.00	64013557	316497198	872171922

	Eventually treated (1)	Never treated (2)	Difference p-value (3)
Panel B			
Unemployment rate	4.57	4.65	0.71
GSP growth rate	1.51	1.17	0.68
State income	45711.5	48522.5	0.17
Fintech entry	1.06	1.54	0.28
Employment (0-3 years, financial service)	1422.17	1835.19	0.14
Job growth (0-3 years, financial service)	121.69	241.81	0.38
Bank establishments	1394.25	1688.33	0.29
Bank employment	24209.5	27146.45	0.53
Bank wages	469660664	555382028	0.44

Table 3: Bank-level summary statistics

Table 3 reports summary statistics at the bank level. Branches are the number of branches of a bank in a state in a give quarter. Branch closure is the number of a bank's branches that are closed in a state in a give quarter. All variables are quarterly.

	Observations (1)	Mean (2)	SD (3)
Branches	3654300.00	0.45	8.40
Branches closure	3654300.00	0.005	0.23

Table 4: Number of fintech start-ups following sandbox adoption

This table reports the stacked difference-in-differences (DiD) test result on how regulatory sandbox affects the number of fintech start-ups. Dependent variable is the logarithm of number of new fintech start-ups. Sandbox is an indicator equal to one if a state has passed sandbox legislation in or before that quarter. State-level control variables are income per-capita, GSP growth rate and unemployment. All control variables are lagged one quarter. Each observation is a state-quarter. All specifications include state and year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	ln(1+ Entry) (1)
Sandbox	0.081** (1.75)
State controls	Yes
State FE	Yes
Year-quarter FE	Yes
No. of observations	1,200
Within R^2(%)	1.26

Table 5: Employment at young financial service firms

This table reports the stacked difference-in-differences (DiD) test results on how regulatory sandbox affects employment at young firms (0-3 year-old) in financial service industry. ln(Employment) is the logarithm of employment at young financial firms. ln(Job growth) is the logarithm of job growth at young financial firms. Sandbox is an indicator equal to one if a state has passed sandbox legislation in or before that quarter. State-level control variables are state income per-capita, GSP growth rate and unemployment. All control variables are lagged one quarter. Each observation is a state-quarter. All specifications include state and year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	ln(Employment) (1)	ln(Job growth) (2)
Sandbox	0.0497* (1.76)	0.0785*** (2.96)
State controls	Yes	Yes
State FE	Yes	Yes
Year-quarter FE	Yes	Yes
No. of observations	1,150	1,150
Within R^2(%)	1.23	1.83

Table 6: Matched sample tests

Dependent variable is the logarithm of the number of fintech start-ups. Sandbox is an indicator equal to one if a state has passed sandbox legislation in or before that quarter. Column (1) estimates how regulatory sandbox affects the number of fintech start-ups *in a matched sample* (described in text). Column (2) describes how regulatory sandbox affects the number of fintech start-ups, excluding fintech firms in CA and MA. State-level control variables are state income per-capita, GSP growth rate and unemployment. All control variables are lagged one quarter. Each observation is a state-quarter. All specifications include state and year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	ln(1+ Entry)	
	Matched sample	Excluding CA and MA
	(1)	(2)
Sandbox	0.078*	0.069*
	(1.81)	(1.70)
State controls	Yes	Yes
State FE	Yes	Yes
Year-quarter FE	Yyes	Yes
No. of observations	480	1,152
Within R^2(%)	1.82	1.91

Table 7: Falsification tests

Dependent variable is the logarithm of the number of fintech start-ups. Sandbox $(t-8)$ is a placebo indicator that equals one starting 8 quarters prior to a state passing its actual regulatory sandbox legislation; this placebo sample goes from 2016Q1 to 2019Q4. State-level control variables are state income per-capita, GSP growth rate and unemployment. All control variables are lagged one quarter. Each observation is a state-quarter. All specifications include state and year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	ln(1+ Entry) (1)
Sandbox $(t-8)$	-0.032 (0.82)
State controls	Yes
State FE	Yes
Year-quarter FE	Yes
No. of observations	1,200
Within R^2(%)	1.13

Table 8: Impact of increased fintech competition on bank employment of high-skilled workers

This table reports the stacked difference-in-differences (DiD) test results on how increased competition from fintech firms affects bank employment and wages. ln(Fintech employment) is the logarithm of a commercial bank' employment of employees with fintech skills and experience at a state at the end a quarter. Sandbox is an indicator equal to one if a state has passed sandbox legislation in or before that quarter. State-level control variables are state income per-capita, GSP growth rate and unemployment. All control variables are lagged one quarter. Each observation is at bank-state-quarter level. All specifications include state and year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	ln(Fintech employment)	
	(1)	(2)
Sandbox	0.094***	0.071***
	(2.89)	(2.92)
State controls	Yes	Yes
Bank-state FE	No	Yes
Bank-year-quarter FE	Yes	Yes
No. of observations	328,711	328,711
Within R (%)	2.11	1.85

Table 9: Impact of increased fintech competition on banks' establishments

This table reports the stacked difference-in-differences (DiD) test results on how increased competition from fintech firms affects banks' number of establishments in a state. ln(Bank establishments) is the logarithm of total number of commercial banks' establishments in a state at the end a quarter. Sandbox is an indicator equal to one if a state has passed sandbox legislation in or before that quarter. State-level control variables are state income per-capita, GSP growth rate and unemployment. All control variables are lagged one quarter. Each observation is at state-quarter level. All specifications include state and year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	ln(Bank establishments)	
	(1)	(2)
Sandbox	-0.118*	-0.101**
	(-1.80)	(-2.03)
State controls	No	Yes
State FE	Yes	Yes
Year-quarter FE	Yes	Yes
No. of observations	1,200	1,200
Within R^2(%)	1.26	1.35

Table 10: Impact of increased fintech competition on bank branches

This table reports the stacked difference-in-differences (DiD) test results on how increased competition from fintech firms affects bank branches at the bank level. ln(1 + #branches) is the logarithm of total number of branches of a bank at the end a quarter. #branchclosure/#branches is the ratio of the number of branch closures of a bank in a state divided by the total number of branches the bank had last quarter in the same state. Sandbox is an indicator equal to one if a state has passed sandbox legislation in or before that quarter. State-level control variables are income per-capita, GSP growth rate. and unemployment rate. All control variables are lagged one quarter. Each observation is at bank-state-quarter level. All specifications include bank-state and bank-year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	log(1+#branches) (1)	#branchclosure/#branches (2)
Sandbox	-0.0047*** (-2.95)	-0.00004* (-1.81)
State controls	Yes	Yes
Bank-state FE	Yes	Yes
Bank-year-quarter FE	Yes	Yes
No. of observations	3,654,300	3,654,300
Adjusted R^2	1.85	2.91

APPENDIX

Figure 1A: Variable Definitions

Variable	**Definitions**
Dependent variables	
Adoption of regulatory sandbox	An indicator equal to one if a state has adopted regulatory sandbox in a quarter
Fintech entry	The number of new fintech start-ups founded in a state in a quarter
Bank establishments	The total number of commercial banks' establishments in a state at the end a quarter
Bank employment	The total number of commercial banks' employment in a state at the end a quarter
Bank wages	The total number of commercial banks' wages in a state at the end a quarter
Branches	The total number of branches of a bank at a state at the end a quarter
Branches closure	The number of branch closures of a bank at a state at the end of a quarter
Independent variables	
Sandbox	An indicator equal to one if a state has adopted regulatory sandbox in a quarter
GSP growth rate	The real growth rate of a state's gross domestic product in a state
State income	Average state income per capita
Unemployment rate	State's unemployment rate
Employment (0-3 years, financial service)	Quarterly data of state-level employment data for financial firms that are founded within 3 years
Job growth (0-3 years, financial service)	Quarterly growth change of state-level job openings for financial firms that are founded within 3 years

Figure 2A: Arizona's Sandbox Alumni

Participant	Product Description	Entered Sandbox	Exited Sandbox
WiseTack, Inc.	A consumer lending platform that enables small business partners to provide lending options at the point of sale for consumers seeking to finance household related projects (e.g., home repair, HVAC, electrical, plumbing, landscaping, etc).	July 11, 2019	January 22, 2020
Verdigris Holdings, Inc.	A solution that combines custom technology and industry expertise to deliver simple transactional financial services at a low cost to unbanked people and the companies that serve them.	July 12, 2019	July 17, 2020
Omni Mobile, Inc. ("OM Cash")	A financial service platform implementing an array of avante garde technologies to improve today's payment systems through the utilization of direct ACH payments through OM's centralized wallet infrastructure.	October 11, 2018	October 11, 2020
Sweetbridge NFP, Ltd.	A blockchain-enabled product designed to purchase financing without a credit check and offer affordable, consumer-friendly vehicle title loans with an APR cap of 20%.	October 29, 2018	October 29, 2020
Grain Technology, Inc.	An application that offers consumers personalized savings plans and credit opportunities through their existing bank account.	October 29, 2018	October 29, 2020
ENIAN, Ltd.	A platform to help investors compare potential investment opportunities by providing an algorithm-based evaluation tool for potential solar and wind power projects looking for funding.	May 8, 2019	January 8, 2021
MO Technologies USA, LLC	An online platform that allows consumers to apply for an interest-free cash advance line of credit through MO's mobile app or web browser. MO Technologies charges a one-time finance charge of 4.99% per advance. This cash advance line of credit lets customers draw, repay, and redraw funds as they desire.	February 15, 2020	January 8, 2021
WithClutch, LLC	A business model for refinancing motor vehicle retail installment contracts that aims to use proprietary technology to provide consumers with lower interest rates.	January 8, 2020	March 4, 2021
ALTA Solutions AZ, LLC (d/b/a "ALTA")	A financial services "club" using money transmission services in connection with the sale of digital assets aimed at providing a cash management solution for licensed medical marijuana providers.	July 12, 2019	April 16, 2021
Align	A business model for income-sharing agreements that provide qualified consumers with a fixed amount of money in exchange for a percentage of the consumer's future income over a scheduled period of time, subject to contingencies involving periods of unemployment or lowered income.	March 20, 2019	April 29, 2021
Valley of the Sun Mint, LLC (d/b/a Satoshiware)	Hardware bitcoin wallets called Satoshi Coins that are pre-loaded with fractional bitcoin.	March 4, 2022	September 8, 2022

Figure 3A: Arizona's Current Sandbox Participants

Participant	Start Date	Product Description
Cryptoenter Corp.	July 19, 2021	A blockchain-based platform that integrates with banks to provide bank customers with cryptocurrency exchange and transfer services.
Yield Park, LLC	March 23, 2022	Cash management tool utilizing digital dollar custodians and decentralized finance protocols.

Welcome To Arizona's Regulatory Sandbox

WE ARE NOW ACCEPTING APPLICATIONS

Under Arizona Revised Statutes ("A.R.S.") §§ 41-5601 to 41-5612, a Regulatory Sandbox ("Sandbox") for innovative products and services is now available in Arizona. The Sandbox enables a participant to obtain limited access to Arizona's market to test innovative financial products or services or other innovations without first obtaining full state licensure or other authorization that otherwise may be required. The Arizona Attorney General's Office is responsible for the admission process into and oversight of the Sandbox.

Submit feedback or questions to sandbox@azag.gov .

Figure 4A: Hawaii's Digital Currency Sandbox Program

Program Milestones

Developments within the DCIL

MARCH 17, 2020

1st Call for Participation

The DCIL announced its call for applications from digital currency companies on March 17, 2020. Only US-based companies are allowed in the program. In this round, early-stage companies or startups were given due consideration since there was enough runway for these companies to establish its operations and introduce its services to residents in Hawaii before the program ends.

19 companies applied for admittance with 12 being accepted into the program to form Cohort 1.

AUGUST 19, 2020

Cohort 1 Announcement

The official start of the first cohort began on August 19, 2020, when the DCIL hosted a virtual kick-off meeting to welcome the participating companies into the program. These companies are Apex Crypto, bitFlyer USA, BlockFi Trading, CEX.IO, Cloud Nalu, Coinme, ErisX, Flexa Network, Gemini Trust Company, Novi Financial, River Financial and Robinhood Crypto

JANUARY 25, 2021

2nd Call for Participation

A second call for participation was announced on January 25, 2021, with this round geared towards established digital currency companies. Since the length of participation is shorter, companies are expected to start operations in Hawaii upon admittance into the program. 14 companies applied to be considered, with 4 being accepted into the DCIL to form Cohort 2.

JUNE 18, 2021

Cohort 2 Announcement

The 4 companies were officially admitted into the DCIL on June 18, 2021 – joining 11 companies* from Cohort 1. These companies are BitStop, Provenance Technologies, SoFi and Uphold.

Figure 4A: Hawaii's Digital Currency Sandbox Program Participants

The DCIL has been extended for another two years, up until **June 30, 2024**!

11 Companies will remain in the DCIL and continue to serve Hawaii's residents.

Appendix Tables

Table A1: Impact of increased fintech competition on bank employment at the state level

This table reports how increased competition from fintech firms affect bank employment in a state. ln(Bank employment) is the logarithm of total number of commercial banks' employment in a state at the end a quarter. Sandbox is an indicator equal to one if a state has passed sandbox legislation in or before that quarter. State-level control variables are state income per-capita, GSP growth rate and unemployment. All control variables are lagged one quarter. Each observation is at state-quarter level. All specifications include state and year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	ln(Bank employment)	
	(1)	(2)
Sandbox	0.115*	0.119*
	(1.72)	(1.68)
State controls	Yes	Yes
State FE	No	Yes
Year-quarter FE	Yes	Yes
No. of observations	1,200	1,200
Within R^2	1.9	1.3

Table A2: Impact of increased fintech competition on bank wages at the state level

This table reports how increased competition from fintech firms affect bank wages in a state. ln(Bank employment) is the logarithm of total number of commercial banks' employment in a state at the end a quarter. ln(Bank wages) is the logarithm of total number of commercial banks' wages in a state at the end a quarter. Sandbox is an indicator equal to one if a state has passed sandbox legislation in or before that quarter. State-level control variables are state income per-capita, GSP growth rate and unemployment. All control variables are lagged one quarter. Each observation is at state-quarter level. All specifications include state and year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	ln(Bank wages	
	(1)	(2)
Sandbox	0.164**	0.152**
	(1.72)	(1.68)
State controls	Yes	Yes
State FE	No	Yes
Year-quarter FE	Yes	Yes
No. of observations	1,200	1,200
Within R^2	1.26	1.3

Table A3: Fintech entry robustness tests

Dependent variable is the logarithm of the number of fintech start-ups. Sandbox is an indicator equal to one if a state has passed sandbox legislation in or before that quarter. In column (1), the dependent variable is the total number of fintech start-ups in a quarter in a state. In column (2), I follow Cohn, Liu, and Wardlaw (2022) to use Poisson regression to estimate the effect of fintech entry following the state adoption of regulatory sandbox . State-level control variables are state income per-capita, GSP growth rate and unemployment. All control variables are lagged one quarter. Each observation is a state-quarter. All specifications include state and year-quarter fixed effects. Robust standard errors are clustered by state. I use $***$, $**$, and $*$ to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Dep. Var. =	Total Fintech Entry (1)	Poisson estimation (2)
Sandbox	0.12*** (2.77)	0.06* (1.89)
State controls	Yes	Yes
Bank-state FE	Yes	Yes
Bank-year-quarter FE	Yes	Yes
No. of observations	1,200	1,200
Adjusted R^2	2.73	3.11

B LINKEDIN DATA CONSTRUCTION

B1. Sample Construction

The lack of employer-employee matched data has been a significant hurdle in studying the labor effects of fintech advancements on banks. The US Census Bureau houses employee data at individual level. However, the information about employee is restricted and can take years to apply for, making it difficult to track bank employees longitudinally. I overcome this challenge by assembling data from LinkedIn. LinkedIn is the world's largest online professional networking platform, which began in 2003 and has since grown to over 740 million users worldwide. LinkedIn is a professional networking platform that allows users to create online profiles that serve as virtual resumes. These profiles typically include information about a user's education and employment history, including details about the schools they attended, the programs they participated in, their work experience and the positions they held at different companies.

LinkedIn data offer two benefits for this study: First, professionals with experience and skillsets consistent for fintech initiatives, the main target for this paper, are more likely to have LinkedIn profiles. Second, LinkedIn profiles are public to all users, making it difficult for individuals to make false claims about their employment. As LinkedIn users back-fill their complete user educational and employment history when creating their profile, I obtain a large and consistent during my sample period (2016–2021). It also provides users ample time to update their employment history, minimizing concerns about data completeness.

First, I obtained the main data of commercial employees at the bank level by assembling all profiles who have ever worked at a commercial bank during my sample period. From the main dataset, I filter out the subset of employees with skills and experiences that would be useful for a fintech initiative - *the fintech employment sample* - from my main data in three steps. First, I include all employees with finance, IT and computer related degrees and/or majors. Second, I include all employees who have experiences working in finance or technology related companies and projects in their working history. Third, I include employees who have listed their skills with technology related, such as having skills in programming languages that include Artificial Intelligence, Python, Java, SQL, Scala and C++.

Large commercial banks such as Bank of America, JPMorgan Chase, Citi and Wells Fargo are the primary employers in both the main sample and the fintech employment sample.

B2. Fintech skills

Below is the listed words that I used to distinguish the high-skilked employees with skills and experiences that would be useful for a fintech initiative - the fintech employment

B3. Collated data

Work experience	Education	Programing/Other
- Experience at a fintech company	- Undergraduate degree and above in computer engineering or science, fintech major	- Python, Java, SQL - Scala, C++ and others
- Experience at a financial firm - Experience at a technology firm	- Finance-related or data driven related degree - Statistical and maths related degree	- Artificial Intelligence

LinkedIn also collates data for firms along with employees. The firm-level data contains firm name, LinkedIn industry, headquarter location, estimates of current firm size, and company website.