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FinTech Lending, Social Networks, and the Transmission of Monetary Policy

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FinTech Lending, Social Networks, and the Transmission of Monetary Policy*

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Abstract

One of the main channels through which monetary policy stimulus affects the real economy is mortgage borrowing. This channel, however, is weakened by frictions in the mortgage market. The rapid growth of financial technology-based (FinTech) lending tends to ease these frictions, given the higher quality services provided under this new lending model. This paper establishes that the role of FinTech lending in the monetary policy transmission is further amplified by consumers' social networks. I provide empirical evidence for this network effect using county-level data and novel identification strategies. A 1 pp increase in the FinTech market share in a county's socially connected markets raises the county's FinTech market share by 0.23-0.26 pps. Moreover, I find that in counties where FinTech market penetration is high, the pass-through of market interest rates to borrowers is more complete. To quantify the role of FinTech lending and its network propagation in the transmission of monetary policy shocks, I build a multi-region heterogeneous-agent model with social learning that embodies key features of FinTech lending. The model shows that the responses of consumption and refinancing to a monetary stimulus are 13% higher in the presence of FinTech lending. Almost half of this improvement is accounted for by FinTech propagation through social networks.

Keywords: FinTech, social networks, mortgage, monetary policy, regional transmission

JEL Codes: E21, E44, E52, G21, G23

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1 Introduction

One of the most important channels through which monetary policy affects the real economy is mortgage borrowing. Lower mortgage rates resulting from expansionary monetary policies reduce long-term borrowing costs, generate liquidity for refinancing borrowers, and stimulate household spending. This channel, however, is weakened by frictions in the mortgage market. One example is the failure of consumers to optimally refinance their mortgages, due to the complicated, infrequent nature of the refinancing process (Keys et al. (2016)). Another type of friction is the capacity constraints faced by lenders that slow their responses to surging demand during refinancing booms (Fuster et al. (2021)).

The rapid growth of financial technology-based ("FinTech") lending after the Great Recession tends to ease these frictions in the U.S. mortgage market. Unlike traditional brick-and-mortar banks, FinTech lenders automate the mortgage origination process, allowing borrowers to complete their applications in a streamlined online process without human interactions with loan officers.[1] Because of automation and the use of labor-saving technology in the underwriting process, these lenders are more resilient to demand shocks.[2] These features of FinTech lending are also expected to enhance the transmission of monetary policy through the mortgage borrowing channel, which is important from a policy maker's point of view. To date, however, macroeconomic models that study the distributional effects of monetary policy shocks have not incorporated FinTech lending.

While the existing empirical literature has focused on the growth of FinTech lenders and the features of their products, it has not investigated the propagation of FinTech lending through consumers' social networks. Social interactions play a key role in consumers' acquisition of information and financial decision-making, so it is conceivable that FinTech adoption is affected by interactions with peers.[3] To the extent that this peer effect is strong, it will amplify the ability of FinTech lending to enhance the monetary transmission. A rigorous

[1]FinTech lenders are classified as in Fuster et al. (2019) and Buchak et al. (2018). See Appendix A for a detailed description of the lender classification. According to this classification, the share of FinTech mortgage originations rose from 2% in 2008 to 11% in 2017 (Appendix Figure A1).

[2]Previous studies have found that faster loan processing does not come at the cost of higher default risks. See Fuster et al. (2019) and Buchak et al. (2018).

[3]See Kuchler and Stroebel (2021) for a comprehensive review of the literature on the role of social interactions in the decision-making of households, investors and financial institutions.

analysis of the role of FinTech lending in the transmission of monetary policy, therefore, has to take into account both FinTech product features and FinTech propagation through consumers' social networks. In this paper, I provide empirical evidence for the spillover of FinTech mortgage lending across social networks using a variety of identification strategies. To quantify the effects of monetary policy shocks on household borrowing and consumption in the presence of FinTech lending, I develop a multi-region heterogeneous-agent model with social learning that incorporates key empirical features of FinTech lending. The model allows for counterfactual analyses to assess separately the role of FinTech product features, the social network effect, and mortgage market frictions in the monetary transmission.

I present two sets of empirical evidence using county-level data that motivate this theoretical model. The first set of evidence quantifies the spillover of FinTech lending across social networks. Specifically, I estimate the response of a county's FinTech market share in mortgage originations to changes in the FinTech market share in the county's socially connected markets. Two measures of social connectedness are considered. One is based on geographical distance, as in gravity models in the trade literature. The other is based on novel social network data developed by Bailey et al. (2018b) that contain the county-pair-level connectedness index constructed from the networks of U.S. Facebook users.

The identification of this spillover effect is challenging for two reasons. First, county markets may be subject to common unobserved shocks that favor FinTech lending. Second, local shocks or characteristics favoring FinTech lending may be correlated across markets. In both cases, FinTech lending increases simultaneously in multiple markets, even in the absence of causal spillovers from one market to another, creating an upward bias in the estimates.[4] To address these concerns, I employ three alternative empirical approaches, which together provide compelling evidence of economically large spillover effects of FinTech lending across social networks.

The first approach takes advantage of the panel nature of the county-level data to avoid issues of simultaneity. As outlined in Manski (1993) and Brock and Durlauf (2001), I exploit variation in lagged changes in the FinTech market share in a county's socially connected

[4]The identification of causal spillovers in the peer-effect literature is discussed in Manski (1993), who distinguishes between the *correlated effect*, the *contextual effect* and the *endogenous effect*. The *endogenous effect* is the most important and policy relevant. It is this effect that my analysis seeks to identify.

markets. To further overcome identification concerns arising from unobserved correlated shocks, all my specifications include county fixed effects, region-specific time trends, and a number of time-varying controls for the economic conditions in the county and its connected markets. This approach reveals a sizable spillover effect. On average, a county's FinTech market share grows by 0.23-0.26 percentage points (pps), when the weighted FinTech market share in its connected markets increases by 1 percentage point (pp). A breakdown of lending by loan purpose suggests that the spillover effect is larger for FinTech refinancing than for FinTech home purchases, consistent with the fact that refinancing is easier to process automatically for FinTech lenders. Moreover, I find that counties with higher social and economic mobility (such as counties located in metropolitan areas, counties having higher shares of college graduates and young people, and counties experiencing larger migration flows in the previous year) are more responsive to FinTech growth in other markets.

While the panel-data approach exploits the dynamic structure of network spillovers to achieve identification, it may not account for all unobserved shocks that trigger FinTech growth in local markets without market-to-market spillovers. My second approach, therefore, relies on instruments to isolate exogenous variation in FinTech growth in counties' connected markets. The choice of the instruments builds on Buchak et al. (2018), who showed that a main driver of faster growth in non-bank (including FinTech) lending after the Great Recession was increasingly stringent banking regulations that effectively reduced banks' presence in mortgage lending. The exposure of a county market to these banking regulations, however, depends on the pre-crisis capital structure of the banks operating in this county, which varies substantially and is plausibly unrelated to post-crisis loan demand. This suggests that the exposure of a county's socially connected markets to rising regulatory burdens can be used to construct instruments for FinTech growth in these markets. This instrumental-variable (IV) strategy corroborates the evidence of a strong spillover effect of FinTech lending.

My third empirical approach relies on a structural-break analysis, which identifies the point at which the growth of a county's FinTech market share starts to accelerate. I then estimate the likelihood that a county experiences such a break around the time when a break happens in its socially connected markets. This approach helps quantify dynamic spillovers on the extensive margin. My estimates rule out the existence of a pre-trend, supporting the identification. More importantly, I find a sharp increase in the likelihood that a county experiences a break in the year after its connected markets saw a break. This result complements my earlier findings and suggests a fast dissemination of information through social networks.

Having established the propagation of FinTech lending through social networks, I provide a second set of empirical evidence for the role of FinTech penetration in the pass-through of market interest rates. I show that, in counties where FinTech market penetration is high, the gap between the average outstanding mortgage rate and the current market rate is narrower, suggesting a more complete pass-through of the market rate to the average borrower in these counties. Furthermore, this effect is almost entirely driven by a higher fraction of existing mortgages being refinanced at the current market rate, rather than FinTech lenders offering below-market rates to borrowers. These results also suggest that the difference in FinTech penetration contributes to regional heterogeneity in the pass-through of interest rates, apart from other factors noted in the literature (see Beraja et al. (2018)).

To quantify the effects of FinTech lending and its propagation through social networks on the transmission of monetary policy shocks to households, I develop a structural model that embeds three key empirical features of FinTech lending. First, FinTech lenders offer higher quality products that make the refinancing process more convenient for consumers (Buchak et al. (2018)). Second, FinTech lenders respond more elastically to demand shocks than traditional lenders (Fuster et al. (2019); Fuster et al. (2021)). Third, social interactions help spread information about FinTech lending, making refinancing even more accessible from the consumer's point of view (as established in this paper).[5]

The core of the model is a heterogeneous-agent, multi-region model designed to study the refinancing channel of monetary policy. The model is characterized by rich household heterogeneity arising from idiosyncratic income shocks, balance sheet conditions, and

[5]These features also reflect anecdotal evidence from customer reviews and industry ratings. The FinTech leader Quicken Loans (Rocket Mortgage), for example, ranked highest in the country between 2010 and 2020 for customer satisfaction for primary mortgage origination, according to J.D. Power, and has an A+ rating from the Better Business Bureau. 96% of clients say they would recommend Quicken Loans per closed customer surveys (see e.g., http://www.thetruthaboutmortgage.com/quicken-loans-review/).

household-specific mortgage rates on long-term debt contracts, all of which matter for refinancing and consumption decisions. While refinancing after a monetary stimulus is beneficial for most households, two types of frictions in the model prevent households from taking this action. One is the non-pecuniary cost associated with refinancing (e.g., time and effort spent on searching for offers, visiting lender's office, talking to the agent and completing the paperwork). The other is capacity constraints faced by traditional lenders (e.g., training costs, hiring difficulties and staffing issues). FinTech lending reduces these frictions and increases the refinancing response to a monetary policy stimulus.

Despite its advantages, FinTech lending is not adopted by everyone. This is because, in the model, households are not fully informed. They learn about FinTech lending through non-interactive sources (e.g., advertisements or search engines) and interactive sources (e.g., social networks) with some probabilities, which in turn determine the market share of FinTech lenders. My model implies that, when FinTech market penetration is calibrated to data in 2017, a 1 pp permanent decline in the mortgage rate raises the refinancing likelihood by 11.3 pps. When FinTech lending is shut down, the refinancing response to the policy shock is 10 pps, suggesting that the presence of FinTech lending increases the refinancing response to a monetary stimulus by 13%. In addition, when only the network spillover is shut down, the refinancing response is 10.7 pps, implying that almost half of the improvement in the monetary policy effect on refinancing is due to FinTech propagation through social networks. Quantitatively similar results are obtained for the improved consumption response.

Finally, the multi-region framework of the model allows for a quantitative analysis of the interaction between FinTech lending and regional economic conditions. The work of Beraja et al. (2018) shows that, absent FinTech lending, the refinancing channel of monetary policy provides (unintentionally) less stimulus to economically depressed regions. An interesting question is whether FinTech lending can alter this unintended consequence. My analysis suggests that this is unlikely to be the case, because FinTech lending cannot help borrowers who do not have enough home equity to be qualified for refinancing, which often happens in economically depressed regions. However, the presence of FinTech lending does effectively increase the refinancing responses in these regions, albeit to a lesser extent than in economically booming regions. This is important from the policy point of view, because, even in economically depressed regions, many households do not refinance, not due to inadequate home equity, but due to the high non-pecuniary costs associated with refinancing. This is where FinTech lending can help.

Relation to the literature. This paper contributes to several strands of the literature. First, it contributes to the macroeconomic literature on the transmission of monetary policy shocks to households, which stresses mortgage borrowing as a main channel (e.g., Beraja et al. (2018); Wong (2019); Greenwald (2018); Garriga et al. (2017); Cloyne et al. (2020); Berger et al. (2021)). My work adds to this literature by incorporating FinTech lending and different types of mortgage market frictions as documented in the recent empirical finance literature (Andersen et al. (2020); Keys et al. (2016); Agarwal et al. (2015); Campbell (2006); Fuster et al. (2021)) into structural modeling.

Second, this paper relates to the finance literature on technological innovations in the mortgage market and their policy implications (Buchak et al. (2018); Fuster et al. (2019); Bartlett et al. (2022); Jagtiani et al. (2020)). This line of research has focused on the causes of FinTech growth, the distinct features of FinTech products, and how this of type of lending may have reduced frictions in the U.S. mortgage market. I contribute to this literature by presenting new evidence for the FinTech propagation through consumers' social networks and quantifying the role of FinTech lending and its propagation in the monetary transmission using a structural model.

Third, my paper connects to the microeconomic literature on the role of social interactions in household decision-making. This literature has provided extensive evidence of the network effect on home purchases (Bailey et al. (2018a)), leverage choices (Bailey et al. (2019); Georgarakos et al. (2014)), mortgage refinancing (Maturana and Nickerson (2019); McCartney and Shah (2021)), product adoption (Bailey et al. (2021)), and consumption (Agarwal et al. (2016); De Giorgi et al. (2020); Moretti (2011)), but the network effect on FinTech mortgage adoption has not been examined. Taking a macroeconomic perspective, I study the extent to which social networks drive consumers to use FinTech lending, and how this network effect amplifies the transmission of monetary policy.

The remainder of the paper is organized as follows. Section 2 provides empirical evidence for the spillover of FinTech lending across socially connected markets. Section 3 empirically assesses the effect of FinTech penetration on interest rate pass-through. Sections 4 and 5 describe the structural model and its calibration. Section 6 quantifies the role of FinTech lending and its spillovers in the monetary transmission using the model and examines how this role interacts with regional economic conditions. Section 7 concludes. To conserve space, a detailed description of the data used in this paper is presented in Appendix B.

2 Evidence of FinTech Spillovers across Social Networks

This section provides new empirical evidence of FinTech spillovers across socially connected county markets. To overcome identification challenges, I employ three alternative strategies: a panel-data approach, an IV approach, and a structural-break analysis. I conclude this section by presenting evidence that the estimated spillover effects reflect demand-side spillovers (i.e., consumer-level social interactions), rather than supply-side spillovers (i.e., FinTech lenders' business strategies).

2.1 The Panel-Data Approach

2.1.1 Measuring Social Connectivity

I start with estimating the response of a county's FinTech market share to changes in the FinTech market share in the county's socially connected markets using quarterly panel data from 2007 to 2017.[6] Social connectedness between two counties is measured in two ways. One is based on geographical distance. The other is based on the novel county-pair-level social connectedness index (SCI) developed by Bailey et al. (2018b) from social networks of U.S. Facebook users.[7] These measures are used to construct the weights for the changes in the FinTech market share in a county's connected markets, such that the largest weights are assigned to markets that are most connected to the county.

Using the distance-based measure of connectedness, the change in the FinTech market

[6] Market shares are computed using mortgage origination volumes. Quarterly county-level mortgage origination data are constructed from the loan-level HMDA data (the confidential version accessed through the Federal Reserve System resources).

[7] The SCI data used in this paper were accessed in October 2020. Social network patterns captured in the SCI data are quite stable over time (Kuchler and Stroebel (2021)).

share in county c's geographically connected areas (GCAs) is constructed as

$$\Delta FinTech_{c,t}^{GCA} \equiv \sum_{j \in J_c^{GCA}} \omega_{j,c}^{GCA} \Delta FinTech_{j,t}, \tag{1}$$

where the weight, $\omega_{j,c}^{GCA} = \frac{1}{1+d_{j,c}}$, is inversely related to the distance ($d_{j,c}$) between counties j and c. J_c^{GCA} denotes the set of GCAs of county c. $\Delta FinTech_{j,t}$ is the four-quarter change in the FinTech market share in county j and quarter t.

Alternatively, using the SCI-based measure of connectedness, the change in the FinTech market share in county c's social connected areas (SCAs) is constructed as

$$\Delta FinTech_{c,t}^{SCA} \equiv \sum_{j \in J_c^{SCA}} \omega_{j,c}^{SCA} \Delta FinTech_{j,t}, \tag{2}$$

where the weight, $\omega_{j,c}^{SCA} = \frac{s_{j,c}}{\sum_{k \in J_c^{SCA}} s_{k,c}}$, increases in the SCI ($s_{j,c}$) between counties j and c. J_c^{SCA} denotes the set of SCAs of county c.

2.1.2 Estimating Spillover Effects

The identification of the causal spillover effect is hindered by the existence of common shocks and correlated local shocks that affect FinTech lending simultaneously in connected markets without market-to-market spillovers. The use of the panel data addresses this issue by exploiting the dynamic structure of network spillovers, as outlined in Manski (1993) and Brock and Durlauf (2001). Specifically, I estimate the effect of lagged changes in the FinTech market share in a county's connected markets on the county's FinTech market share,

$$\Delta FinTech_{c,t} = \gamma_{d,t} + \gamma_c + \beta_1 \Delta FinTech_{c,t-1}^{M} + \beta_2 \mathbf{x}_{c,t} + \beta_3 \bar{\mathbf{x}}_t^{M} + \varepsilon_{c,t}. \tag{3}$$

where $M \in \{GCA, SCA\}$. $\Delta FinTech_{c,t-1}^{M}$ is the key explanatory variable described in equations (1) and (2). β_1 is the parameter of interest capturing the FinTech spillover effect.

To remove possible confounding factors, the regression includes census division-by-quarter fixed effects, $\gamma_{d,t}$, county fixed effects, γ_c, and a set of time-varying controls for the demographic and economic conditions of the county and its connected areas, $\mathbf{x}_{c,t}$ and $\bar{\mathbf{x}}_t^M$.[8] I assume a linear-in-mean form of the control variables for the county's connected areas, as in Brock and Durlauf (2001). This means that $\bar{\mathbf{x}}_t^M$ includes the same set of variables as in $\mathbf{x}_{c,t}$, but each of these variables is a weighted average across counties in M. The standard errors are clustered at the county level.[9]

For the main analysis, I include counties within 200 miles of county c in J_c^{GCA}, and counties ranked as top 200 socially connected counties to county c, according to the SCI, in J_c^{SCA}. Increasing these thresholds gives very similar estimates of the spillover effect, as shown in Appendix Table D1.[10]

2.1.3 Results

Panel I of Table 1 shows the estimated spillover effect using the distance-based measure of connectedness. Controlling for county fixed effects only, column (1) shows that a 1 pp increase in GCAs' FinTech market share raises a county's FinTech market share by 0.3 pps. When including county-level controls, the estimate is unaffected (column 2). When the census division-by-time fixed effect is included, however, the spillover effect drops to 0.25 pps and R-squared increases substantially (column 3). This suggests that region-specific time trends can explain much of variation in FinTech lending growth. Failing to account for these trends would overestimate the spillover effect.

Columns (4) and (5) include additional control variables for counties and their GCAs, showing a similar effect. The preferred specification in column (5) shows that a 1 pp increase in GCAs' FinTech market share raises a county's FinTech market share by 0.26 pps. This effect is sizable. It implies that, if the growth of GCAs' FinTech market share rises from the 10th to the 90th percentile of the distribution, the county's FinTech market share will increase by 22% relative to the historical mean (6%).

[8]The control variables include the percent changes in the house price, employment and population, and the shares of young population, minority population and subprime borrowers.

[9]Since county-level lending activity features substantial heterogeneity, the regression is estimated by weighted least squares using counties' historical average volume of mortgage originations as the weight. Using county population as the weight gives similar results.

[10]My results are robust to alternative GCA or SCA thresholds because, first, changes in the FinTech market share in a county's geographically or socially distant markets are assigned very small weights. Second, even controlling for the diminishing weights, the spillover from these distant markets is statistically and economically insignificant (see Section 2.1.4).

Panel II of Table 1 shows the spillover effect using the SCI-based measure of connectedness. The results are similar to Panel I. The preferred specification in column (5) suggests that a 1 pp increase in SCAs' FinTech market share raises a county's FinTech market share by 0.23 pps. The similarity of the estimates in panels I and II is not surprising, given that the two measures of social connectedness are highly correlated (with a correlation of 0.89 between $\Delta FinTech_{c,t}^{GCA}$ and $\Delta FinTech_{c,t}^{SCA}$).

The SCI-based connectedness measure has the advantage of being able to isolate variation in FinTech lending in a county's socially connected, but geographically distant markets.[11] Exploiting this variation helps address the concern that geographically close markets are subject to unobserved common shocks that are hard to control for. One could design a strategy that instruments $\Delta FinTech_{c,t-1}^{SCA}$ with changes in the FinTech market share in county c's geographically distant but socially connected markets.[12] This approach gives almost identical estimates to the baseline SCI-based estimate of 0.23 (see Appendix Table D2).

So far, the spillover effect is estimated for all types of FinTech lending, i.e. refinancing and home purchases. An interesting question is which type of lending is more responsive to FinTech growth in other markets. Table 2 shows the estimated spillover effect by loan purpose (columns 1 and 2). It confirms that FinTech refinancing is more responsive, consistent with the fact that refinancing is easier to process automatically for FinTech lenders. A 1 pp increase in GCAs' FinTech market share raises a county's FinTech refinancing share by 0.25 pps and its FinTech home-purchase share by 0.18 pps. Similar estimates are obtained when using the SCI-based measure of connectedness.

In addition, I provide evidence that the rise in the FinTech market share resulting from the spillover is associated with the growing volume of FinTech lending. To see this, column 3 of Table 2 shows the effect on the four-quarter change in FinTech lending volume normalized by previous-year total originations. It increases by 0.33 pps (0.28 pps) for a 1 pp increase in GCAs' (SCAs') FinTech market share. Given the average FinTech market share being 6%,

[11] An example of the differences between GCAs and SCAs is provided in Appendix Figure D1 for Cook county, IL, where Chicago is located.

[12] This strategy was originally proposed by Bailey et al. (2018a) to isolate exogenous changes in the house prices experienced by a person's friends and to study how these changes affect the person's housing investments.

these estimates imply a 4.7%-5.5% increase in the FinTech lending volume. Consistent with the earlier finding, the effect on FinTech refinancing volume is larger than that on FinTech home-purchase volume (columns 4 and 5).

2.1.4 Heterogeneity in FinTech Spillovers

While the estimates in Section 2.1.3 inform us about the average spillover effect, they mask substantial heterogeneity across counties. In this subsection, I examine how the spillover effect varies with the degree of connectedness and which counties are more responsive to FinTech growth in other areas.

First, I test whether a gravity relationship holds for the spillover effect, that is, whether a county's most connected markets exert the greatest impact on the county's FinTech lending. For this purpose, I reconstruct $\Delta FinTech^{M}_{c,t-1}$ such that it includes only a subset of connected markets in a given category (e.g., GCAs within 50 miles). Table 3 displays the pattern: Markets that are most connected to a county have the largest impact on the county's FinTech lending, regardless of the measure of connectedness. The effect monotonically increases with connectedness. Beyond certain thresholds (150 miles away or outside of top 150 SCAs), the impact is statistically and economically insignificant. In Appendix Figure D2, I also estimate the spillover effect separately coming from each of the top 10 GCAs and the top 10 SCAs, which provides additional support to the gravity relationship.

Given FinTech growth in other markets, which counties are more responsive to this change? One may hypothesize that counties with higher social and economic mobility display larger responses. To evaluate this hypothesis, I interact $\Delta FinTech^{SCA}_{c,t-1}$ with one of the five county characteristics shown in Table 4. The results show that, the spillover effect is larger for counties located in metropolitan areas with higher population (column 1), for counties with higher shares of college graduates (column 2), young people (column 3) and African Americans (column 4), and for counties having larger migration flows in the previous year (column 5), which seems to support the hypothesis.

2.2 The Instrumental-Variable Approach

While the panel-data approach exploits the dynamic structure of network spillovers for identification, it may not account for all unobserved shocks that trigger FinTech growth in local markets without market-to-market spillovers. To isolate exogenous variation in FinTech lending growth and the resulting spillovers, I design an IV strategy that exploits exogenous shifts in the post-crisis U.S. banking regulations that led to differential impacts on county-level FinTech growth.

As documented in Buchak et al. (2018), traditional banks experienced increasingly stringent regulations after the Great Recession. One prominent example is the minimum risk-based capital ratio requirement of the Dodd-Frank Act, which resulted in banks' tier 1 risk-based capital ratios (or T1 ratios) rising substantially in the years after the crisis, as shown in Figure 1. Building up regulatory capital, however, comes at the cost of reducing balance sheet lending and mortgage originations. This created opportunities for FinTech lenders (and more generally non-bank lenders), which did not face these burdens, to grow.

At the county level, however, the exposure to tightening regulations depends on the pre-crisis capital structure of the banks operating in a county, which varies substantially and is plausibly unrelated to post-crisis loan demand. This suggests that the exposure of a county's socially connected markets to rising regulatory burdens can be used to construct instruments for FinTech growth in these markets. For the baseline IV estimates, I construct two instrumental variables using a straightforward extension of Buchak et al.'s approach. Alternative instruments that measure counties' exposure to regulation shits are discussed later in the robustness section.

The two variables are: (i) The origination-share-weighted change in banks' T1 ratio in each connected market of county c, further weighted by a market connectedness measure,

$$\Delta Regulation_c^M \equiv \sum_{j \in J_c^M} \omega_{j,c}^M \sum_{b \in B^j} s_{b,j} \Delta T1Ratio_b, \tag{4}$$

where $\omega_{j,c}^M$, $M \in \{GCA, SCA\}$, is defined as in equations (1) and (2). $s_{b,j}$ denotes bank b's market share of originations in county j before the Great Recession. $\Delta T1Ratio_b$ denotes the change in bank b's T1 ratio between 2008 and 2015. (ii) The share of mortgages originated by banks in each connected market of county c before the Great Recession, weighted by a market connectedness measure,

$$BankShare_c^M \equiv \sum_{j \in J_c^M} \omega_{j,c}^M BankShare_j. \tag{5}$$

The two-stage least-squares (2SLS) estimation is implemented as

$$\begin{aligned} \textit{1st Stage:} \quad \Delta FinTech_c^M =& \alpha_1 \Delta Regulation_c^M + \alpha_2 BankShare_c^M + \alpha_3 \bar{\mathbf{x}}_c^M + \alpha_4 \mathbf{x}_c + \nu_c^M \\ \textit{2nd Stage:} \quad \Delta FinTech_c =& \beta_1 \Delta \widehat{FinTech}_c^M + \beta_2 \bar{\mathbf{x}}_c^M + \beta_3 \mathbf{x}_c + \varepsilon_c, \end{aligned} \tag{6}$$

with county c's change in the T1 ratio and bank share included in $\mathbf{x}_c$ as controls, together with other county-level controls discussed earlier. The first-stage regression is akin to a difference-in-difference specification for the effect of regulatory shifts on FinTech growth. The assumption underlying the exclusion restriction is that, after controlling for the county's own exposure to regulatory shifts, the regulatory change experienced by its connected markets does not affect the county's FinTech lending directly, but indirectly through the impact on the FinTech lending in these connected markets.[13]

Table 5 presents the results. The first-stage regression shows that counties where banks faced the greatest regulatory pressure after the Great Recession experienced the largest growth of FinTech lending, consistent with Buchak et al. (2018). Conditional on changes in the T1 ratio, counties with banks seizing larger market shares before the recession actually saw lower growth in FinTech lending. The second-stage IV estimates show that a 1 pp increase in the FinTech market share in a county's GCAs (SCAs) leads to an increase in the county's FinTech market share by 0.77 pps (1.77 pps). These estimates are larger than in the panel-data approach, possibly due to the difference in the estimation horizon. This difference is also reflected in the OLS estimates (compared to Table 1). Overall, the IV

[13] Variation across counties in the exposure to regulatory shifts comes from two sources: (i) the composition of mortgage lenders in a local market before the crisis, and (ii) changes in the T1 ratios of the banks that operate in a local market. The premise of my IV strategy is that changes in the bank-level T1 ratio were driven by tightening banking regulations. One could argue that these changes may instead reflect post-crisis loan demand. I address this concern in the robustness section by developing alternative instruments.

estimates reinforce the view that FinTech lending displays economically and statistically large spillovers across socially connected markets.

Robustness. One concern about this IV strategy is that changes in the T1 ratio may be endogenous to demand for FinTech lending in the post-crisis period. To address this concern, I construct an alternative instrument based on the origination-share-weighted T1 ratio in 2008, as opposed to the change in this ratio from 2008 to 2015 in the baseline estimates. The rationale is that counties where banks had lowest regulatory capital in 2008 were counties where banks decreased their capital the most before the Great Recession, which cannot be determined by post-recession FinTech growth. These counties also experienced the largest capital increase after the crisis at the cost of balance-sheet lending.[14] The results based on this alternative instrument are shown in Table D3 (the first two columns in each panel). The instrument has high predictive power in the first stage, and the second stage estimates are similar to those in Table 5.

Another concern about using changes in the T1 ratio as the instrument is that these changes may also affect non-mortgage lending, introducing confounding factors for the identification. To address this concern, I construct yet another instrument that measures counties' exposure to regulatory changes specifically targeting mortgage lending. The instrument is the origination-share-weighted mortgage-servicing assets as a percent of T1 capital ratio (MSR) in 2008 in counties' connected areas. The rationale is that, since holding mortgage-servicing assets became more costly under the post-crisis regulations, banks with higher MSRs before the crisis would be more exposed to the regulatory shift and reduce their mortgage lending more. The results are shown in Table D3 (the last two columns in each panel). The 2SLS estimates are similar to those in Table 5 and support the existence of strong FinTech spillovers.

2.3 The Structural-Break Approach

An alternative strategy for estimating the spillover effect is to first identify the structural break point at which FinTech growth starts to accelerate in a county's connected markets,

[14] For this reason, using the instrument based on the origination-share-weighted change in the T1 capital ratio between 2006 and 2008 gives very similar estimates to this IV strategy.

and then estimate the dynamic likelihood of this county experiencing FinTech growth acceleration around these points. This approach helps quantify the extensive-margin spillovers. It has been often used in the literature, for example, to identify sharp unexpected changes in house price growth (Ferreira and Gyourko (2011); DeFusco et al. (2018); Charles et al. (2018); Dokko et al. (2019)).

This approach requires a reasonably large number of observations in the time dimension, making the availability of high-frequency mortgage origination data particularly useful. Using quarterly county-level data from 2007 to 2017, I estimate the following specification similar to Charles et al. (2018) for a single structural break for each county:

$$FinTech_{c,t} = \gamma_c + \alpha_c t + \beta_c (t - t_c^*) \mathbb{I}(t \geq t_c^*) + \varepsilon_{c,t}, \quad t_c^* \in [\underline{t}, \bar{t}], \tag{7}$$

where $FinTech_{c,t}$ is the FinTech market share in county c and quarter t. t_c^* is the potential break point located between time $\underline{t}$ and $\bar{t}$. $\mathbb{I}(\cdot)$ is an indicator function. If the structural break point, denoted by $\hat{t}_c^*$, exists, equation (7) implies that county c's FinTech market share grows at rate α_c before the break and at rate $\alpha_c + \beta_c$ after the break.[15] The break point for each county is estimated by searching for the location of the break that maximizes the R^2 of equation (7) subject to the constraint that $\beta_c > 0$, which represents the acceleration of FinTech growth. The break point is restricted to occur between 2008Q2 and 2016Q2.[16]

Figure 2 illustrates the estimation results for two counties: Fairfax, VA, where no break is found, and Salt Lake, UT, where the break occurred in 2011Q2. Among the 3,039 counties for which data are available, 1,267 counties had a break. Panel (a) of Figure 3 plots the distribution of the timing of the break, suggesting substantial variation across counties. Panel (b) plots the average FinTech market share around the break, which is 3% in the two years before the break, rises sharply after the break, and reaches about 10% in three years.

Given the break points identified at the county level, I use an event-study approach to estimate the change in the probability that a county experiences a break around the time

[15] I model structural breaks for the level of the FinTech market share rather than its change, because the regressions in changes fit the data poorly.

[16] This method may be modified to allow for the estimation of multiple structural breaks (e.g. Dokko et al. (2019); DeFusco et al. (2018)). Since the overall sample period is short and there is no evidence for a second wave of fast FinTech growth in the data, I focus on the case of one structural break.

when at least one of its socially connected markets experience such a break,

$$Break_{c,t} = \gamma_{d,t} + \gamma_c + \sum_{k=-3}^{3} \beta_1^k \mathbb{I}(t - \hat{t}^*_{c,M} \in k) + \beta_2 \mathbf{x}_{c,t} + \beta_3 \bar{\mathbf{x}}^M_{c,t} + \varepsilon_{c,t}, \tag{8}$$

where $M \in \{GCA, SCA\}$. $Break_{c,t}$ is an indicator for a break in county c and quarter t. $\mathbb{I}(t - \hat{t}^*_{c,M} \in k)$ takes the value of one if quarter t is in the kth year since the quarter in which any of county c's connected markets experiences a structural break. Other terms are similarly defined as in equation (3). The omitted category is the four-quarter period prior to the break point in the county's connected markets. The parameters of interest, $\{\beta_1^k\}_k$, capture the dynamic spillover effect.

Table 6 shows the results for the set of 25, 50, 75 and 100 most connected markets. The results can be summarized in four points. First, there is no pre-trend, alleviating the concern of simultaneity. Second, there is a sharp increase in the probability that a county experiences a break in the year after its connected markets experienced a break. Third, the breaks that happened in a county's most connected markets have the largest impact on the county's probability of experiencing a break. Fourth, spillovers occur relatively fast, and no significant effects are detected beyond the first year.

To shed light on the speed of the spillover, I focus on 25 most connected markets of a given county and estimate the spillover effect for each quarter. Figure 4 plots the dynamic response. It shows that the probability of a county experiencing a break increases the most in the second quarter after a break in its connected markets, before gradually returning to the trend. Consistent with the patterns in Table 6, there is no pre-trend, and the estimates are robust to alternative measures of connectedness. These results complement my earlier findings, suggesting a fast dissemination of information across social networks.

2.4 Demand-Side Spillovers vs Supply-Side Spillovers

My analysis thus far has established a strong spillover effect of FinTech lending across socially connected markets. This effect is consistent with demand-side spillovers driven by social interactions among consumers, but it is also consistent with supply-side spillovers. FinTech lenders that are successful in one county, for example, may decide to expand their businesses to similar counties. In general, it is hard to disentangle these two channels, as transaction data are generated in equilibrium and capture both demand- and supply-side shifts.

I tackle this problem using a new dataset on mortgage lenders' advertising. If the spillover reflects FinTech lenders' business strategy, one would expect it to be reflected in lenders' marketing strategy as well. Mintel Comperemedia tracks direct mail and print advertising in the U.S. and provides data on the volume of advertisements sent by each mortgage lender to households at the zip-code-month level. The dataset includes all major lenders, both FinTech and non-FinTech. The sampling procedure ensures that the estimates are nationally representative (see Appendix B for a detailed description).

These data allow me to address two questions: (i) Whether the volume of advertisements sent by FinTech lenders to a county is affected by the volume of FinTech advertisements sent to the county's connected markets, and (ii) whether controlling for changes in FinTech advertising in counties and their connected markets affects the estimated spillover effect.

The results in panel I of Table 7 provide the answer to the first question by estimating equation (3) with $\Delta FinTech_{c,t}$ and $\Delta FinTech^{M}_{c,t-1}$ replaced by the corresponding log changes in FinTech advertising. There is no evidence for the spillover of FinTech advertising. Panel II addresses the second question by including log changes of FinTech advertising in counties and their connected markets as controls in equation (3). The spillover-effect estimates are unchanged from column (5) of Table 1. These results support the view that the spillover effect reflects the demand-side propagation through consumers' social interactions.

3 Evidence of FinTech Lending and Interest Rate Pass-Through

The findings in the preceding section suggest that the spillover of FinTech lending through social networks is a key determinant of FinTech market penetration. This section provides evidence that higher FinTech market penetration leads to a more complete pass-though of market interest rates to the average borrower, which helps improve the transmission of monetary policy.

Why is the pass-through of market interest rates incomplete in the U.S. in the first place? This is because the prevalence of long-term fixed-rate mortgages (FRMs) prevents an instantaneous pass-through of the market rate to existing borrowers, creating a gap between the average outstanding mortgage rate and the current market rate on new mortgages. As shown in Figure 5a, the prevailing market rate declined sharply after the Great Recession, but the average outstanding mortgage rate came down only gradually. This rate gap narrows when existing mortgages are refinanced or new home-purchase loans are originated at the market rate (Figure 5b). All else equal, a larger reduction in the rate gap implies a more complete pass-through of lower interest rates to the average borrower over this period.

Higher FinTech market penetration may reduce the rate gap through the *price* effect and the *quantity* effect, as shown mathematically in Appendix C. The *price* effect refers to FinTech lenders offering lower rates to borrowers than non-FinTech lenders. The *quantity* effect refers to FinTech lenders originating higher shares of new mortgages in the overall mortgage stock. I estimate each of these effects separately for home purchases and refinancing, using county-level quarterly data between 2007 and 2017 constructed from the loan-level HMDA and McDash datasets (see Appendix B for a detailed data description).

The regression is specified as

$$y_{c,t} = \gamma_c + \gamma_t + \beta_1 FinTech_{c,t-1} + \beta_2 \mathbf{x}_{c,t} + \varepsilon_{c,t}. \tag{9}$$

$y_{c,t}$ is one of the outcome variables among: (i) the gap between county c's average outstanding mortgage rate and the market rate of 30-year FRMs at time t, (ii) the average rate of newly originated home-purchase mortgages in county c at time t, (iii) the average rate of newly originated refinancing mortgages in county c at time t, (iv) the number of newly originated home-purchase mortgages as a fraction of total outstanding mortgages in county c at time t, and (v) the number of newly originated refinancing mortgages as a fraction of total outstanding mortgages in county c at time t, which is a proxy for the refinancing propensity.[17]

To measure FinTech penetration in a county market, I follow Fuster et al. (2019) in

[17]When constructing these variables, I use conventional first-lien 30-year FRMs that are below the jumbo cutoff. This selection is based on the fact that the prevailing market rate is more representative for the rates on these mortgages, and that these borrowers are more likely to meet underwriting criteria if they were to refinance or to buy a new home.

using the one-quarter lagged, four-quarter moving-average share of FinTech originations, $FinTech_{c,t-1}$. $\mathbf{x}_{c,t}$ is a set of county-level control variables including the average FICO score, house prices growth, the lagged average interest rate, the fraction of young people, and the fraction of African Americans. γ_c and γ_t denote county and quarter fixed effects. The standard errors are clustered at the county level.

Panel I of Table 8 shows a negative and statistically significant relationship between FinTech market penetration and the rate gap (columns 1 and 2). Including county-level controls, the estimate of -0.069 in column (2) implies that an increase in FinTech market penetration from the 10th to the 90th percentile is associated with a reduction in the rate gap of 3 basis points at an annualized rate, which corresponds to 34% (6%) of the mean (standard deviation) of the annual change in the rate gap. Thus, the effect is economically meaningful. Next, I decompose this total effect into the price effect and the quantity effect.

Price effect. The price effect is obtained by regressing the average rate of newly originated home-purchase mortgages or of refinancing mortgages on the FinTech penetration measure. Panel I of Table 8 shows that the decrease in the rate gap is not driven by the price effect. FinTech lenders do not seem to offer lower rates than traditional lenders to home buyers (columns 3 and 4) or to refinancing borrowers (columns 5 and 6). The estimated price effects are statistically insignificant.

Quantity effect. Columns (1) and (2) in panel II of Table 8 show that higher FinTech market penetration is associated with a significant increase in newly originated mortgages (as a fraction of total outstanding mortgages), supporting the role of the quantity effect in explaining the rate-gap decline. The next four columns decompose this effect into the changes in home-purchase originations and in refinancing. Nearly all of the quantity effect is driven by the increased refinancing propensity (columns 5 and 6), not so much by the increase in the home-purchase share (columns 3 and 4). In particular, column (6) shows that 86% of the increase in the new originations share associated with higher FinTech penetration is due to refinancing.[18]

[18]The estimated change in the refinancing propensity is in line with Fuster et al. (2019). By estimating the price and quantity effects separately, I establish the new result that the rising refinancing propensity associated with higher FinTech market penetration is the main channel through which FinTech lending helps reduce the rate gap.

Heterogeneity. To evaluate whether higher FinTech market penetration leads to more efficient refinancing, I test the hypothesis that the refinancing effect is larger when the refinancing benefit is higher. For this purpose, I interact $FinTech_{c,t-1}$ with one of the two proxies for refinancing benefits: (i) the change in the prevailing market rate over eight quarters, $\Delta R_{t,t-8}$ (with the sign normalized such that $\Delta R_{t,t-8} > 0$ represents a fall in the market rate); and (ii) the indicator for the lagged rate gap, $Gap_{c,t-1}$, in a given category: greater than 175 bps, 125-175 bps, 75-125 bps and less than 75 bps. Columns 1 and 2 of Table 9 suggest a higher refinancing propensity when the prevailing market rate falls, which contributes to a further decline in the rate gap (columns 3 and 4). Likewise, higher FinTech market penetration increases the refinancing propensity (and hence reduces the rate gap) the most in counties where the potential interest savings are the highest (i.e., $Gap_{c,t-1} > 175$ bps). This evidence supports the hypothesis that higher FinTech market penetration leads to more efficient refinancings.

4 Model

To quantify the role of FinTech lending and its propagation through social networks in the transmission of monetary policy shocks to households, I develop a heterogeneous-agent model that incorporates three key empirical features of FinTech lending. First, FinTech lenders offer a higher quality product that makes the refinancing process more convenient for consumers. Second, FinTech lenders respond more elastically to demand shocks than traditional lenders. Third, social interactions help spread information about FinTech lending, making refinancing even more accessible from the consumer's point of view. This baseline model is then extended to incorporate multiple regions, as in Beraja et al. (2018), to shed light on the interaction between FinTech lending, monetary transmission and regional economic conditions.

Preferences. The economy is populated by a continuum of infinitely-lived households, indexed by i located in region j, $j = 1, ..., J$. Households maximize their expected life-time utility

$$\mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t u(c_{i,t}^j)\right],$$

where $c_{i,t}^j$ denotes consumption of household i in region j at time t. The utility derived from housing services does not explicitly enter the maximization problem, given the assumption that households are endowed with one unit of housing and do not adjust their housing size.[19]

Income and house prices. Households face idiosyncratic uninsurable income shocks. Log-income is generated from the AR(1) process

$$\log(y_{i,t}^j) = (1-\rho^y)\mu^y + \rho^y \log(y_{i,t-1}^j) + \varepsilon_{i,t}^{y,j}, \quad \varepsilon_{i,t}^{y,j} \sim^{\text{i.i.d.}} (0, \sigma_y^2), \tag{10}$$

where μ^y and ρ^y capture the unconditional mean and the persistence of the process. $\varepsilon_{i,t}^{y,j}$ is a mean zero i.i.d. shock with variance σ_y^2. Similarly, the log of regional house prices is generated by the AR(1) process,

$$\log(p_t^j) = (1-\rho^p)\mu^p + \rho^p \log(p_{t-1}^j) + \varepsilon_t^{p,j}, \quad \varepsilon_t^{p,j} \sim^{\text{i.i.d.}} (0, \sigma_p^2), \tag{11}$$

with unconditional mean μ^p, persistence ρ^p, and an idiosyncratic shock $\varepsilon_t^{p,j}$.

Mortgage debt, refinancing, and liquid savings. Mortgage debt is long-term, which requires a fixed recurring payment of $r_{t_0}^b b_{i,t_0}^j$ every period, determined at the time of origination, t_0. Households can refinance their mortgage at any time $t_1 > t_0$ by paying off the existing balance and originating a new mortgage of b_{i,t_1}^j at the current market rate, $r_{t_1}^b$. The resulting new payment is $r_{t_1}^b b_{i,t_1}^j$. Upon refinancing, households cash out the maximum available home equity, if any, or, in the case of being underwater, pay back the amount owed to satisfy the loan-to-value requirement. This implies that households hit the collateral constraint exactly at the time of refinancing,

$$b_{i,t_1}^j = \gamma p_{t_1}^j,$$

where γ is the maximum loan-to-value ratio set by the lender.

Refinancing involves two types of costs. One is a fixed closing cost proportional to the

[19]The recent macroeconomic literature on heterogeneous-agent life-cycle models has emphasized the role of housing investments in the transmission of aggregate shocks (Zhou (2021)). My model abstracts from this aspect of the household problem, because I focus on the refinancing channel of monetary policy, and because FinTech lending is much more important in refinancing than in home purchases. The insight of the current model on the role of FinTech lending, however, remains valid if housing choices are endogenous.

new borrowing amount, $\phi b^j_{i,t_1}$. The other is non-pecuniary, reflecting the time and effort spent on refinancing-related activities, such as searching for offers, visiting lender's office, talking to the agent and completing the paperwork. The non-pecuniary cost, $f^j_{i,t}$, varies across households. I assume that $f^j_{i,t}$ is drawn from an i.i.d. process with the cumulative distribution function F_f. Households have access to liquid assets, $a^j_{i,t}$, that pay a rate of return, $r^a < r^b$. Moreover, households are subject to the liquidity constraint, $a^j_{i,t} \geq 0$.

FinTech lending. One important feature of FinTech lending is higher-quality services, such as reduced paperwork, at-home origination and faster loan processing, making the refinancing process more convenient for consumers. I model this feature as a utility gain, q, when consumers refinance their mortgage with a FinTech lender.[20]

Not every consumer has access to information about FinTech lending, however, possibly due to inattention, learning barriers, or financial illiteracy. In the model, the arrival of FinTech information from non-network sources (e.g., advertising and search engines) is a random variable, Q, drawn from an i.i.d. Bernoulli process. With probability p^q, information about FinTech lending arrives ($Q = 1$). Conditional on such information, the consumer decides whether to refinance her mortgage. If she chooses to refinance, she will also choose to do so with a FinTech lender. If she chooses not to refinance, a mortgage payment must be made according to the existing contract. With probability $1 - p^q$, the consumer does not receive information about FinTech ($Q = 0$). In this case, she decides whether to refinance with a traditional lender.

The arrival of FinTech information, Q, captures learning without social interactions. Consumers may also learn about FinTech through their interactions with friends, relatives and coworkers, either in-person, on-phone, or online, as considered next.

FinTech spillovers through social interactions. Let the arrival of FinTech information from social networks be a random variable, E, drawn from an i.i.d. Bernoulli process, which is also independent from the arrival of FinTech information from non-interactive sources, Q. Social interactions, allowing the exchange of information and the sharing of experiences, are

[20] My model assumes that FinTech lenders and traditional lenders charge the same closing costs and the same mortgage rates. The former is supported by evidence in Buchak et al. (2018). The latter is supported by the empirical evidence in Table 8.

likely to further simplify the refinancing process and increase consumers' satisfaction with FinTech lending. In the model, with probability p^e, a consumer learns about FinTech from social interactions ($E = 1$). If she chooses to refinance with a FinTech lender upon social learning, she receives a utility premium, $e > q$. With probability $1 - p^e$, the consumer does not learn about FinTech information from her social network.[21]

Since consumers may obtain FinTech information from two sources, there are different paths that lead to a refinancing decision. First, with probability $(1-p^q)(1-p^e)$, the consumer does not learn about FinTech from either source ($Q = E = 0$), and decides whether to refinance with a traditional lender. Second, with probability $p^q(1 - p^e)$, the consumer learns about FinTech only from non-interactive sources ($Q = 1$, $E = 0$), and decides whether to refinance with a FinTech lender. Third, with probability p^e, the consumer learns about FinTech through social interactions ($E = 1$), which may or may not happen simultaneously with non-interactive learning, and decides whether to refinance with a FinTech lender. The overall utility gain from refinancing with a FinTech lender, therefore, is $\max\{qQ, eE\}$.

Monetary policy stimulus and capacity constraints. I consider the effects of an unexpected, permanent decline in the mortgage rate driven by a monetary policy stimulus. As documented in the literature, in response to this kind of aggregate demand shocks, traditional lenders are less resilient and face significant capacity constraints such as the cost of training, difficulties in hiring and staffing issues (Fuster et al. (2019); Fuster et al. (2021)). These constraints are likely to be translated to higher non-pecuniary costs for consumers, for example, the difficulty in finding a lender and delayed loan processing.

I model the implications of these constraints as a cost of refinancing in response to the monetary policy shock. Suppose a one-time unexpected permanent decline in the mortgage rate happens at time $T + 1$. Due to capacity constraints faced by traditional lenders, their refinancing clients pay a utility cost

$$\chi(r^b_T, r^b_{T+\tau}) \equiv \mathbb{I}(r^b_T > r^b_{T+\tau})(r^b_T - r^b_{T+\tau})(\chi\tau^{-\alpha}), \quad \tau = 1, 2, ... \tag{12}$$

[21] Note that I model social networks as an exogenous process (as opposed to an endogenously determined formation). This approach reflects the pattern in the data that one county is affected by many socially connected markets and that the impact of a specific county on the social network is likely to be small.

where $r^b_T - r^b_{T+\tau}$ represents the size of the rate reduction, and τ is the number of periods since the rate reduction. $\chi > 0$ and $\alpha > 0$ are parameters to be calibrated. This specification captures several key features of the capacity-constraint-induced cost: (i) it is asymmetric to positive and negative rate changes, (ii) it is proportional to the size of the demand shock, and (iii) it diminishes over time.[22] Without loss of generality, I assume that FinTech lenders do not face capacity constraints.

Regions. I introduce regions to study how regional economic conditions affect the transmission of monetary policy in the presence of FinTech lending (Section 6.2). A region is a collection of households who face the same mortgage market condition and correlated economic shocks. As in Beraja et al. (2018), I consider three types of regional economic conditions: (i) the low-house price region, hit by a permanent negative shock that lowers house prices by 10%; (ii) the mid-house price region, seeing no change in the house price; and (iii) the high-house price region, hit by a permanent positive shock that raises house prices by 10%. In Appendix E, I extend the model to incorporate correlated shocks to house prices and income. In that case, the region in depressed (booming) economic condition is hit by permanent negative (positive) shocks to both house prices and income.

Recursive formulation. The model has a recursive formulation. At the household level, the state variables include mortgage debt (b), liquid assets (a), income (y), the mortgage rate on the existing contract (r^b_0), the non-pecuniary cost of refinancing (f), and the arrival of FinTech information from non-interactive sources (Q) and from social interactions (E). At the regional level, the state variable is the house price (p). At the aggregate level, the state variable is the prevailing market mortgage rate (r^b). Appendix E provides a detailed description of the recursive formulation of this baseline model and the solution methods. For the purpose of conducting counterfactual analyses, a model without FinTech lending (the *no-FinTech model*) and a model with FinTech lending but no FinTech spillovers (the *no-FinTech-spillover model*) are also formulated in Appendix E. All model simulations are based on the optimal choices of 100,000 households.

[22]In the model, households do not internalize lenders' capacity constraints into their own maximization problem, but instead perceive these utility costs as unexpected shocks.

5 Calibration

The model frequency is annual. Preference parameters are calibrated as in standard consumption models. The utility function takes the form of constant relative risk aversion (CRRA), $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$. σ is set to 2, implying an intertemporal elasticity of substitution of 0.5. I set $\beta = 0.95$, consistent with the calibrated value of the discount factor in the heterogeneous-agent consumption literature (e.g., Berger et al. (2018); Guren et al. (2021)).

The AR(1) coefficient of the log-income process, ρ_y, is set to 0.9, and the standard deviation of the idiosyncratic income shock, σ_y, is set to 0.1, consistent with the estimates based on the Panel Study of Income Dynamics (PSID) data in Zhou (2021). To obtain the unconditional mean, μ^y, I assume that the income variable, y, follows a log-normal distribution with $\mathbb{E}(y) = 1$ for normalization. The properties of the log-normal distribution imply that $\mu^y = -\frac{\sigma_y^2}{2[1-(\rho^y)^2]}$.

The AR(1) coefficient of the log-house-price process, ρ_p, and the standard deviation of the corresponding idiosyncratic shock, σ_p, are calibrated by fitting the historical CoreLogic national home price index deflated by the CPI into equation (11), which gives $\sigma_p = 0.95$ and $\rho_p = 0.05$. To obtain the unconditional mean, μ^p, I assume that the house price, p, follows a log-normal distribution. I set $\mathbb{E}(p) = 4\mathbb{E}(y)$, based on the historical average ratio of home sale prices (from the National Association of Realtors) over annual household pre-tax income (from the Consumer Expenditure Survey). This implies that $\mu^p = log(4) - \frac{\sigma_p^2}{2[1-(\rho^p)^2]}$.

The refinancing closing cost, ϕ, is set to 3%, consistent with the estimate by the Federal Reserve Board in "*A Consumer's Guide to Mortgage Refinancings*", as well as recent estimates by the FinTech lender Rocket Mortgage.[23] The maximum loan-to-value ratio, γ, is set to 80%, consistent with government-sponsored enterprises' (GSE) guidelines for conforming mortgages without private mortgage insurance. The return on liquid assets, r^a, is set to 1%, based on the historical average of the 1-year treasury rate net of inflation. The steady-state mortgage rate, r^b, is set to 4%, which equals the historical average of the 30-year FRM rate net of inflation. The distribution of initial liquid assets and loan-to-value ratios is set to match the PSID data for households with mortgages over the period of 2007-2017.

[23] According to the recent estimate by Rocket Mortgage, a refinancing borrower is expected to pay 2%-3% of the remaining principal in closing costs (see, https://www.rocketmortgage.com/learn/cost-to-refinance).

The non-pecuniary cost of refinancing, f, is drawn from a discrete i.i.d. process with two realizations, f^H and f^L, and the corresponding probabilities, p^f and $1 - p^f$. I set $f^L = 0$, as in models without non-pecuniary refinancing costs. f^H and p^f are calibrated such that in the absence of FinTech lending (see Appendix E, the no-FinTech model), the refinancing propensity is zero conditional on receiving f^H, and the overall refinancing rate before the monetary policy shock is consistent with the average county-level refinancing propensity prior to QE1 in the McDash data.

The parameter governing the effect of capacity constraints, χ, is calibrated to match the refinancing response to the monetary policy shock in the absence of FinTech lending, which is 9.4% (annual rate) in Beraja et al. (2018). The persistence of capacity constraints is captured by α, which is set to 3, implying that the impact of these constraints largely dissipates after one year, consistent with the evidence in Fuster et al. (2021).

There are four key parameters related to FinTech lending: the probabilities of the arrival of FinTech information from non-interactive sources, p^q, and from social interactions, p^e, and the FinTech utility premiums obtained without social interactions, q, and with social interactions, e. These parameters are jointly calibrated to target four moments. First, the FinTech market share is 20% before the monetary policy shock in the baseline model. Second, when FinTech spillovers are shut down (i.e. the no-FinTech-spillover model), the FinTech market share is 11% before the monetary policy shock. Third, the overall refinancing rate before the policy shock in the no-FinTech-spillover model is 6% higher than in the no-FinTech model. Fourth, the overall refinancing rate before the policy shock in the baseline model is 20% higher than in the no-FinTech model. These moments match key patterns in the data, as discussed next.

The first moment corresponds to the average county-level FinTech refinancing share in 2017. The second moment is a back-of-the-envelope calculation for the FinTech market share in a (counterfactual) no-FinTech-spillover county.[24] This calibration yields $p^q = 7\%$

[24]This counterfactual is calculated as follows. Table 1 shows that a 1 pp increase in the FinTech market share in a county's connected areas raises the county's FinTech market share by 0.26 pps. The increase of the explanatory variable from its smallest value to its mean is about 10 pps, implying a 2.6 pp increase in the county's FinTech market share due to spillovers. This effect accounts for 43% of the historical average FinTech market share in a county (6%). Removing this effect from the 2017 average share suggests that the FinTech share in the counterfactual county is 11% (=20%*[1-43%]). This is likely to be an upper bound,

and $p^e = 6\%$, implying that only a small fraction of households receive information about FinTech lending, either from non-interactive or interactive sources, as of 2017. The remaining two moments are set by estimating the following regression using county-level data,

$$Refi_{c,t} = \gamma_{d,t} + \gamma_c + \beta_1 \Delta FinTech_{c,t-1} + \beta_2 \Delta FinTech^M_{c,t-1} + \beta_3 \mathbf{x}_{c,t} + \beta_4 \bar{\mathbf{x}}^M_t + \varepsilon_{c,t},$$

where the LHS is the county-level refinancing propensity in the McDash data, and the RHS variables are similarly to equation (3). This regression estimates the effects of FinTech lending in a county's own market and in its connected markets simultaneously, giving $\hat{\beta}_1 = 0.011$ and $\hat{\beta}_2 = 0.026$ (both significant at the 1% level). This implies that a 10 pp increase in $\Delta FinTech_{c,t-1}$ (i.e. moving from the 10th to 90th percentile of the distribution) is associated with a 6% higher refinancing rate (holding FinTech spillovers constant), and that a 10 pp increase in $\Delta FinTech^M_{c,t-1}$ and a 10 pp increase in $\Delta FinTech_{c,t-1}$ together are associated with a 20% higher refinancing rate.[25]

6 FinTech Lending, Monetary Policy and Regional Heterogeneity

In this section, I use the calibrated model to address three key questions. First, to what extent can FinTech lending and its propagation through social networks change the responses of refinancing and consumption to a monetary stimulus? Second, how do regional economic conditions further affect these responses? Third, as FinTech lending continues to grow in the U.S. mortgage market and social interactions become more effective through online platforms, how would these trends affect households' responses to monetary stimulus in the future? Answering these questions using a structural model has the advantage that empirically confounding factors hindering the identification of monetary policy shocks are held constant in the model, and that counterfactual analysis can be performed to assess the role of FinTech propagation alone.

because the empirical estimate only captures spillovers at the one-year horizon.

[25] The first effect is obtained by (0.011*10)/2 =6%, where the denominator is the refinancing rate before the policy shock in the no-FinTech model. The second calculation uses the FinTech spillover effect (0.26) estimated in Table 1. The effect of a 1 pp increase in $\Delta FinTech^M_{c,t-1}$ is the direct effect β_2 plus the spillover effect multiplied by β_1. Therefore, the total effect with both FinTech and its spillovers is [0.011*10+ (0.26*0.011+0.026)*10]/2=20%.

6.1 FinTech Lending and Monetary Policy

To what extent can FinTech lending and its spillovers through social networks change the responses of borrowing and consumption to a monetary stimulus? I answer this question by simulating the refinancing propensity and consumption before and after a monetary stimulus that lowers the mortgage rate by 1 pp permanently in four cases: (1) the no-FinTech case; (2) the no-FinTech-spillover case, where FinTech lending is available but there is no spillover across social networks; (3) the baseline case, as calibrated in Section 5; and (4) the high-spillover case, where households are more likely to learn about FinTech from social interactions.[26]

Figure 6 shows the levels of the refinancing propensity and consumption (left column) and the implied responses to the monetary policy shock (right column). Upon the shock being realized, refinancing and consumption increase in all cases, and the increases are larger in the presence of FinTech lending and its spillovers. In the baseline case, the refinancing propensity increases by 11.3 pps. In the case of no FinTech lending, the refinancing propensity only increases by 10 pps, implying that the presence of FinTech lending (calibrated to 2017 data) raises the refinancing response to a monetary policy shock by 13%. When FinTech spillovers are shut down, the refinancing propensity increases by 10.7 pps, implying that almost half (46%) of the improvement in the refinancing response to the monetary policy shock is due to FinTech propagation through social networks, and the other half is due to FinTech product features and lender resilience.

Quantitatively similar results are obtained for the consumption response. The increases in consumption upon the policy shock are 1.25%, 1.11%, and 1.17% in the baseline, no-FinTech and no-FinTech-spillover cases, respectively. This implies that slightly more than half (57%) of the improvement in the consumption response to the monetary policy shock in the presence of FinTech lending is due to FinTech propagation. When the network effect is stronger, as in the high-spillover case, the refinancing and consumption responses to the policy shock are larger, 13.4 pps and 1.5%, respectively, equivalent to a 34% and a 36% improvement compared to the no-FinTech case. The contribution of FinTech propagation rises to 79% for

[26] In this high-spillover case, p^e is set to 0.25. The implied FinTech market share matches the 90th percentile of the distribution of county-level FinTech refinancing shares in 2017.

refinancing, and to 85% for consumption.

To understand these effects, Figure 7 plots the refinancing propensity for each type of households before and after the policy shock, as well as the distribution of the household type (determined by the realization of f, Q and E). Since the overall refinancing propensity is obtained by aggregating type-specific refinancing propensities using the type distribution, this exercise helps understand the drivers behind the differences in the refinancing response.

The upper panel shows that, absent FinTech lending, a decline in the mortgage rate increases the refinancing propensity among consumers with low non-pecuniary costs (i.e. $f = f^L$), but not among those with high non-pecuniary costs . The second panel shows that, when FinTech information can be obtained from non-interactive sources, households who receive this information (i.e. $Q = 1$) have a higher refinancing propensity than otherwise identical households who do not receive this information. Moreover, when the mortgage rate declines, some households with f^H who otherwise would not have refinanced, choose to refinance with FinTech lenders. In the baseline case (the third panel), given f, the refinancing propensity is highest among households receiving FinTech information from social interactions. In the high-spillover case (the fourth panel), a larger share of households are able to refinance with FinTech lenders, driving up the overall refinancing propensity on the extensive margin, despite that type-specific refinancing propensities are almost unchanged from the baseline case.

6.2 FinTech Lending, Monetary Policy and Regional Economy

How does FinTech lending interacted with regional economic conditions affect the transmission of monetary policy? This question is important, because the work of Beraja et al. (2018) shows that expansionary monetary policies through the refinancing channel provide unintentionally more stimulus to economically thriving regions, whereas economically depressed regions benefit less. This happens because households in economically depressed regions are less likely to satisfy the refinancing underwriting criteria, due to low home values, and have less home equity to cash out.

Using the model, I examine whether this pattern can be reversed in the presence of

FinTech lending. I consider three types of regional economic conditions: low house prices, middle house prices, and high house prices, under three scenarios: no FinTech lending, no FinTech spillovers, and the presence of both FinTech lending and spillovers (calibrated as in the baseline case). Figures 8 and 9 show the responses to a 1 pp decline in the mortgage rate on impact and over a ten-year horizon.

There are three key findings from this exercise. First, the conclusions in Beraja et al. (2018) are corroborated in the no-FinTech case. Upon the policy shock, the refinancing propensity increases by 3.3 pps, 10 pps, and 12.4 pps in the low-, mid-, and high-house price regions, respectively. The impulse responses further confirm that the refinancing and consumption responses are persistently higher in the high-house price region.

Second, even in the presence of FinTech lending (with or without spillovers), the refinancing response is still highest in the high-house-price region. Hence, the model suggests that the presence of FinTech lending is unlikely to alter the pattern that economically booming regions are more responsive to a monetary stimulus. This is not surprising, given the institutional features of the U.S. mortgage market (captured in the calibration). In the U.S., refinancing has to satisfy a set of underwriting criteria, one of which is the standard 80% loan-to-value ratio for the mortgage to be backed by GSEs. Since FinTech lenders heavily rely on GSE securitization to originate their mortgages, they cannot help borrowers who do not have enough home equity or who fail to meet other underwriting criteria to refinance, which often happens in economically depressed regions.

Third, nevertheless, FinTech lending and its spillovers can effectively increase the refinancing response in economically depressed regions, although to a lesser extent than in economically booming regions. This is important from the policy point of view, because, even in economically depressed regions, many households do not refinance, not due to inadequate home equity, but due to high non-pecuniary costs associated with refinancing. This is where FinTech lending can help. Table 10 provides support for this view through the lens of the model. Column (1) shows the fraction of households with positive home equity in each region after the policy shock. Even in the low-house price region, 40% of households have positive home equity, who can potentially benefit from refinancing. Without any frictions, the propensity to refinance conditional on positive home equity is 100% (column 2). With either type of frictions, the conditional refinancing propensity declines, and the decline is largest when both frictions are present (columns 3-5). As FinTech lending becomes available, however, the conditional refinancing propensity increases (column 6), and the increase is larger with FinTech spillovers (column 7). Similar patterns are observed for other regions.[27]

6.3 Policy Counterfactuals

The patterns in Table 10 suggest that there is room for policies to further reduce frictions in the mortgage market. Moreover, as FinTech lending continues to expand in the U.S. mortgage market, its role in the monetary transmission is likely to become more important. This motivates counterfactual analysis for three types of policies: (i) those encouraging the expansion of FinTech lending, (ii) those enhancing social interactions and information exchanges, and (iii) those reducing capacity constraints faced by traditional lenders. Each of these policies maps to a parameter in the model that determines the refinancing response.

First, consider policies that promote the growth of existing and new FinTech lenders, that encourage traditional lenders to adopt new technology, and that make consumers more aware of FinTech lending. These policies increase the probability that FinTech lending directly reaches to the consumer, resulting in a higher p^q in the model. Panel (a) of Figure 10 plots regional refinancing responses for different values of p^q, holding other parameter values fixed. As p^q increases from 0.07 in the baseline to 0.5 (implying a 70% FinTech market share on average), for example, the refinancing responses would increase by 53%, 38% and 47% in the low-, mid- and high-house price region, respectively.

Next, consider policies that expand consumers' networks and their ability to share information. These changes correspond to a higher probability of FinTech information being acquired from social interactions, p^e. Panel (b) of Figure 10 plots regional refinancing responses for different values of p^e, holding other parameter values fixed. As p^e increases

[27] In an extension of the model, I incorporate correlated shocks to regional income and house prices. The patterns of regional refinancing and consumption responses are qualitatively similar to the baseline model (see Appendix Figure E1). In fact, demand for refinancing is even stronger in economically depressed regions, because negative income shocks trigger the consumption-smoothing motive, on top of lower borrowing costs. This pattern argues for an even more important role of FinTech lending in transmitting monetary stimulus to these regions.

from 0.06 in the baseline to 0.5 (implying a 71% FinTech market share on average), for example, the refinancing responses increase by 45%, 41% and 45% in the low-, mid- and high-house price region, respectively. Panel (c) of Figure 10 considers the case when both p^q and p^e increase. The refinancing responses are substantially higher in all regions. When $p^q = p^e = 0.5$ (implying a 85% FinTech market share on average), the refinancing responses would increase by 73%, 60% and 71% in the low-, mid- and high-house price region, respectively, relative to the baseline calibration.[28]

Lastly, consider policies that ease capacity constraints faced by traditional lenders. This corresponds to a lower value of χ in the model. In Figure 11, I compare regional refinancing responses for different values of χ in three cases: no FinTech, no FinTech spillover, and FinTech with spillovers. In each case, easing capacity constraints helps boost the refinancing response in all regions, facilitating the monetary transmission. With FinTech lending and its spillovers, for example, reducing the capacity-constraint-induced costs by 20% from the baseline calibration would raise the refinancing responses by 73%, 43% and 35% in the low-, mid- and high-house price region, respectively.

7 Conclusion

One of the most important channels through which monetary policy affects the real economy is mortgage borrowing. This channel, however, is weakened by consumers' failure to refinance their mortgages and capacity constrains faced by traditional lenders. The rapid growth of FinTech lending tends to ease frictions, because of the higher quality products provided under this new lending model and lenders' greater resilience to demand shocks.

The role of FinTech lending in the transmission of monetary policy, however, goes beyond what FinTech products and lenders' resilience can account for. This is because consumers and their social networks help propagate the adoption of FinTech lending. Using county-level data, I show that FinTech lending displays a sizable spillover effect across socially connected markets, and that this effect is particularly strong in areas with higher social and economic

[28] Table E1 in the Appendix shows how the refinancing propensity conditional on positive home equity changes from the baseline calibration to various counterfactuals. The results highlight the role of FinTech lending in reducing frictions in the mortgage market.

mobility.

I develop a structural model in order to quantify the importance of FinTech propagation relative to FinTech product features and greater lender resilience for the transmission of monetary policy. The refinancing response to a 1 pp decline in the mortgage rate, for example, is 13% higher with FinTech lending. Almost half of this improvement is due to FinTech propagation through social networks, and the other half is accounted for by FinTech product features and lender resilience. Quantitatively similar patterns are seen in the consumption response.

As FinTech lending continues to expand in the U.S. mortgage market, one would expect it to further enhance the monetary policy transmission. My counterfactual analysis assesses household borrowing and consumption responses when FinTech market penetration is higher and when social interactions are more informative. I show that, for example, an increase in the FinTech market share to 70%, all else equal, would raise the refinancing response to a monetary policy stimulus by 40%, compared to 2017, and by 60% compared to the case of no FinTech lending.

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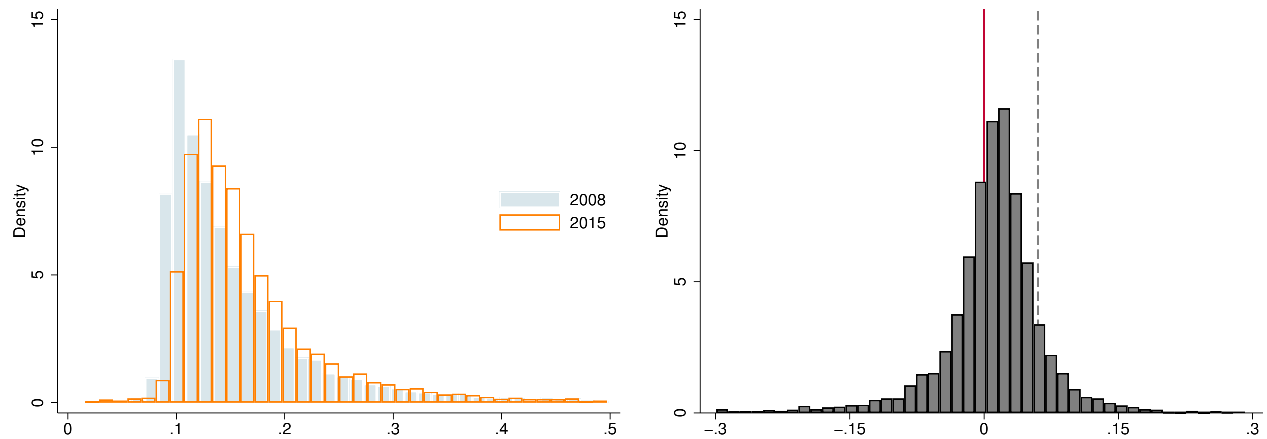
Figure 1: Distribution of bank tier 1 (T1) capital ratio

(a) Level of T1 ratio

(b) Change in T1 ratio, 2008-2015

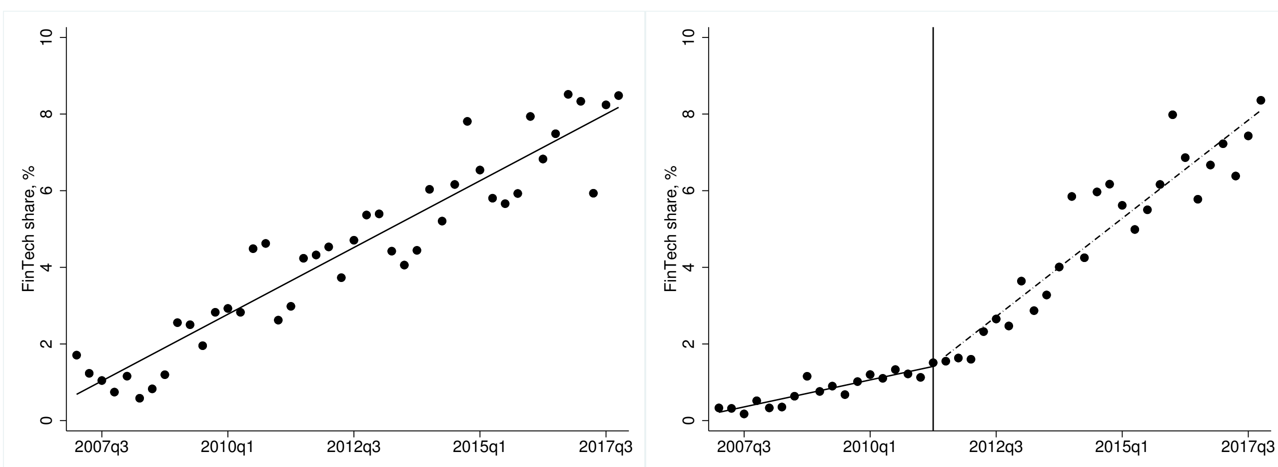


Sources: Bank call reports obtained from FFIEC. The average change in the T1 ratio is 0.06, indicated by the dash line in panel (b).

Figure 2: Structural break of FinTech lending growth in selected counties

(a) No break: Fairfax county, VA

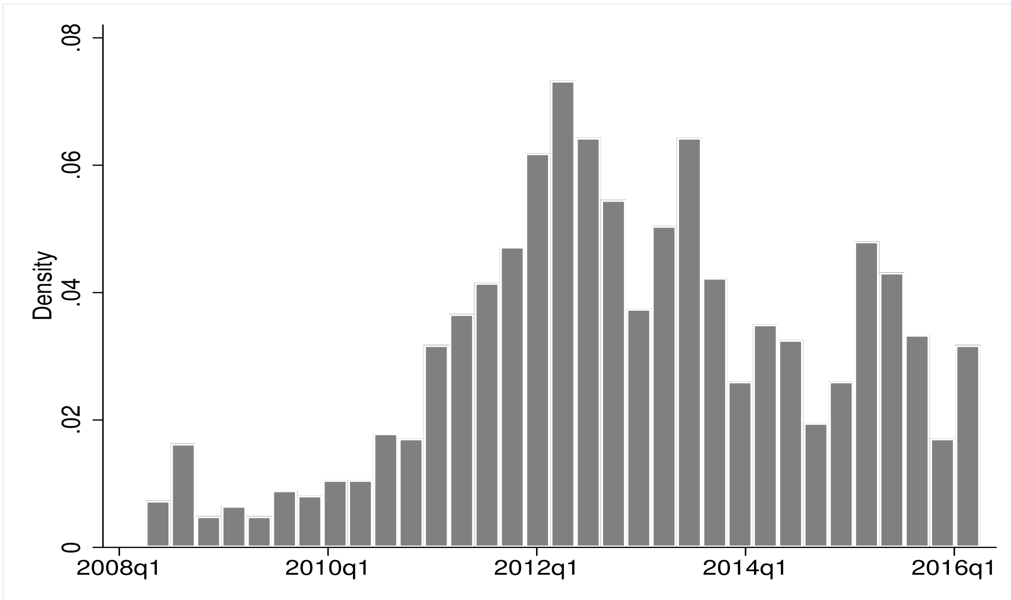
(b) One break: Salt Lake county, UT



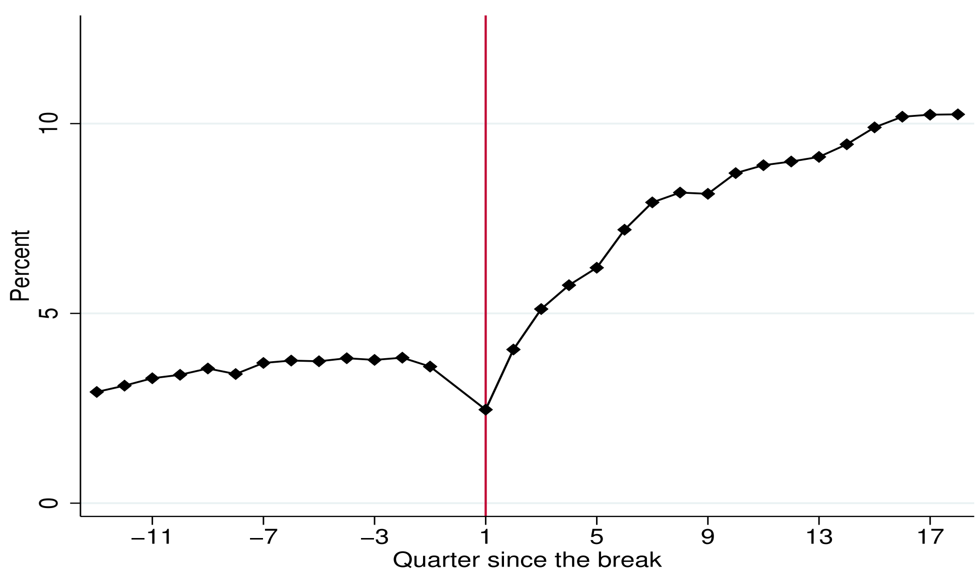
Source: HMDA confidential data 2007-2017. Notes: The solid vertical line in panel (b) indicates the timing of the structural break. The regression fitted lines are obtained by estimating equation (7) using data before and after the break.

Figure 3: Structural break of FinTech lending growth in U.S. counties

(a) Distribution of the timing of the structural break



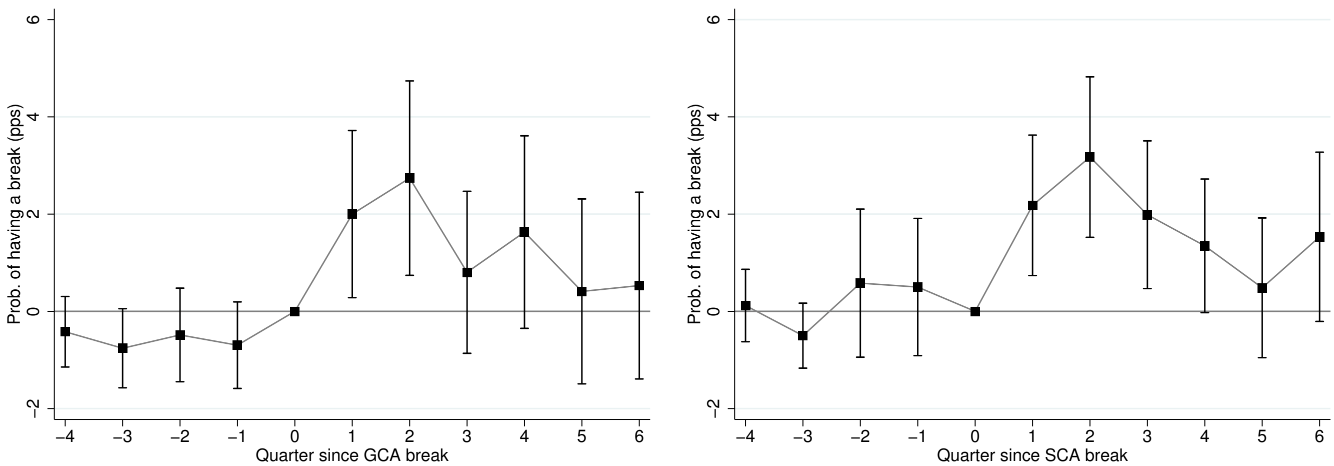
(b) FinTech market share around the structural break



Source: HMDA confidential data. Notes: The structural break point is estimated using equation (7) for each county based on quarterly data between 2007 and 2017.

Figure 4: Dynamic spillover effects

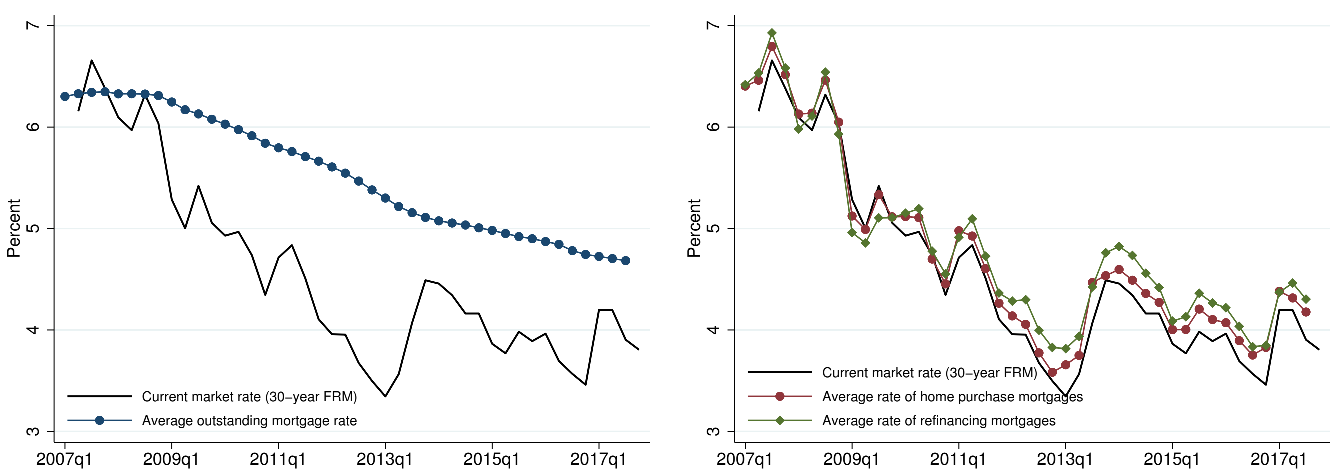
(a) Response to a GCA break (b) Response to an SCA break



Notes: Point estimates and the 95% confidence intervals obtained using an event-study approach that estimates a version of equation (8).

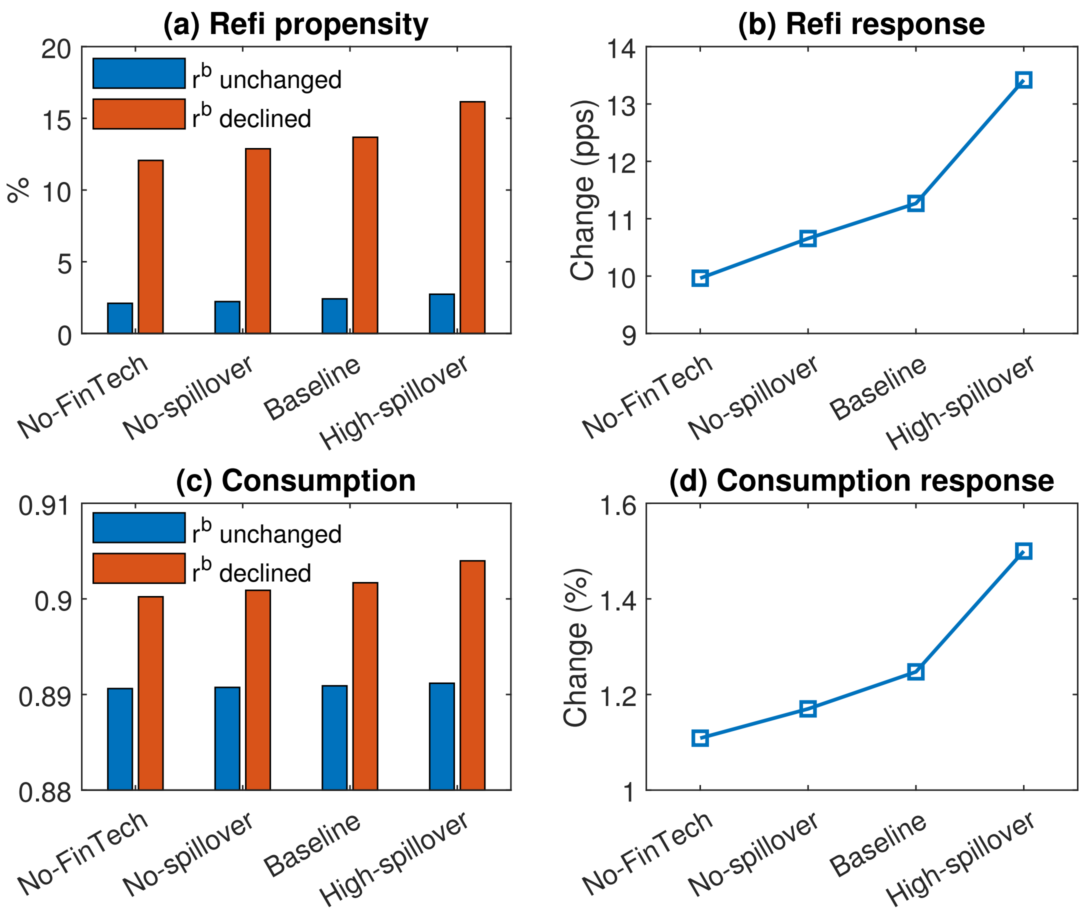
Figure 5: Outstanding mortgage rate and current market rate

(a) The rate gap (b) Rates on newly originated mortgages



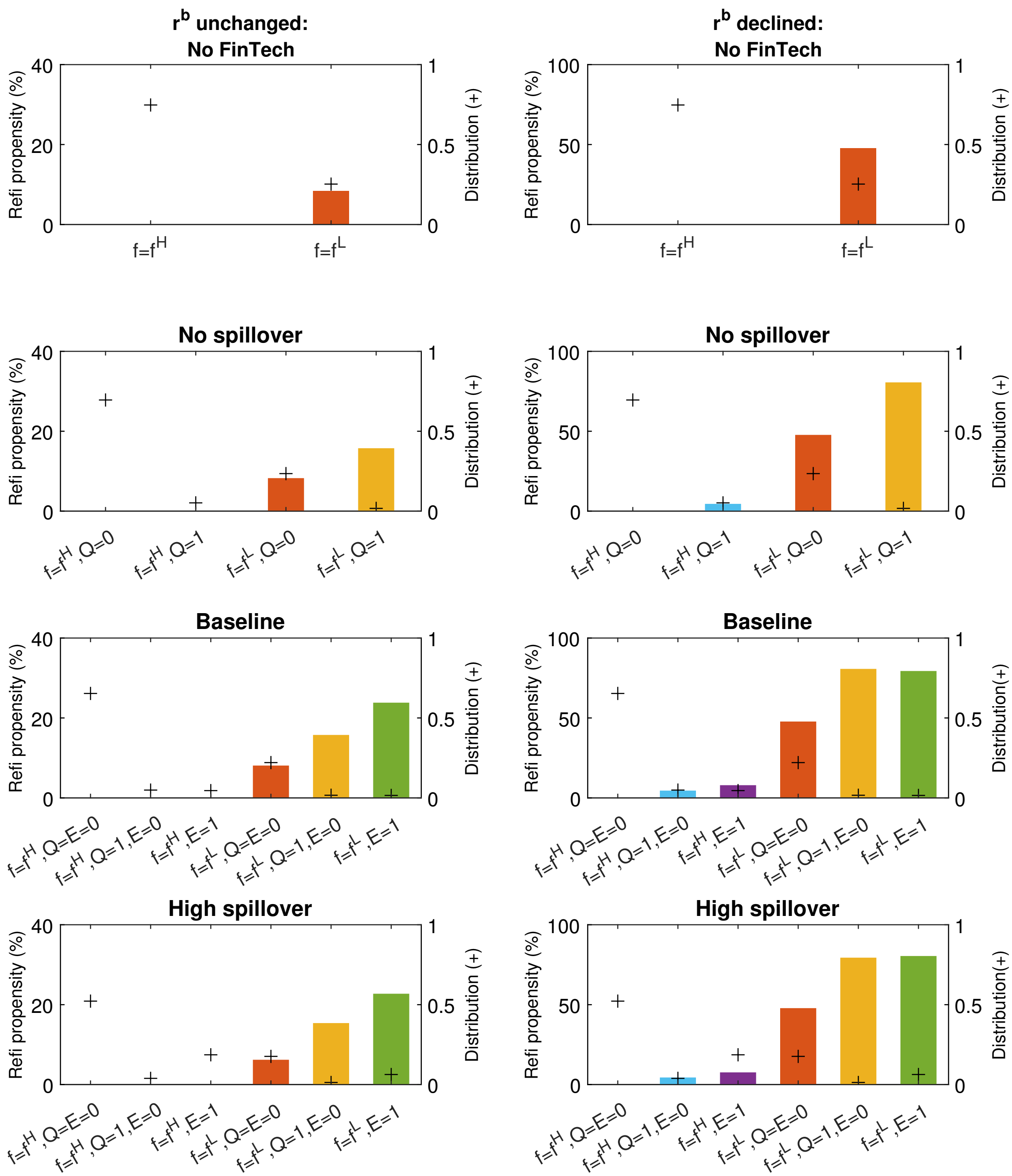
Sources: FRED; Black Knight McDash. Notes: The current market rate is the 30-year FRM rate obtained from FRED. All other average-rate series are constructed using the Black Knight McDash loan-level data.

Figure 6: Responses to an unexpected monetary policy stimulus



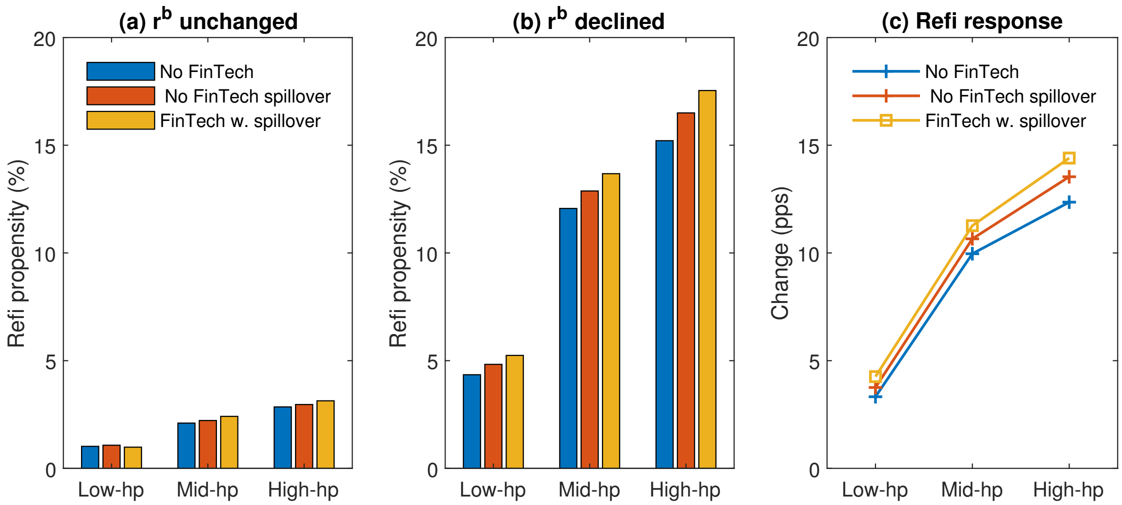
Notes: Simulations from the calibrated model for the impact period. The refinancing response is the change in the refinancing propensity. The consumption response is the log change in consumption.

Figure 7: Household type-specific refinancing propensities



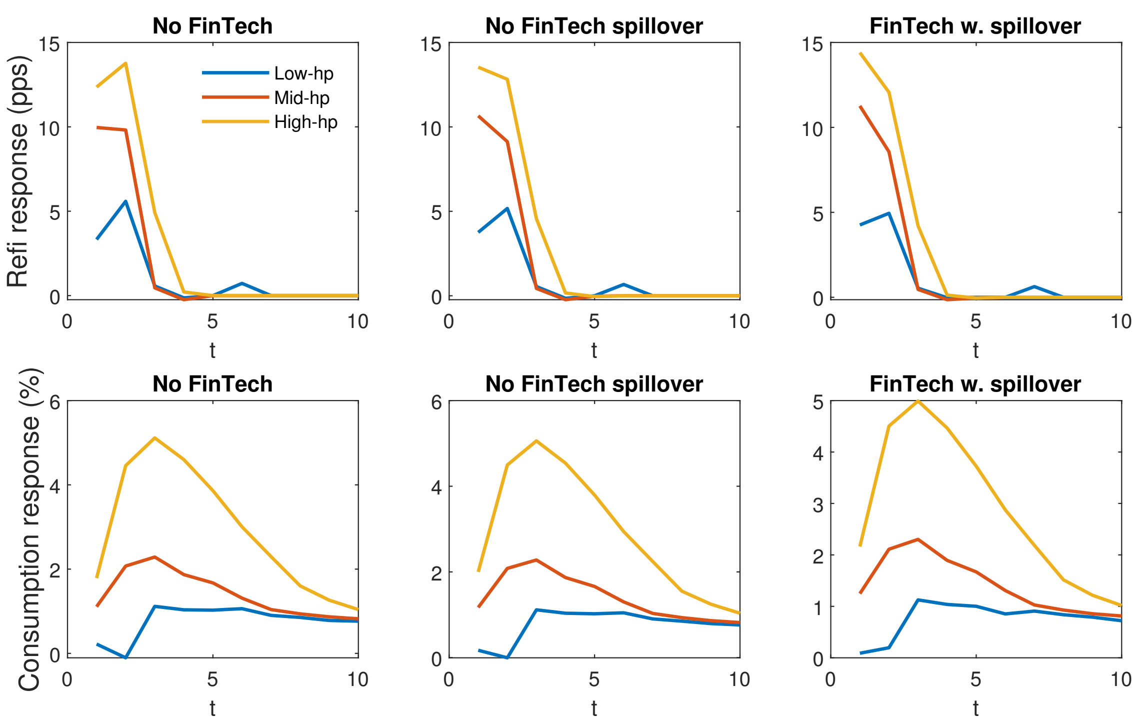
Notes: Household type-specific refinancing propensities (colored bars) and the distribution of household type (+ signs) simulated from the calibrated model for the impact period.

Figure 8: Refinancing responses and regional economic conditions



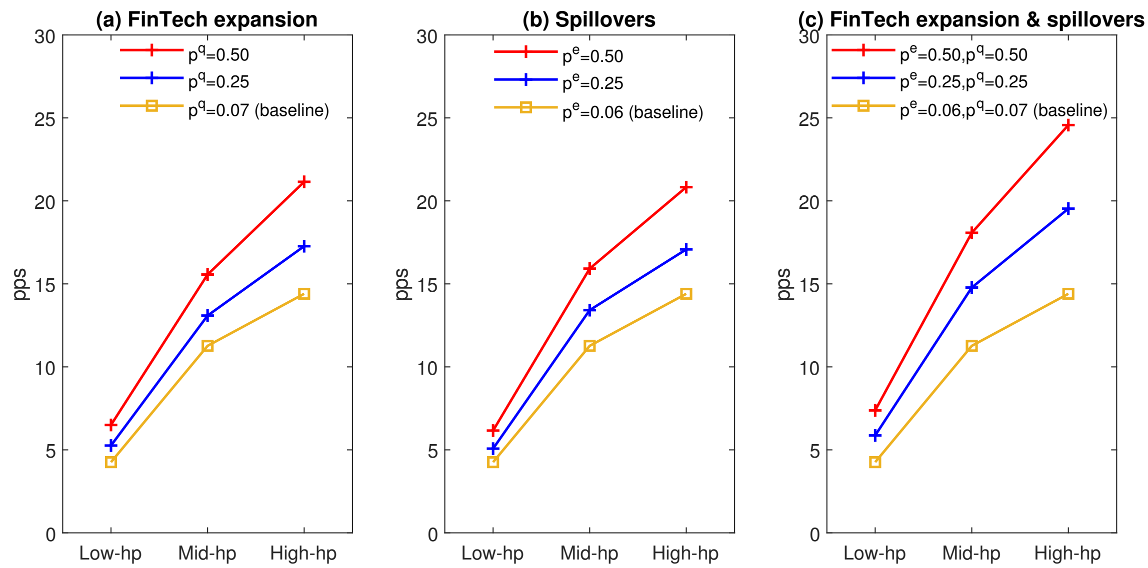
Notes: Simulated impact responses from the calibrated model for low-, mid- and high-house price regions.

Figure 9: Impulse responses of refinancing and consumption



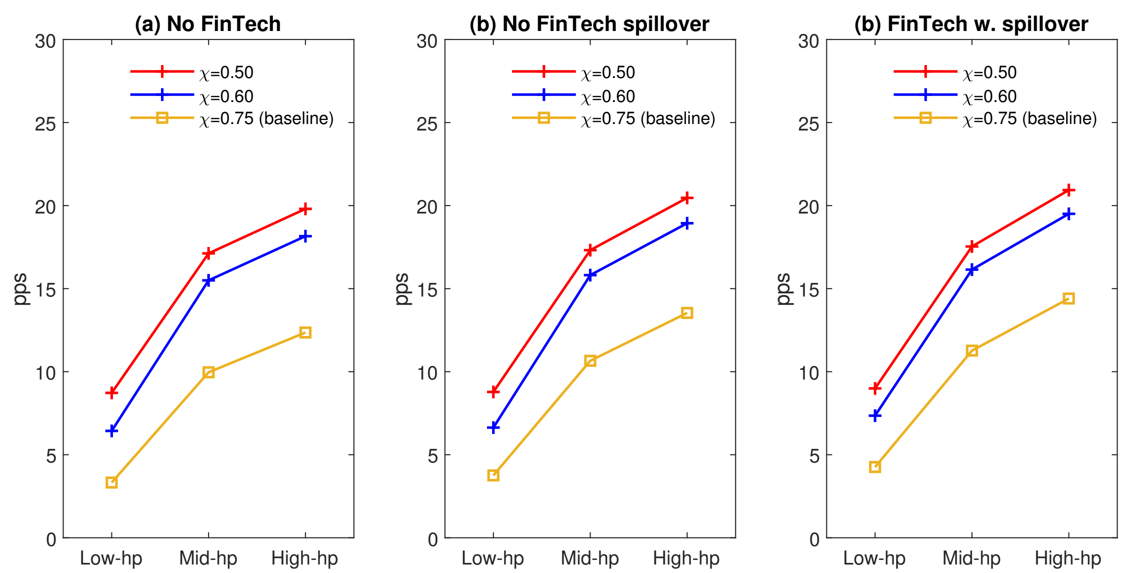
Notes: Simulated impact responses from the calibrated model for low-, mid- and high-house price regions.

Figure 10: Policy experiments: expanding FinTech lending and its spillovers



Notes: Simulated impact responses from the calibrated model and policy counterfactuals for low-, mid- and high-house price regions.

Figure 11: Policy experiments: easing capacity constraints



Notes: Simulated impact responses from the calibrated model and policy counterfactuals for low-, mid- and high-house price regions.

Table 1: FinTech spillover effect

Panel I.	Dependent variable: ΔFinTech share				
Spillover from GCAs	(1)	(2)	(3)	(4)	(5)
ΔFinTech share$^{GCA}_{-1}$	0.301***	0.295***	0.247***	0.248***	0.257***
	(0.018)	(0.018)	(0.020)	(0.020)	(0.020)
County FE	x	x	x	x	x
County controls		x		x	x
Division-by-quarter FE			x	x	x
GCA controls					x
R-squared	0.055	0.057	0.325	0.327	0.329
# Obs.	118,490	118,434	118,490	118,434	118,434
Panel II.					
Spillover from SCAs	(1)	(2)	(3)	(4)	(5)
ΔFinTech share$^{SCA}_{-1}$	0.378***	0.373***	0.236***	0.234***	0.232***
	(0.023)	(0.024)	(0.022)	(0.017)	(0.017)
County FE	x	x	x	x	x
County controls		x		x	x
Division-by-quarter FE			x	x	x
SCA controls					x
R-squared	0.072	0.074	0.327	0.328	0.329
# Obs.	118,463	118,427	118,463	118,427	118,427

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

Table 2: FinTech spillover effect by loan purpose

	ΔFinTech refi share (1)	ΔFinTech purchase share (2)	ΔFinTech volume (3)	ΔFinTech refi volume (4)	ΔFinTech purchase volume (5)
Panel I. Spillover from GCAs					
ΔFinTech share$_{-1}^{GCA}$	0.248***	0.176***	0.327***	0.230***	0.098***
	(0.024)	(0.020)	(0.024)	(0.018)	(0.012)
County FE	x	x	x	x	x
County controls	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x
GCA controls	x	x	x	x	x
R-squared	0.304	0.189	0.592	0.634	0.276
# Obs.	116,276	116,252	118,434	118,434	118,434
Panel II. Spillover from SCAs					
ΔFinTech share$_{-1}^{SCA}$	0.241***	0.168***	0.276***	0.178***	0.098***
	(0.019)	(0.017)	(0.020)	(0.015)	(0.010)
County FE	x	x	x	x	x
County controls	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x
SCA controls	x	x	x	x	x
R-squared	0.306	0.189	0.591	0.633	0.273
# Obs.	116,269	116,245	118,427	118,427	118,427

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

Table 3: Market connectedness and FinTech spillover effect

Panel I.	Dependent variable: ΔFinTech share				
Spillover from GCAs	Within 50 miles	50-100 miles	100-150 miles	150-200 miles	200-500 miles
ΔFinTech share$^{GCA}_{-1}$	0.569***	0.346***	0.188***	0.057	-0.036
	(0.050)	(0.035)	(0.037)	(0.041)	(0.028)
County FE	x	x	x	x	x
County controls	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x
GCA controls	x	x	x	x	x
# Obs.	115,009	118,434	118,434	118,434	118,434

Panel II.					
Spillover from SCAs	Top 50 SCAs	Top 50-100	Top 100-150	Top150-200	Top 200-500
ΔFinTech share$^{SCA}_{-1}$	0.188***	0.045***	0.028***	0.017	0.001
	(0.016)	(0.012)	(0.010)	(0.014)	(0.042)
County FE	x	x	x	x	x
County controls	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x
SCA controls	x	x	x	x	x
# Obs.	118,427	118,427	118,427	118,427	118,427

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

Table 4: Heterogeneity in FinTech spillover effect

Dept. variable: ΔFinTech share	(1)	(2)	(3)	(4)	(5)
ΔFinTech share$^{SCA}_{-1}$	0.073***	0.146***	0.179***	0.124***	0.077***
	(0.029)	(0.018)	(0.018)	(0.021)	(0.014)
ΔFinTech share$^{SCA}_{-1}$ × Nonmetro, urban pop∈[2.5K-20K)	0.022				
	(0.033)				
ΔFinTech share$^{SCA}_{-1}$ × Nonmetro, urban pop≥20K	0.062				
	(0.034)				
ΔFinTech share$^{SCA}_{-1}$ × Metro, pop<250K	0.108***				
	(0.039)				
ΔFinTech share$^{SCA}_{-1}$ × Metro, pop∈[250K,1M)	0.205***				
	(0.045)				
ΔFinTech share$^{SCA}_{-1}$ × Metro, pop≥ 1M	0.293***				
	(0.039)				
ΔFinTech share$^{SCA}_{-1}$ × Higher share of Bachelor's degree		0.113***			
		(0.025)			
ΔFinTech share$^{SCA}_{-1}$ × Higher share of young			0.076***		
			(0.023)		
ΔFinTech share$^{SCA}_{-1}$ × Higher share of black				0.160***	
				(0.028)	
ΔFinTech share$^{SCA}_{-1}$ × Higher migration flow$_{-1}$					0.189***
					(0.023)
County FE	x	x	x	x	x
County controls	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x
SCA controls	x	x	x	x	x
# Obs.	118,427	118,427	118,427	118,427	118,295

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

Table 5: Banking regulation shocks as IV for FinTech spillover effect

Dept. variable: ΔFinTech share	GCA spillover OLS	GCA spillover 2SLS 1st stage	GCA spillover 2SLS 2nd stage	SCA spillover OLS	SCA spillover 2SLS 1st stage	SCA spillover 2SLS 2nd stage
ΔFinTech share^M	0.786***		0.767***	0.981***		1.769***
	(0.044)		(0.192)	(0.039)		(0.442)
ΔRegulation^M		1.937***			0.605***	
		(0.153)			(0.155)	
Bank share^M		-0.035***			-0.033***	
		(0.005)			(0.007)	
State FE	x	x	x	x	x	x
County controls	x	x	x	x	x	x
GCA/SCA controls	x	x	x	x	x	x
1st stage F-stat		80.2			13.0	
# Obs.	3,095	3,095	3,095	3,095	3,095	3,095

Notes: ** and *** denote significance at the 5% and 1% level, respectively. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

Table 6: Dynamic spillover effects from the structural-break analysis

Dept. variable:	GCA spillover				SCA spillover			
$\mathbb{I}$(*have a Break*)	25 GCAs	50 GCAs	75 GCAs	100 GCAs	25 SCAs	50 SCAs	75 SCAs	100 SCAs
Two years before	-0.525	-0.261	-0.166	-0.146	-0.166	-0.540	-0.519	-0.473
	(0.469)	(0.288)	(0.351)	(0.362)	(0.452)	(0.319)	(0.351)	(0.269)
One year before	-0.667	0.153	0.181	0.138	0.115	0.022	-0.123	-0.280
	(0.403)	(0.313)	(0.374)	(0.419)	(0.425)	(0.330)	(0.343)	(0.178)
One year after	1.891**	1.567***	1.055	0.728	2.224***	1.460***	1.259**	0.936
	(0.762)	(0.551)	(0.636)	(0.695)	(0.536)	(0.526)	(0.556)	(0.504)
Two years after	0.330	0.163	-0.088	0.110	1.236	1.578	0.173	-0.158
	(0.862)	(0.817)	(0.824)	(0.889)	(0.745)	(0.808)	(0.631)	(0.653)
Three years after	-0.267	-0.105	-0.076	0.011	0.686	0.873	-0.062	-0.749
	(0.871)	(0.690)	(0.754)	(0.783)	(0.719)	(0.788)	(0.626)	(0.801)
County FE	x	x	x	x	x	x	x	x
County controls	x	x	x	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x	x	x	x
GCA/SCA controls	x	x	x	x	x	x	x	x
# Obs.	49,301	52,612	53,890	54,450	49,101	52,527	53,684	54,359
Prob. at least one GCAs/SCAs have a break	0.20	0.31	0.39	0.45	0.19	0.29	0.37	0.43

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

Table 7: Examining supply-side spillovers

Panel I. FinTech marketing spillover	GCA spillover		SCA spillover	
	ΔFinTech Ads	ΔFinTech Ads	ΔFinTech Ads	ΔFinTech Ads
ΔFinTech Ads$^{M}_{-1}$	0.033	0.030	0.026	0.018
	(0.033)	(0.033)	(0.032)	(0.032)
County FE	x	x	x	x
Division-by-quarter FE	x	x	x	x
County controls		x		x
GCA/SCA controls		x		x
# Obs.	118,490	118,434	118,463	118,427

Panel II. Accounting for marketing effect	GCA spillover		SCA spillover	
	ΔFinTech share	ΔFinTech share	ΔFinTech share	ΔFinTech share
ΔFinTech share$^{M}_{-1}$	0.248***	0.257***	0.235***	0.232***
	(0.020)	(0.020)	(0.017)	(0.017)
ΔFinTech Ads	0.001	0.000	-0.008	-0.009**
	(0.003)	(0.003)	(0.004)	(0.004)
ΔFinTech Ads^{M}	0.006	0.003	-0.000	-0.001
	(0.006)	(0.006)	(0.003)	(0.003)
County FE	x	x	x	x
Division-by-quarter FE	x	x	x	x
County controls		x		x
GCA/SCA controls		x		x
# Obs.	118,490	118,434	118,463	118,427

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables. County-level mortgage lender advertising data are obtained from Mintel Comperemedia. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

Table 8: Effect of FinTech penetration on interest rate pass-through

Panel I. **Price effect**	Rate gap (1)	Rate gap (2)	Average purchase rate (3)	Average purchase rate (4)	Average refi rate (5)	Average refi rate (6)
FinTech share$_{-1}$	-0.086***	-0.069***	0.254	0.180	0.170	-0.006
	(0.023)	(0.022)	(0.166)	(0.143)	(0.087)	(0.072)
County FE	x	x	x	x	x	x
Quarter FE	x	x	x	x	x	x
County controls		x		x		x
# Obs.	119,095	119,073	102,485	102,485	101,254	101,254

Panel II. **Quantity effect**	New originations (1)	New originations (2)	Purchase share (3)	Purchase share (4)	Refi propensity (5)	Refi propensity (6)
FinTech share$_{-1}$	0.077***	0.044***	0.015	0.006	0.062***	0.038***
	(0.017)	(0.014)	(0.009)	(0.009)	(0.013)	(0.010)
County FE	x	x	x	x	x	x
Quarter FE	x	x	x	x	x	x
County controls		x		x		x
# Obs.	119,095	119,073	119,095	119,073	119,095	119,073

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables.

Table 9: Heterogeneity in the effect of FinTech penetration on interest rate pass-through

	Refi propensity		Rate gap		Refi propensity		Rate gap	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FinTech share$_{-1}$	0.060***	0.036***	-0.081***	-0.065***	0.025**	0.013	-0.007	0.000
	(0.013)	(0.010)	(0.023)	(0.023)	(0.011)	(0.009)	(0.024)	(0.026)
FinTech share$_{-1}$	0.015	0.019**	-0.036**	-0.033**				
$\times \Delta R_{t,t-8}$	(0.009)	(0.008)	(0.015)	(0.015)				
FinTech share$_{-1}$					0.019**	0.009	-0.027	-0.022
$\times Gap_{-1} \in (75, 125]$					(0.009)	(0.007)	(0.016)	(0.016)
FinTech share$_{-1}$					0.061***	0.042***	-0.135***	-0.126***
$\times Gap_{-1} \in (125, 175]$					(0.011)	(0.009)	(0.024)	(0.023)
FinTech share$_{-1}$					0.067***	0.054***	-0.184***	-0.176***
$\times Gap_{-1} > 175$					(0.010)	(0.009)	(0.024)	(0.023)
County FE	x	x	x	x	x	x	x	x
Quarter FE	x	x	x	x	x	x	x	x
County controls		x		x		x		x
# Obs.	119,095	119,073	119,095	119,073	119,095	119,073	119,095	119,073

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables.

Table 10: Refinancing propensity condition on having positive home equity

	Share of households (1)	No frictions (2)	Lender frictions (3)	Consumer frictions (4)	Both frictions (5)	FinTech. w.o. spillover (6)	FinTech. w. spillover (7)
Low-HP region	40.2%	100	42.5	27.0	10.8	12.0	13.1
Mid-HP region	80.1%	100	55.2	28.2	15.1	16.1	17.1
High-HP region	94.0%	100	63.3	34.3	16.2	17.6	18.7

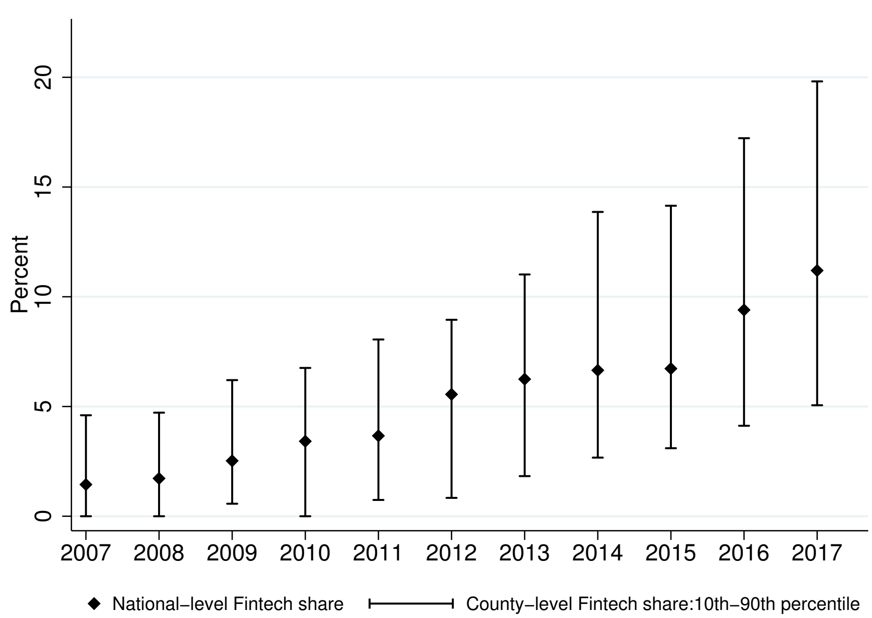
Notes: Simulations from the calibrated model for the impact period. Column (1) shows the share of households having positive home equity. Columns (2)-(5) report the refinancing propensity of households having positive home equity in the absence of FinTech lending. Columns (6)-(7) report this conditional refinancing propensity in the no-FinTech spillover case and in the baseline calibration. Lender frictions refer to capacity constraints; consumer frictions refer to non-pecuniary costs associated with refinancing.

Appendices to "FinTech Lending, Social Networks, and the Transmission of Monetary Policy"

A Lender Classification

I follow Buchak et al. (2018) and Fuster et al. (2019) in identifying FinTech lenders. The former study identifies FinTech lenders as those having a strong online presence and allowing nearly all of the mortgage application process to take place online without human interaction from the lender. The latter study identifies FinTech lenders as those who enable a mortgage applicant to obtain a preapproval online. The two classification methods differ only in the case of a few small FinTech lenders, and the resulting FinTech market shares are similar both at the national and regional levels.[29] My analysis uses the combined list of FinTech lenders from these two studies, as in Jagtiani et al. (2020). The empirical results are unaffected if FinTech lenders are classified as in either study. Figure A1 plots the FinTech market share in the aggregate and the dispersion of this share in the county-level market. Table A1 shows the list of major FinTech lenders and their respective market share in 2017 in the HMDA data.

Figure A1: FinTech market share in mortgage originations



Source: HMDA public-version data 2007-2017. Notes: FinTech market shares computed using the volume of originations.

[29]While both studies consider the possibility of "FinTech bank lenders", they do not classify any banks as FinTech lenders as of 2017. This is because the existing business model and legacy system in the traditional banking sector have hindered banks' ability to adopt new technology.

Table A1: Major FinTech lenders in 2017

Lender name	Market share (%)
Quicken Loans	5.00
Loandepot.com	2.08
Guranteed Rate	1.08
Movement Mortgage	0.77
Everett Financial	0.46
Cardinal Financial	0.24
Envoy Mortgage	0.21
FBC Mortgage	0.21
Evergreen Moneysource Mortgage	0.17
Amerisave Mortgage	0.16
ARK-LA-TEX Financial Services	0.16
Skyline Financial	0.15
American Neighborhood Mortgage	0.13
Homeward Residential	0.10

Source: HMDA public-version data 2007-2017. Notes: FinTech market shares computed using the volume of originations.

B Data Description

The empirical analysis in this paper draws on a number of mortgage loan-level, bank-level, county-level and aggregate economic and financial data sets. This section describes the sources of these data and key information contained in these data sets.

Home Mortgage Disclosure Act (HMDA). This data set contains the vast majority of home-mortgage application and approval records in the United States. It provides detailed information on loan and borrower characteristics, as well as the lender identifier, making it the most suitable source to study FinTech presence in the U.S. national and regional mortgage markets. The public version of the data can be obtained from the Consumer Financial Protection Bureau. The confidential version of the data, accessible to Federal Reserve System employees, has additional information on the exact date when an action (e.g., origination, denial or withdrawal) is taken (rather than just the year as in the public version). This information is crucial for implementing my empirical strategies. Therefore, I use the confidential version of the HMDA data for most of my analysis.

Black Knight McDash Dataset (McDash). This data set consists of servicing portfolios of the largest mortgage servicers, covering two-thirds of installment-type loans in the U.S. residential mortgage servicing market. The data contain loan-level information at origination and monthly update on the performance. Unlike the HMDA data set that measures the flow into mortgage debt, the McDash data measures the stock of mortgages in the U.S. I use these data to construct several key variables at the county-quarter level: the average outstanding mortgage rate, the average rate of newly originated mortgages by loan purpose, the fraction of newly originated mortgages in total outstanding mortgages, and the average FICO score. For reasons discussed in Section 3, I restrict the sample to conventional first-lien 30-year FRMs below the jumbo cutoff. The data set is accessed through the Federal Reserve System's RADAR Data Warehouse (FRS-RADAR-DW).

Measures of Social Connectedness. My empirical analysis employs two alternative measures of social connectedness. One is based on geographical distance, accessed through the NBER County Distance Database. The other is based on novel social network data developed by Bailey et al. (2018b) that contain the county-pair-level social connectedness index (SCI).[30] The index uses an anonymized snapshot of active Facebook users and their friendship networks as of August 2020 to capture the intensity of social interactions between locations. The SCI between two locations i and j is constructed as

$$SCI_{i,j} = \frac{FB\ Connections_{i,j}}{FB\ Users_i \times FB\ Users_j}, \tag{13}$$

where $FB\ Users_i$ and $FB\ Users_j$ are the number of Facebook users in locations i and j, and $FB\ Connections_{i,j}$ is the total number of Facebook friendship links between individuals in the two locations.[31] Bailey et al. (2018b) show that the index is strongly negatively correlated with distance, varies substantially across locations, and is correlated with bilateral social and economic activity. The index has been increasingly used by researchers to study the role of social interactions in driving economic outcomes of individuals, neighborhoods, regions and nations (see Kuchler and Stroebel (2021)).

Mintel-Comperemedia Direct Mail and Print Advertising Volume. This data set contains information that can be used to construct the volume of advertisements sent by each mortgage lender to households (in direct mails) at the county-quarter level since 2007. The underlying microdata are from a panel of 70,000 households who share the direct mails and print advertisements they received with the Mintel company team on a weekly basis. The sampling of the households is designed to be representative for the U.S. population, and it is updated every month to include new households for the panel to be continuously representative. Given this sample design, the aggregate advertising volume can be reliably constructed with appropriate weighting.

[30] Accessed in October 2020 through https://data.humdata.org/dataset/social-connectedness-index.

[31] The public SCI data are scaled to have the maximum value of 10^9 and the minimum value of 1. They measure the relative probability of a Facebook friendship between a user in county i and a user in county j.

To get a sense of the aggregate trend in mortgage advertising, panel (a) of Figure B1 plots the aggregate volume of mortgage offers since 2007 and by loan purpose. It shows that home purchase and refinancing offers each accounted for about half of the overall advertising volume, but refinancing offers surged particularly during the refinancing boom of 2012-2013. Panel (b) plots the shares of advertisements sent by FinTech lenders for all mortgage offers, home purchase offers and refinancing offers. FinTech offers have grown rapidly since 2011, which has been mainly driven by refinancing offers, consistent with the pattern in the HMDA data.

Bank Balance Sheet Data. Bank tier 1 capital ratios are constructed using bank call reports accessed through the Federal Financial Institutions Examination Council's (FFIEC) Central Data Repository. This information is then merged with the HMDA dataset using the Avery file.[32]

County-level Demographic and Economic Data. These data are collected from various sources. The population estimates by demographic group are obtained from the Census Bureau. Employment statistics are obtained from the Quarterly Census of Employment and Wages published by the Bureau of Labor Statistics. The share of subprime borrowers is constructed using the New York Fed (FRBNY) Consumer Credit Panel/Equifax Data (accessed through FRS-RADAR-DW).[33] It is defined as the fraction of consumers having an Equifax Risk Score below 670 among all consumers of age 22-80 in a county. County-to-county migration data (both inflows and outflows) are obtained from the Internal Revenue Service Tax Statistics. The rural-urban continuum code is obtained from the U.S. Department of Agriculture.

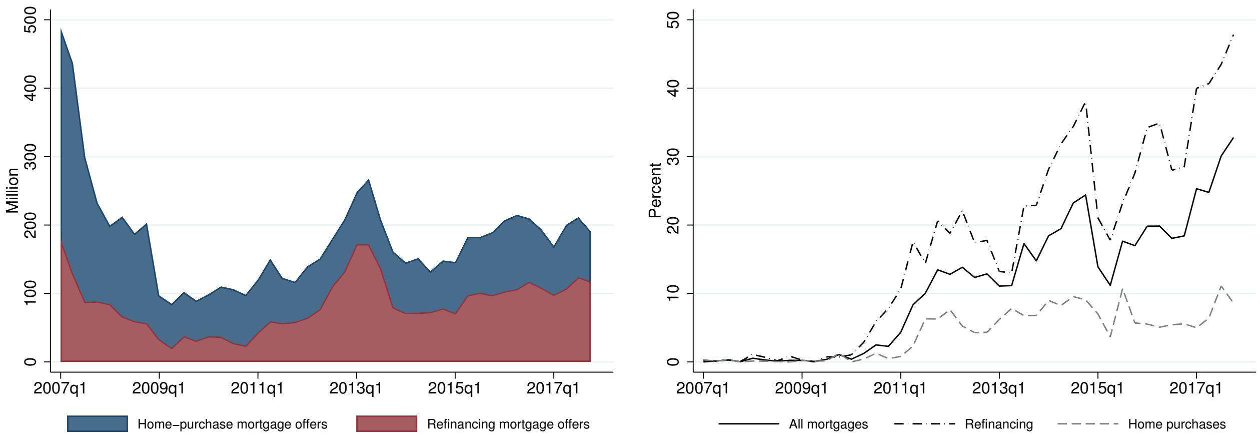
The CoreLogic home price index (HPI), accessed through FRS-RADAR-DW, is used to construct house price growth. The advantage of the CoreLogic data is that they are representative of all types of loans in the market (rather than just conforming loans in the FHFA HPI), and that they are available at relatively high frequency. The disadvantage is that they have limited coverage at fine geographic levels (e.g., county-level). To address this issues, for counties whose HPI data are unavailable, I use the house price growth in their corresponding MSAs. If a county is missing the HPI data and is not located in an MSA, I use the house price growth in its corresponding state. Additional analysis using the alternative FHFA county-level HPI data gives similar empirical results.

[32]Constructed by Robert Avery, the Avery file contains matching information for all lenders between the HMDA data and the FFIEC Call reports in each filing year. I downloaded the Stata version of this file made available by Neil Bhutta on his homepage: https://sites.google.com/site/neilbhutta/data.

[33]The New York Fed (FRBNY) Consumer Credit Panel/Equifax Data is a nationally representative anonymous random sample from Equifax credit files. The data track all consumers with a US credit file residing in the same household from random, anonymous sample of 5% of US consumers with a credit file. These data are used as a source of data but all calculations, findings, assertions are that of the author.

Figure B1: Advertising of U.S. mortgage lenders

(a) Aggregate volume of mortgage offers (b) Offers made by FinTech lenders



Source: Mintel-Comperemedia Direct Mail and Print Advertising Volume Dataset.

C Decomposing the Rate Gap

Let $\bar{r}_{c,t}$ denote the average mortgage rate of all outstanding mortgages in county c at time t,

$$\bar{r}_{c,t} \equiv \frac{\sum_{i=1}^{N_{c,t}} r_{i,c,t}}{N_{c,t}} = \frac{N_{c,t}^{refi}\bar{r}_{c,t}^{refi} + N_{c,t}^{pur}\bar{r}_{c,t}^{pur} + (N_{c,t} - N_{c,t}^{refi} - N_{c,t}^{pur})\bar{r}_{c,t-1}^{ex}}{N_{c,t}}, \tag{14}$$

where $N_{c,t}^{refi}$ and $N_{c,t}^{pur}$ denote the numbers of newly refinanced mortgages and newly originated home-purchase mortgages, respectively, in county c at time t. $\bar{r}_{c,t}^{refi}$, $\bar{r}_{c,t}^{pur}$ and $\bar{r}_{c,t-1}^{ex}$ denote the average rates of newly refinanced mortgages, newly originated home-purchase mortgages, and existing mortgages originated in $t-1$ or earlier. Rewrite equation (14) as

$$\bar{r}_{c,t} = s_{c,t}^{refi}\bar{r}_{c,t}^{refi} + s_{c,t}^{pur}\bar{r}_{c,t}^{pur} + (1 - s_{c,t}^{refi} - s_{c,t}^{pur})\bar{r}_{c,t-1}^{ex}, \tag{15}$$

where $s_{c,t}^{refi}$ and $s_{c,t}^{pur}$ are the shares of newly refinanced and newly originated home-purchase mortgages in all outstanding mortgages at time t.

The county-level rate gap, $Gap_{c,t}$, is the difference between the average outstanding mortgage rate and the prevailing market rate, i.e., $Gap_{c,t} \equiv \bar{r}_{c,t} - R_t$. Using equation (15) gives

$$Gap_{c,t} = s_{c,t}^{refi}\left(\bar{r}_{c,t}^{refi} - R_t\right) + s_{c,t}^{pur}\left(\bar{r}_{c,t}^{pur} - R_t\right) + (1 - s_{c,t}^{refi} - s_{c,t}^{pur})\left(\bar{r}_{c,t-1}^{ex} - R_t\right). \tag{16}$$

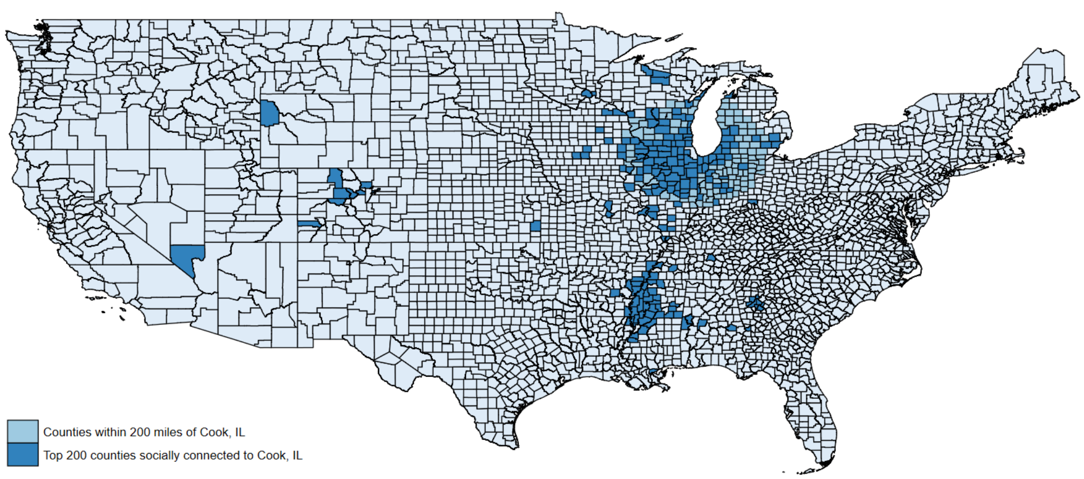
Equation (16) shows that, controlling for $\bar{r}_{c,t-1}^{ex}$, FinTech lending may reduce the rate gap through two effects:

1. **The price effect**. If FinTech lenders offer lower mortgage rates to new borrowers and/or refinancing borrowers than traditional lenders, $\bar{r}_{c,t}^{refi}$ and $\bar{r}_{c,t}^{pur}$ are smaller. All else equal, the rate gap is smaller.

2. **The quantity effect** Suppose all lenders offer new borrowers and refinancing borrowers the same rate at the market level, i.e., $\bar{r}_{c,t}^{refi} = \bar{r}_{c,t}^{pur} = R_t$. Since $\bar{r}_{c,t-1}^{ex} > R_t$, the rate gap falls if $s_{c,t}^{refi}$ and/or $s_{c,t}^{pur}$ increase. In other words, if FinTech lenders originate more new mortgages (either refinancing or home purchases) at the current market rate, all else equal, the rate gap shrinks. The equal-rate condition, $\bar{r}_{c,t}^{refi} = \bar{r}_{c,t}^{pur} = R_t$, can be relaxed. In fact, as long as $\bar{r}_{c,t-1}^{ex} > \bar{r}_{c,t}^{refi}$ and $\bar{r}_{c,t-1}^{ex} > \bar{r}_{c,t}^{pur}$, which is true over the sample period, originating more new mortgages will always reduce the rate gap.

D Additional Empirical Results

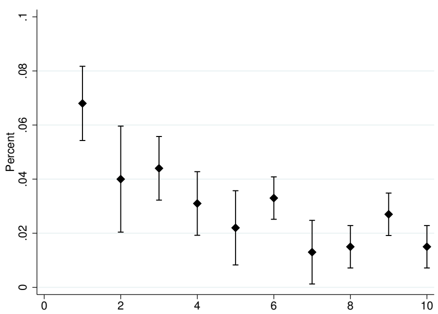
Figure D1: Geographically connected areas (GCAs) and socially connected areas (SCAs) of Cook county, IL



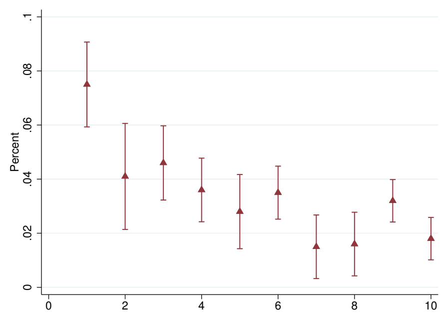
Notes: This figure highlights the GCAs (light blue) and the SCAs (dark blue) of Cook county, IL, which differ in several dimensions. First, many counties in Michigan are geographically connected to Cook county but are not socially connected to it (based on the SCI index). Second, many counties in Mississippi, Arkansas and Louisiana are located far away from Cook county but are socially connected to it. This is likely explained by past migration of African Americans from the South to the urban North during the Great Migration period.

Figure D2: Spillover effects from top 10 GCAs (top panel) and top 10 SCAs (bottom panel)

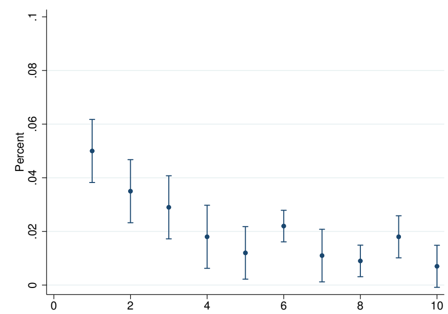
(a) GCA: All mortgages



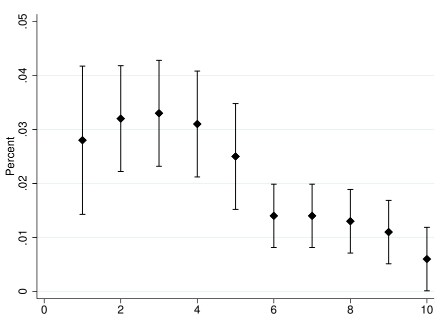
(b) GCA: Refinancing



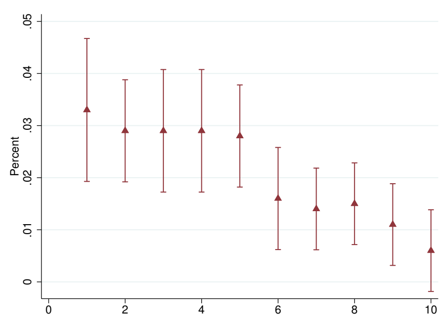
(c) GCA: Home purchases



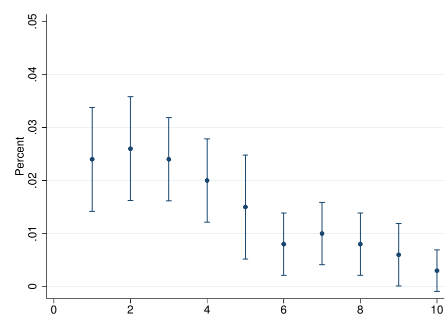
(d) SCA: All mortgages



(e) SCA: Refinancing



(f) SCA: Home purchases



Notes: Point estimates and the 95% confidence intervals obtained by estimating the specification in column (5) of Table 1 separately for each of the 10 closest GCAs and 10 closest SCAs. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

Table D1: Robustness to changing GCA and SCA thresholds

Panel I.	Dependent variable: ΔFinTech share					
Spillover from GCAs	Within 200 miles	Within 250 miles	Within 300 miles	Within 500 miles	Within 1000 miles	All counties
ΔFinTech share$^{GCA}_{-1}$	0.257***	0.237***	0.221***	0.187***	0.211***	0.239***
	(0.020)	(0.018)	(0.017)	(0.016)	(0.018)	(0.028)
County FE	x	x	x	x	x	x
County controls	x	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x	x
GCA controls	x	x	x	x	x	x
# Obs.	118,434	118,434	118,434	118,434	118,434	118,434

Panel II.						
Spillover from SCAs	Top 200 SCAs	Top 250 SCAs	Top 300 SCAs	Top 500 SCAs	Top 1000 SCAs	All counties
ΔFinTech share$^{SCA}_{-1}$	0.232***	0.240***	0.244***	0.253***	0.261***	0.257***
	(0.017)	(0.018)	(0.018)	(0.019)	(0.020)	(0.021)
County FE	x	x	x	x	x	x
County controls	x	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x	x
SCA controls	x	x	x	x	x	x
# Obs.	118,427	118,427	118,427	118,427	118,427	118,427

Notes: Results obtained by estimating the specification in column (5) of Table 1 for each alternative set of connected markets. ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

Table D2: Using FinTech growth in geographically distant but socially connected markets as IV for SCA spillover effect

Dept. variable:	Out of CZ		Out of 200 miles	
ΔFinTech share	1st stage	2nd stage	1st stage	2nd stage
ΔFinTech share$_{-1}^{SCA}$ (Fitted)		0.224***		0.221***
		(0.014)		(0.046)
ΔFinTech share$_{-1}^{SCA,out}$	0.785***		0.153***	
	(0.005)		(0.005)	
County FE	x	x	x	x
County controls	x	x	x	x
Division-by-quarter FE	x	x	x	x
SCA controls	x	x	x	x
# Obs.	118,419	118,419	118,419	118,419

Notes: This table shows the 2SLS estimates using an IV strategy similar to Bailey et al. (2018a). In the first stage, $\Delta FinTech_{c,t-1}^{SCA}$ is instrumented by $\Delta FinTech_{c,t-1}^{SCA,out}$, where SCA, out represents a subset of SCAs that are located (i) out of county c's commuting zone (CZ), or (ii) at least 200 miles away from county c. ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data. The second stage estimates are almost identical to the baseline estimate in Table 1.

Table D3: Alternative IV estimates exploiting banking regulation shifts

Dept. variable:	GCA spillover				SCA spillover			
ΔFinTech share	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFinTech share^M		0.936***		1.308***		0.798***		1.397***
		(0.117)		(0.445)		(0.198)		(0.516)
Capital ratio$^M_{2008}$	-2.391***				-1.113***			
	(0.110)				(0.109)			
MSR $^M_{2008}$			0.100***				0.052**	
			(0.019)				(0.024)	
State FE	x	x	x	x	x	x	x	x
County controls	x	x	x	x	x	x	x	x
GCA/SCA controls	x	x	x	x	x	x	x	x
1st stage F-stat	235.6		14.7		58.4		8.5	
# Obs.	3,095	3,095	3,095	3,095	3,095	3,095	3,095	3,095

Notes: The first two columns in each panel present the results from estimating an IV specification that uses the origination-share-weighted T1 capital ratio in 2008 as the instrument. The last two columns in each panel present the results from estimating an IV specification that uses the origination-share-weighted MSR over T1 capital in 2008 as the instrument. ** and *** denote significance at the 5% and 1% level, respectively. See text for the description of county-level control variables. County-level subprime shares are constructed using the FRBNY Consumer Credit Panel/Equifax data.

E Model Appendix

E.1 Recursive Formulation

The no-FinTech model. It is useful to first describe the recursive formulation of the model without FinTech lending. The household maximizes its expected lifetime utility by comparing the value of refinancing, V^R, and the value of not refinancing, V^N. The value function is $V = \max\{V^R, V^N\}$. Suppressing the region index, j, for notational simplicity,

$$\begin{aligned} V^R(b, a, y, r_0^b, r^b, f, p) = \max_{a', c} \quad & u(c) - f - \chi(r_0^b, r^b) + \beta \mathbb{E} V(b', a', y', r^b, r^{b'}, f', p') \\ s.t. \quad c + a' =& y + (1 + r^a)a - (1 + r^b)b + (1 - \phi)b' \\ b' =& \gamma p; \quad a' \geq 0, \end{aligned}$$

$$\begin{aligned} V^N(b, a, y, r_0^b, r^b, f, p) = \max_{a', c} \quad & u(c) + \beta \mathbb{E} V(b', a', y', r_0^b, r^{b'}, f', p') \\ s.t. \quad c + a' =& y + (1 + r^a)a - (1 + r_0^b)b + b' \\ b' =& b; \quad a' \geq 0, \end{aligned}$$

with $\log(y')$ and $\log(p')$ evolving according to equations (10) and (11).

The no-FinTech-spillover model. Next, consider the model in which FinTech lending is available but there is no FinTech spillover across social networks. In this case, the household maximizes its expected utility by choosing between V^R and V^N, where

$$\begin{aligned} V^R(b, a, y, r_0^b, r^b, f, p, Q) = \max_{a', c} \quad & u(c) - f + qQ - (1 - Q)\chi(r_0^b, r^b) + \beta \mathbb{E} V(b', a', y', r^b, r^{b'}, f', p', Q') \\ s.t. \quad c + a' =& y + (1 + r^a)a - (1 + r^b)b + (1 - \phi)b' \\ b' =& \gamma p; \quad a' \geq 0, \end{aligned}$$

$$\begin{aligned} V^N(b, a, y, r_0^b, r^b, f, p) = \max_{a', c} \quad & u(c) + \beta \mathbb{E} V(b', a', y', r_0^b, r^{b'}, f', p', Q') \\ s.t. \quad c + a' =& y + (1 + r^a)a - (1 + r_0^b)b + b' \\ b' =& b; \quad a' \geq 0, \end{aligned}$$

with $\log(y')$ and $\log(p')$ evolving according to equations (10) and (11).

The full model with FinTech lending and its spillovers (the baseline model). In the model where FinTech information can be obtained from both interactive and non-interactive sources, the household maximizes its expected utility by choosing between V^R and V^N, where

$$\begin{aligned}V^R(b,a,y,r_0^b,r^b,f,p,Q,E) = \max_{a',c} \quad & u(c) - f + \max\{qQ,eE\} - \mathbb{I}\left(\max\{qQ,eE\}=0\right)\chi(r_0^b,r^b) + \\ & \beta\mathbb{E}V(b',a',y',r^b,r^{b'},f',p',Q',E') \\ s.t. \quad c + a' =& y + (1+r^a)a - (1+r^b)b + (1-\phi)b' \\ b' =& \gamma p; \quad a' \geq 0,\end{aligned}$$

$$\begin{aligned}V^N(b,a,y,r_0^b,r^b,f,p) = \max_{a',c} \quad & u(c) + \beta\mathbb{E}V(b',a',y',r_0^b,r^{b'},f',p',Q',E') \\ s.t. \quad c + a' =& y + (1+r^a)a - (1+r_0^b)b + b' \\ b' =& b; \quad a' \geq 0,\end{aligned}$$

with $\log(y')$ and $\log(p')$ evolving according to equations (10) and (11).

Solution methods. The full model is characterized by a large number of state variables. One way to reduce the state space is to define a new random variable that combines information in f, Q and E. Let $Z = -f + \max\{qQ,eE\}$, with the cumulative density function F_Z. The value of refinancing, V^R, can be rewritten as

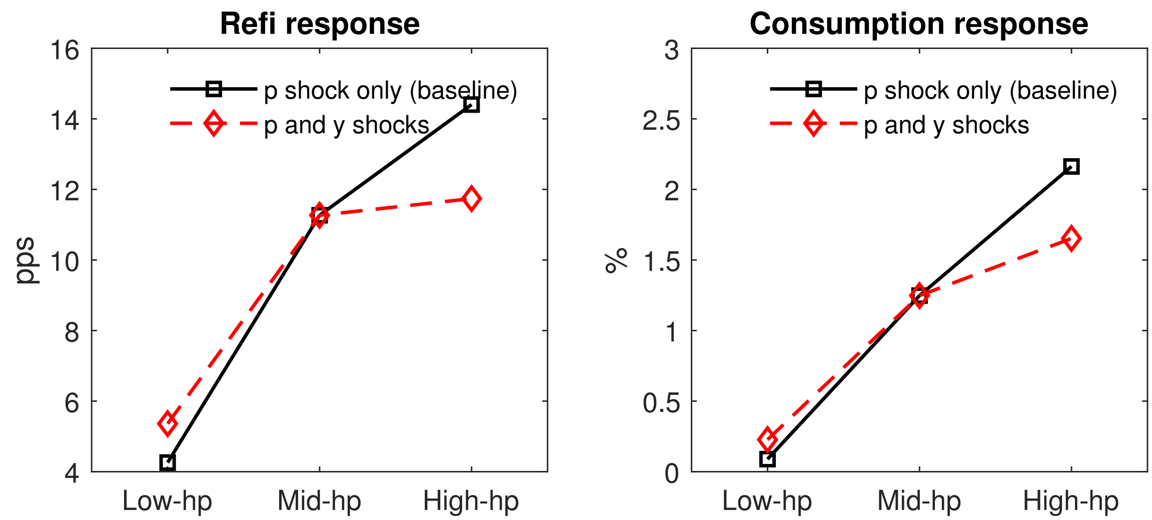
$$V^R(b,a,y,r_0^b,r^b,p,Z) = \max_{a',c} \quad u(c) + Z - \mathbb{I}\left(Z=-f\right)\chi(r_0^b,r^b) + \beta\mathbb{E}V(b',a',y',r^b,r^{b'},p',Z'),$$

subject to the same constraints.

The model is solved numerically using a value function iteration method. In the first step, the state space is discretized and the value functions are solved over fixed grids of the state space. In the second step, the policy functions are obtained by solving the maximization problem over finer grids conditional on the value functions obtained from the first step. All model simulations are based on the optimal choices of 100,000 households.

E.2 Additional Quantitative Results

Figure E1: Modeling correlated regional shocks to house prices and income



Notes: Simulated impact responses to a 1 pp permanent decline in the mortgage rate. In the baseline model, regions differ in the shocks to the house price. In the alternative model, regions are hit by correlated shocks to both house prices and income.

Table E1: Refinancing propensity conditional on having positive home equity

		FinTech expansion		Stronger spillovers		FinTech expansion and stronger spillovers	
	Baseline	$p^q = 0.25$	$p^q = 0.5$	$p^e = 0.25$	$p^e = 0.5$	$p^q = 0.25, p^e = 0.25$	$p^q = 0.5, p^e = 0.5$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low-HP region	13.1	16.0	19.8	16.1	20.0	18.4	23.5
Mid-HP region	17.1	19.7	23.0	20.2	24.3	22.2	27.2
High-HP region	18.7	21.9	26.4	22.1	26.8	24.8	30.9

Notes: Simulations from the calibrated model and alternative policy experiments for the impact period. See notes in Table 10.