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# Investing in the Shadows: FinTech Growth and Mortgage Market Dynamics\*

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## Abstract

The adoption of new technologies is widely viewed as a key driver of the rapid growth of nonbanks in the U.S. mortgage market after the Global Financial Crisis (GFC). This paper studies technology investment by mortgage lenders and its implications for post-GFC market structure. Using a new dataset on lender-level technology investment merged with loan origination records and balance-sheet information, we document that technology-related human capital investment has risen over time, driven disproportionately by banks and larger lenders, and that such investment predicts higher subsequent productivity. We then estimate lenders' investment responses to two major shocks: the expansion of FinTech lending and monetary policy-driven demand shocks. Our instrumental-variable estimates suggest that banks increase technology investment in response to FinTech growth, whereas nonbanks respond weakly or even negatively; in contrast, nonbanks respond more strongly to positive demand shocks. To quantify the relative contributions of these shocks to changes in market structure, we build a heterogeneous-firm model consistent with the empirical evidence. The model implies that the post-GFC nonbank expansion was largely driven by a combination of favorable shocks—strong demand and tighter bank regulation—rather than broad-based technological advantages among nonbanks. Consequently, in a prolonged high-interest-rate environment with relaxed bank regulation, as may characterize the post-2025 policy environment, the model predicts a decline, rather than continued growth, in nonbanks' market share.

**Keywords:** FinTech, mortgage, financial intermediation, firm dynamics, investment, labor

**JEL Codes:** D22, D25, E22, E24, E44, G21, G23

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# 1 Introduction

The adoption of new financial technologies (FinTech) has reshaped the U.S. mortgage market since the Global Financial Crisis (GFC). Online platforms, faster processing, and large-scale data analytics have enabled technologically advanced nonbank lenders to capture market share (Buchak et al., 2018; Fuster et al., 2019). For instance, the combined origination share of the three largest FinTech lenders (“Top 3”)—Rocket Mortgage, Guaranteed Rate, and LoanDepot—increased from 2% in 2010 to 13% in 2021, accounting for about 31% of the overall expansion in nonbanks’ market share over this period.<sup>1</sup> These trends suggest that technological innovation has been a main driver of nonbanks’ rapid growth and is widely viewed as central to their continued expansion in the mortgage market.

The rapid growth of a few leading FinTech lenders masks substantial heterogeneity in technology adoption across mortgage lenders, however. To date, there is limited evidence on (i) how the vast majority of nonbank lenders—and incumbent banks—allocate resources to technology, (ii) how their technology investment responds to aggregate shocks, particularly the rise of FinTech lending and demand fluctuations, and (iii) how these responses shape industry dynamics in terms of output, prices, and market shares. Drawing on new datasets, this paper provides a systematic analysis of technology investment by mortgage lenders and its implications for post-GFC industry dynamics. We find that banks increase technology investment in response to FinTech growth but are relatively insensitive to demand shocks. By contrast, nonbanks respond strongly to demand shocks, but weakly or even negatively to FinTech growth. As a result, in a prolonged high-interest-rate environment, nonbanks underinvest in technology relative to banks, which in turn reduces their market share.

A key component of our empirical analysis is the measurement of technology investment. Our primary data source is a comprehensive dataset of online job postings from Lightcast, which covers nearly the universe of posted vacancies and provides a forward-looking measure of firms’ investment in human capital. The data provide job-level information on the title, occupation, location, and employer, along with detailed skill requirements. We measure

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<sup>1</sup>Nonbanks are defined as non-deposit-taking institutions, following Buchak et al. (2018). According to Home Mortgage Disclosure Act (HMDA) data, the nonbank share of mortgage originations (in dollar amount) increased from 27% in 2010 to 64% in 2021.

lenders’ technology investment as their demand for computer- or IT-related occupations and skills. We then merge these data with loan origination records from the Home Mortgage Disclosure Act (HMDA), loan servicing records from McDash, bank and nonbank Call Reports, and other economic data, which allow us to link technology investment to lenders’ output, balance sheets, and demand conditions. Figure 1 shows that labor expenses are the largest cost component for the industry, far exceeding other components that are potentially related to technology investment—such as data processing, hardware and software, and outsourcing—which we also use to supplement our main analysis. Figure 1 thus highlights the importance of human capital investment and the value of labor-market data for understanding investment in this industry.

In the first part of the paper, we use merged Lightcast–HMDA data to establish three stylized facts about mortgage lenders’ labor demand and technology investment. First, labor demand in the mortgage industry is highly concentrated in a few occupational groups and skill categories. Three groups—computer and IT, mortgage processing, and sales and customer service—account for the majority of the industry’s job postings. The composition of labor demand, however, varies substantially across lender types: FinTech lenders primarily demand computer- and IT-related occupations and skills, other nonbanks concentrate on mortgage processing, and banks focus on general sales and customer services. Second, although technology investment has increased across all lender types in recent years, banks are more likely to invest than nonbanks, and larger lenders are more likely to invest than smaller lenders. Third, higher technology investment is associated with greater productivity, as measured by faster loan origination growth and larger market shares.

Having established the trends and heterogeneity in technology investment in the mortgage industry, the second part of the paper studies lenders’ investment responses to two major shocks that impacted the industry in the post-GFC period, using matched firm-level data. The first relates to the supply side of mortgage services: the rise of FinTech lending, proxied by the growing market share of the Top 3 FinTech lenders. The second relates to the consumer side: demand shocks arising from interest rate fluctuations.

To estimate the effect of the first shock, we measure lender-specific exposure to rising

FinTech as the change in the Top 3 FinTech lenders' county-level market shares, weighted by the lender's origination shares across counties in the previous year. Identification is potentially complicated by factors that jointly affect a lender's technology investment and the growth of the Top 3 FinTech lenders, most notably demand-side conditions. To address this concern, we include origination-share-weighted controls for demographics, labor and housing market conditions, borrower credit characteristics, and market concentration, along with time and lender-state fixed effects.

To further strengthen identification, we employ a leave-one-out shift-share instrumental variable (IV) strategy that interacts the Top 3 FinTech lenders' initial county-level market shares with their subsequent aggregate growth in the county's census region (excluding the county itself) to predict county-level and thus lender-level exposure to FinTech growth. Both OLS and IV estimates reveal a stark contrast between banks and nonbanks: banks respond to FinTech growth shocks by increasing their technology investment, whereas nonbanks' responses are muted. This divergence persists for at least two years and is driven primarily by smaller nonbanks, which in some cases even reduce technology investment.

The muted—and in some cases negative—responses of nonbanks to FinTech growth raise the question of what drives their technology investment. After all, our stylized facts show an overall increase in nonbanks' technology investment. We therefore investigate the role of demand shocks, given that several rounds of large-scale monetary stimulus following the GFC generated mortgage lending booms. For identification, we construct county-level “rate incentives”—the gap between the average interest rate on outstanding mortgages and the prevailing market rate—and then aggregate these incentives to the lender level to instrument for local origination growth faced by each lender. The IV estimates show that, while all lenders increase their technology investment facing positive demand shocks, nonbanks' responses are more pronounced.

Together, our empirical evidence suggests that, although technology investment increases across all lender types after the GFC, banks and nonbanks respond differently to different types of shocks. The reduced-form analysis, however, cannot quantify the relative importance of these shocks in shaping the market structure, nor can it address whether technology

improvements alone would sustain nonbanks’ continued expansion under alternative policy environments. Answering these questions is policy relevant, as mortgage industry dynamics affect credit supply and housing market activity. To this end, we develop a structural model of the mortgage industry consistent with our empirical evidence. We use the model to quantify contributions of various shocks to lenders’ technology investment after the GFC. We then conduct counterfactual experiments that assess future industry dynamics under alternative policy paths, including a scenario with persistently high interest rates and relaxed banking regulation, which plausibly characterizes the post-2025 economic environment.

The core of the model is a heterogeneous-firm model with lumpy technology investment. Mortgage lenders differ in productivity and, in each period, choose labor input and whether to invest in new technology. Technology investment requires a fixed cost and raises productivity permanently. The model features three lender types—banks, technologically advanced (FinTech) nonbanks, and other nonbanks— that differ along two dimensions: the returns to technology investment and regulatory burdens. We use the model to recover three shocks, technology, demand, and regulation, which jointly account for the post-GFC evolution in mortgage industry output, technology investment, and market shares of nonbanks.

Model simulations suggest that the post-GFC expansion of the nonbank sector was driven by a combination of favorable shocks—strong demand and tightening bank regulation—rather than broad-based technological advantages among nonbanks. In fact, technology shocks have widened the investment gap between banks and non-FinTech nonbanks. These results have important implications for future industry dynamics. In a policy environment characterized by “higher-for-longer” interest rates, bank deregulation, and technological innovation with substantial upfront costs, the model forecasts a decline, rather than continued growth, in the market share of the nonbank sector.

**Relation to the Literature.** Our paper contributes to a growing and influential literature on technology adoption, market structure and nonbank growth in post-GFC mortgage market. [Fuster et al. \(2019\)](#), for example, provide direct evidence that technology adoption improves operational efficiency, easing frictions in the traditional lending model (see also [Fuster et al. 2013](#); [Fuster et al. 2024](#); [Fuster et al. 2025](#)). [Buchak et al. \(2018\)](#) document the

rapid rise of nonbanks since the GFC and emphasize technological innovations and regulatory differences in shaping industry dynamics. In related work, [Buchak et al. \(2024\)](#) develop a structural framework departing from the classic bank-balance-sheet view by incorporating nonbanks, highlighting the role of regulation interacted with market structure in shaping policy responses. [Jiang \(2023\)](#) studies the funding side of the nonbank business model, stressing strategic interactions between banks and nonbanks. [Gete and Reher \(2021\)](#) focus on the role of securitization and access to secondary-market in expanding nonbank market shares, while [Begley and Srinivasan \(2022\)](#) examine how FinTech and nonbank entry affects small banks' lending and local credit supply. We build on these insights by providing new evidence on lenders' technology investment in the labor market and by developing a macro-style model with endogenous technology investment that quantifies the contributions of technology, regulation and aggregate demand shocks to evolving industry dynamics.

On technology investment by financial institutions, our paper is closely related to recent empirical work that develops new measures of technology investment and studies its drivers and real effects. [He et al. \(2025\)](#), for instance, use data representative of large commercial banks' IT spending to examine how banks adjust investment in response to demand shocks and the entry of P2P lending platforms. [Modi et al. \(2022\)](#) construct measures of banks' IT investment from public Call Reports and study its relationship with lending behavior. [Puri et al. \(2024\)](#) employ novel data on banks' equity investments in FinTech startups and document incumbents' strategic responses to FinTech competition. This line of work has exclusively focused on banks' technology investment. An exception is [Shen et al. \(2025\)](#), who extend the analysis to a handful of FinTech lenders and study the link between technology investment and mortgage pricing using patent filings and LinkedIn employee profiles, but do not include non-FinTech nonbanks. While our findings on banks' investment are consistent with these studies, our primary contribution is to develop a unified measure of technology investment for the full set of mortgage lenders, including banks, FinTech lenders, and other nonbanks, which enables a systematic analysis of heterogeneity in investment behavior and its implications for market structure through the lens of a structural model.

Finally, our paper relates to a broader literature on the implications of FinTech and technology innovations for banking and the macroeconomy. A large body of work studies

FinTech adoption in consumer credit markets (e.g., [Di Maggio and Yao, 2021](#); [Jagtiani et al., 2021](#); [Yang, 2025](#); [Alok et al., 2024](#); [Berg et al., 2022](#)), its implications for welfare, inequality and regulation (e.g., [Bartlett et al., 2022](#); [Bhutta et al., 2025b](#)), the opportunities and disruptions it creates for highly exposed industries and occupations ([Jiang et al., 2025](#); [Philippon, 2016](#)), and its role in the transmission of monetary policy ([Zhou, 2025](#)). A growing and related strand of literature focuses on AI adoption, human capital investment, and firm performance across all sectors of the economy (e.g., [Acemoglu et al., 2022](#); [Babina et al., 2024](#); [Kalyani et al., 2025](#); [Adams et al., 2025](#)). Our contribution is to provide a detailed analysis of FinTech growth in the mortgage market, emphasizing how it reshapes industry dynamics with potential relevance for understanding the increasing concentration of U.S. service industries (e.g., [Kwon et al., 2024](#); [Hsieh and Rossi-Hansberg, 2023](#)), household credit allocation ([Benson et al., 2025](#)) and financial stability ([Kim et al., 2018](#)).

The remainder of the paper is structured as follows. Section 2 describes the data and measurement of technology investment. Section 3 presents new facts about labor demand and technology investment in the mortgage industry. Section 4 examines the effects of macroeconomic shocks on lenders’ technological investment, heterogeneity and its dynamics patterns. Section 5 develops a structural model of the mortgage industry and describes our calibration strategy. Section 6 presents the quantitative results. Section 7 concludes.

## 2 Data and Measurement of Technology Investment

Our empirical analysis draws on a number of datasets at the job-posting, mortgage-loan, lender, county and national levels. This section describes the datasets, data matching procedure, and construction of technology investment measures. Throughout the paper, we use the terms “*firm*” and “*mortgage lender*” interchangeably. Unless stated otherwise, we combine commercial banks and credit unions into a single category referred to as banks.

### 2.1 Data

**Lightcast Job Postings Data (Lightcast):** We use job posting-level data from Lightcast (formally Burning Glass Technologies), which aggregate a near-universe of online job postings

from employer websites and major job boards in the U.S. from 2010 onward. Each posting contains information on the employer, job title, occupation, location, as well as detailed skill, education and experience requirements extracted from the job description, using Lightcast’s proprietary text-parsing algorithms (Carnevale et al., 2014). The data are de-duplicated to remove reposted vacancies and to identify newly posted jobs.

These data provide a forward-looking measure of firms’ investment in human capital, allowing us to assess the causes and implications of mortgage lenders’ technology investment. Regarding the representativeness, prior work shows that Lightcast data closely track the evolution of overall job postings in the U.S. as measured by the nationally representative Job Openings and Labor Turnover Survey (JOLTS).<sup>2</sup> In Appendix Figure A1, we show that this relationship remains strong when more recent data are included, particularly for the financial sector which includes banks and nonbanks.<sup>3</sup>

**Home Mortgage Disclosure Act (HMDA):** This dataset covers nearly the universe of residential mortgage applications and originations in the U.S. It includes lender identifiers, along with detailed loan-level information and borrower characteristics, making it one of the most comprehensive data sources for studying the U.S. mortgage market. The public version of HMDA data is available from the Consumer Financial Protection Bureau. We use them to construct lender- and county-level origination volumes, individual lenders’ market shares, and measures of market concentration. We also use the restricted-access HMDA data from the Federal Reserve Board, which contain additional information on loan application dates, allowing us to infer loan processing time and use it as a lender productivity measure.<sup>4</sup>

**ICE McDash Dataset (McDash):** This dataset contains loan-level records from large U.S. mortgage servicers and, unlike HMDA data, measures not only newly originated mortgages but also the stock of mortgages. McDash data have broad coverage, accounting for about two thirds of loans serviced in the U.S. market. We use these data to construct county-level “rate gaps”— the difference between the average interest rate on outstanding

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<sup>2</sup>See, for example, Hershbein and Kahn (2018), Carnevale et al. (2014) and Acemoglu et al. (2022).

<sup>3</sup>Prior work also suggests that the volume of online job advertisements is a reliable predictor of actual hiring activity in the subsequent quarter (Templin and Hirsch, 2013).

<sup>4</sup>The loan-processing-time analysis uses non-public HMDA data but does not require knowing the identities of any HMDA filer; accordingly, we exclude the Top 3 FinTech lenders from that analysis (see Section 3).

mortgages in a county and the national benchmark 30-year fixed mortgage rate—as well as county-level shares of government backed loans (FHA and VA) and jumbo loans.

**FFIEC Bank Call Reports:** Bank Call Reports are standardized regulatory filings that provide detailed information on the financial condition and performance of commercial banks and savings institutions in the U.S. They are submitted to federal regulators and cover all FDIC-insured institutions nationwide. The reports, available from the Federal Financial Institutions Examination Council (FFIEC), include balance sheet items, which we use to measure the size of an institution; income statements, which allow us to assess various expenditure categories; and other key information on capital structure and operations.

**NMLS Mortgage Call Reports:** This dataset is developed by state regulators and provided to the Federal Reserve Board by the Conference of State Banking Supervisors under restricted access. It collects detailed information on loan origination activity for all state-licensed mortgage companies and firms employing state-licensed mortgage loan originators, filed through the Nationwide Multistate Licensing System (NMLS). We use company-level financial information to measure the size of nonbank mortgage lenders and the expenditure data to construct measures of technology-related investment.

**Other Datasets:** We also use expenditure data for credit unions from Credit Union and Corporate Call Reports provided by the National Credit Union Association. Our county-level characteristics are drawn from multiple sources: demographics variables are obtained from the U.S. Census Bureau; employment data are from the Bureau of Labor Statistics; house price indices are obtained from Freddie Mac for the county’s MSA (when available) or state; the share of subprime borrowers is constructed using the New York Fed Consumer Credit Panel/Equifax Dataset.<sup>5</sup>

## 2.2 Merged Datasets

**Lightcast-HMDA:** We match firms in Lightcast and HMDA data using employer names. First, we clean and standardize employer names in both datasets, pooling all years of

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<sup>5</sup>The New York Fed Consumer Credit Panel/Equifax Dataset is a nationally representative, anonymized 5% random sample of U.S. consumers with a credit file drawn from Equifax credit records. These data are used as an input for our analysis; all calculations, findings, and conclusions are those of the authors.

data. This ensures that the matching algorithm captures changes in employer names over time, especially for HMDA lenders, who can be consistently tracked using their federal Tax Identification Number. Second, we perform exact matches using the cleaned employer names from the two datasets. Third, for HMDA lenders that remain unmatched, we implement a fuzzy-matching procedure using Lightcast firms in the finance sector (NAICS two-digit code 52). Specifically, we apply a probabilistic record-linkage algorithm that computes similarity scores based on bigram overlap and aggregates them into a single weighted match score.<sup>6</sup> Finally, we retain fuzzy matches with a weighted score of 0.98 or higher and select the highest-score match for each HMDA lender.

Our matching algorithm successfully links approximately two thirds of HMDA lenders over the 2010–2023 period. The match rate is lower in the early years, about 30–40% prior to 2015, but increases to roughly 40–90% thereafter. Fuzzy matches account for about 20% of the matched firm-level observations. Our empirical results are robust to alternative thresholds for the match-score cutoff and to restricting the sample to exact matches only.

Panel (a) of Figure 2 shows the number of job postings separately for banks and nonbanks. Both groups experienced steady growth in labor demand during 2010–2019. In 2020, nonbank postings spiked, likely reflecting the mortgage lending boom associated with historically low interest rates during the pandemic, but subsequently declined. In contrast, banks’ postings fell in 2020 and then rose sharply over the following two years. Panel (b) of Figure 2 shows the share of nonbank postings since 2010, which suggests a relatively stable share of about 10% overall, with a notable spike during the pandemic.

**HMDA-Call-Reports:** We match banks’ call reports with HMDA data using the RSSD ID, which uniquely identifies a banking entity in the Federal Reserve’s supervisory data system. For nonbanks, the call reports contain a unique NMLS ID for each nonbank, but this identifier is not available in HMDA data. We follow Jiang et al. (2024) in constructing a crosswalk using the NMLS Consumer Access platform, where the user can search for nonbank registration information such as NMLS ID using lender name and address.<sup>7</sup> We were able to

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<sup>6</sup>Since our objective is to determine whether two records refer to the same firm, rather than to compare the semantic content of text, we use probabilistic record linkage, which is well suited for matching noisy string identifiers such as firm names.

<sup>7</sup>The platform can be accessed through <https://nmlsconsumeraccess.org/>.

match 650 nonbanks each year on average, which account for about 80% of nonbank lenders in HMDA data.

## 2.3 Measurement of Technology Investment

To measure lenders’ technology investment, we first classify each job into categories based on occupation and skill requirements described in the job posting (detailed below). We then aggregate these job-level indicators to the lender-year level to capture labor demand at both the extensive margin—whether a lender posts at least one job in a given category—and the intensive margin—the number of jobs posted in that category.

**Occupation classification:** We classify occupations into six major groups and an “Other” category based on the six-digit detailed Standard Occupational Classification (SOC) codes in the Lightcast data: (A) computer and IT, (B) sales and customer services, (C) mortgage specialists, (D) managers, human resource specialists, and administrative workers, (E) legal and compliance, and (F) financial analysts. Each job posting is associated with a single occupation. Table A1 lists the SOC codes included in each group. These categories together account for more than 80% of all job postings in the mortgage industry (see Section 3 for further discussion on the composition).

**Skill classification:** Lightcast classifies skills using a hierarchical taxonomy that ranges from individual skills (e.g., Python) to broader skill clusters (e.g., Scripting Languages) and skill cluster families (e.g., Information Technology). Leveraging this taxonomy, together with additional text analysis designed to capture skills commonly required in the financial sector, we classify skills in the matched Lightcast-HMDA data into six major categories and an “Other” group: (A) computer and IT (basic and advanced), (B) sales and customer services, (C) mortgage processing, (D) management and support, (E) legal, risk management and compliance, and (F) financial analysis and trading.

Table A2 provides details on our skill classification. For example, we classify a skill as computer and IT, if it (i) belongs to the skill family “Information Technology” or “Analysis”, (ii) falls within the skill cluster “Web Analytics”, “Marketing Software”, or “FinTech”, (iii) contains the word “Computer”, or (iv) is categorized as software by Lightcast. Following

Deming and Kahn (2018), we further distinguish advanced computer skills from basic ones, as investments in advanced skills are likely to yield higher returns for firms.

Because a job posting typically lists multiple skills, we construct job-level indicators for each skill category, equal to one if the posting requires at least one skill in the corresponding category. In matched Lightcast-HMDA data, 98% of job postings require at least one skill in categories (A)-(F), and 92% require at least one skill in the three core categories, (A)-(C).<sup>8</sup>

### 3 Stylized Facts: Technology Investment and Labor Demand in the Mortgage Industry

Using merged Lightcast-HMDA data, this section establishes three key facts about labor demand and technology investment in the mortgage industry. We compare banks, leading FinTech lenders, and other nonbanks—three institutional types emphasized in the literature as shaping the industry’s dynamics. We use the Top 3 FinTech lenders to capture nonbanks that have relative technological advantages, differing from other nonbanks in the extensive use of new technologies and nationwide lending network. Our results are robust to including all FinTech lenders classified by the literature (see Buchak et al., 2018; Fuster et al., 2019), as non-Top 3 FinTech lenders account for only a small share of originations and job postings (see Figure B1). Table B1 provides a brief description of the Top 3 FinTech lenders, their leading role in technology adoption, and their strong presence in the U.S. mortgage market.

#### **Fact 1. Labor demand is highly concentrated but varies across lenders.**

Although previous studies have explored alternative measures of technology investment by financial institutions, there is little evidence on how resources are allocated between technology and other investments. We start by documenting human capital investment across

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<sup>8</sup>We also separately identify AI-related skills, which are already included in our computer and IT skill category (Category A). Specifically, we follow the broad classification in Acemoglu et al. (2022), using the skill clusters “Machine Learning”, “Natural Language Processing (NLP)”, “Data Mining”, “Data Science” and “Artificial Intelligence”. These skills remain relatively rare in mortgage lenders’ job postings, accounting for about 1.7% of all postings over the sample period. Although their prevalence has increased over time, it reached only 3.1% in 2022.

categories and heterogeneity across lender types, before focusing on technology investments. The upper panel of Figure 3 shows the composition of occupations required by each type of lender over the period of 2010-2023. Labor demand is heavily concentrated: a few occupational groups account for the majority of job postings in the industry. In particular, three groups—computer and IT occupations (e.g., software developers), mortgage processing specialists (e.g., loan officers), and sales and customer service workers—collectively represent about 60% of all job postings in the industry.

The composition of job postings, however, differs systematically across lender types. Banks’ postings are dominated by sales and customer service positions, top FinTech lenders concentrate hiring in computer and IT occupations, and other nonbanks primarily post mortgage processing roles. These patterns point to distinct business strategies across industry participants.<sup>9</sup> Appendix Figure B3 shows that even among banks most reliant on mortgage lending—those in the highest quartile of the origination-to-asset ratio—postings remain dominated by sales and customer service jobs. This heterogeneity across lender types is stable over time, as shown in Figure 4, both in the composition of postings (left column) and in the number of jobs posted (right column).

To formally test heterogeneity in labor demand across lender types, we estimate the following linear probability model with job-level data, which facilitates the inclusion of high-dimensional fixed effects:

$$\mathbb{I}(Occ_{i,j,t} = k) = \beta_0^k + \beta_1^k Nonbank_j + \beta_2^k Top3FinTech_j + X_{i,t}\alpha^k + MSA_i \times Year_t + \epsilon_{i,j,t}^k, \quad (1)$$

where the dependent variable is an indicator for whether job  $i$  posted by lender  $j$  in year  $t$  falls into occupation  $k$ .  $Top3FinTech_j$  and  $Nonbank_j$  (excluding the Top 3 FinTech lenders) are indicators for lender  $j$ ’s type. The regression controls for MSA-by-year fixed effects, as well as education and experience dummies required by the job ( $X_{i,t}$ ). Standard errors are clustered at the lender level. Panel A of Table 1 reports the results. Banks (the omitted category) are more likely to post sales and customer service positions than nonbanks. By

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<sup>9</sup>Additional categories include managerial, human resources and administrative staff, financial analysts, and legal and compliance officers (see Appendix Figure B2). Together with the three major groups discussed above, these occupations account for more than 80% of all job postings in the mortgage industry over 2010–2023.

contrast, the Top 3 FinTech lenders are more likely to recruit technology-related personnel, while other nonbanks are more likely to post positions for mortgage processing specialists.

Turning to skill requirements, we observe patterns that closely resemble those for occupational demand. The lower panel of Figure 3 shows the share of job postings that require skills in a given category. These shares do not sum to 100 because one job posting may list multiple skills. An interesting pattern is that all lenders exhibit strong demand for computer and IT skills. However, a closer inspection reveals a substantial difference: banks and nonbanks other than the Top 3 FinTech lenders tend to have higher demand for basic computer skills—such as Microsoft Excel—whereas the Top 3 FinTech lenders have more intensive demand for advanced skills, such as database management and web application development.

Overall, the compositional heterogeneity observed in occupational requirements persists in skill requirements, both in the full sample and over time (Figure B4). Furthermore, regression results in panel B of Table 1 show that, even after controlling for occupation, banks are more likely to require sales and customer service skills (for example, among computer user support specialists), while nonbanks more often emphasize mortgage processing skills, and the Top 3 FinTech lenders focus more on advanced computer skills.

Taken together, these patterns suggest that mortgage lenders adopt distinct human capital investment strategies to stay competitive in the industry. Banks, which offer a broad range of financial services, exhibit greater concentration in sales and customer service positions, consistent with cross-selling and customer retention motives. In contrast, nonbanks tend to specialize in mortgage lending, and their emphasis on mortgage specialists with deep industry knowledge who can assist customers throughout the process helps them to gain market share. A third strategy relies on the intensive use of technology to deliver more convenient services, as implemented by the Top 3 FinTech lenders. These results complement prior work that documents differences across lenders in the loan origination market (Buchak et al., 2018) and on the financing side (Jiang, 2023)—we focus on the input side of the industry, and in particular, heterogeneity in labor demand.

**Fact 2. Technology-related labor demand increased over time, with larger increases among banks and larger lenders.**

Despite variation in the composition of labor demand, all types of lenders have increased technology-related labor demand over time. Figure 5 plots the share of job postings requiring a computer- or IT-related occupation (panel a) and the share requiring an advanced computer or IT skill (panel b), for banks and nonbanks excluding the Top 3 FinTech lenders. Banks steadily increased their shares of postings for technology-related occupations (from 7% in 2010 to 15% in 2021) and advanced skills (from 18% to 35% over the same period). These shares have been more volatile for nonbanks but overall display similar upward trends.

The aggregate trends by lender type, however, may be driven by a small number of firms in each segment. To assess the prevalence of technology investment across lenders of the same type, we examine firm-level patterns. Panel (a) of Figure 6 plots the share of firms that post at least one computer- or IT-related job in a given year, separately for banks and for nonbanks (excluding the Top 3 FinTech lenders). Consistent with Figure 5, the fraction of lenders demanding technology-related labor increased over time, with banks exhibiting higher shares than nonbanks.

In panel (b) of Figure 6, we further separate lenders into large and small ones based on whether their origination in a year is above the median of the distribution in that year. Large banks are most likely to post computer- and IT-related jobs, followed by large nonbanks. In contrast, small lenders, especially small nonbanks, are the least likely to invest and exhibit little evidence of an upward trend. These patterns are robust to alternative measures of technology investment (e.g., advanced computer and IT skills) and lender size (e.g., assets reported in Call Reports).

Table 2 tests this heterogeneity pattern by estimating the following firm-level regression,

$$TechInv_{j,t} = \beta_0 + \beta_1 Nonbank_j + \beta_2 Large_{j,t} + Ctr_{j,t} + \gamma_{s(j)} + \delta_t + u_{j,t}, \quad (2)$$

where  $TechInv_{j,t}$  is a measure of technology investment by lender  $j$  in year  $t$ .  $Nonbank_j$  and  $Large_{j,t}$  are indicators for the lender's type (bank or nonbank) and size (large or small).

We exclude the Top 3 FinTech lenders from the regression to ensure that our estimates of  $\beta_1$  and  $\beta_2$  are not driven by their outside investment. To account for demand-side factors that may be correlated with lender type and investment, we construct lender-level controls as origination-share-weighted averages of county characteristics in the lender’s footprint. These characteristics capture local demographics (population growth and the share of residents with a bachelor’s degree), labor and housing market conditions (employment growth and house price growth), borrower credit risk (the subprime borrower share), and mortgage market concentration (the Herfindahl–Hirschman Index). The regression also includes lender-state fixed effects,  $\gamma_{s(j)}$ , and year fixed effects  $\delta_t$ , with standard errors clustered at the lender level.

In Table 2, the first two columns use indicator variables for whether a firm posts jobs requiring computer- or IT-related occupations and skills (i.e., extensive-margin investment). The next two columns examine counts of these jobs (i.e., intensive-margin investment), estimated using Poisson maximum likelihood models appropriate for count data. The final two columns focus on the shares of these jobs. Across all specifications, banks tend to invest more in technology than nonbanks, and, holding lender type constant, large lenders invest more in technology than small lenders.

**Fact 3. Higher technology investment is associated with higher productivity.**

What do firms gain from investing in technology? Standard economic theory predicts higher productivity when the investment improves the underlying production technology. Since underlying technology is not directly observable, we examine the empirical link between mortgage lenders’ technology investment and productivity. This evidence helps inform the production side of the model developed in Section 5.

We consider three measures of lender-level productivity growth: (i) the growth rate of loan origination count, (ii) the change in market share, and (iii) the change in loan processing time, measured in days as the time from application to origination, using restricted-use HMDA data.<sup>10</sup> We estimate the following specification, excluding the Top 3 FinTech lenders

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<sup>10</sup>To construct lender-level processing time, we first residualize loan-level processing time with respect to loan characteristics (the loan amount, loan purpose, and borrower’s income, race, ethnicity, and gender) as

to ensure that our results are not driven by their investment and productivity:

$$\Delta Productivity_{j,t} = \beta_0 + \beta_1 TechInv_{j,t} + \beta_2 TechInv_{j,t-1} + Ctr_{j,t} + \gamma_{s(j)} + \delta_t + e_{j,t} \quad (3)$$

where  $\Delta Productivity_{j,t}$  is a measure of productivity growth for lender  $j$  in year  $t$ .  $TechInv_{j,t}$  and  $TechInv_{j,t-1}$  are current and lagged technology investment. As in equation (2), we control for local demand conditions faced by each lender, lender-state fixed effects, and year fixed effects. In addition, we include controls for lender size, measured by the log of lagged origination count, and differential productivity growth of nonbanks. Standard errors are clustered at the lender level.

Table 3 shows that technology investment, through the hiring of computer- or IT-related occupations and skills, is associated with higher loan origination growth (columns 1-2) and market share growth (columns 3-4). Both current and lagged technology investments contribute to these increases.<sup>11</sup> We do not find evidence of faster processing (columns 5-6), however, suggesting that technology-related hiring is more closely related to higher lending volumes, as opposed to shorter application-to-origination times.<sup>12</sup>

## 4 Firm-Level Evidence: Drivers of Technology Investment

In this section, we study lenders’ technology investment responses to two major shocks that have impacted the mortgage industry since the GFC. The first is a supply-side shock—the expansion of FinTech lending—and the second is a demand-side shock driven by interest rate fluctuations associated with monetary stimulus. We show that banks respond more strongly to FinTech growth shocks but are less responsive to rate-induced demand shocks than nonbanks. These differential responses highlight distinct channels through which

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well as county fixed effects. We then average the resulting residuals at the lender–year level.

<sup>11</sup>We also estimate specifications that interact technology investment measures with a nonbank indicator to allow for differential effects across lender types. The interaction terms are not statistically significant.

<sup>12</sup>Our findings are complementary to those in Fuster et al. (2019), who document that FinTech lenders process mortgages faster than traditional lenders in the cross section. While that evidence highlights level differences in processing times across lender types, our analysis focuses on within-lender variation and examines whether incremental technology-related hiring improves processing speed at the margin. Our result that additional technology investment is associated with higher lending volumes but not faster processing for lenders other than those at the technological frontier may reflect constraints by underwriting practices or institutional frictions.

shocks affect investment.

## 4.1 FinTech Expansion

A major post-GFC development in the U.S. mortgage market was the expansion of technology-based lenders (Buchak et al., 2018; Fuster et al., 2019). As shown in panel (a) of Figure 7, the market share of FinTech lenders increased from 4% in 2010 to 17% at its peak in 2021, driven primarily by the growth of the Top 3 lenders.<sup>13</sup> In the cross section, however, FinTech growth has been uneven across counties, as shown in panel (b) of Figure 7. This indicates that some lenders are more affected by this shock than others.

In this section, we first measure lender-level exposure to FinTech growth, excluding the Top 3 FinTech lenders, and then estimate its effect on lenders’ technology investment. Before turning to our empirical strategy, we note that related work has examined a similar shock. For example, Puri et al. (2024) construct a FinTech competition shock akin to ours and study its effects on banks’ equity investment in FinTech startups. In contrast, we focus on investments in technology-related personnel and skills, and we study responses by both banks and nonbanks. In addition, we implement a new IV strategy that strengthens the causal interpretation of our estimates. Our focus on labor-based technology investment, together with our analysis of heterogeneity and dynamic responses, complements their findings and provides new evidence on the investment behavior of financial institutions.

### 4.1.1 Empirical Strategy

We measure the exposure of lender  $j$  to FinTech growth as the weighted sum of changes in the county-level market share of the Top 3 FinTech lenders ( $\Delta Top3FinShare_{c,t}$ ), with weights given by  $j$ ’s origination shares across counties in the previous year:

$$FinExpo_{j,t} \equiv \sum_c \Delta Top3FinShare_{c,t} \times \frac{Origination_{j,c,t-1}}{\sum_k Origination_{j,k,t-1}}, \quad (4)$$

where  $Origination_{j,c,t-1}$  is the mortgage volume originated by lender  $j$  in county  $c$  at year  $t - 1$ . We then estimate the relationship between lagged FinTech exposure and current

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<sup>13</sup>We use the combined list of FinTech lenders identified by Buchak et al. (2018) and Fuster et al. (2019), and additionally include SoFi following Jagtiani et al. (2021).

technology investment using the following specification:

$$y_{j,t} = \beta_0 + \beta_1 FinExpo_{j,t-1} + \beta_2 FinExpo_{j,t-1} \times Nonbank_j + Ctr_{j,t} + \gamma_{s(j)} + \delta_t + \varepsilon_{j,t}, \quad (5)$$

where  $y_{j,t}$  is a measure of technology investment by lender  $j$  in year  $t$ .  $Nonbank_j$  is an indicator for nonbanks. Control variables and fixed effects are similarly defined as in equation (3), with standard errors clustered at the lender level.  $\beta_1$  and  $\beta_2$  are the key parameters of interest, capturing the response of banks and the differential response of nonbanks.<sup>14</sup>

Identification of  $\beta_1$  and  $\beta_2$  may be compromised by factors that jointly affect lenders' technology investment and FinTech growth, most notably demand-side conditions. We address these concerns through several features of our empirical design. First, when constructing exposure, we focus on the market share growth of the Top 3 FinTech lenders, who originate loans nationwide and are less likely to be impacted by investments made by smaller lenders or by idiosyncratic local shocks. Second, we estimate specifications using lagged exposure to Top 3 FinTech growth, which mitigates simultaneity concerns arising from common shocks that may jointly affect lenders' investment and FinTech expansion. Third, we include a rich set of controls that capture demand conditions across the counties in which each lender operates, thereby directly addressing potential demand-side confounding factors.

To further strengthen identification, we implement a leave-one-out shift-share IV strategy, instrumenting  $FinExpo_{j,t}$  in equation (4) with

$$\sum_c \left( \sum_{f \in Top3} \omega_{f,c,t_0} \times \Delta Share_{f,-c,t} \right) \times \frac{Origination_{j,c,t-1}}{\sum_k Origination_{j,k,t-1}}. \quad (6)$$

This instrument replaces the actual market share growth of the Top 3 FinTech lenders in a

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<sup>14</sup>Our baseline specification excludes lender fixed effects (FE). The panel is constructed at the lender-year level but is conditional on the lender posting at least one vacancy in a given year. The outcome therefore measures the propensity to post IT-related vacancies conditional on posting. In this setting, lender FE would restrict identification to within-lender switches between posting and not posting IT jobs. Given the short panel dimension (lenders are observed for an average of four times), such switches are relatively infrequent and yield imprecise estimates. In addition, lenders' exposure to FinTech expansion is largely driven by pre-determined differences in geographic footprint; including lender FE would remove economically meaningful cross-sectional variation. Instead, we include year FE, lender-state FE (as in Puri et al. 2024), and a rich set of controls to account for aggregate shocks, local demand conditions, and observable heterogeneity. Our results are robust to specifications that include lender FE, though estimates are less precise.

county,  $\Delta Top3FinShare_{c,t}$ , with predicted growth, given by the term in parenthesis. The predicted growth is constructed as a weighted sum of individual Top 3 FinTech lenders' aggregate market share growth in county  $c$ 's census division, excluding county  $c$  itself from the aggregation.<sup>15</sup> The weight,  $\omega_{f,c,t_0}$ , is lender  $f$ 's market share in county  $c$  among the Top 3 FinTech lenders in an initial period,  $t_0$ , where  $f \in \{\text{Rocker Mortgage, Guaranteed Rate, or LoanDepot}\}$ .<sup>16</sup> By interacting aggregate growth trends of the Top 3 FinTech lenders with predetermined local exposure, this shift-share instrument mitigates concerns that observed FinTech growth in a given county may be driven by county-specific factors that, at the same time, affect the technology investment decisions of others lenders operating there.

#### 4.1.2 Results

Table 4 reports OLS estimates of the effects of FinTech growth shocks on technology investment by banks and nonbanks. The first two columns focus on the extensive-margin responses. A one percentage-point (pp) increase in the exposure to Top 3 FinTech market growth in the previous year increases the probability that a bank posts a computer- or IT-related job by 1.3 percentage points, corresponding to about 4% of the sample mean. The same increase raises the probability of posting a job requiring an advanced computer skill by 1.5 pp (about 3% relative to the mean). By contrast, nonbanks had significantly weaker responses: their estimated responses are 4.4 pp and 3.9 pp smaller than those of banks, respectively. Translating these differential effects into level responses implies that a one pp increase in FinTech exposure reduces the likelihood that a nonbank posts a computer- or IT-related job by 3.1 pp (about 10% relative to the mean) and the likelihood of posting a job requiring an advanced computer skill by 2.4 pp (about 5% relative to the mean).

The remaining columns of Table 4 examine the intensive-margin responses. The middle two columns estimate the effects of FinTech growth on the number of technology-related jobs using Poisson maximum likelihood regressions, appropriate for count outcomes. The

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<sup>15</sup>There are nine census divisions in the U.S.: two in the Northeast (New England and Middle Atlantic), two in the Midwest (East and West North Central), three in the South (South Atlantic; East and West South Central), and two in the West (Mountain and Pacific). Our results are robust to using the four census regions. Using national market shares of the Top 3 FinTech lenders, however, would substantially reduce cross-sectional variation and lead to a weak IV problem. We therefore construct the instrument using division- or region-level market shares.

<sup>16</sup>We set  $t_0$  to 2010-2013 in the baseline, and our results are robust to changing the initial period.

final two columns estimate semi-elasticities using the log number of technology-related jobs as the dependent variable, conditional on non-zero observations. Across specifications, the results are consistent with the pattern in the first two columns: banks respond positively to FinTech growth by increasing their demand for computer- or IT-related occupations and skills, whereas nonbanks' responses are muted and, in some cases, negative.

To identify which nonbanks drive this divergence, Table 5 examines heterogeneity by lender size. Lender size is measured using origination counts from HMDA data (first two columns) and assets reported in Call Reports (last two columns). We find robust evidence that smaller nonbanks are the least responsive to FinTech growth shocks and, in most specifications, cut back on their technology investment. In contrast, larger nonbanks respond more positively, with magnitudes comparable to those observed for banks.

Turning to the IV estimates, we first show that the leave-one-out shift-share instrument strongly predicts county-level FinTech growth and, in turn, firm-level exposure. The instrument is strong, as shown by the first-stage bin scatter plot in panel (a) of Figure 9. Table 6 reports the IV estimates of extensive-margin technology-investment responses and contrast them with the corresponding OLS estimates. The IV estimates display a similar pattern to OLS estimates: banks respond positively to FinTech growth shocks, whereas nonbanks' responses are muted and, in some cases, negative.

Finally, we examine the persistence of these responses. Given the relatively short panel dimension of our firm-level data, we include one lag of the FinTech growth shock and its interaction with the nonbank indicator, although our conclusions remain unchanged when two lags are included. Table 7 reports the responses over two years following the shock. The OLS and IV estimates are similar. Two main findings emerge. First, consistent with earlier results, banks respond positively in both years following the shock, while the differential responses for nonbanks remain negative over this horizon. Second, the differential effect is even more negative and significant in the second year, indicating a persistent pullback in technology investment among nonbanks following FinTech growth.

Together, these results show that banks respond positively to FinTech growth shocks by increasing their demand for technology-related personnel and skills, whereas nonbanks'

responses are more muted and, in some cases, negative, driven primarily by cutbacks among smaller nonbanks. This difference persists for at least two years, suggesting that FinTech market penetration has lasting effects on the dynamics of the mortgage industry. We will explore these implications in more detail through the lens of our structural model.

## 4.2 Monetary-Policy Induced Demand Shocks

The muted and even negative responses of nonbanks to FinTech growth suggest that other forces play an important role in driving nonbanks’ technology investment during the post-GFC period. After all, the stylized facts documented earlier show that technology investment by nonbanks increased substantially, particularly during 2010-2014, when successive rounds of monetary stimulus generated mortgage origination and refinancing booms (e.g., Di Maggio et al., 2020; Beraja et al., 2019; Agarwal et al., 2023; Abel and Fuster, 2021). We therefore turn to examine the role of demand shocks arising from interest rate fluctuations in driving lenders’ technology investment.

### 4.2.1 Empirical Strategy

We begin by measuring the demand shocks faced by individual mortgage lenders using origination-share-weighted changes in county-level origination growth:

$$DemandShock_{j,t} \equiv \sum_c \Delta Origination_{c,t} \times \frac{Origination_{j,c,t-1}}{\sum_k Origination_{j,k,t-1}}, \quad (7)$$

where  $\Delta Origination_{c,t}$  denotes the growth rate of origination volume in county  $c$  and year  $t$ . We then estimate the relationship between the demand shock and technology investment using a specification similar to equation (5):

$$y_{j,t} = \beta_0 + \beta_1 DemandShock_{j,t} + \beta_2 DemandShock_{j,t} \times Nonbank_j + Ctr_{j,t} + \gamma_{s(j)} + \delta_t + \nu_{j,t}. \quad (8)$$

Note that unlike in equation (5), equation (8) focuses on current-year demand shocks.<sup>17</sup> This is because these shocks are identified based on changes in benchmark mortgage rates induced by large-scale monetary stimulus, i.e. QEs, which were salient to both consumers

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<sup>17</sup>We exclude the Top 3 FinTech lenders from regression (8) so that the estimation sample matches that in Section 4.1. The results are robust to including these lenders.

and lenders and typically triggered lending booms within the year of the policy action. In contrast, FinTech growth follows a more gradual trajectory, consistent with a diffusion process in technology adoption. We examine the dynamic effects of demand shocks in Section 4.2.2.

Identification in this setting may be challenged by reverse causality and omitted variables. For example, technology investment may improve lending services and thereby increase loan originations. In addition, unobserved shocks correlated with local lending booms may affect investment decisions through other channels. To address these concerns, we construct an instrument that captures borrowers’ predetermined “rate incentives” when prevailing market rates change. This instrument is motivated by Berger et al. (2021), who show that the rate gap, defined as the difference between the rate on an existing mortgage and the current market rate, is a strong predictor of mortgage prepayment, including both refinancing and moving.<sup>18</sup>

Panel (a) of Figure 8 shows that, at the national level, the rate gap widened during 2010-2013 and 2020-2021—periods of large-scale monetary stimulus through QEs. Panel (b) of Figure 8 shows that, in the cross section, the magnitude of the rate gap exhibits substantial variation, which we exploit in our IV strategy. Specifically, we instrument  $DemandShock_{j,t}$  in equation (7) with

$$\sum_c \Delta RateGap_{c,t-1} \times \frac{Origination_{j,c,t-1}}{\sum_k Origination_{j,k,t-1}}, \quad (9)$$

where  $RateGap_{c,t-1}$  is the difference between the average interest rate on outstanding mortgages in county  $c$  and the national benchmark 30-year-fixed mortgage rate at the end of year  $t - 1$ . Our preferred instrument, as shown in equation (9), uses the change in the rate gap to account for level differences across counties, but for robustness we also present IV estimates that use the level, instead of the change, of the rate gap. To strengthen identification, we include additional controls for county-level shares of government-backed

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<sup>18</sup>Recent studies have used rate gaps to construct instruments that isolate plausibly exogenous variation in mortgage rate changes that impact household decisions. For example, Fonseca and Liu (2024) study mortgage rate lock-in and residential mobility; Zhou (2022) examines the responses of consumer spending and housing investment to mortgage rate changes.

loans (e.g., FHA and VA) and jumbo loans, which may be correlated with the rate gap measure (Abel and Fuster, 2021). In addition, we control for FinTech exposure, as defined in equation (4), to account for potential supply-side confounding factors.

#### 4.2.2 Results

Table 8 reports OLS estimates of the effects of demand shocks on technology investment. As in the case of FinTech growth shocks, we examine both extensive- and intensive-margin responses. Across specifications, we find that banks exhibit little response to these demand shocks, whereas nonbanks respond positively and significantly. A 10 pp increase in the demand shock increases the probability that a nonbank posts a computer- or IT-related job by 1.2 pp and the probability of posting a job requiring advanced computer skills by 1.1 pp. We find some evidence that this positive response is primarily driven by larger nonbanks—those in the top quartile of loan origination—although this heterogeneity is not present when lender size is measured using assets (Table C1).

Table 9 reports IV estimates using two alternative instruments—one based on the level of the rate gap and the other based on the change in the rate gap—focusing on extensive-margin responses. Consistent with the OLS results, nonbanks respond positively to demand shocks and more strongly than banks. The two sets of IV estimates differ primarily in the implied response of banks: the rate-gap-change instrument yields a sizable positive response, whereas the level-based instrument implies no response. We prefer the rate-gap-change instrument because it controls for county-level heterogeneity unrelated to monetary policy movements and delivers a stronger first stage. Panel (b) of Figure 9 presents a binned scatter plot for the preferred first stage, indicating substantial relevance.

The finding that nonbanks respond more strongly than banks to demand shocks may be explained by several mechanisms explored in the literature. For example, banks may update expectations more gradually following large demand shocks due to institutional frictions or greater reliance on historical experience (e.g., Begenau et al., 2026), whereas nonbanks may place greater weight on recent market conditions (e.g., Xiao, 2020).

Table 10 examines the persistence of these effects. Both the OLS and IV estimates point to significantly higher and positive responses of nonbanks in the first year following the

shock. In the second year, however, the differential effects attenuate and, if anything, turn negative. Taken together, these results suggest that rate-driven demand shocks provide one reason why nonbanks increased their technology investment in the post-GFC period, but such increase is short-lived, reverting to the trend after one year.

### 4.3 Additional Evidence and Robustness

We conduct additional analyses to complement our baseline empirical findings. First, we use nonbank Call Report data, which provide alternative measures of technology investment, to estimate the broader effects of FinTech growth shocks and demand shocks. Second, we perform a series of robustness checks using alternative sample restrictions and empirical specifications for the baseline estimates in Sections 4.1 and 4.2.

#### 4.3.1 Evidence from Nonbank Call Reports

As described in Section 2, NMLS call report data contain alternative investment measures for nonbanks. Expenditures on hardware and software offer a direct measure of technology investment. We also consider two additional expenditure categories that are likely to capture technology-related investment: equipment and outsourcing. Comparable measures are not available in banks' Call Reports, although prior work shows that text-based methods may be used to infer large technology investments (Modi et al., 2022). We therefore focus on these technology-related measures in nonbanks' Call Reports, examining both their trends and their responses to the shocks identified earlier.

Nonbanks' expenditures on hardware and software increased substantially over time, from \$77 million in 2012 to \$270 million in 2021, a 250% increase over this period. The share of this category in total expenditures also rose, from 1.4% in 2012 to 2.1% in 2021 (Figure 1, panel c). By contrast, although expenditures on equipment and outsourcing increased in dollar terms, by approximately 86% and 66%, respectively—their shares of total expenditures declined modestly.

Table C2 presents semi-elasticity estimates of these expenditure measures to FinTech growth shocks and demand shocks. The results are qualitatively similar to those reported in Sections 4.1 and 4.2. All measures of technology-related expenditures decline in response

to FinTech growth shocks, with the declines in hardware, software and equipment being statistically significant. In response to demand shocks, expenditures on equipment and outsourcing increase, although the latter effect is not statistically significant. The final column of Table C2 reports the responses of personnel expenditures. Consistent with our earlier findings based on job postings, personnel expenditures decline in response to FinTech growth shocks and increase in response to demand shocks. Overall, the evidence from nonbank Call Report data supports our earlier empirical results.

### 4.3.2 Robustness

The baseline estimates in Sections 4.1 and 4.2 are robust to a range of alternative sample definitions and regression specifications. One potential concern is that banks and nonbanks differ systematically in their business models and customer bases, so the estimated responses reflect differences across lender types rather than differential responses to the shocks of interest. Note that our baseline sample is already restricted to mortgage lenders in HMDA data, making banks and nonbanks comparable in their participation in the residential mortgage market. While they may differ along other dimensions relevant for investment decisions—differences that we explicitly account for in the structural model—we show that our baseline results are robust to additional sample restrictions that ensure the bank sample is more comparable to nonbanks.

Specifically, we conduct three robustness checks. First, we restrict the bank sample to institutions with asset sizes similar to those of nonbanks (i.e., banks with assets below the 95th percentile of the nonbank asset distribution). Since banks tend to have higher assets than nonbanks, this restriction effectively excludes large banks. Second, we restrict the bank sample to institutions with origination volumes comparable to nonbanks (i.e., banks with origination counts above the 10th percentile of the nonbank origination distribution). Since the average bank originates fewer mortgages than the average nonbank, this restriction excludes banks with small origination volumes. Third, we restrict the bank sample to those with relatively high exposure to mortgage lending (i.e., banks with an origination-to-asset ratio above the 25th percentile of the distribution). Table C3 reports the responses of technology investment to FinTech growth shocks and demand shocks under each restriction.

Across all specifications, the qualitative pattern remains unchanged: nonbanks exhibit weaker, and in some cases negative, responses to FinTech growth shocks, but stronger and positive responses to demand shocks.

The second set of robustness checks concerns the matching procedure used to link Lightcast firms to HMDA lenders based on company names. While a substantial share of the baseline sample consists of exact matches (approximately 80%), the remaining observations rely on fuzzy matches, which may raise concerns about matching precision. To address this issue, we re-estimate the specifications in Sections 4.1 and 4.2 using only exactly matched lenders, discarding all fuzzy matches. Panel A of Table C4 shows that the baseline results are largely unchanged.

Third, we examine whether our estimates are driven by banks that engage in equity investments in FinTech startups. Banks that are more likely to enter such investment relationships may be more inclined to hire technology-related personnel following the deals, potentially confounding the causal link between the shocks of interest and technology-related hiring. To address this concern, we exclude banks that make equity investments in FinTech startups, as identified by Puri et al. (2024), which are predominantly large banks in terms of both assets and origination volumes. Panel B of Table C4 shows that the baseline estimates are robust to this sample restriction.

Finally, we estimate a specification that jointly includes FinTech growth shocks and demand shocks. If our IV strategy successfully isolates plausibly exogenous variation in each case, the coefficients estimated in separate regressions earlier should be similar to those obtained from the joint specification. Panel C of Table C4 shows that this is indeed the case.

## 5 A Model of Technology Investment in the Mortgage Industry

Having established the trends in mortgage lenders' technology investment and their responses to aggregate shocks, we next develop a structural model to understand investment decisions at the micro level and how these decisions interacted with shocks in shaping post-GFC industry dynamics. We address three questions. First, can a firm-level model consistent with the empirical facts in Section 3 generate the responses to shocks documented

in Section 4? Second, what are the relative contributions of different shocks in explaining post-GFC mortgage market dynamics, including market share and technology investment by lender type? Third, how would the industry evolve in an environment with persistently high interest rates, deregulation, and substantial upfront technology investment costs—a plausible characterization of the post-2025 U.S. economic landscape? These questions are policy relevant, as mortgage industry dynamics affect credit supply and financial stability, and they cannot be addressed using reduced-form empirical analysis alone.

## 5.1 Setup

The model builds on a canonical heterogeneous-firm framework with lumpy technology investment and an institutional setting that captures key features of the U.S. mortgage origination market in the post-GFC period. The production side is motivated by the stylized facts documented in Section 3, while the institutional setting is consistent with prior work highlighting key differences across banks, shadow banks, and FinTech lenders (Buchak et al. 2018; Buchak et al. 2024).

**Households.** We keep the household side parsimonious, so that demand for mortgage services depends only on prices and an aggregate demand shifter. Specifically, in each period the representative household consumes a mortgage service bundle,  $Y_t$ , and a numeraire good,  $C_t$ . Preferences are quasi-linear:  $U(Y_t, C_t) = u(Y_t; \theta_t) + C_t$ , where  $\theta_t$  denotes an aggregate demand shifter. The mortgage service bundle aggregates services produced by a continuum of monopolistically competitive mortgage lenders, indexed by  $j \in [0, 1]$ ,

$$Y_t = \left( \int_0^1 y_{j,t}^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}},$$

where  $\sigma > 1$  is the elasticity of substitution. Given the set of individual service prices,  $p_j$ ,  $j \in [0, 1]$ , the household's utility maximization implies the demand curve faced by lender  $j$  and the price index,  $P_t$ , for the mortgage service bundle,

$$p_{j,t} = y_{j,t}^{-\frac{1}{\sigma}} P_t [Y(P_t; \theta_t)]^{\frac{1}{\sigma}}; \quad P_t \equiv \left( \int_0^1 p_{j,t}^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}}.$$

**Firms.** There are three types of mortgage lenders. A measure  $N_B$  are banks, a measure  $N_F$  are technologically advanced (FinTech) lenders, and the remaining  $1 - N_B - N_F$  are non-FinTech nonbanks. The latter two groups constitute the nonbank sector. Lenders produce mortgage services using labor and labor-augmenting technology:  $y_{j,t} = a_{j,t}l_{j,t}$ , where  $a_{j,t}$  is lender-specific productivity at time  $t$ . Given the wage  $w_t$ , the cost function is  $\frac{w_t}{a_{j,t}}y_{j,t}$ .

Productivity growth is endogenous. In each period, conditional on current productivity  $a_{j,t}$ , a lender chooses whether to invest in technology. If it invests, the lender pays an upfront cost  $F$ , and its productivity increases to  $\lambda_{j,t}a_{j,t}$  permanently, where  $\lambda_{j,t} > 1$  is a productivity boost that differs across lender types. These features are consistent with two stylized facts documented earlier. First, technology investment is associated with higher productivity. Second, the presence of upfront costs implies a cutoff rule under which only relatively large lenders invest in technology. Following [Buchak et al. \(2018\)](#), we incorporate regulatory burden into lenders' profit maximization problem. Regulatory costs differ across lender types and are modeled as a revenue tax,  $1 - \xi_{j,t}$ , where  $0 < \xi_{j,t} < 1$ .

**Investment decision.** In each period, given endogenous state  $a_{j,t}$  and exogenous aggregate state  $S_{j,t} \equiv (\lambda_{j,t}, \xi_{j,t}, \theta_t, w_t)$ , a lender that chooses to invest in technology solves:

$$V^{Inv}(a_{j,t}, S_{j,t}) = \max_{p_{j,t}, y_{j,t}} \left\{ \xi_{j,t} p_{j,t} y_{j,t} - \frac{w_t}{\lambda_{j,t} a_{j,t}} y_{j,t} - F + \beta \mathbb{E}_t V(a_{j,t+1}, S_{j,t+1}) \right\}$$

$$s.t. \quad p_{j,t} = P_t [Y(P_t; \theta_t)]^{\frac{1}{\sigma}} y_{j,t}^{-\frac{1}{\sigma}}; \quad a_{j,t+1} = \lambda_{j,t} a_{j,t}.$$

If the lender chooses not to invest, it solves:

$$V^{NInv}(a_{j,t}, S_{j,t}) = \max_{p_{j,t}, y_{j,t}} \left\{ \xi_{j,t} p_{j,t} y_{j,t} - \frac{w_t}{a_{j,t}} y_{j,t} + \beta \mathbb{E}_t V(a_{j,t+1}, S_{j,t+1}) \right\}$$

$$s.t. \quad p_{j,t} = P_t [Y(P_t; \theta_t)]^{\frac{1}{\sigma}} y_{j,t}^{-\frac{1}{\sigma}}; \quad a_{j,t+1} = a_{j,t}.$$

The value function of the lender is given by

$$V(a_{j,t}, S_{j,t}) = \max \left\{ V^{Inv}(a_{j,t}, S_{j,t}), V^{NInv}(a_{j,t}, S_{j,t}) \right\}.$$

We show in [Appendix D](#) that the model implies a cutoff decision rule: a lender invests if

its current productivity exceeds a threshold, i.e.,  $a_{j,t} \geq a^*(S_{j,t}; \Phi)$ , where  $\Phi \equiv (F, \beta, \sigma)$  is a vector of model parameters.

**Solution methods.** The model is characterized by a large number of exogenous aggregate states  $(\lambda_{j,t}, \xi_{j,t}, \theta_t, w_t)$ . To solve the model, we assume that lenders form no-change forecasts for these variables, so that expected future realizations equal their current values. This assumption reflects limited predictability of these aggregate variables from the individual lender’s point of view. We solve the model numerically using a value function iteration method in two steps. In the first step, the state space is discretized and the value function is solved over fixed grids of the state space. In the second step, the policy function is solved conditional on the realized states and value function obtained from the first step. All model simulations are based on the optimal choices of 6,000 firms.

## 5.2 Calibration Strategy

Our calibration proceeds in two steps. First, we calibrate standard parameters using values from the literature and guidance from our empirical evidence. Second, given the model structure and the endogenous variables observed in the data, we recover the underlying shocks to technology, demand and regulation. This recovery enables counterfactual analysis—for example, shutting down particular shocks—and allows us to quantify the contributions of these shocks to the outcomes of interest, as we do in Section 6.

**Standard calibration.** Each model simulation consists of 6,000 firms, of which 15% are nonbanks, consistent with the average number of lenders and the share of nonbank lenders in annual HMDA data since 2010. We set the share of FinTech lenders to 0.3% of all lenders (2% of nonbanks). Preferences take the form  $U(Y, C) = \theta \log(Y) + C$ , which implies demand for the mortgage service bundle  $Y$  of  $D(Y) = \frac{\theta}{P}$ . We set the elasticity of substitution to  $\sigma = 2$ , reflecting low borrower substitution due to search and informational frictions documented in U.S. mortgage markets (e.g., [Bhutta et al., 2025a](#); [Buchak et al., 2018](#); [Gurun et al., 2016](#)). The discount factor is  $\beta = 0.96$  at annual frequency. The upfront investment cost  $F$  is set to 0.1 units of the numeraire good to match banks’ initial investment propensity.

The initial distribution of productivity,  $a_{j,2010}$ , is assumed to be log-normal, as is standard

in heterogeneous-firm models, with lender-type-specific means and standard deviations. We normalize the mean of banks' initial productivity to one. We then choose the standard deviation for banks, as well as the means and standard deviations for FinTech lenders and other nonbanks, to match the 2010 cross-sectional distribution of lender-level originations (in logs). The resulting calibration implies that mean productivity is highest for FinTech lenders, followed by other nonbanks and banks, while productivity dispersion is largest among other nonbanks. Finally, we calibrate the wage series,  $w_t$ , using the annual growth rate of loan-officer wages from the Bureau of Labor Statistics' Occupational Employment and Wage Statistics Survey.

**Recovering structural shocks.** Since we observe total mortgage origination, banks' market share, and investment propensities by lender type in the data, we use the model to recover the underlying shocks,  $\{\theta_t, \lambda_{j,t}, \xi_{j,t}\}_{t=2010}^{2023}$ , such that the model-implied evolution of these endogenous variables matches their empirical counterparts. Intuitively, demand shocks ( $\theta_t$ ) govern aggregate origination, technology shocks ( $\lambda_{j,t}$ ) discipline investment propensities, and regulatory shocks ( $\xi_{j,t}$ ) pin down banks' market share.

Unlike demand shocks, changes in regulation and technology are likely to be gradual. To avoid overfitting, we parameterize technology and regulation shocks as linear paths governed by a small number of parameters. For regulation shocks, we assume

$$\xi_{j,t} = \begin{cases} 1, & j \notin N_B, \\ \xi - (t - t_0)\Delta\xi, & j \in N_B. \end{cases}$$

This specification implies that the regulatory burden rises over time: it costs  $1 - \xi$  percent of banks' revenue in  $t_0 = 2010$  and increases by  $\Delta\xi$  pp each year since then, while nonbanks are unaffected. For technology shocks, we assume

$$\lambda_{j,t} = \begin{cases} \lambda_N, & j \in 1 - N_B - N_F, \\ \lambda_F + (t - t_0)\Delta\lambda_F, & j \in N_F, \\ \lambda_B + (t - t_0)\Delta\lambda_F\Gamma, & j \in N_B, \end{cases}$$

where  $\lambda_F > \lambda_B > \lambda_N$  denotes the baseline productivity boosts from technology investment for FinTech lenders, banks, and non-FinTech nonbanks, respectively. This ordering captures the technological advantage of FinTech lenders, as well as the higher investment payoff for banks, potentially reflecting their multi-line business model and scale advantages. Moreover, the technology boost for FinTech lenders increases over time, captured by  $\Delta\lambda_F > 0$ . A fraction  $\Gamma \in (0,1)$  of this improvement passes through to banks, reflecting knowledge spillovers from technological leaders.

We calibrate  $\theta_t$ ,  $\xi$ ,  $\Delta\xi$ ,  $\lambda_N$ ,  $\lambda_F$ ,  $\lambda_B$ ,  $\Delta\lambda_F$  and  $\Gamma$  by minimizing the absolute distance between the data- and model-implied paths of total origination (in 2019 dollars), the market shares of banks and FinTech lenders, and the investment propensities by lender type over 2010-2023. The recovered paths,  $\{\theta_t, \lambda_{j,t}, \xi_{j,t}\}_{t=2010}^{2023}$ , are shown in Appendix Figure D1.

## 6 Quantitative Results

In this section, we first show that the calibrated model fits the data well, both for targeted and untargeted moments. We then conduct a series of counterfactual experiments to quantify the effects of each structural shock on key model variables and to assess their relative contributions to post-GFC industry dynamics. Finally, we analyze technology investment and market share dynamics under alternative scenarios that plausibly characterize the post-2025 economic environment.

### 6.1 Structural Shocks and Post-GFC Industry Dynamics

Using the structural shocks recovered from the model, Figure 10 plots the model-implied and empirical evolution of key endogenous variables over 2010–2023. The model generates volatile mortgage originations, a declining market share of banks, and rising shares of nonbanks and FinTech lenders. In addition, while technology investment increases across all lender types over time, banks exhibit a higher investment propensity than non-FinTech nonbanks. These patterns closely match the data.

The model also matches several untargeted moments reasonably well. First, it generates an endogenous price index for the mortgage service bundle, which can be interpreted as the

price of financial intermediation (Figure 10, lower right panel). Fuster et al. (2024) document a strong upward trend in this price and estimate an increase of roughly 30% between 2011 and 2014. Our model-implied price change is consistent with their estimates. Second, the model captures heterogeneity in technology investment: as shown in Figure D2, banks and larger lenders are more likely to invest, consistent with Fact 2 in Section 3.

Given the model’s fit, we next conduct a series of counterfactual experiments that shut down one shock at a time to quantify its effects on key model variables. Appendix Figures D3-D5 present the full time paths under these counterfactuals over 2010-2023.

**Technology shocks (Shocks to FinTech lenders’ technology).** To assess the role of technology (FinTech) shocks, we reduce the technological advantage of FinTech lenders in a counterfactual. Specifically, we eliminate FinTech lenders’ initial advantage by setting  $\lambda_F = \lambda_N$  and reduce their technology acceleration,  $\Delta\lambda_F$ , to 25% of its baseline value. This lower acceleration is passed through to both banks and nonbanks by a fraction of  $\Gamma$ . Under this counterfactual, industry productivity is lower, mortgage service prices are higher, and aggregate output is lower than in the baseline. Consistent with the empirical evidence in Section 4.1, the negative technology shock reduces banks’ technology investment while slightly increasing investment by nonbanks. This is because the loss of FinTech’s technological advantage exerts negative externality to banks, lowering banks’ returns to investment. At the same time, nonbanks, who are less directly affected, absorb the market share displaced from FinTech lenders and increase investment at the margin.

**Demand shocks.** To assess the role of demand shocks, we shut down demand fluctuations by holding  $\theta_t$  fixed at its 2010 level. Under this counterfactual, industry output is lower. Consistent with the IV estimates in Section 4.2, both banks and nonbanks reduce technology investment. However, since the technology process is the same as in the baseline calibration, changes in individual firms’ investment decisions do not materially translate into changes in the aggregate price. In addition, because demand shocks are common across lenders in the model, market shares are largely unchanged.

**Regulation shocks.** To assess the role of regulation shocks, we remove post-GFC regulatory tightening by holding  $\xi_{j,t}$  fixed at its 2010 level. These shocks are a key determinant of banks’

market share and technology investment. Absent regulatory tightening, banks' productivity, origination volume, market share, and technology investment would have been much higher, and the equilibrium mortgage service price would have been lower. FinTech lenders would have expanded more slowly, and their growth would have come primarily at the expense of other nonbanks. Overall, the model implies that the nonbank sector would not have expanded had post-GFC shifts in banking regulation not occurred.

**Relative contributions of shocks.** Our model also provides a laboratory for assessing the joint effects of shocks and their relative contributions over time. To this end, we simulate a counterfactual that incorporates all parameter changes from the previously isolated exercises, which we refer to as the *joint counterfactual*. We focus on the change from 2010 to 2021, when nonbank and FinTech market shares reached their peak. We treat the difference between the baseline-calibrated change and the joint-counterfactual change over this period as the total change and decompose this change into components attributable to each shock.

Figure 11 presents the results. Relative to the joint counterfactual, banks' market share is 45 pp lower and FinTech lenders' market share is 14 pp higher from 2010 to 2021. The model attributes banks' declining market share primarily to regulatory tightening, while FinTech expansion reflects both regulatory and technology shocks. These findings are consistent with [Buchak et al. \(2018\)](#).

The model offers additional insights into technology investment and the role of demand shocks. Accommodative monetary policy over 2010-2021 stimulated demand for mortgage services and increased technology investment by both banks and nonbanks. Regulatory tightening depressed banks' investment but failed to boost nonbanks' investment, even though it shifted market share toward the nonbank sector. By contrast, technology shocks contributed positively to banks' investment but reduced nonbanks' investment relative to the joint counterfactual. Overall, our analysis highlights the importance of the composition of shocks for understanding post-GFC mortgage market dynamics, and in particular the interaction between technological innovation, endogenous investment, and market share growth. We next consider how industry dynamics change under alternative scenarios with different shock paths.

## 6.2 Industry Dynamics under Alternative Post-2025 Scenarios

Our analysis so far has focused on 2010-2023. The economic environment over the subsequent decade, however, is likely to differ substantially, given the prospect of prolonged high interest rates projected by the Federal Open Market Committee as of 2024 and the stated intent of the current administration to relax bank regulation. These changes may reshape the mortgage industry dynamics, raising the question of whether the nonbank sector can continue to expand.

We use the model to shed light on this question. In Figure 12, we consider two alternative scenarios over 2024-2033. First, we construct a weak-demand scenario (blue line), in which demand conditions resemble those during 2010-2018, bank regulations remain as tight as in 2023, and technology progress continues along its baseline path. Second, we consider a deregulation scenario layered on top of weak demand, in which regulatory burdens on banks gradually ease, with  $\xi_t$  retuning to its 2018 level by 2033.

Model simulations imply that the nonbank sector's market share does not continue to expand as in earlier years. In the weak-demand scenario, FinTech and other nonbank lenders scale back investment relative to earlier years, while banks increase investment as regulatory burdens flatten. As a result, banks do not continue to lose market share. In the deregulation scenario, regulatory easing further boosts banks' technology investment and market share, while weak demand continues to depress nonbanks' technology investment. Consequently, the nonbank sector contracts overall—including FinTech lenders—even though their technological advantages remain.

Overall, the model suggests that the post-GFC expansion of the nonbank sector was driven by a combination of favorable shocks—strong demand and tightening bank regulation—rather than broad-based technological advantages among nonbanks. Most nonbanks remain away from the technological frontier, and technology shocks play a limited or even negative role in explaining their investment. Because sustained productivity growth is critical for firm expansion in a stable or adverse macroeconomic environment, these results cast doubt on whether the nonbank sector will continue to gain market share under persistently high interest rates and deregulation.

## 7 Conclusion

The marked growth of nonbanks in the post-GFC mortgage origination market has popularized the view that technological innovation has been a main driver of their rise and will continue to propel their expansion. Yet, technological innovation is not exogenous: it depends on firms' investment decisions, which respond endogenously to economic shocks. To date, evidence remains limited on how the vast majority of mortgage lenders—both banks and nonbanks—invest in technology, how these investments respond to shocks, and how such responses shape industry dynamics.

This paper provides a systematic analysis of technology investment in the mortgage industry and its implications for the post-GFC market structure. Using a novel dataset on lender-level labor demand merged with loan origination records and balance-sheet information, we document three salient facts. First, unlike leading FinTech lenders, banks and most nonbanks have historically concentrated hiring in labor-intensive rather than technology-related positions. Second, while demand for technology-related human capital increased over time, this increase was mainly driven by banks and large nonbanks. Third, technology-related hiring is strongly associated with higher subsequent productivity. We then estimate the causal effects of two major shocks on lenders' technology investment: the expansion of leading FinTech lenders, fueled by their technological advantage, and demand shocks induced by successive rounds of monetary stimulus following the GFC. We find that nonbanks cut back technology investment in response to FinTech growth but increased technology investment in response to demand shocks. In contrast, banks increased technology investment facing the FinTech rise but displayed less sensitivity to demand shocks.

These empirical findings discipline a structural model that allows us to study micro-level investment behavior, rationalize the heterogeneous responses observed in the data, and quantify the relative contributions of shocks to post-GFC industry dynamics. The model implies that the expansion of the nonbank sector after the GFC was largely driven by a combination of favorable shocks—strong demand and tightening bank regulation—rather than broad-based technological advantages among nonbanks. Under an environment of persistently high interest rates and relaxed bank regulation, which plausible characterize

the post-2025 economic landscape, the model suggests that continued nonbank expansion is far from assured.

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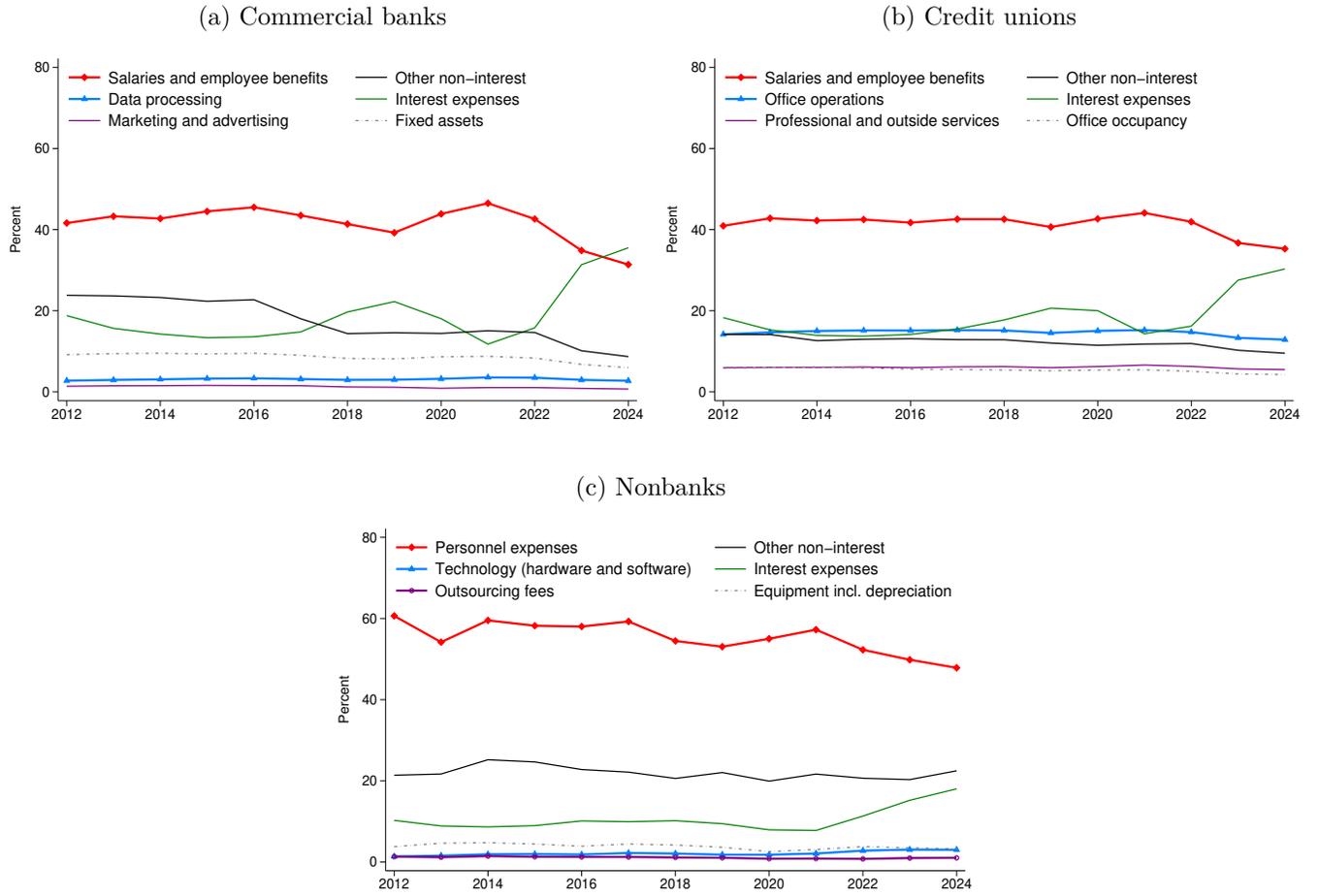
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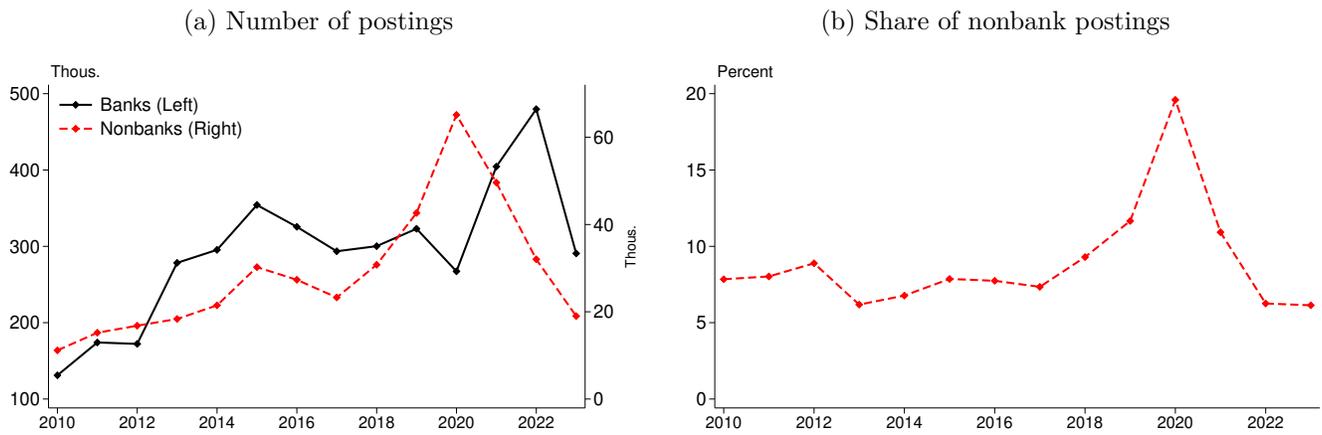
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Figure 1: Expenses of mortgage lenders



Sources: FFIEC Bank Call Reports; Conference of State Bank Supervisors NMLS Mortgage Call Reports; Credit Union and Corporate Call Reports; HMDA. Notes: Expense shares plotted are conditional on the sample of HMDA lenders.

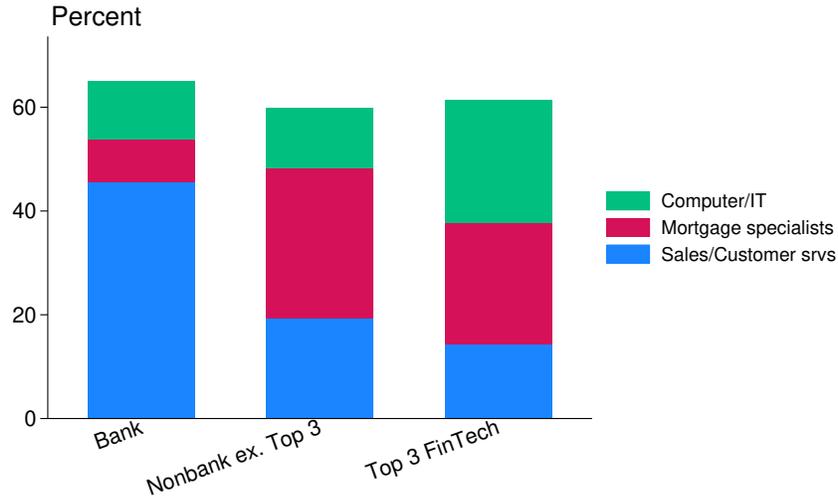
Figure 2: Job postings by mortgage lenders



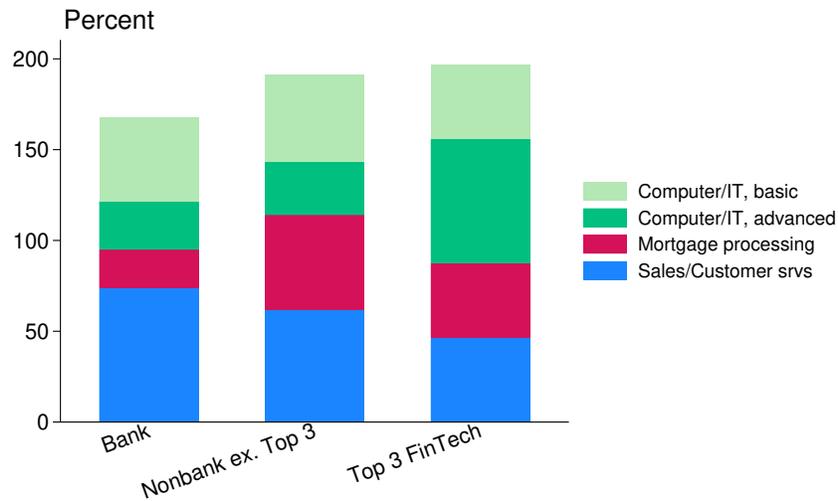
Sources: Merged Lightcast-HMDA job posting-level data. Notes: See Section 2.2 for the description of the matching algorithm.

Figure 3: Composition of job postings by mortgage lenders, 2010-2023

(a) Occupation requirement



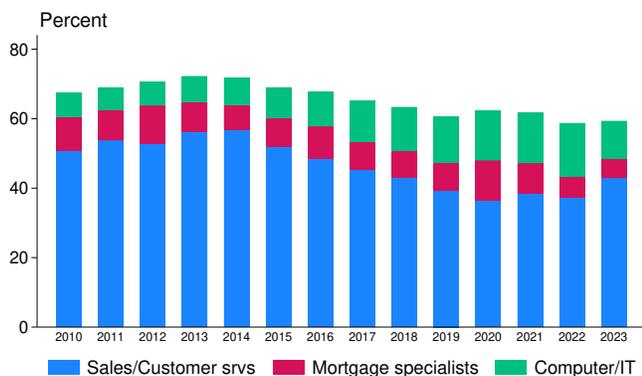
(b) Skill requirement



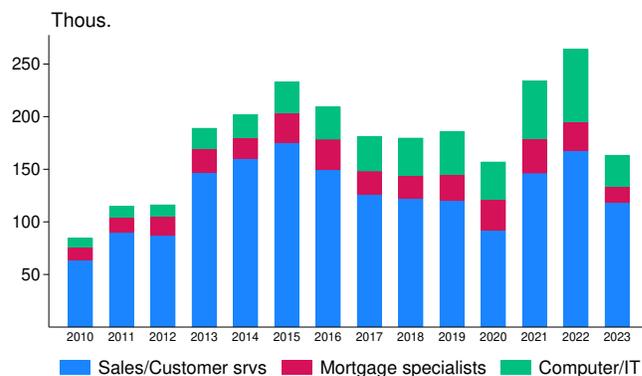
Sources: Merged Lightcast-HMDA job posting-level data. Notes: See Section 2.3 and Appendix A for the classification of occupation and skill categories. In panel (b), percentages do not sum to 100, because one job posting may require multiple skills.

Figure 4: Occupational composition over time

(a) Share of jobs: Banks



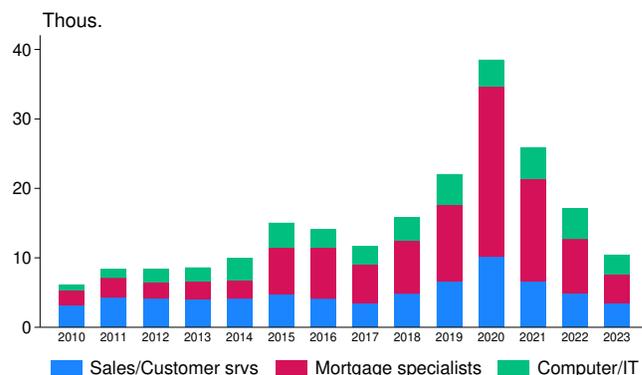
(b) Number of jobs: Banks



(c) Share of jobs: Nonbanks ex. Top 3 FinTech



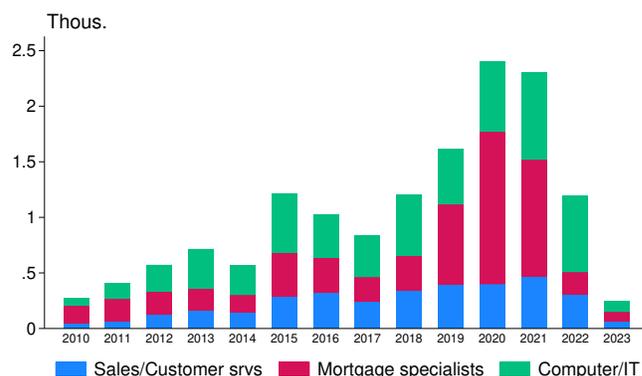
(d) Number of jobs: Nonbanks ex. Top 3 FinTech



(e) Share of jobs: Top 3 FinTech

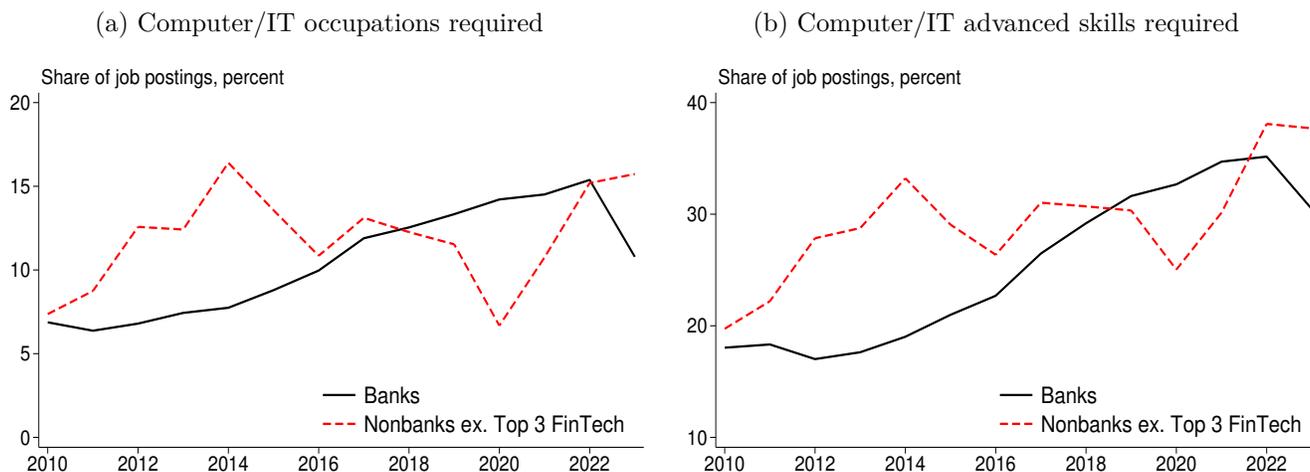


(f) Number of jobs: Top 3 FinTech



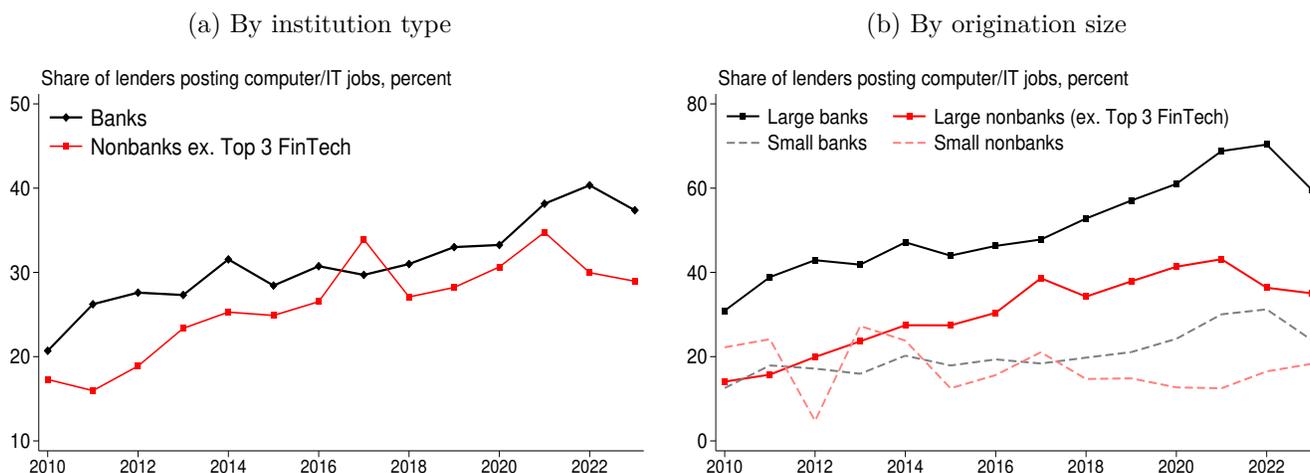
Sources: Merged Lightcast-HMDA job posting-level data. Notes: See Section 2.3 and Appendix A for the classification of occupation categories.

Figure 5: Trends in technology investment by mortgage lenders



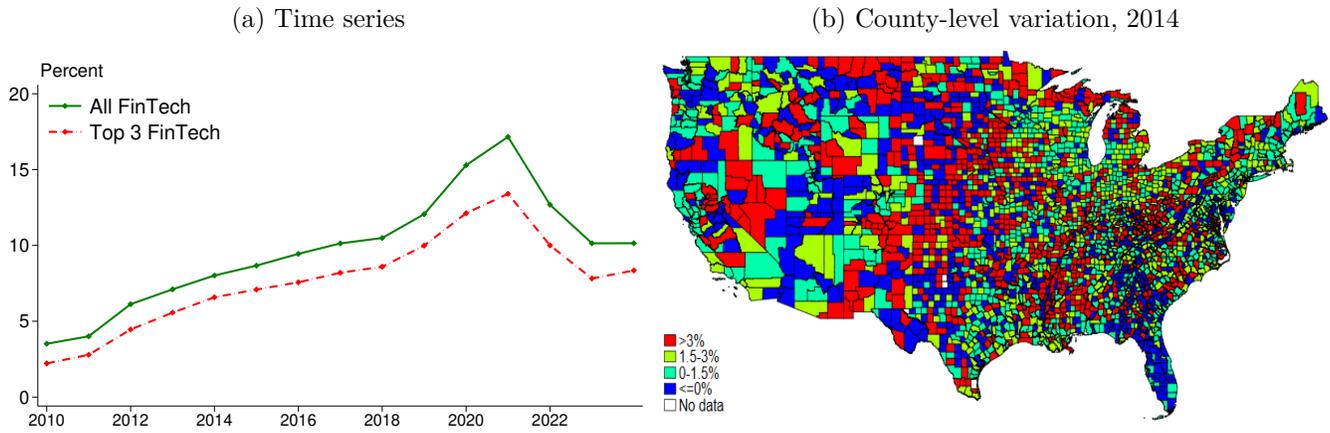
Sources: Merged Lightcast-HMDA job posting-level data. Notes: Panel (a) shows the share of jobs that require a computer- or IT-related occupation among the postings by banks (black) and among the postings by nonbanks (red). Panel (b) shows the share of jobs that require an advanced computer or IT skill among the postings by banks (black) and among the postings by nonbanks (red). See Section 2.3 and Appendix A for the measurement of technology investment.

Figure 6: Heterogeneity in technology investment across mortgage lenders



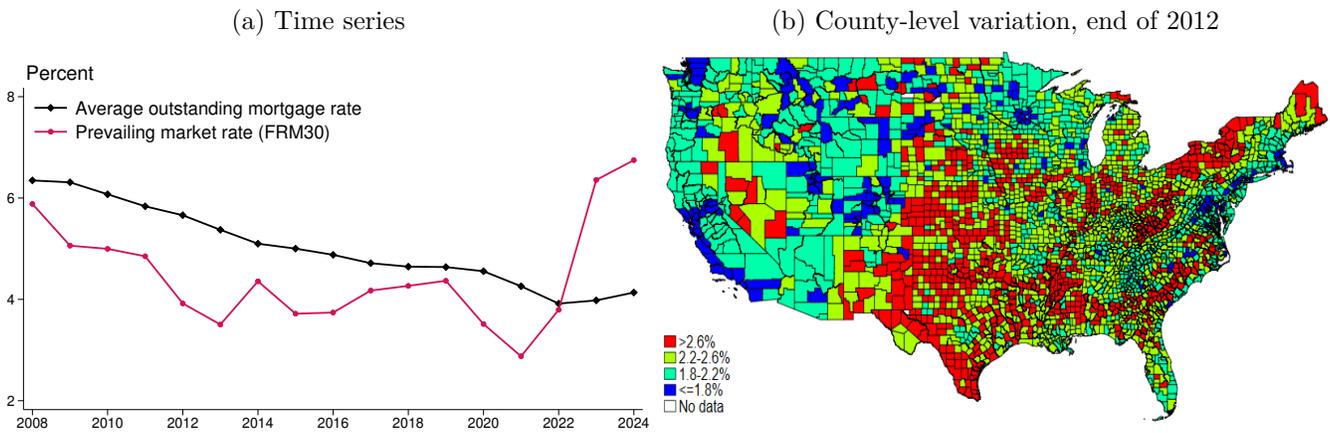
Sources: Merged Lightcast-HMDA firm-level data. Panel (a) shows the share of lenders that post a job that requires a computer- or IT-related occupation among banks (black) and among nonbanks (red). Panel (b) separates lenders in each type into large and small ones. Large lenders are those above the median of the loan-origination distribution. See Section 2.3 and Appendix A for the measurement of technology investment.

Figure 7: Aggregate and cross-sectional variation in FinTech growth



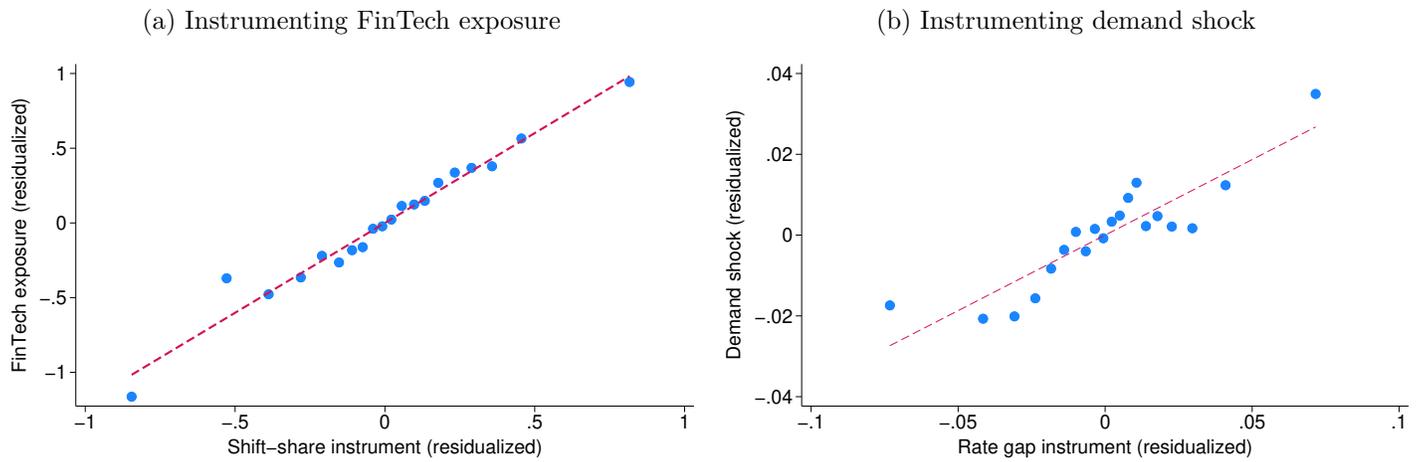
Source: HMDA. Notes: Panel (a) shows the market shares of all FinTech lenders (classified by [Fuster et al. 2019](#) and [Buchak et al. 2018](#)) and the Top 3 FinTech lenders. Panel (b) shows the county-level market share growth of the Top 3 FinTech lenders in 2014.

Figure 8: Aggregate and cross-sectional variation in the rate gap



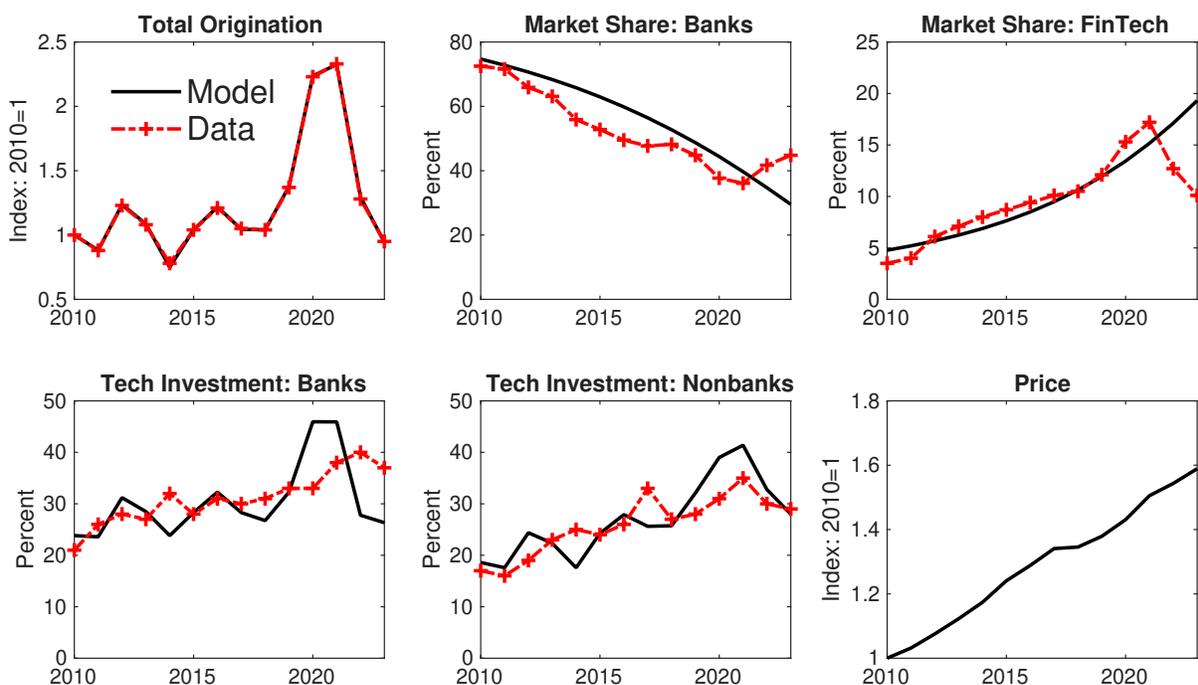
Source: ICE McDash; Freddie Mac. Notes: Panel (a) shows the average outstanding mortgage rate at the national level (black) and the benchmark 30-year fixed mortgage rate (red). Panel (b) shows the county-level rate gap, which is the difference between the county-level average outstanding mortgage rate and the benchmark 30-year fixed mortgage rate, at the end of 2012.

Figure 9: First-stage bin scatter plot



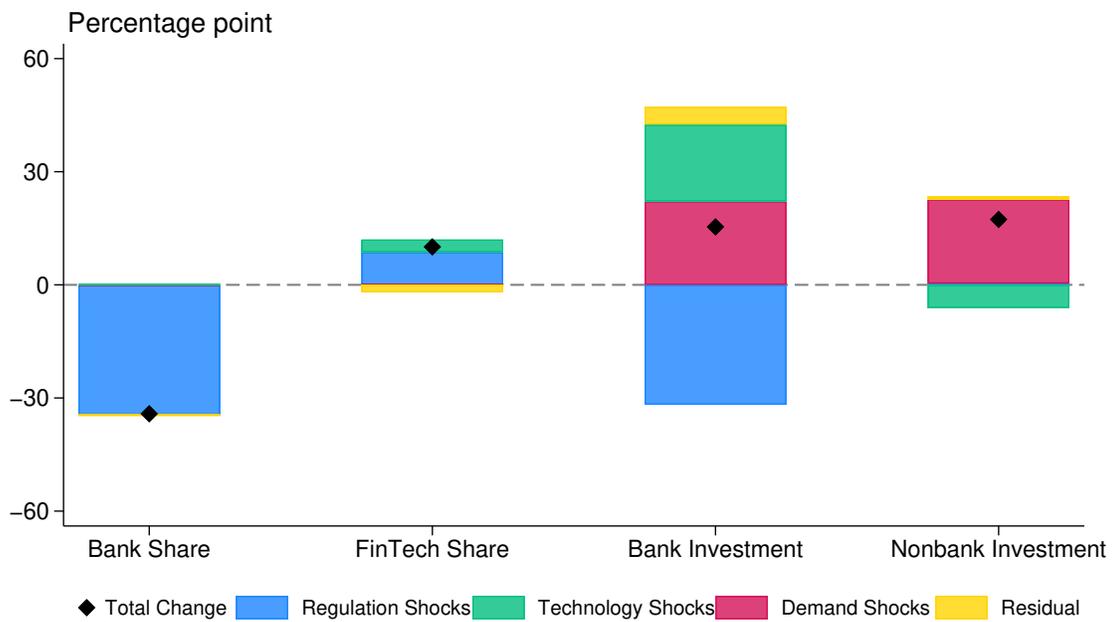
Notes: This figure shows the bin scatter plot for the first stage of equation (5) in panel (a) and the bin scatter plot for the first stage of equation (8) in panel (b). The variables are residualized (using other control variables) to be consistent with the first-stage regression. Panel (a) plots the endogenous variable, FinTech exposure in equation (4), against the leave-one-out shift-share instrument in equation (6). Panel (b) plots the endogenous variable, demand shock in equation (7), against the rate-gap instrument in equation (9) constructed using ICE McDash data.

Figure 10: Model fit



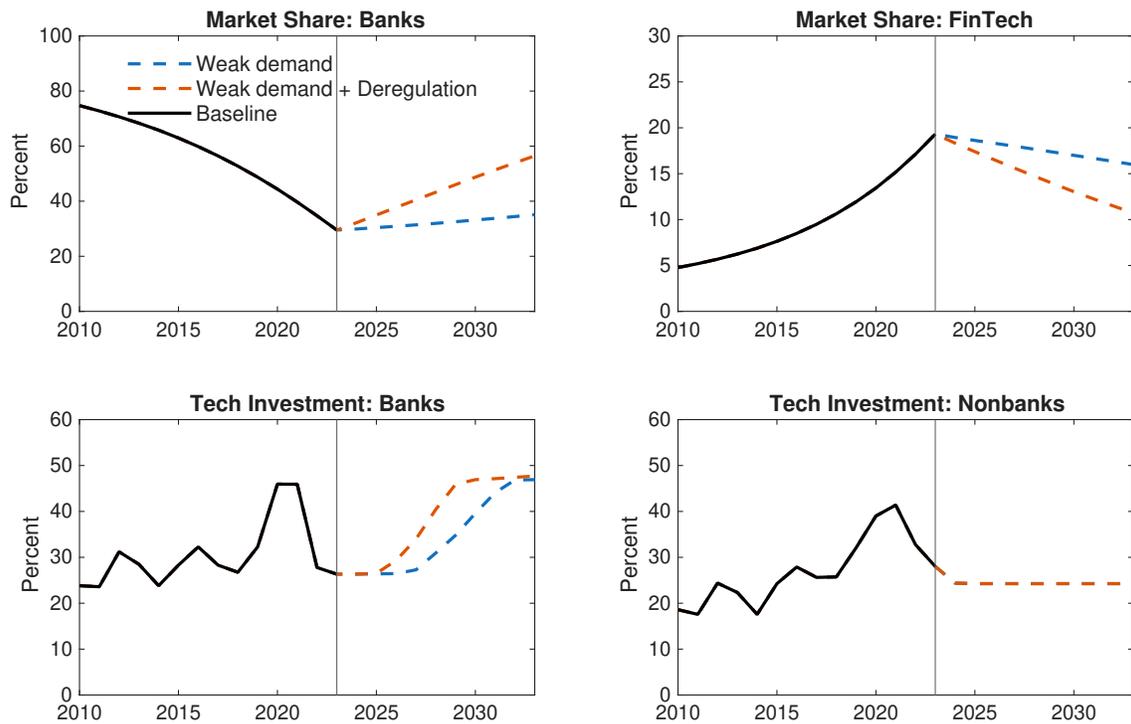
Notes: Data on the total origination volume in 2019 dollars (normalized to be 1 for 2010) and market shares of banks and FinTech lenders are from HMDA data. Data on technology investment by banks and non-FinTech nonbanks are from Lightcast, measured by the share of lenders in each type that post a job requiring a computer- or IT-related occupation in a year. In the model, total origination volume refers to aggregate industry-level output; the market share refers to the share of output accounted for by a lender type; technology investment refers to the share of lenders in each type that decide to invest in technology.

Figure 11: Contributions of structural shocks to key variables



Notes: The *total change* of an endogenous variable refers to the difference between the baseline-calibration implied change between 2010-2021 and the joint-counterfactual implied change over the same period. The actual change is then decomposed into components explained by each type of shock. The residual component captures the gap between the total change and the sum of shock-explained components, reflecting nonlinearities of the model.

Figure 12: Mortgage industry dynamics in alternative economic environments



Notes: See Figure 10 for definitions of model variables. The *weak-demand* scenario assumes that, after 2023, the demand condition resembles that during 2010-2018, regulations are as tight as in 2023, and technology progresses as in the baseline. The *weak-demand plus deregulation* scenario replaces the regulation assumption in the weak-demand scenario by that regulations gradually loosen, returning to the level of 2018 by 2033.

Table 1: Concentration and heterogeneity in labor demand

Dependent variable: $k =$	A. Job requires occupation $k$			B. Job requires skill $k$		
	Sales/Customer	Mortgage	Computer/IT	Sales/Customer	Mortgage	Computer/IT
Nonbank ex. Top 3	-0.185*** (0.037)	0.133*** (0.034)	0.013 (0.008)	-0.019 (0.030)	-0.038 (0.024)	0.005 (0.013)
Top 3 FinTech	-0.192*** (0.038)	0.029 (0.057)	0.183*** (0.052)	-0.133*** (0.022)	-0.106*** (0.031)	0.241** (0.106)
Occupation FE				x	x	x
MSA-by-Year FE	x	x	x	x	x	x
Educ & Experience FE	x	x	x	x	x	x
# Obs.	1,948,744	1,948,744	1,948,744	1,945,938	1,945,938	1,945,938

Notes: The omitted group is banks. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the lender level. Occupation and skill classifications are shown in Tables A1 and A2.

Table 2: Technology investment and lender size

Dependent variable:	Lender technology investment measured by					
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	$Q(\text{IT jobs})$	$Q(\text{IT skills, adv})$	$S(\text{IT jobs})$	$S(\text{IT skills, adv})$
Nonbank ex. Top 3	-0.217*** (0.017)	-0.160*** (0.015)	-0.693*** (0.181)	-0.674*** (0.156)	-0.019*** (0.003)	-0.024*** (0.008)
Large	0.297*** (0.010)	0.274*** (0.010)	1.757*** (0.138)	1.632*** (0.124)	0.022*** (0.002)	0.051*** (0.005)
Controls	x	x	x	x	x	x
Lender-State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
# Obs.	28,972	28,972	28,972	28,972	28,972	28,972

Notes: Lender size is measured by the origination volume. Large lenders are those above the median of the distribution.  $\mathbb{I}(\text{IT jobs} > 0)$  and  $\mathbb{I}(\text{IT skills, adv} > 0)$  are indicators for a lender posting a job in a year that requires a computer- or IT-related occupation (column 1) or that requires at least one advanced computer skills (column 2).  $Q(\text{IT jobs})$  and  $Q(\text{IT skills, adv})$  are the numbers of jobs posted by a lender in a year that require a computer- or IT-related occupation (column 3) or that require at least one advanced computer skills (column 4).  $S(\text{IT jobs})$  and  $S(\text{IT skills, adv})$  are the shares of jobs posted by a lender in a year that require a computer- or IT-related occupation (column 5) or that require at least one advanced computer skills (column 6). Control variables include origination-share-weighted demand-side factors: demographics (population growth and the share of population with a Bachelor's degree), labor and housing market conditions (employment and house price growth), creditworthiness (the share of subprime borrowers constructed using FRBNY Consumer Credit Panel/Equifax data), and mortgage market concentration (the Herfindahl-Hirschman Index) in the counties whether the lender originates loans. Columns 1, 2, 5 and 6 are obtained from estimating linear panel regressions, while columns 3 and 4 are from estimating Poisson maximum likelihood regressions with multi-way fixed effects. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the lender level.

Table 3: Technology investment and productivity

Dependent variable:	Origination volume growth		Market share growth		Loan processing time	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(\text{IT jobs} > 0)_t$	4.958*** (1.174)		0.260*** (0.077)		0.013 (0.249)	
$\mathbb{I}(\text{IT jobs} > 0)_{t-1}$	3.360*** (1.169)		0.188** (0.076)		-0.146 (0.270)	
$\mathbb{I}(\text{IT skills, adv} > 0)_t$		5.699*** (1.141)		0.247*** (0.085)		1.954 (1.790)
$\mathbb{I}(\text{IT skills, adv} > 0)_{t-1}$		2.445** (1.079)		0.143** (0.071)		-0.614 (0.643)
Controls	x	x	x	x	x	x
Lender-State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
# Obs.	18,982	18,982	18,982	18,982	18,796	18,796

Notes:  $\mathbb{I}(\text{IT jobs} > 0)_t$  is the indicator for a lender posting a job in year  $t$  that requires a computer- or IT-related occupation.  $\mathbb{I}(\text{IT skills, adv} > 0)_t$  is the indicator for a lender posting a job in year  $t$  that requires an advanced computer skill. Control variables include a measure of lender size (lagged loan origination count in log), the differential productivity growth of nonbanks, and a vector of origination-share-weighted demand-side controls as described in Table 2. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the lender level.

Table 4: Technology investment responses to FinTech shock: Average effects

Dependent variable:	Technology investment measured by:					
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	$Q(\text{IT jobs})$	$Q(\text{IT skills, adv})$	$\log Q(\text{IT jobs})$	$\log Q(\text{IT skills, adv})$
FinTech Exposure $_{t-1}$	0.013*** (0.004)	0.015*** (0.004)	0.083*** (0.024)	0.068** (0.030)	0.061*** (0.017)	0.057*** (0.015)
FinTech Exposure $_{t-1} \times \text{Nonbank}$	-0.044*** (0.010)	-0.039*** (0.011)	-0.106** (0.048)	-0.093* (0.049)	-0.034 (0.048)	-0.127*** (0.041)
Controls	x	x	x	x	x	x
Lender-State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
# Obs.	18,146	18,146	18,146	18,146	7,742	11,511

Notes: See Table 2 for the definition of the outcome variable in each column and Table 3 for the list of control variables. Columns 3-4 are estimated using Poisson maximum likelihood regressions with multi-way fixed effects. The other columns are estimated using linear panel regressions. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the lender level.

Table 5: Technology investment responses to FinTech shock: Heterogeneous effects

Dependent variable:	Technology investment measured by			
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$
FinTech Exposure $_{t-1}$	0.016*** (0.004)	0.018*** (0.004)	0.010** (0.004)	0.014*** (0.004)
FinTech Exposure $_{t-1} \times \text{Nonbank}$	-0.069*** (0.014)	-0.053*** (0.018)	-0.041*** (0.012)	-0.044*** (0.014)
FinTech Exposure $_{t-1} \times \text{Nonbank} \times \text{Large origination}_{t-1}$	0.065*** (0.021)	0.045* (0.024)		
FinTech Exposure $_{t-1} \times \text{Nonbank} \times \text{Large assets}_{t-1}$			0.014 (0.021)	0.049** (0.020)
Controls	x	x	x	x
Lender-State FE	x	x	x	x
Year FE	x	x	x	x
# Obs.	18,146	18,146	17,257	17,257

Notes: “Large origination” refers to lenders whose previous-year origination is in the top quartile of the origination distribution. “Large assets” refers to lenders whose previous-year assets are in the top quartile of the asset distribution. See Table 2 for the definition of the outcome variable in each column and Table 3 for the list of control variables. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the lender level.

Table 6: Technology investment responses to FinTech shock: OLS vs IV estimates

Dependent variable:	OLS estimates		2SLS estimates		1st stage
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	FinTech Exposure $_{t-1}$
FinTech Exposure $_{t-1}$	0.013*** (0.004)	0.015*** (0.004)	0.019* (0.010)	0.021** (0.010)	
FinTech Exposure $_{t-1} \times$ Nonbank	-0.044*** (0.010)	-0.039*** (0.011)	-0.013 (0.017)	-0.049*** (0.016)	
Shift-share instrument					0.965*** (0.025)
Shift-share instrument $\times$ Nonbank					0.129*** (0.031)
Controls	x	x	x	x	x
Lender-State FE	x	x	x	x	x
Year FE	x	x	x	x	x
1st-stage F-stat			1,365	1,365	1,365
# Obs.	18,146	18,146	18,146	18,146	18,146

Notes: See Table 2 for the definition of the outcome variable in each column and Table 3 for the list of control variables. The leave-one-out shift-share instrument is described in equation (6). Both the FinTech exposure and its interaction with the nonbank indicator are instrumented. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the lender level.

Table 7: Technology investment responses to FinTech shock: Persistence

Dependent variable:	OLS estimates		2SLS estimates	
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$
FinTech Exposure $_{t-1}$	0.009** (0.005)	0.009** (0.004)	0.016 (0.011)	0.006 (0.011)
FinTech Exposure $_{t-2}$	0.010** (0.004)	0.007 (0.005)	0.030*** (0.011)	0.006 (0.010)
FinTech Exposure $_{t-1} \times$ Nonbank	-0.033** (0.013)	-0.033** (0.013)	-0.008 (0.021)	-0.035* (0.018)
FinTech Exposure $_{t-2} \times$ Nonbank	-0.072*** (0.016)	-0.052*** (0.013)	-0.129*** (0.016)	-0.089*** (0.017)
Controls	x	x	x	x
Lender-State FE	x	x	x	x
Year FE	x	x	x	x
1st-stage F-stat			468	468
# Obs.	13,416	13,416	13,416	13,416

Notes: See Table 2 for the definition of the outcome variable in each column and Table 3 for the list of control variables. The leave-one-out shift-share instrument is described in equation (6). All regressors shown in left column are instrumented based on the shift-share instrument, its lag and their interactions with the nonbank indicator. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively.

Table 8: Technology investment responses to demand shock: Average effects

Dependent variable:	Technology investment measured by:					
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	$Q(\text{IT jobs})$	$Q(\text{IT skills, adv})$	$\log Q(\text{IT jobs})$	$\log Q(\text{IT skills, adv})$
Demand Shock	-0.039 (0.036)	-0.039 (0.036)	-0.352* (0.195)	-0.240 (0.170)	-0.035 (0.130)	-0.160 (0.118)
Demand Shock $\times$ Nonbank	0.122*** (0.021)	0.107*** (0.022)	0.575*** (0.089)	0.672*** (0.092)	0.254*** (0.084)	0.537*** (0.074)
Controls	x	x	x	x	x	x
Lender-State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
# Obs.	19,972	19,972	19,972	19,972	8,326	12,480

Notes: See Table 2 for the definition of the outcome variable. Control variables include those in Table 3 and origination-share-weighted controls for the county-level FHA/VA share and the jumbo loan share, as well as the FinTech growth exposure. Columns 3-4 are estimated using Poisson maximum likelihood regressions with multi-way fixed effects. The other columns are estimated using linear panel regressions. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the lender level.

Table 9: Technology investment responses to demand shock: IV estimates

Dependent variable:	2SLS: $RateGap$ IV		1st stage	2SLS: $\Delta RateGap$ IV		1st stage
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	DD shock	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	DD shock
Demand Shock	-0.466 (1.473)	-1.188 (1.463)		0.693** (0.327)	0.506 (0.330)	
Demand Shock $\times$ Nonbank	0.444* (0.246)	0.773*** (0.283)		0.083** (0.039)	0.017 (0.039)	
Rate-gap instrument			0.034*** (0.006)			0.336*** (0.025)
Rate-gap instrument $\times$ Nonbank			-0.004 (0.003)			0.002 (0.002)
Controls	x	x	x	x	x	x
Lender-State FE	x	x	x	x	x	x
Year FE	x	x	x	x	x	x
1st-stage F-stat	17	17	17	169	169	169
# Obs.	19,972	19,972	19,972	19,972	19,972	19,972

Notes: See Table 2 for the definition of the outcome variable. Control variables include those in Table 3 and origination-share-weighted controls for the county-level FHA/VA share and the jumbo loan share, as well as the FinTech growth exposure.  $\Delta RateGap$  IV is described in equation (9), constructed using ICE McDash data.  $RateGap$  IV is constructed similarly using the level instead of change of the rate gap in equation (9). Both the demand shock and its interaction with the nonbank indicator are instrumented. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively.

Table 10: Technology investment responses to demand shock: Persistence

Dependent variable:	OLS estimates		2SLS estimates	
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$
Demand Shock <sub>t</sub>	-0.020 (0.038)	-0.030 (0.037)	0.631** (0.291)	0.511* (0.290)
Demand Shock <sub>t-1</sub>	-0.012 (0.041)	-0.044 (0.043)	0.269 (0.221)	0.161 (0.230)
Demand Shock <sub>t</sub> × Nonbank	0.131*** (0.022)	0.110*** (0.023)	0.131*** (0.028)	0.110*** (0.030)
Demand Shock <sub>t-1</sub> × Nonbank	-0.003 (0.032)	-0.048 (0.032)	-0.043 (0.038)	-0.096*** (0.037)
Controls	x	x	x	x
Lender-State FE	x	x	x	x
Year FE	x	x	x	x
1st-stage F-stat			92	92
# Obs.	18,146	18,146	18,146	18,146

Notes: See Table 2 for the definition of the outcome variable. Control variables include those in Table 3 and origination-share-weighted controls for the county-level FHA/VA share and the jumbo loan share, as well as the FinTech growth exposure. The rate-gap instrument is described in equation (9), constructed using ICE McDash data. All regressors shown in the left column are instrumented based on the rate-gap instrument, its lag and their interactions with the nonbank indicator. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively.

# Online Appendices

## A Occupation and Skill Classification

Table A1: Classification of occupational groups

A. Computer and IT	B. Sales and Customer Services	C. Mortgage Specialists
15-1121 Computer Systems Analysts	11-2021 Marketing Managers	13-2072 Loan Officers
15-1122 Information Security Analysts	11-2022 Sales Managers	13-2021 Appraisers and Assessors of Real Estate
15-1132 Software Developers, Applications	11-2031 Public Relations and Fundraising Managers	43-4131 Loan Interviewers and Clerks
15-1134 Web Developers	13-2052 Personal Financial Advisors	11-9141 Property and Real Estate Managers
15-1141 Database Administrators	13-1161 Market Research Analysts and Marketing Specialists	41-9022 Real Estate Sales Agents
15-1142 Network and Computer Systems Administrators	41-1011 First-Line Supervisors of Retail Sales Workers	
15-1143 Computer Network Architects	41-2031 Retail Salespersons	
15-1151 Computer User Support Specialists	41-3021 Insurance Sales Agents	
15-1199 Computer Occupations, All Other	41-3031 Financial Services Sales Agents	
15-2031 Operations Research Analysts	41-3099 Sales Representatives, Services, All Other	
	41-4012 Sales Representatives, Wholesale and Manufacturing	
	43-3071 Tellers	
	43-4051 Customer Service Representatives	
D. Managers/HR/Administrative Workers	E. Legal and Compliance	F. Financial Analysts
11-1021 General and Operations Managers	13-1041 Compliance Officers	11-3031 Financial Managers
11-9199 Managers, All Other	13-2011 Accountants and Auditors	13-2041 Credit Analysts
13-1071 Human Resources Specialists	13-2051 Financial Analysts	
13-1111 Management Analysts	13-2099 Financial Specialists, All Other	
43-1011 First-Line Supervisors of Office and Support Workers		
43-3031 Bookkeeping, Accounting, and Auditing Clerks		
43-6014 Secretaries and Administrative Assistants		

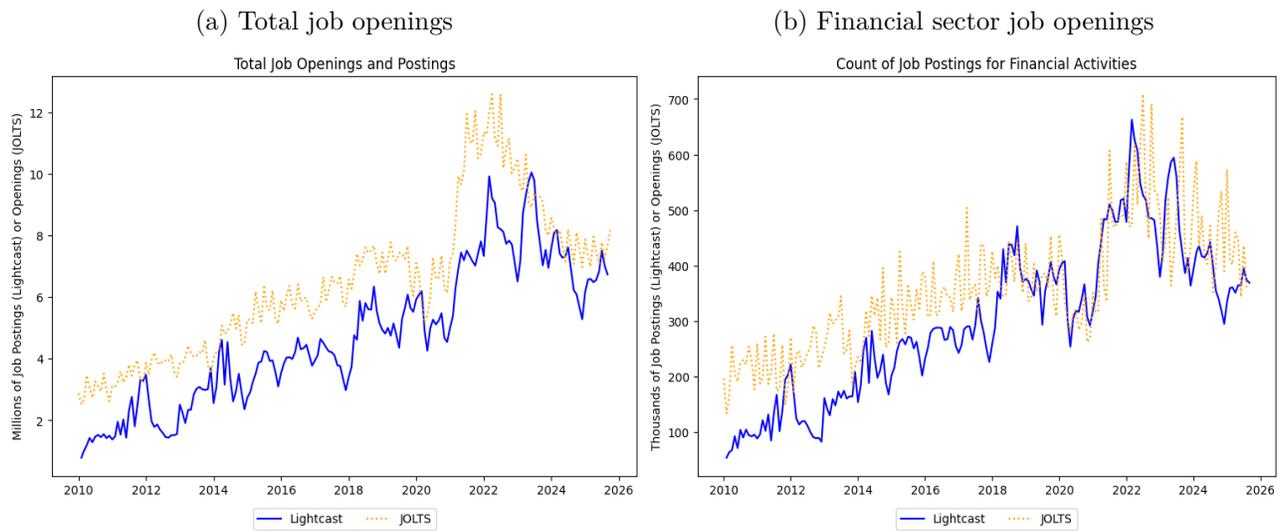
Notes: Classification of major occupational groups in merged Lightcast-HMDA data based on the 6-digit Standard Occupational Classification (SOC) system.

Table A2: Classification of skill categories

Skill Category	Skill Cluster Family	Skill Cluster	Skill Keyword	Additional Condition
A. Computer and IT	Information Technology Analysis	Web Analytics Marketing Software FinTech	“Computer”	Software=1
–Basic Computer Skill		Basic Computer Knowledge Advanced Microsoft Excel Microsoft Office and Productivity Tools Microsoft Windows Social Media	“Computer Literacy” “Microsoft Excel” “Microsoft Word”	Baseline=1
B. Sales and customer services	Customer and Client Support Marketing and Public Relations Sales	Banking Services Billing and Invoicing Cash Management Financial Advisement		
C. Mortgage processing		Mortgage Lending General Lending	“Mortgage” “Real Estate”	
D. Management and Support	Human Resources	Business Management Business Process and Analysis Business Strategy People Management Performance Management Process Improvement Project Management General Accounting		
E. Legal, risk and compliance	Legal	Auditing Financial Regulations Financial Reporting Financial Risk Management		
F. Financial analysis and trading		Financial Accounting Financial Analysis Financial Management Financial Modeling Financial Trading Investment Management		

Notes: Classification of major skill categories in merged Lightcast-HMDA data based on the Lightcast skill classification system and additional text analysis designed to capture common skills required by the financial sector.

Figure A1: Lightcast and JOLTS data comparison



Sources: Lightcast; Job Openings and Labor Turnover Survey (JOLTS) data from the Bureau of Labor Statistics.

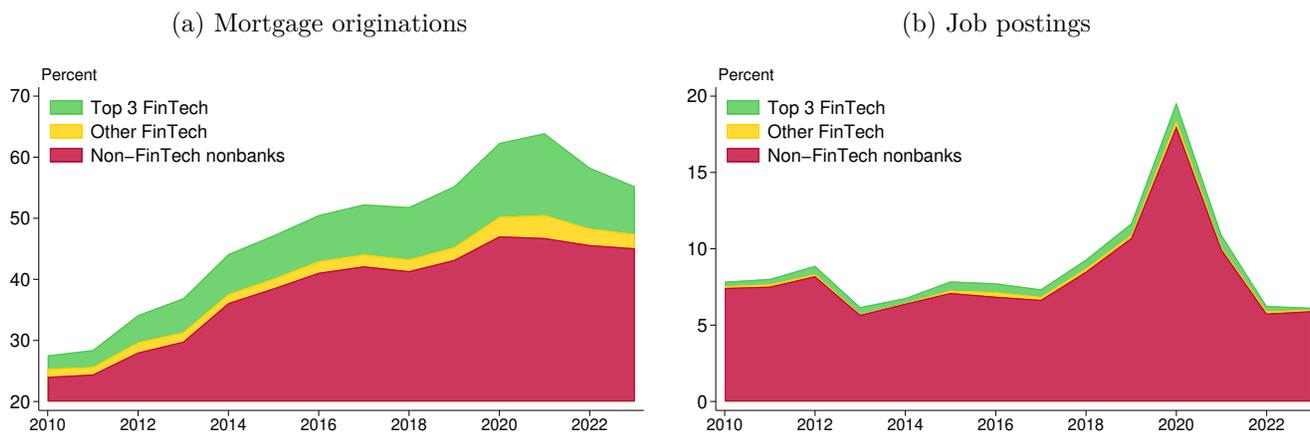
## B Stylized Facts: Additional Tables and Figures

Table B1: Top 3 FinTech mortgage lenders

Lender	Funding Year	FinTech Advantages	Market Coverage and Dominance
Rocket Mortgage (formerly Quicken Loans)	· 1985 (launched digital platform in 2015) · Acquired Redfin and Mr. Cooper in 2025	· Pioneered fully digital mortgage application process · AI-driven underwriting and automation · 100% online, no physical branches · End-to-end digital closing capability · Integrated homeownership ecosystem	· Largest retail mortgage lender (2025) · Available in all 50 states and Washington D.C. · \$4.9B adjusted revenue (2024, up 30% YoY) · Plans to reach 8% purchase market share by 2027
Rate (formerly Guaranteed Rate)	· 2000 · Rebranded as Rate in 2024	· FlashClose digital mortgage platform · AI-powered underwriting · Same-day approvals available · Closing in as little as 10 days · MyAccount customer portal · Digital/physical presence · Won HousingWireTech100 award · Language Access Program	· #2 retail mortgage lender in US · #4 overall among all mortgage lenders (2024) · 850 branches across 50 states and D.C. · Helped 2M+ homeowners since funding · Named Best Overall By Fortune (May 2025) · Forbes Best for First-Time Homebuyers (2025)
LoanDepot	· 2010 · 2014, mello® platform invested \$80M	· mello® proprietary platform · mello® smartloan: 7-minute loan evaluation, 8-day closings · Digital verification (income, employment, assets) · Appraisal bypass technology · Hybrid digital/local model with 3,300 loan officers · Lifetime Guarantee (waived fees on future refis)	· #7 largest mortgage lender (2024) · 79,814 loans/\$23.8B originated (2024) · Consistently ranked top 25 lenders · Over 200 physical locations nationwide · 1.6M daily customer contacts

Sources: Company websites; FinTech Finance News;  
<https://www.bankrate.com/mortgages/reviews/rocket-mortgage/how-bankrate-scored-rocket-mortgage>.

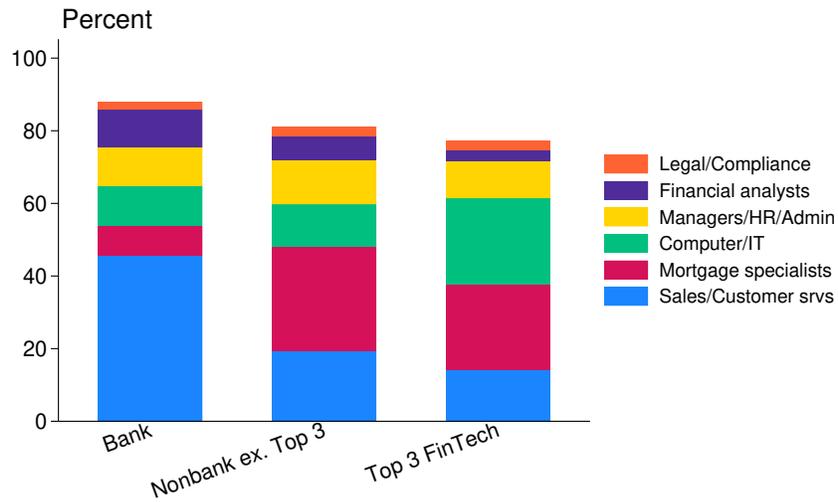
Figure B1: Nonbank presence in mortgage originations and job postings



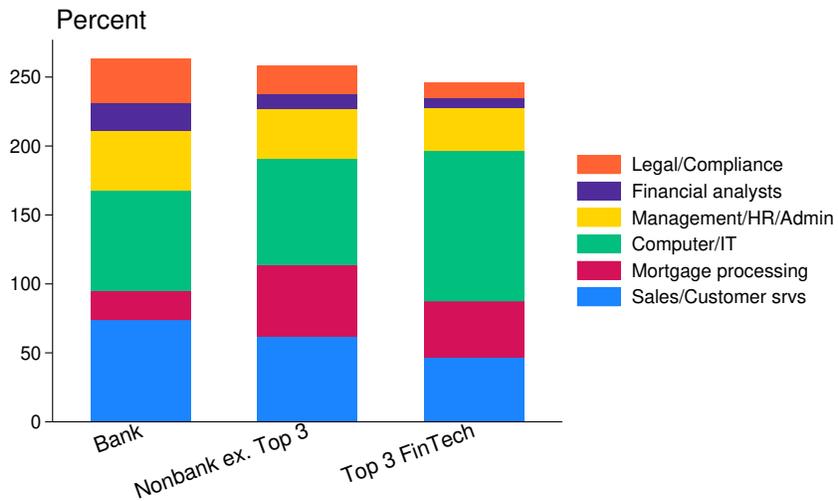
Sources: HMDA; Merged Lightcast-HMDA job posting-level data.

Figure B2: Composition of job postings by mortgage lenders, 2010-2023

(a) Occupation requirement



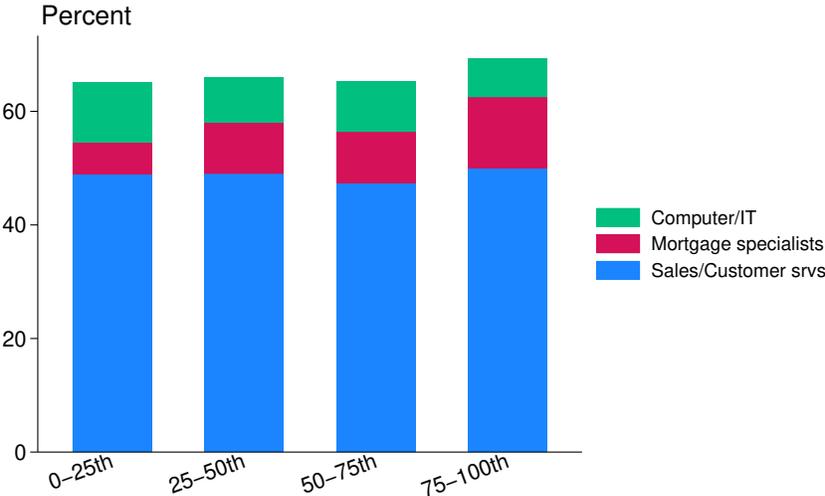
(b) Skill requirement



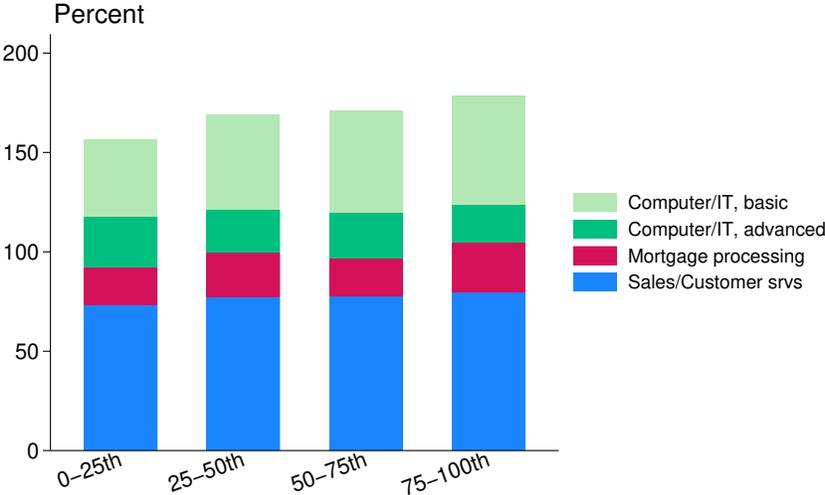
Sources: Merged Lightcast-HMDA job posting-level data. Notes: See Section 2.3 and Appendix A for the classification of occupation and skill categories. In panel (b), percentages do not sum to 100, because one job posting may require multiple skills.

Figure B3: Banks' job postings and mortgage lending exposure

(a) Occupation requirement, banks only



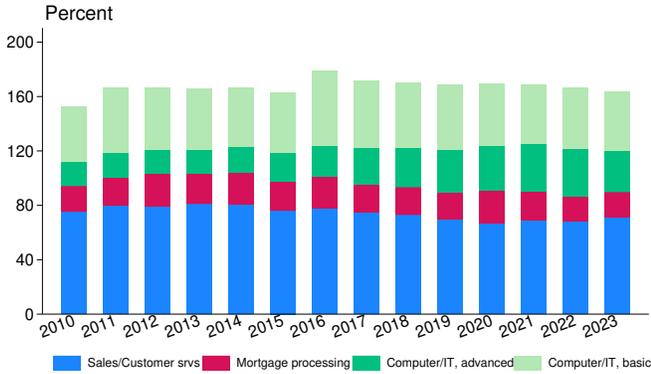
(b) Skill requirement, banks only



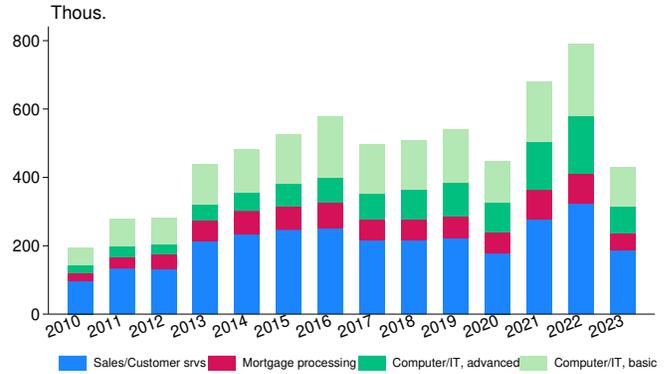
Sources: Merged Lightcast–HMDA data, restricted to banks, 2010–2023. Notes: The horizontal axis reports quartiles of banks' mortgage-lending exposure, measured as the ratio of mortgage origination volume to total assets in a given year. The *0–25th* percentile corresponds to the lowest exposure, and the *75–100th* percentile to the highest exposure. See Section 2.3 and Appendix A for details on the classification of occupation and skill categories. In panel (b), percentages do not sum to 100 because a single job posting may list multiple required skills.

Figure B4: Skill composition over time

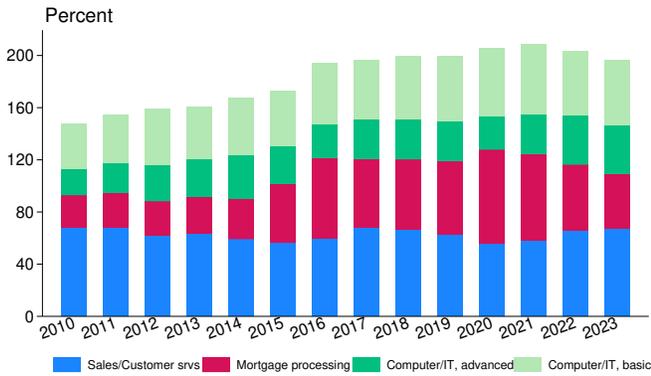
(a) Share of jobs: Banks



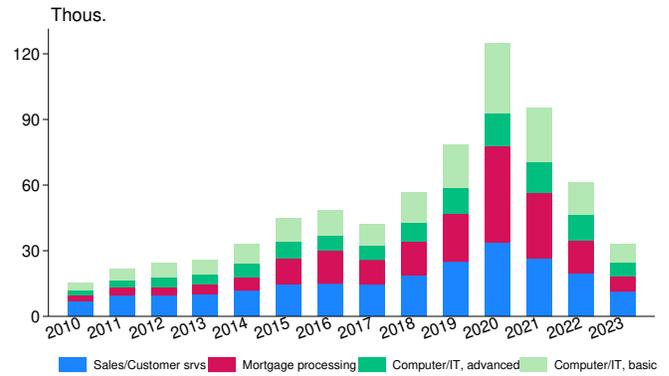
(b) Number of jobs: Banks



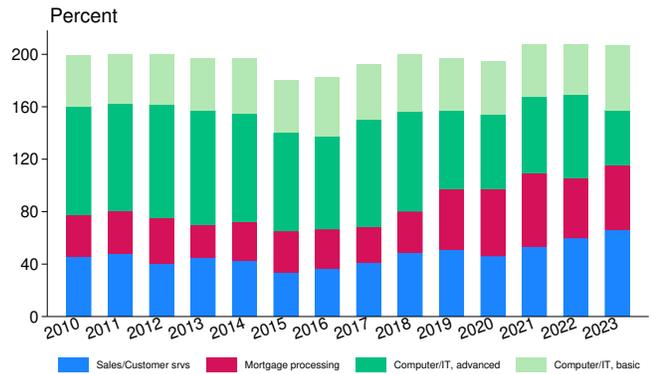
(c) Share of jobs: Nonbanks ex. Top 3 FinTech



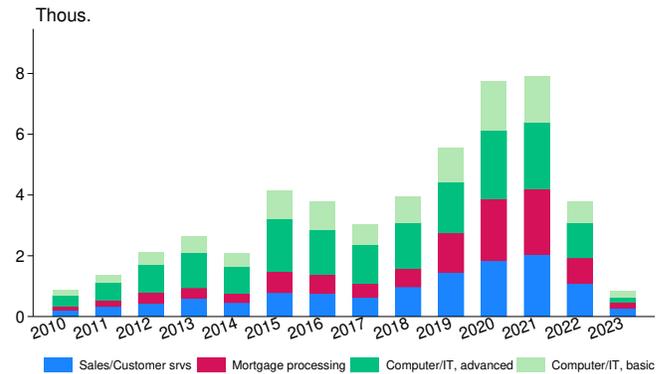
(d) Number of jobs: Nonbank ex. Top 3 FinTech



(e) Share of jobs: Top 3 FinTech



(f) Number of jobs: Top 3 FinTech



Sources: Merged Lightcast-HMDA job posting-level data. Notes: See Section 2.3 and Appendix A for the classification of skill categories. In the left column, percentages do not sum to 100, because one job posting may require multiple skills.

## C Firm-Level Evidence: Additional Results and Robustness

Table C1: Technology investment responses to demand shock: Heterogeneous effects

Dependent variable:	Technology investment measured by			
	I(IT jobs > 0)	I(IT skills, adv > 0)	I(IT jobs > 0)	I(IT skills, adv > 0)
Demand Shock	-0.040 (0.037)	-0.042 (0.037)	-0.054 (0.037)	-0.051 (0.037)
Demand Shock × Nonbank	-0.009 (0.034)	0.016 (0.042)	0.163*** (0.026)	0.119*** (0.027)
Demand Shock × Nonbank × Large origination <sub>t-1</sub>	0.162*** (0.044)	0.109** (0.051)		
Demand Shock × Nonbank × Large assets <sub>t-1</sub>			-0.115* (0.063)	-0.003 (0.058)
Controls	x	x	x	x
Lender-State FE	x	x	x	x
Year FE	x	x	x	x
# Obs.	19,972	19,972	18,849	18,849

Notes: “Large origination” refers to lenders whose previous-year origination is in the top quartile of the origination distribution. “Large assets” refers to lenders whose previous-year assets is in the top quartile of the asset distribution. See Table 2 for the definition of the outcome variable. Control variables include those in Table 3 and origination-share-weighted controls for the county-level FHA/VA share and the jumbo loan share, as well as the FinTech growth exposure. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the lender level.

Table C2: Effects of macroeconomic shocks on broader technology investment

Dependent variable:	<u>Log annual expenses reported for</u>			
	Software & Hardware	Equipment	Outsourcing	Personnel
FinTech Exposure	-0.185*** (0.055)	-0.124** (0.049)	-0.011 (0.100)	-0.111** (0.044)
Controls	x	x	x	x
Lender-State FE	x	x	x	x
Year FE	x	x	x	x
# Obs.	1,723	1,918	743	1,970
Demand Shock	-0.019 (0.454)	0.677* (0.392)	0.951 (0.951)	0.858** (0.340)
Controls	x	x	x	x
Lender-State FE	x	x	x	x
Year FE	x	x	x	x
# Obs.	1,801	2,011	782	2,067

Notes: Expenses are from Conference of State Bank Supervisors NMLS Call Report data. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the lender level.

Table C3: Robustness: Alternative bank samples

Dependent variable:	OLS estimates		2SLS estimates	
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$
<b><u>A. Similar assets to nonbanks</u></b>				
FinTech Exposure $_{t-1}$	0.013*** (0.004)	0.016*** (0.004)	0.035*** (0.012)	0.030** (0.012)
FinTech Exposure $_{t-1} \times$ Nonbank	-0.039*** (0.010)	-0.040*** (0.012)	-0.020 (0.018)	-0.059*** (0.017)
Demand Shock	-0.040 (0.041)	-0.078* (0.042)	0.946** (0.383)	0.812** (0.403)
Demand Shock $\times$ Nonbank	0.111*** (0.022)	0.106*** (0.023)	0.070* (0.041)	0.001 (0.042)
<b><u>B. Similar origination volume to nonbanks</u></b>				
FinTech Exposure $_{t-1}$	0.018*** (0.006)	0.019*** (0.005)	0.013 (0.013)	0.005 (0.012)
FinTech Exposure $_{t-1} \times$ Nonbank	-0.049*** (0.010)	-0.040*** (0.012)	-0.011 (0.018)	-0.038** (0.017)
Demand Shock	-0.037 (0.048)	-0.001 (0.048)	0.289 (0.427)	0.094 (0.419)
Demand Shock $\times$ Nonbank	0.131*** (0.023)	0.117*** (0.023)	0.105** (0.042)	0.042 (0.041)
<b><u>C. Higher exposure to mortgage lending</u></b>				
FinTech Exposure $_{t-1}$	0.015*** (0.004)	0.017*** (0.004)	0.015 (0.011)	0.020* (0.010)
FinTech Exposure $_{t-1} \times$ Nonbank	-0.045*** (0.010)	-0.040*** (0.011)	-0.010 (0.017)	-0.049*** (0.016)
Demand Shock	-0.049 (0.040)	-0.059 (0.040)	0.670* (0.374)	0.156 (0.377)
Demand Shock $\times$ Nonbank	0.126*** (0.022)	0.108*** (0.022)	0.079** (0.040)	0.014 (0.040)

Notes: Estimates obtained using the same specifications and instruments as in Table 6 for Fintech growth shocks and as in Tables 8 and 9 for demand shocks. Panel A excludes banks with assets that are higher than the 95th percentile of the nonbank asset distribution. Panel B excludes banks with origination counts that are lower than the 10th percentile of the nonbank origination distribution. Panel C excludes banks whose origination-to-asset ratios are below the 25th percentile of the distribution. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively.

Table C4: Robustness: Alternative lender samples and specifications

Dependent variable:	OLS estimates		2SLS estimates	
	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$	$\mathbb{I}(\text{IT jobs} > 0)$	$\mathbb{I}(\text{IT skills, adv} > 0)$
<b>A. Exactly merged HMDA-Lightcast sample</b>				
FinTech Exposure <sub>t-1</sub>	0.011*** (0.004)	0.016*** (0.004)	0.016 (0.010)	0.021** (0.010)
FinTech Exposure <sub>t-1</sub> × Nonbank	-0.040*** (0.010)	-0.038*** (0.011)	-0.009 (0.018)	-0.049*** (0.016)
Demand Shock	-0.021 (0.039)	-0.039 (0.039)	0.329 (0.303)	0.171 (0.313)
Demand Shock × Nonbank	0.137*** (0.022)	0.113*** (0.023)	0.106*** (0.040)	0.027 (0.040)
<b>B. Excluding FinTech startup investors</b>				
FinTech Exposure <sub>t-1</sub>	0.013*** (0.004)	0.014*** (0.004)	0.019* (0.010)	0.021** (0.010)
FinTech Exposure <sub>t-1</sub> × Nonbank	-0.042*** (0.010)	-0.040*** (0.011)	-0.011 (0.017)	-0.050*** (0.016)
Demand Shock	-0.042 (0.037)	-0.047 (0.036)	0.674** (0.328)	0.496 (0.331)
Demand Shock × Nonbank	0.122*** (0.021)	0.110*** (0.022)	0.082** (0.039)	0.014 (0.039)
<b>C. Joint estimation</b>				
FinTech Exposure <sub>t-1</sub>	0.010*** (0.004)	0.012*** (0.004)	-0.007 (0.016)	-0.000 (0.016)
FinTech Exposure <sub>t-1</sub> × Nonbank	-0.036*** (0.010)	-0.032*** (0.011)	-0.032* (0.017)	-0.064*** (0.017)
Demand Shock	-0.017 (0.037)	-0.020 (0.036)	0.534** (0.264)	0.442* (0.266)
Demand Shock × Nonbank	0.118*** (0.022)	0.102*** (0.023)	0.147*** (0.040)	0.121*** (0.041)

Notes: Estimates obtained using the same specifications and instruments as in Table 6 for Fintech growth shocks and as in Tables 8 and 9 for demand shocks. Panel A restricts to lenders that can be exactly merged in HMDA and Lightcast data based on standardized company names. Panel B excludes banks that make equity investment in FinTech startups as identified by Puri et al. (2024). In Panel C, the effects of two types of shocks are estimated jointly in one regression. \*, \*\* and \*\*\* denote significance at the 10%, 5% and 1% level, respectively.

## D Model Appendix

### D.1 Investment Decision Rule

Let  $\pi(a_{j,t}, S_{j,t}) = \tilde{\sigma} \theta_t \xi_{j,t}^\sigma P_t^{\sigma-1} (a_{j,t}/w_t)^{\sigma-1}$  be the flow profit function given the state variables, where  $\tilde{\sigma} \equiv (\sigma - 1)^{\sigma-1} / \sigma^\sigma$ . It can be shown that

$$\begin{aligned} V^{Inv}(a_{j,t}, S_{j,t}) &= \lambda_{j,t}^{\sigma-1} \pi(a_{j,t}, S_{j,t}) - F + \beta \mathbb{E}_t V(\lambda_{j,t} a_{j,t}, S_{j,t+1}), \\ V^{NInv}(a_{j,t}, S_{j,t}) &= \pi(a_{j,t}, S_{j,t}) + \beta \mathbb{E}_t V(a_{j,t}, S_{j,t+1}). \end{aligned}$$

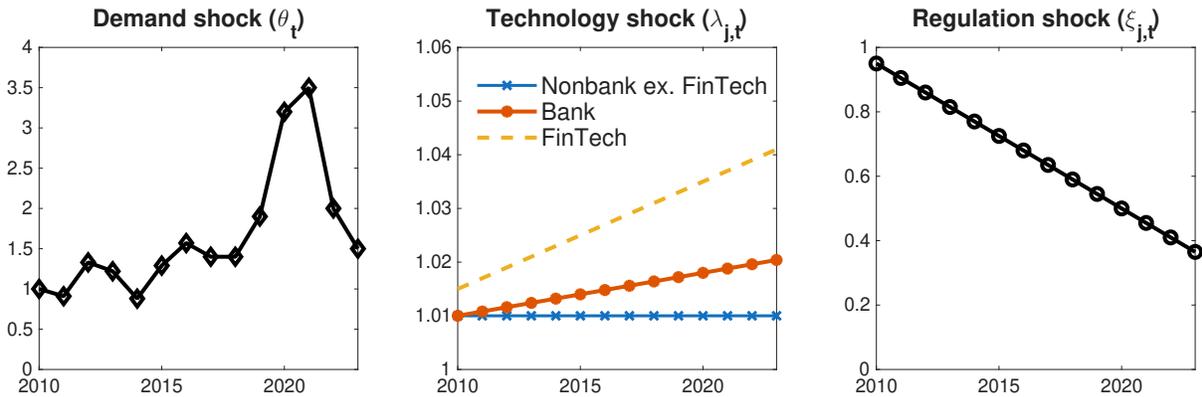
The lender invests, if  $V^{Inv}(a_{j,t}, S_{j,t}) > V^{NInv}(a_{j,t}, S_{j,t})$ , which is equivalent to

$$\Omega(a_{j,t}, S_{j,t}) \equiv (\lambda_{j,t}^{\sigma-1} - 1) \pi(a_{j,t}, S_{j,t}) + \beta [\mathbb{E}_t V(\lambda_{j,t} a_{j,t}, S_{j,t+1}) - \mathbb{E}_t V(a_{j,t}, S_{j,t+1})] > F.$$

Since  $\lambda_{j,t} > 1$  and  $\sigma > 1$ , and  $\pi(a_{j,t}, S_{j,t})$  is increasing in  $a_{j,t}$ ,  $\Omega(a_{j,t}, S_{j,t}) \rightarrow 0$  as  $a_{j,t} \rightarrow 0$ . Moreover, it is straightforward to show that  $\Omega(a_{j,t}, S_{j,t})$  is strictly increasing in  $a_{j,t}$ . Therefore, there exists a cutoff,  $a^*(S_{j,t}; \Phi)$ , where  $\Phi \equiv (F, \beta, \sigma)$  is the set of model parameters, such that the lender invests, if  $a_{j,t} \geq a^*(S_{j,t}; \Phi)$ .

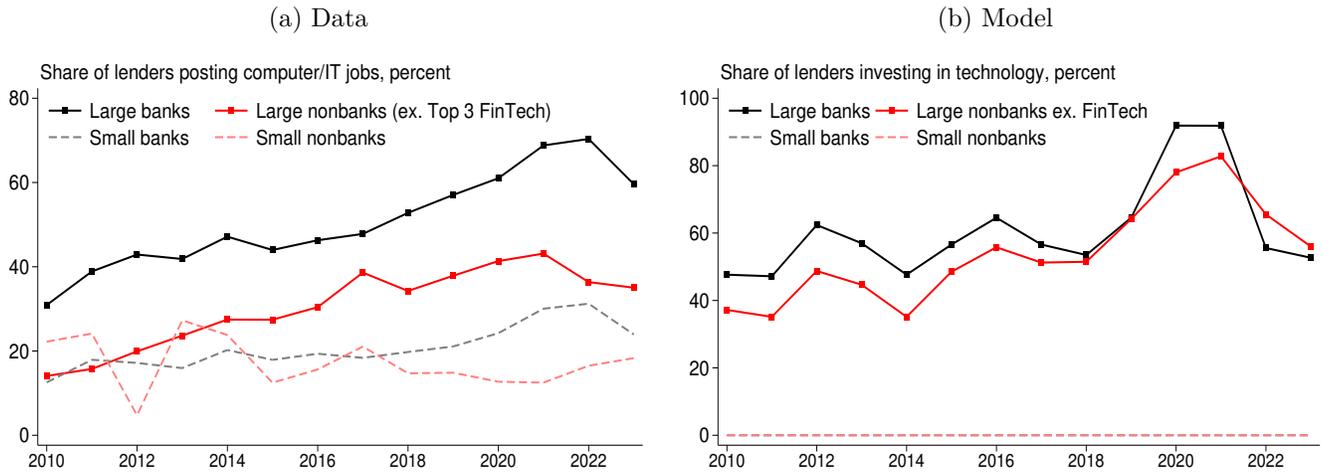
### D.2 Additional Model Figures

Figure D1: Structural shocks to the U.S. mortgage market



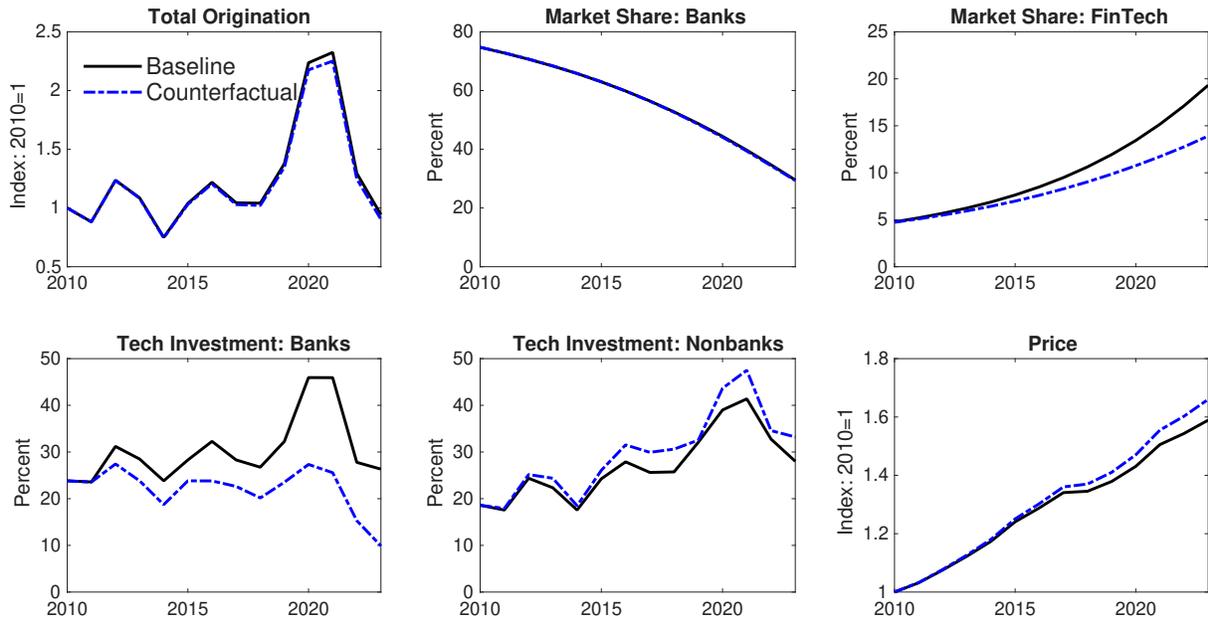
Notes: The figure depicts structural shocks recovered from the model for the 2010-2023 period. See Section 5.2 for methodology.

Figure D2: Investment heterogeneity: model vs data



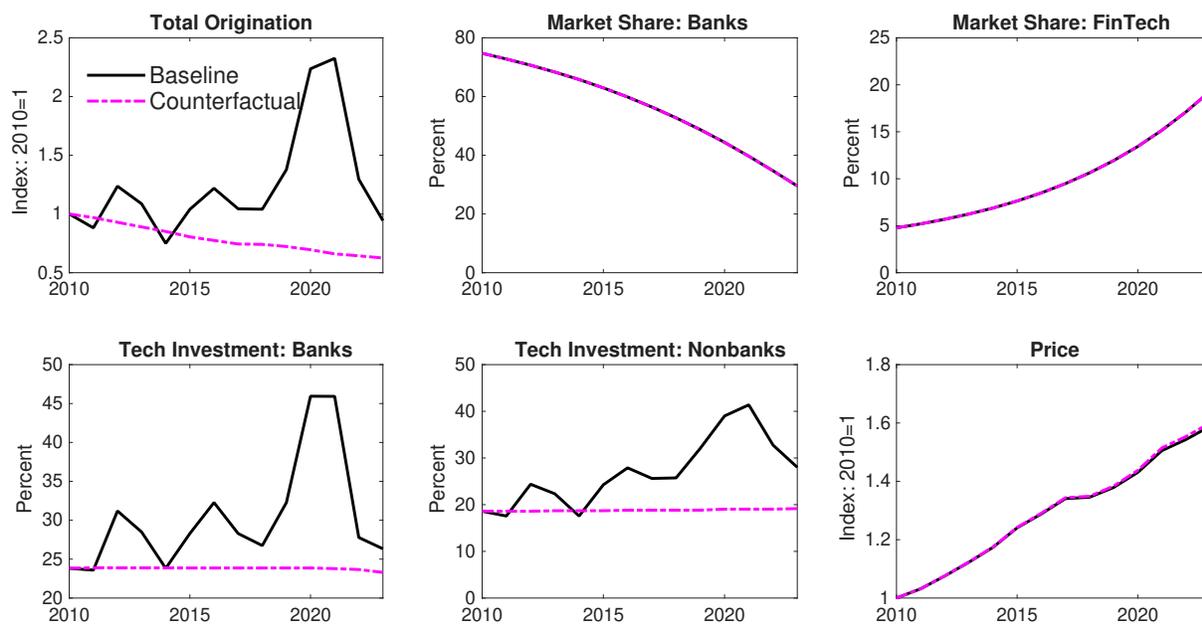
Notes: See notes in Figure 6 panel (a) for definitions of technology investment and lender size. In the model, large lenders are defined as those whose origination is above the median within lender type.

Figure D3: The role of FinTech shocks



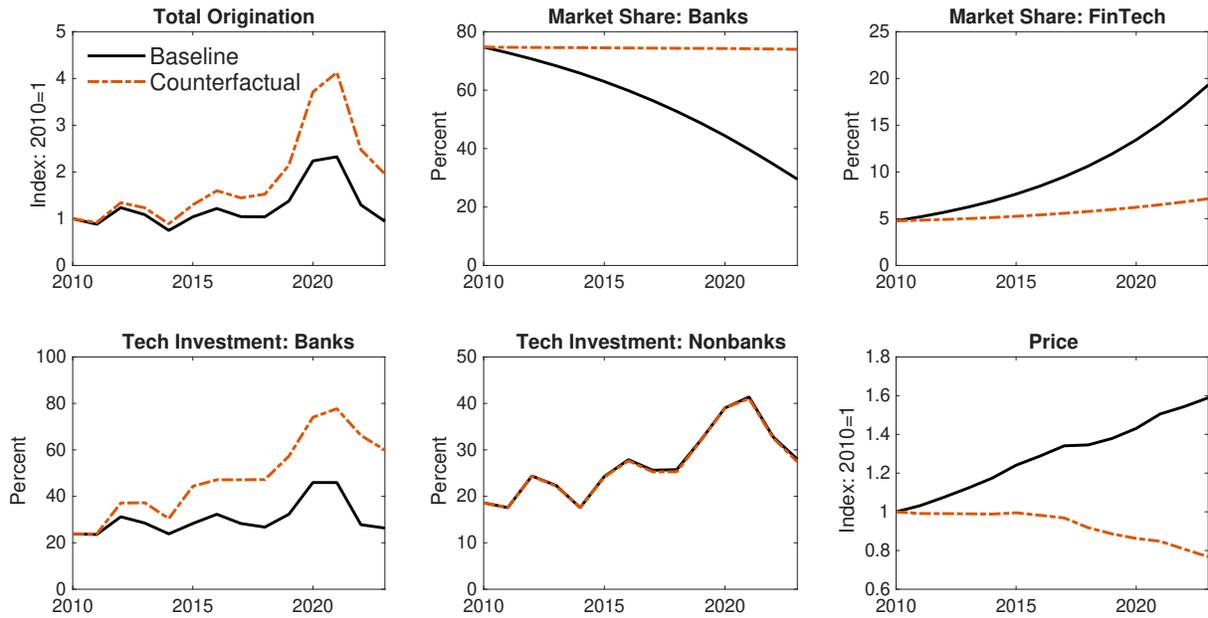
Notes: This figure depicts the evolution of key model variables under the baseline calibration and the counterfactual that weakens the technological advantage of FinTech lenders.

Figure D4: The role of demand shocks



Notes: This figure depicts the evolution of key model variables under the baseline calibration and the counterfactual that the demand condition stays at the 2010 level.

Figure D5: The role of regulation shocks



Notes: This figure depicts the evolution of key model variables under the baseline calibration and the counterfactual that regulation is held at the 2010 level.