Financial Technology and the Transmission of Monetary Policy: The Role of Social Networks

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Abstract

Financial technology-based (FinTech) lending is expected to ease U.S. mortgage market frictions that have weakened the transmission of monetary policy to households. This paper establishes that social networks play a key role in the spread of FinTech lending, further amplifying the effect of monetary stimulus. I provide causal estimates of the network effect of FinTech adoption: A one percentage-point 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. To quantify the role of FinTech lending and its network spillover in the transmission of monetary policy shocks, I build a heterogeneous-agent model with social learning. The model shows that refinancing and consumption responses to a monetary stimulus are 13% higher in the presence of FinTech lending and network spillovers, and that almost half of this improvement is accounted for by network spillovers. Counterfactual analysis suggests that a rise of the FinTech market share to 70% would increase consumption and refinancing responses by 50%-60% relative to the same economy without FinTech lending.

Keywords: FinTech, social network, mortgage, monetary policy, consumption, regional heterogeneity

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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, has been weakened by frictions in the U.S. mortgage market. One example is the failure of consumers to optimally refinance their mortgages, due to the complicated, infrequent nature of the refinancing process (e.g., Keys et al. (2016)). Another type of friction is capacity constraints faced by mortgage lenders that slow their responses to surging demand during periods of low interest rates (e.g., Fuster et al. (2021)).

The rapid growth of financial technology-based ("FinTech") lending after the financial crisis is expected to ease these frictions. Unlike traditional brick-and-mortar banks, FinTech lenders automate the mortgage origination process, allowing borrowers to complete their applications online in a streamlined 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 also more resilient to demand shocks.[2] These features are likely to facilitate the transmission of monetary policy through the household borrowing channel. 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 firms and features of their products, it has not investigated the propagation of FinTech through social networks. Social interactions play a key role in consumers' acquisition of information and financial decision-making. It stands to reason that FinTech adoption is affected by interactions with peers. To the extent that this peer influence is strong, the effect of a monetary stimulus will be further amplified. A rigorous analysis of the role of FinTech

[1] FinTech lenders in this paper 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 with an even higher presence in the refinancing market.

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

lending in the transmission of monetary policy has to take into account both FinTech product features and FinTech propagation. Using a variety of identification strategies, I provide causal estimates of the spillover of FinTech lending across U.S. county-level social networks. To quantify the effects of monetary policy shocks on household borrowing and consumption in the presence of FinTech lending, I develop a heterogeneous-agent model that incorporates key features of FinTech lending and social learning. The model facilitates counterfactual analyses to assess separately the role of FinTech product features, social networks, and mortgage market frictions in the monetary transmission.

I start by providing empirical evidence on how FinTech lending is propagated across U.S. counties through social networks. The causal inference faces two major challenges: (i) how to measure social networks of U.S. counties, and (ii) how to solve the identification issue arising from the existence of unobserved common shocks or corrected local shocks that drive FinTech to grow simultaneously in multiple markets without market-to-market spillovers.[3] To overcome the first challenge, I employ the novel social connectedness index developed by Bailey et al. (2018b), who use granular data on social networks of U.S. Facebook users and aggregate this information to the county-pair level. This index better captures social interactions between counties than conventional measures such as geographical distance. To overcome the identification challenge, I employ three distinct but complementary empirical strategies, which together provide compelling evidence for a sizable spillover of FinTech lending through social networks.

The first strategy takes advantage of the panel nature of county-level data, exploiting variation in lagged FinTech growth in a county's socially connected markets (as prescribed by Manski (1993) and Brock and Durlauf (2001)). My empirical specifications also control for county fixed effects, region-specific time trends and a number of time-varying characteristics of counties and their networks to address the concern of endogeneity. Despite the inclusion of this rich set of controls, however, it is still possible that some unobserved shocks may trigger FinTech responses in neighboring markets through channels other than social interactions. To establish identification, I adapt the instrumental-variable (IV) strategy of Bailey et al.

[3] The identification of causal spillovers in the peer effects 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.

(2018a) to the panel setting, exploiting variation in lagged FinTech growth in a county's socially connected but geographically distant markets.

This strategy supports a sizable FinTech spillover effect. A county's FinTech market share increases by 0.23-0.26 percentage points (pps), when FinTech market shares in its socially connected markets grow by 1 pp. A breakdown by loan purpose suggests that the spillover is larger for FinTech refinancing than for FinTech home purchases, consistent with the fact that refinancing, unlike home-purchase mortgages, is easier to automate. Moreover, I find that counties with higher social and economic mobility, such as those located in metropolitan areas, having higher shares of college graduates and experiencing larger migration flows in the previous year, are more responsive to the network spillover.

While the panel IV approach exploits variation across counties' geographically distant social networks, it remains agnostic about the underlying structural causes of FinTech growth in regional markets. This question is addressed by a second identification strategy, which is motivated by the finding in the banking literature that an important driver of the fast growth of non-bank lending after the financial crisis was increasingly stringent banking regulations, which effectively reduced banks' presence in the mortgage market (Buchak et al. (2018)). At the county level, the exposure of a market to these banking regulations depends on the pre-crisis capital structure of the banks operating in that county, which varies substantially in the cross section and is plausibly unrelated to post-crisis demand for FinTech loans. This suggests that the exposure of a county's social network to rising regulatory burdens can be used to construct instruments for FinTech growth in these markets. This cross-sectional IV strategy reveals a strong spillover effect of FinTech lending in the long run, corroborating the findings from the panel IV strategy.

Unlike the two IV approaches, my third empirical approach is designed to capture the dynamics, and in particular, the speed and persistence of a FinTech spillover. In the data, many counties experienced a noticeable acceleration in FinTech growth at some point, which may be statistically identified as a structural break. My approach is to determine the timing of the structural break for each county (if the break exists), and to estimate the probability that a county experiences such a break around the time when a break happens elsewhere in its network.[4] Using this event-study approach, I find that the probability of experiencing a break increases significantly in the four quarters following a break in the counties it is socially connected to, with the peak response observed in the second quarter. These patterns suggest a rapid spillover of FinTech lending, which gradually dissipates after one year.

My empirical analysis points to an important role of social networks in the market penetration of FinTech lending. To assess the implications of FinTech market penetration for the transmission of monetary policy, as well as to inform my modeling choices in the quantitative analysis, I turn to another dataset that covers the stock of U.S. mortgages (McDash) and document two additional facts. First, in counties where FinTech market penetration is high, the pass-through of market interest rates to the average borrower is more complete. Second, this effect is almost entirely driven by a higher fraction of borrowers refinancing their mortgages at the market rate (i.e., the composition effect), rather than FinTech lenders offering lower rates than other lenders (i.e., the price effect).

Motivated by these empirical findings, I develop a structural heterogeneous-agent model to quantify the role of FinTech lending and its network spillovers in the transmission of monetary policy shocks to households. The model incorporates three key features of FinTech lending. First, FinTech lenders offer more convenient services, which are valued by consumers (Buchak et al. (2018)). Second, FinTech lenders respond more elastically to surging demand (Fuster et al. (2019); Fuster et al. (2021)). Third, social interactions help spread information about FinTech lending, making a mortgage transaction even more accessible from the consumer's point of view.

The model has rich heterogeneity on the household side arising from idiosyncratic income shocks, balance sheet conditions, and household-specific long-term mortgage rates, all of which matter for consumption and refinancing choices. While refinancing amid a monetary stimulus benefits most households, two types of frictions in the model prevent households from taking the action. One is the non-pecuniary cost associated with refinancing (e.g., the time and effort spent searching for offers, visiting the lender's office and completing the paperwork). The other is capacity constraints faced by traditional lenders (e.g., hiring

[4] This approach has also been used, for example, to identify sharp unexpected changes in house price growth (e.g., Ferreira and Gyourko (2011); DeFusco et al. (2018); Charles et al. (2018); Dokko et al. (2019)).

difficulties, training costs and staffing issues). FinTech lending reduces these frictions and increases the refinancing and consumption responses to the monetary stimulus. Despite its advantages, however, FinTech lending is not adopted by everyone, because households are not fully informed. They learn about FinTech lending through interactive sources (e.g., social networks) and non-interactive sources (e.g., advertisements or search engines) with some probabilities, which in turn determine the market share of FinTech lenders.

My model shows that, when FinTech market penetration and social network intensity are calibrated to data in 2017, a monetary stimulus that lowers the mortgage rate by 1 pp raises the refinancing propensity by 11.3 pps. In an otherwise identical economy without FinTech lending and network spillovers, the refinancing propensity only increases by 10 pps upon the policy shock, suggesting a 1.3 pp (or a 13%) improvement in the effect of the monetary stimulus. When the network spillover is shut down, the refinancing propensity rises by 10.7 pps (or 7%), suggesting that almost half of the improved monetary-policy effect is due to FinTech network spillovers. Quantitatively similar results are obtained for consumption responses.

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 a counterfactual analysis of how the use of FinTech changes the effects of monetary policy. The model helps distinguish between two sources of FinTech market penetration: the firm-side expansion (e.g., entry of new lenders, growth of existing FinTech lenders and transition of traditional lenders) and the social-network expansion (e.g., more ways to connect with friends). Model simulations show that a rise of the FinTech market share to 70%, for example, would increase consumption and refinancing responses by 50%-60% compared to the same economy without FinTech lending.

Relation to the literature. This paper first contributes to the macroeconomic literature on the transmission of monetary policy shocks through the mortgage borrowing channel (e.g., Beraja et al. (2018); Wong (2019); Greenwald (2018); Garriga et al. (2017); Cloyne et al. (2020); Berger et al. (2021)). So far, this literature has not incorporated different types of market frictions as documented in the empirical finance literature (Andersen et al.

(2020); Keys et al. (2016); Agarwal et al. (2015); Campbell (2006); Fuster et al. (2021)). Nor has it considered the role of financial technology in the monetary transmission. This paper incorporates FinTech lending within the analysis of the household problem, rendering the effects of monetary policy state-dependent. As FinTech lending continues to expand in the U.S. mortgage market, conventional models with standard calibration are likely to underestimate the changing responsiveness of the household sector to monetary policy shocks.

This paper also adds to a new literature on technological innovations in the mortgage industry 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 new lending model may impact future regulations. I contribute to this literature by presenting evidence on the role of social networks in amplifying monetary-policy effects with FinTech, calling further attention from policy makers to the broad implications of technology innovations.

This paper also contributes to the microeconomic literature studying social interactions and household financial decision-making.[5] This literature has offered extensive evidence on peer effects, for example, in home purchases (Bailey et al. (2018a)), leverage choices (Bailey et al. (2019); Georgarakos et al. (2014)), electronic product adoption (Bailey et al. (2021)) and consumption (Agarwal et al. (2016); De Giorgi et al. (2020); Moretti (2011)), but these estimates are not informative about the magnitude of the peer effects in FinTech mortgage adoption. While the related work by Maturana and Nickerson (2019) and McCartney and Shah (2021) estimates the peer effects in mortgage refinancing and lender choices, it focus on a specific setting (interactions between Texas school teachers) or a small geographic area (Los Angeles). Moreover, their estimates do not speak to the effect on FinTech refinancing, which is likely to be stronger than on a typical refinancing because of the highly standardized online application system offered by FinTech lenders. I provide causal estimates for this effect, and more importantly, use these estimates to discipline a structural model that studies the implications of FinTech lending for the transmission of monetary policy shocks.

Finally, this paper connects to the literature on how shadow banks affect the transmission

[5]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.

of monetary policy through different channels. Xiao (2020) focuses on upstream shadow banks that take deposits from households and shows that deposits flow out of the banking system to the uninsured shadow banking sector when the Fed raises interest rates, affecting the deposits channel of monetary policy (Drechsler et al. (2017)). Buchak et al. (2022) focus on downstream shadow banks that specialize in loan origination and study their interaction with traditional banks in affecting the consequences of aggregate policies such as quantitative easing (QE). Unlike these studies, I focus on the role of consumers' social interaction in spreading the footprint of FinTech shadow banks, which amplifies the transmission of monetary policy through the refinancing channel.

The remainder of the paper is organized as follows. Section 2 provides estimates of the FinTech spillover effect using three distinct identification strategies. Section 3 documents additional empirical evidence linking FinTech market penetration to the pass-through of market interest rates. Sections 4 and 5 describe the structural model and its calibration. Section 6 quantifies the role of FinTech lending and network networks in the monetary transmission and highlights the policy implications of the model through a series of counterfactual analyses. Section 7 concludes. To conserve space, the description of the datasets used in this paper is provided in Appendix B.

2 FinTech Spillovers across Social Networks

This section presents three distinct and complementary empirical strategies for estimating the causal spillover effect of FinTech lending across county-level social networks: (i) a panel IV approach that exploits variation in lagged FinTech growth in a county's geographically distant social networks, (ii) a cross-sectional IV approach that exploits variation across counties in the exposure to post-crisis banking regulations, and (iii) an event-study approach that characterizes the dynamic spillover effect. I conclude this section by presenting evidence that the estimated spillover effects reflect demand-side spillovers (i.e., consumers' social interactions) rather than supply-side spillovers (i.e., FinTech lenders' business strategies).

2.1 The Panel IV Approach

2.1.1 Measuring Network Spillovers

Estimating the network spillover effect first requires measuring social networks. At the county level, a conventional measure of connectedness is based on geographical distance, in line with theory and evidence in the trade literature that bilateral trade tends to fall with distance. An alternative measure, the social connectedness index (SCI), was introduced by Bailey et al. (2018b) who used granular data on friendship links of U.S. Facebook users and aggregated this information to the county-pair level. This index directly captures the intensity of social interactions between individuals in any two counties.[6]

Given either one of these measures, I construct a network spillover variable, which is the weighted change in the FinTech market shares in a county's connected markets.[7] Using the distance-based measure, for example, the spillover from county c's geographically connected areas (GCAs) is

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

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, so that the largest weights are assigned to the counties that are most connected to county c. $\Delta FinTech_{j,t}$ is the four-quarter change in the FinTech market share in county j and quarter t. J_c^{GCA} denotes the set of GCAs of county c.

Alternatively, using the SCI-based measure, the spillover from county c's socially connected areas (SCAs) is

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

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.

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

[7]The FinTech market share in a county over a specific period (e.g., a quarter) is computed as the share of total mortgage originations of the county over this period accounted for by FinTech lenders. The loan-level HMDA data are used to construct county-level mortgage originations (see Appendix B for data description).

I include counties within 200 miles of county c in J_c^{GCA}, and counties ranked as top 200 socially connected counties of county c (according to the SCI) in J_c^{SCA}. Increasing these thresholds has little impact on the estimated spillover effect, as shown in Appendix Table D1.[8] An example of a county's GCAs and SCAs is illustrated in Appendix Figure D1 for Cook county, IL, where Chicago is located.

2.1.2 Estimating Spillover Effects

The main empirical question in this paper is how FinTech growth in a county's social network affects this county's FinTech growth. The identification of this causal effect is complicated by the existence of common shocks or correlated local shocks that may cause FinTech to grow simultaneously in connected markets without market-to-market spillovers. As outlined in Manski (1993) and Brock and Durlauf (2001), the use of panel data alleviates the concern of simultaneity, if the dynamic structure of network spillovers is exploited. I therefore estimate the effect of lagged spillover from a county's GCAs and SCAs on the county's FinTech market share growth,

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

where $M \in \{GCA, SCA\}$. $\Delta FinTech^M_{c,t-1}$ is the network spillover variable described in equations (1) and (2). β_1 is the key parameter of interest capturing the FinTech spillover effect. The regression includes census division-by-quarter fixed effects, $\gamma_{d,t}$, county fixed effects, γ_c, and a number of time-varying controls of the county's and its connected markets' social, economic and demographic conditions, $\mathbf{x}_{c,t}$ and $\bar{\mathbf{x}}^M_{c,t}$.[9] The standard errors are clustered at the county level.[10]

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

[9] The control variables include the percent changes in the house price, in the employment and in the population, as well as the shares of the young population, of the minority population and of subprime borrowers. As is standard in the peer effects literature, the controls for the county's network, $\bar{\mathbf{x}}^M_{c,t}$, take the linear-in-mean form. This means that $\bar{\mathbf{x}}^M_{c,t}$ includes the same set of variables as $\mathbf{x}_{c,t}$, but each of these variables is a connectedness-weighted average across counties in M.

[10] Since county-level lending activities feature 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 yields similar results.

The presence of unobserved shocks that affect neighboring counties is a potential challenge. It is possible that some shocks only affect a very narrow geographical range and will not be picked by the census division-by-time fixed effect, or that counties with more neighboring markets respond more strongly to shocks for reasons other than social interactions. Though my control variables include house price changes, demographic shifts and other county-level characteristics to help account for loan demand, I use instruments to further abstract from these confounding factors. The IV approach recognizes that the SCI-based connectedness measure can isolate variation in FinTech lending in a county's socially connected but geographically distant markets, easing the concern that geographically connected markets are prone to common shocks that are hard to control for.[11] Specifically, I instrument $\Delta FinTech^{SCA}_{c,t-1}$ in equation (3) with the change in the FinTech market shares in county c's socially connected but geographically distant markets, $\Delta FinTech^{SCA,Out}_{c,t-1}$. As in Bailey et al. (2018a), I use FinTech growth in SCAs that are out of county c's commuting zone as the instrument, but I show in robustness checks that using alternative distance thresholds (e.g., at least 100 or 200 miles away) gives almost identical estimates.

2.1.3 Results

Panel I of Table 1 presents the estimated spillover effect using the distance-based measure of connectedness. The estimate is stable across specifications, showing that a 1 pp increase in the GCAs' FinTech market share raises a county's FinTech market share by 0.25-0.26 pps. Panel II shows very similar estimates: A 1 pp increase in the SCAs' FinTech market share raises a county's FinTech market share by 0.23-0.24 pps. Panel III presents the IV estimates using FinTech growth in a county's out-of-commuting-zone SCAs as the instrument. The effect is 0.23, similar to the OLS estimates, suggesting that the inclusion of a rich set of controls and fixed effects is effective in addressing concerns of endogeneity. These estimates imply a sizable spillover effect: If the growth of the GCAs' or SCAs' FinTech market share moves from the 10^{th} to 90^{th} percentile of the distribution, it will raise the county's FinTech market share by 1.3 pps, a 22% increase relative to the unconditional mean (about 6 pps).

[11] Bailey et al. (2018a) originally proposed this strategy to isolate exogenous changes in the house prices experienced by a person's friends and to study how these changes affect this person's housing investments. I adapt their approach to the panel setting.

The fact that GCA and SCA spillover effects are similar 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 $\Delta FinTech_{c,t}^{SCA}$).

So far, the spillover effect is estimated for all types of FinTech mortgages including both refinancing and home purchases. An interesting question is which type of lending is more responsive to the network spillover. Table 2 shows the spillover effect by loan purpose (columns 1 and 2), focusing on the SCI-based connectedness. Both OLS and IV estimates confirm that FinTech refinancing is more responsive, consistent with the fact that refinancing is easier to process automatically from the lender's point of view, unlike home-purchasing loans that require coordination with other parties. Specifically, a 1 pp increase in the SCAs' FinTech market share raises a county's FinTech refinancing share by 0.25 pps, almost twice as much as the effect on the FinTech home-purchasing share.

Additional evidence shows that the rise in the FinTech market share is associated with a growing volume of FinTech lending. Column 3 of Table 2 shows the effect on the four-quarter change in the FinTech lending volume (normalized by the previous-year total originations). It increases by about 0.3 pps for a 1 pp increase in the SCAs' FinTech market share. Given that FinTech originations accounted for 6% of the overall market, this result implies that the FinTech volume grows by about 5% as a result of the spillover effect. Both refinancing and purchasing volumes grow (columns 4 and 5), while the effect on the FinTech refinancing volume is twice as high as that on the home-purchasing volume.

Robustness. Appendix Table D2 presents results from several robustness checks. Columns (1) and (2) use alternative instruments — FinTech growth in a county's SCAs that are at least 100 or 200 miles miles away from this county. The next three columns replace the network-spillover variable, $\Delta FinTech_{c,t-1}^{M}$, with the one based on SCAs' or GCAs' FinTech refinancing shares (as opposed to overall FinTech shares in the baseline), which addresses the concern of noisy estimates due to the seasonality and volatility in home-purchasing originations. The last three columns present the dynamic quarterly responses with four lags (as opposed to the four-quarter cumulative response in the baseline). The results from these analyses are similar to and consistent with the estimates in Table 1.

2.1.4 Heterogeneity in FinTech Spillover Effects

While the estimates in Section 2.1.3 inform us about the average spillover effect, they mask substantial heterogeneity across counties and their connected markets. In this subsection, I use the panel IV strategy to examine how the spillover effect varies with the degree of connectedness and which counties are more responsive to the network spillover.

First, I test whether a gravity relationship holds for the spillover effect, i.e., 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 (e.g., top 50 SCAs). The instrument is also reconstructed accordingly using counties in this subset but geographically distant from county c. Table 3 presents the IV estimates, which show a clear and intuitive pattern that markets most connected to a county have the largest impact on the county's FinTech lending, and that the effect monotonically increases with social connectedness. Appendix Figure D2 shows the spillover effect separately estimated for a county's top 10 SCAs and top 10 GCAs. The robust declining pattern (over the connectedness measure) provides further support to a gravity relationship.

Which counties are more responsive to the network spillover? One natural hypothesis is that counties that are more connected to the outside world and are more socially and economically mobile are likely to be more responsive. To evaluate this hypothesis, I interact $\Delta FinTech^{SCA}_{c,t-1}$ with one of the four county characteristics in Table 4. The instruments are constructed accordingly by interacting $\Delta FinTech^{SCA,Out}_{c,t-1}$ with these characteristics. The IV estimates show that, the spillover effect is larger for counties located in metropolitan areas with larger population (column 1), for counties with higher shares of college graduates (column 2), for counties with higher shares of African Americans (column 3), and for counties having larger migration flows in the previous year (column 4), which jointly supports the hypothesis.

2.2 The Cross-Sectional IV Approach

While the panel IV strategy exploits variation across counties' distant social networks, it is agnostic about the underlying structural causes of FinTech growth in regional markets.

To strengthen the identification of causal spillovers, I now turn to an approach that uses instruments to isolate a specific source of the differential growth of FinTech in county markets: shifts in U.S. banking regulations after the financial crisis.

As documented in Buchak et al. (2018), traditional banks experienced increasingly stringent regulations after the financial crisis. One prominent example is the minimum requirement on risk-based capital ratios imposed by the Dodd-Frank Act. As a result, banks' tier 1 capital (T1) ratios rose 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, which did not face these regulatory burdens, to grow.

At the county level, however, the exposure of a market to tightened regulations depends on the pre-crisis capital structure of the banks operating in that county, which varies substantially and is plausibly unrelated to post-crisis demand for FinTech loans. This suggests that the exposure of a county's social network to rising regulatory burdens can be used to construct instruments for FinTech growth in these markets. Since the nature of the shock is cross-sectional and it took banks several years to adapt to the new regulations, my analysis focuses on FinTech growth in the period of 2008-2015, as in Buchak et al. (2018) and Begley and Srinivasan (2022). For the baseline IV estimate, I construct instruments using a straightforward extension of Buchak et al.'s approach. In general, alternative IV strategies may be designed to exploit variation in counties' exposure to banking regulation shifts. I discuss several alternatives of this kind in the robustness section.

The key instrumental variable for the baseline estimate is the origination share-weighted change in banks' T1 ratios in a county's network markets, further weighted by the county connectedness measure:

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

where $M \in \{GCA, SCA\}$. $\omega_{j,c}^M$ is defined as in equations (1) and (2). $s_{b,j}$ denotes bank b's origination share in county j in 2008. $\Delta T1Ratio_b$ denotes the change in bank b's T1 ratio between 2008 and 2015.

Another instrumental variable included is the share of mortgages originated by banks in county c's network markets in 2008, weighted by the county connectedness measure:

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

Note that the two instrumental variables would be the same if the change in the T1 ratio, $\Delta T1Ratio_b$, were constant across banks. The two-stage least-squares (2SLS) estimation is implemented as

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

County c's own change in the T1 ratio and bank share are included in $\mathbf{x}_c$ as controls, together with other variables that may affect loan demand (i.e., house price growth, employment growth and demographics). State fixed effects are included to account for any state-level differences in trends that drive loan growth across lenders. The assumption underlying the exclusion restriction is that, after controlling for the county's own exposure to regulatory shifts, the regulatory changes experienced by its network counties only affect this county's FinTech lending indirectly through their impact on the network counties' FinTech growth.[12]

Table 5 presents the baseline IV estimates. The first-stage regression shows that counties where banks faced the greatest regulatory pressure after the financial crisis experienced the largest growth of FinTech lending, consistent with Buchak et al. (2018). Conditional on the change in the T1 ratio, counties with higher bank shares at the onset of the crisis actually saw lower FinTech growth in subsequent years. 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 IV approach, likely due to the longer horizon of the cross-sectional estimation.

[12] In this strategy, variation across counties in the exposure to regulatory shifts comes from two sources: (i) the composition of mortgage lenders in a county before the crisis, and (ii) changes in the T1 ratios of the banks operating in the county. The premise is that changes in the bank-level T1 ratio are driven by unexpected shifts in banking regulations after the crisis. One may be concerned that these changes may instead reflect consumer demand for FinTech lending after the crisis. I address this concern in the robustness section by developing alternative instruments.

Overall, the cross-sectional IV strategy reveals a strong spillover effect of FinTech lending in a longer horizon, corroborating the finding using the panel IV approach.

Robustness. The idea of exploiting variation across counties in the exposure to post-crisis banking regulations may be extended to develop a number of alternative IV strategies. This section presents three implementations. The results are summarized in Appendix Table D3 for the SCI-based connectedness measure, showing a spillover effect of 1-1.4 pps, similar to the estimate in Table 5.

One concern about the baseline cross-sectional IV strategy is that changes in the T1 ratio after the crisis may be endogenous to demand for FinTech loans over this period. To address this concern, I construct an instrument using changes in banks' T1 capital ratios between 2006 and 2008 (as opposed to changes in T1 ratios from 2008 to 2015 in the baseline). The rationale is that counties where banks increased their capital buffer the most after the crisis were counties where banks decreased their capital the most before the crisis. This decrease was largely due to insufficient supervisory scrutiny and cannot possibly be determined by post-crisis demand for FinTech.[13] The results are shown in the first two columns of Table D3. The instrument has the expected sign and a high predictive power in the first stage, and the second stage estimate of the spillover effect is similar to the baseline.

The second alternative strategy is motivated by the finding in Begley and Srinivasan (2022) that the massive regulatory burdens following the crisis fell disproportionately on the "Big Four" banks (Bank of America, Citibank, JP Morgan and Wells Fargo) and, as a result, they contracted mortgage lending the most. This suggests that the exposure of a county's social network to Big4 lending before the crisis may be used as an instrument. The rationale is that counties where Big4 had the highest presence before the crisis were most likely to experience Big4 withdrawal in response to the regulatory burdens. I therefore construct a network IV that weights the Big4 share of mortgage origination in 2008 in a county's network market by the social connectedness measure. The estimation results are shown in the middle two panels of Table D3, supporting the baseline estimates.

[13]For the same reason, using the instrument based on the origination share-weighted levels of T1 ratios in 2008 gives very similar estimates. Counties where banks had the lowest level of regulatory capital in 2008 were counties where banks decreased their capital the most before the recession.

A general concern about using T1 ratio-based instruments is that these variables may also capture the impact of regulations on non-mortgage lending, likely introducing confounding factors through other channels. To address this concern, I construct another instrument based on counties' exposure to regulatory changes specifically targeting mortgage lending. The instrument is similar to that in equation (4), with the term in the parenthesis replaced by the origination share-weighted mortgage servicing assets as a percent of T1 capital (or MSR ratio) in county j in 2008. Intuitively, since holding mortgage-servicing assets became more costly under post-crisis regulations, banks with higher MSR ratios before the crisis are more likely to reduce their mortgage lending. The results are shown in the last two columns of Table D3, and the spillover effect is similar to the baseline estimate.

2.3 The Event-Study Approach

The use of panel and cross-section IV strategies in Sections 2.1 and 2.2 strengthens the identification of causal spillovers, but these approaches are not designed to capture the full dynamics (e.g., the pre-trend, speed and persistence) of the FinTech spillover. To shed light on this issue, my third empirical approach uses an event study. In the data, many counties display a noticeable acceleration in FinTech growth at some point, which may be statistically identified as a structural break. My approach is to first find the timing of the structural break for each county, and then estimate the probability that a county experiences such a break around the time when a break happens in its network.

Using a procedure similar to Charles et al. (2018), I estimate a series of regressions for each county with quarterly data and search for a single structural break:

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

where $FinTech_{c,t}$ is the FinTech market share in county c and quarter t. t_c^* is a potential structural break point between time $\underline{t}$ and $\bar{t}$. $\mathbb{I}(\cdot)$ is an indicator function. Equation (7) implies that, if the structural break point exists (denoted by $\hat{t}_c^*$), county c's FinTech market share grows at rate α_c before the break and at rate $\alpha_c + \beta_c$ after the break.[14] The break point

[14] I model the structural break for levels of FinTech market shares rather than for changes (e.g., Ferreira and Gyourko (2011) and DeFusco et al. (2018)), because the regressions in changes fit the data poorly.

maximizes the R^2 of equation (7) subject to the constraint that $\beta_c > 0$ and the boundary condition that it is located between 2008Q2 and 2016Q2.[15]

Figure 2 illustrates this procedure for two counties: Fairfax in Virginia, where no break is found, and Salt Lake in Utah, where a break occurred in 2011Q2. Among the 3,039 counties for which data are available, 1,267 counties experienced a break. Panel (a) of Figure 3 plots the distribution of the break timing, showing large variation across counties. Panel (b) plots the average FinTech market share around the break, which rises sharply from 3% prior to the break to about 10% in three years.

Since these break points are identified statistically, one concern is that they may be correlated with factors affecting loan demand, confounding the identification. To address this concern, Appendix Table D4 shows the results from estimating a panel linear probability model that predicts the timing of the structural break using observables (house price changes, employment growth and demographics). None of these variables has any explanatory power. Appendix Figure D3 shows the dynamic responses of six outcome variables around the break. The only variable that displays a significant change after the break is the FinTech market share. There is no evidence that the identified breaks are driven by or associated with changes in local economic and demographic conditions.

Given identified structural breaks, I use an event-study specification to estimate the change in the probability that a county experiences a break around the time when at least one of its network markets experiences such a break,

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

where $M \in \{GCA, SCA\}$. $\mathbb{I}(Break)_{c,t}$ is an indicator for a break in county c at quarter t. $\mathbb{I}(t - \hat{t}^*_{c,M} \in k)$ equals one if quarter t is in the kth year since the quarter in which any of county c's network markets experiences a structural break. The omitted category is the four-quarter period prior to the network's break. β_1^k captures the dynamic spillover effect.

Table 6 shows the event-study estimates for the set of 25, 50, 75 and 100 most connected

[15] 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.

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 following a break elsewhere in its network. Third, breaks that happen in a county's most connected markets (e.g., top 25 SCAs) have the largest impact on the county's probability of experiencing a break. Fourth, the spillover effect diminishes after one year. To shed light on the speed of the spillover, I focus on the 25 most connected markets of a county and estimate the county's quarterly response. Figure 4 shows that the response peaks in the second quarter following the network's break before gradually coming down, suggesting a fast dissemination of information across networks.

2.4 Demand-Side Spillovers vs. Supply-Side Spillovers

My analysis thus far has established a strong spillover effect of FinTech lending across social networks. 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 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 lenders' business strategies, one would expect the spillover to be reflected in lenders' advertising strategies as well. Mintel Comperemedia Inc. 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 answer two questions. First, whether the volume of advertising sent by FinTech lenders to a county is affected by the volume of FinTech advertising sent to the county's social network. Second, whether controlling for changes in FinTech advertising in counties and their networks affects the estimated spillover effect. Given the panel feature of the advertising data, I use the panel IV approach to address these questions.

The results in panel I of Table 7 answer 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, $\Delta FinAds_{c,t}$ and $\Delta FinAds^{M}_{c,t-1}$. The instrument, $\Delta FinAds^{SCA,Out}_{c,t-1}$, is constructed accordingly to exploit variation in FinTech advertising in county c's distant social networks. There is no evidence for a spillover of FinTech advertising, regardless of the identification strategy. Panel II addresses the second question by including log changes in FinTech advertising in counties and their connected markets as controls in equation (3). The spillover-effect estimates are unchanged from the baseline estimates in Table 1. These results provide no support to the view that supply-side spillovers drive my causal estimates.

On the demand side, it is difficult to provide direct evidence showing that it is the chats with friends and family that lead to FinTech adoption, as loan-level data do not reveal borrower-level relations. Instead, my analysis has relied on two measures of social connectedness to approximate these interactions at the county level, and I have used three distinct empirical strategies to rule out the simultaneity due to non-interaction channels. Nevertheless, external evidence provides some direct support to this narrative. The PricewaterhouseCoopers (PwC) consumer finance group conducted a national survey in 2015 to study consumer preferences in loan origination.[16] Two results from this survey shed light on the role of technology and social interactions in mortgage origination. First, whereas most consumers in 2013 preferred completing mortgage applications in traditional methods and interacting with lenders, most consumers in 2015 preferred completing this task online, suggesting preferences shift toward technology-based lending. Second, as shown in Appendix Figure D4, consumers rank "friends and family" as the second most influential referral source for mortgages (27%). The most influential source is "existing banking relation" (29%), which is not applicable in the case of FinTech origination because FinTech lenders do not take deposits and specialize in mortgage originations. Interestingly, social media beyond friends and family (e.g., social media campaigns) are not an important referral source; it is friends and family whom consumers may interact with through social media matter for their

[16]The survey had approximately 2,000 respondents above the age of 18 across the U.S., who were chosen based on their ownership of four major lending products (auto loans, home mortgages, student loans and personal loans) using a population-targeting survey approach. It was administered online in June 2015. The full report "Consumer lending: Understanding today's empowered borrower" is available at PwC's website.

loan decisions.

3 FinTech Penetration and Interest Rate Pass-Through

My analysis has established that social networks play a key role in the market penetration of FinTech lending. To assess the implications of FinTech market penetration for the transmission of monetary policy, I turn to the dataset covering the stock of U.S. mortgages (McDash) and document two additional facts. First, in counties where FinTech market penetration is high, the pass-through of interest rates to the average borrower is more complete. Second, this effect is almost entirely driven by a higher fraction of borrowers refinancing their mortgages at the market rate, rather than FinTech lenders offering lower rates than traditional lenders. These facts motive my modeling choices and inform the quantitative analysis.

The literature has used the mortgage rate gap —the difference between the average outstanding mortgage rate and the market rate on new mortgages— to measure the degree of interest rate pass-through (e.g., Berger et al. (2021)). In the past decade, this gap has been positive, because the market rate declined sharply after the financial crisis, while the average rate came down gradually as borrowers refinance their long-term fixed-rate mortgages or as new borrowers enter the market (Figure 5). All else equal, a fall in the rate gap implies a more complete pass-through of lower market rates to the average borrower. I use the following specification to estimate the effect of FinTech market penetration on the rate gap

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

$RateGap_{c,t}$ is measured by the difference between county c's average outstanding mortgage rate and the 30-year FRM rate at time t. Following Fuster et al. (2019), I use the one-quarter lagged, four-quarter moving-average FinTech market share, $FinPenetration_{c,t-1}$, as the measure of FinTech penetration. The regression includes county and quarter fixed effects, as well as controls for the loan market composition and demand shifters (e.g., the average FICO score, house prices growth, lagged average rates and demographics), with standard errors 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 all controls and fixed effects, the estimate in column (2), -0.069, implies that an increase in FinTech market penetration from the 10th to 90th percentile is associated with a 3 basis-point annualized decline in the rate gap, corresponding to 34% (6%) of the mean (standard deviation) of the annual rate-gap change. Thus, the effect is economically meaningful.

This overall effect can be decomposed to (i) a price effect, due to lower mortgage rates offered by FinTech lenders, and (ii) a composition effect, due to higher fractions of mortgages originated by FinTech lenders at the declining market rate (see proof in Appendix C). To understand which effect dominates, I estimate equation (9) with the LHS variable replaced by the county's new home-purchasing and refinancing rates for gauging the price effect, and by the county's new home-purchasing and refinancing shares in the mortgage stock for gauging the composition effect.

Panel I of Table 8 shows that the fall in the rate gap is not driven by the price effect. FinTech lenders do not offer lower rates to home buyers (columns 3 and 4) or refinancing borrowers (columns 5 and 6) than traditional lenders. In contrast, the composition effect is key (panel II). By originating more mortgages at the declining market rate, FinTech lending helps facilitate the market rate pass-through (columns 1 and 2). The composition effect is almost entirely driven by a higher refinancing share in counties with higher FinTech market penetration (columns 5 and 6), not so much by increases in home-purchasing shares (columns 3 and 4).[17] These results highlight the role of FinTech lending in the refinancing channel of monetary policy, informing the quantitative analysis in Section 4.

Appendix Table D5 delves deeper into the question of whether higher FinTech market penetration also leads to more efficient refinancing. I briefly summarize the results here. Using two proxies of potential refinancing benefits (the two-year change in the prevailing market rate and the initial local rate gap), I find that higher FinTech penetration raises further the refinancing propensity and lowers further the rate gap in counties facing larger

[17]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.

potential refinancing benefits, supporting the view that FinTech penetration increases refinancing efficiency.

4 Model

Motivated by these empirical findings, I develop a heterogeneous-agent model to quantify the role of FinTech lending and its network spillovers in the transmission of monetary policy shocks to households. The model incorporates three key features of FinTech lending. First, FinTech lenders offer more convenient services that are valued by consumers.[18] Second, FinTech lenders respond more elastically to surging demand. Third, social interactions help spread information about FinTech lending, making mortgage transactions even more accessible from the consumer's point of view. Through a series of counterfactual analyses and policy experiments, I quantify the improvement in the monetary policy effects due to FinTech features and social networks, and shed light on the interaction between FinTech lending and regional heterogeneity in changing the monetary transmission.

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 enter the maximization problem explicitly, 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.

[18] See supporting evidence in Buchak et al. (2018) and Fuster et al. (2019). Evidence from customer reviews and industry ratings also supports this feature. For example, Quicken Loans (the largest FinTech lender) has ranked the highest in primary mortgage originations for customer satisfaction since 2010. This evidence suggests that the average consumer values the quality of services offered by FinTech lenders, although some consumers may still prefer traditional lenders and human interactions, especially for inexperienced borrowers.

[19] The recent literature on heterogeneous-agent life-cycle models has emphasized the role of housing investments in the transmission of aggregate shocks (e.g., Zhou (2022)). My model abstracts from this aspect, because I focus on the refinancing channel of monetary policy, and because FinTech lending is much more important in refinancing than in home-purchase originations. The qualitative assessment of the role of FinTech lending from my model remains valid even if housing investments are endogenous.

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. It requires a fixed recurring payment of $r_{t_0}^b b_{i,t_0}^j$ every period, which was 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 maximum available home equity; in the case of being underwater, they have to pay back the amount that meets 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 new borrowing amount, $\phi b_{i,t_1}^j$. 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, $f_{i,t}^j$, varies across households. I assume that $f_{i,t}^j$ is drawn from an i.i.d. process with the cumulative distribution function F_f. Households have access to liquid assets, $a_{i,t}^j$, that pay a rate of return, $r^a < r^b$. Moreover, households are subject to the liquidity constraint, $a_{i,t}^j \geq 0$.

FinTech lending. One important feature of FinTech lending is improved services, such as reduced paperwork, at-home origination and faster loan processing, making the refinancing process more convenient for consumers.[20] I model this feature as a utility gain, q, when consumers refinance their mortgage with a FinTech lender. Not every consumer has access to information about FinTech lending. 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 social networks, 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. With probability p^e, a consumer learns about FinTech from social interactions ($E = 1$). If she chooses to refinance with a FinTech lender in this case, she receives a utility gain, $e > q$. This inequality captures the notion that social interactions promote the exchange of information and sharing of experience, further simplifying the refinancing process and raising consumer satisfaction. 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

[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.

[21] I model social networks as being exogenously formed, given that the impact of a specific county on the social network is likely to be small.

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 $\max\{qQ, eE\}$.[22]

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 rising training costs, hiring difficulties and staffing issues (Fuster et al. (2019); Fuster et al. (2021)). These constraints are likely to induce higher non-pecuniary costs for consumers due to delayed processing and credit rationing.

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

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

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 positive demand shock, and (iii) it diminishes over time.[23] Without loss of generality, I assume that FinTech lenders do not face capacity constraints.

Regions. A region is a collection of households who face the same mortgage market condition and correlated economic shocks. To study the interaction between regional

[22] In the model, the draws of Q and E are independent across time. Allowing draws to be persistent would have the same effect as feeding into the model rising paths of p^q and p^e. Section 6.2 uses counterfactual analysis to show how alternative values of p^q and p^e would change the efficacy of monetary policy.

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

economic conditions and FinTech lending (Section 6.3), I consider three types of regions as in Beraja et al. (2018): (i) a housing-bust region hit by a permanent shock that lowers house prices by 10%; (ii) a normal region experiencing no change in the house price; and (iii) a housing-boom region hit by a permanent shock that raises house prices by 10%.

Recursive formulation. This baseline model has a recursive formulation (see Appendix E). For the purpose of conducting counterfactual analysis, I also formulate a model without FinTech lending (the *no-FinTech economy*) and a model with FinTech lending but absent FinTech spillovers (the *no-FinTech-spillover economy*). Appendix E details their recursive formulations and outlines the solution method.

5 Calibration

The model frequency is annual. 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 as in standard consumption models, implying an intertemporal elasticity of substitution of 0.5. β is set to 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, and the standard deviation of the idiosyncratic income shock, σ_y, are set to 0.9 and 0.1, respectively, consistent with estimates using the Panel Study of Income Dynamics (PSID) data (e.g., Zhou (2022)). To obtain μ^y, $y^j_{i,t}$ is assumed to follow a log-normal distribution with $\mathbb{E}(y^j_{i,t}) = 1$, which implies that $\mu^y = -\frac{\sigma_y^2}{2[1-(\rho^y)^2]}$. The AR(1) coefficient of the log house price, 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 μ^p, p^j_t is assumed to follow a log-normal distribution with $\mathbb{E}(p^j_t) = 4\mathbb{E}(y^j_{i,t})$, 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 Federal Reserve Board's estimate in "*A Consumer's Guide to Mortgage Refinancings*" and recent industry estimates.[24] The maximum loan-to-value ratio, γ, is set to 80%, consistent with GSE guidelines for conforming loans 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%, consistent with the historical average of the 30-year FRM rate net of inflation. The distributions of initial liquid assets and loan-to-value ratios match PSID data for mortgage borrowers over the period of 2007-2017.

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. p^f is calibrated such that the refinancing propensity before the monetary policy shock in the no-FinTech economy matches the average refinancing propensity prior to QE1 in the McDash data. f^H is set to 1.25 so that the refinancing propensity conditional on drawing f^H is zero in the no-FinTech economy.[25] The parameter governing the effect of capacity constraints, χ, is calibrated to match the refinancing response to the monetary policy shock in the no-FinTech economy, which is 9.4% at an annualized rate (Beraja et al. (2018)). The persistence of capacity constraints, α, is set to 3, implying that these constraints largely dissipate after one year, consistent with the evidence in Fuster et al. (2021).

There are four key parameters related to FinTech lending: the probabilities of FinTech information arriving from interactive and non-interactive sources, p^e and p^q, and FinTech utility benefits with and without social interactions, e and q. These parameters are jointly calibrated to target four moments. First, the FinTech market share is 20% in the baseline economy before the policy shock, matching the average county-level FinTech refinancing share in 2017. Second, the FinTech market share is 11% in the no-FinTech-spillover economy before the policy shock, matching the projected FinTech market share in a counterfactual no-FinTech-spillover county in 2017.[26] This calibration yields $p^q = 7\%$ and $p^e = 6\%$. Third,

[24]For example, Rocket Mortgage estimates that a refinancing borrower is expected to pay 2%-3% of the remaining principal in closing costs. http://www.rocketmortgage.com/learn/cost-to-refinance.

[25]On the one hand, f^H has to be large enough so that the conditional refinancing propensity (on drawing f^H) is zero in the no-FinTech economy. On the other hand, f^H cannot be too large since that would imply a very low refinancing rate even absent capacity constraints, which is inconsistent with external evidence (e.g. Figure 5 in Fuster et al. (2021)). I experiment with alternative values of f^H satisfying these restrictions and find that the quantitative results are robust.

[26]The counterfactual is calculated as follows. Table 1 shows that a 1 pp increase in the FinTech market

the refinancing rate in the no-FinTech-spillover economy is 6% higher than in the no-FinTech economy before the policy shock. Fourth, the refinancing rate in the baseline economy is 20% higher than in the no-FinTech economy before the policy shock. The latter two moments are set by estimating the following regression

$$Refi_{c,t} = \gamma_{d,t} + \gamma_c + \beta_1 \Delta FinTech_{c,t-1} + \beta_2 \Delta FinTech^M_{c,t-1} + \beta_3 \mathbf{x}_{c,t} + \beta_4 \bar{\mathbf{x}}^M_{c,t} + \varepsilon_{c,t}, \quad (13)$$

where $Refi_{c,t}$ denotes the county-level refinancing propensity in the McDash data. The RHS variables are similarly defined as in equation (3). In equation (13), the effects of FinTech lending in a county and in its network on this county's refinancing are estimated simultaneously. The estimates, $\hat{\beta}_1 = 0.011$ and $\hat{\beta}_2 = 0.026$ (both significant at the 1% level), imply that a 10 pp increase in $\Delta FinTech_{c,t-1}$ (equivalent to moving from the 10th to 90th percentile) is associated with a 6% higher refinancing rate, and that 10 pp increases in $\Delta FinTech^M_{c,t-1}$ and $\Delta FinTech_{c,t-1}$ are associated with a 20% higher refinancing rate.[27]

6 Quantitative Results

In this section, I use the calibrated model to address three questions. First, to what extent have FinTech lending and its network spillovers changed consumption and refinancing responses to a monetary stimulus? Second, as FinTech lenders continue to grow and social interactions become more effective, how would these developments change the effects of a monetary stimulus in the future? Third, can FinTech lending alter the unintended consequence of monetary policy that economically depressed regions benefit relatively less from a monetary stimulus (Beraja et al. (2018))? Using a structural mode to answer these questions has the advantage that empirically confounding factors hindering the identification of monetary policy shocks are held constant in the model, and that counterfactual analysis

share in a county's network raises the county's FinTech market share by as much as 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 FinTech refinancing share suggests that the counterfactual share is 11% (=20%*[1-43%]).

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

can be performed to isolate the role of FinTech spillovers in the monetary transmission.

6.1 FinTech Lending and Monetary Policy Transmission: The Role of Social Networks

To what extent have FinTech lending and its network spillovers changed consumption and refinancing responses to a monetary stimulus that lowers the mortgage rate by 1 pp? Panel (a) of Figure 6 plots the refinancing propensities in three economies before and after the policy shock: the no-FinTech economy, the no-FinTech-spillover economy and the baseline economy (with FinTech and its spillovers) calibrated to data in 2017. Before the policy shock, the refinancing propensity is 2.1%, 2.2% and 2.4%, respectively, in the three economies, reflecting a small fraction of households who have low liquidity and extract home equity to smooth their consumption. The policy shock lowers the borrowing cost, triggering a refinancing boom in all three economies. Panel (b) plots the effect of the policy shock on the refinancing propensity, which increases by 10 pps, 10.7 pps, and 11.3 pps, respectively, in the three economies. While the policy shock stimulates refinancing in all economies, it has the largest impact when FinTech and network spillovers are present. My quantitative analysis suggests that FinTech and network spillovers together boost the monetary policy effect on refinancing by 1.3 pps, or 13% relative to the no-FinTech economy. Shutting down network spillovers would improve the policy effect only by 0.7 pps, or 7%, implying that almost half (47%) of the overall improvement is accounted for by FinTech network spillovers.

Quantitatively similar results are obtained for consumption responses. As shown in the lower panels of Figure 6, consumption increases by 1.11%, 1.17% and 1.25%, respectively, in response to the policy shock in the three economies. With FinTech lending and network spillovers, consumption is 13% more responsive to the policy shock than in the no-FinTech economy. Shutting down network spillovers would increase the consumption response only by 5%, implying that slightly more than half (57%) of the overall improvement in the consumption response is accounted for by network spillovers.

To understand these effects, Figure 7 plots refinancing propensities conditional on household types before and after the policy shock in the three economies, as well as distributions of household types (characterized by f, Q and E). Note that the aggregate refinancing propensities are obtained by weighting these type-specific refinancing propensities using the type distribution. The upper two panels show that, absent FinTech lending, a decline in the mortgage rate increases the refinancing propensity among consumers with f^L, but not among those with f^H. The middle panels show that, households who receive FinTech information from non-interactive sources have a higher refinancing propensity than otherwise identical households who do not receive this information, contributing to a higher overall refinancing rate than in the no-FinTech economy. Moreover, when the mortgage rate declines, some households who otherwise would not refinance (with f^H) choose to refinance with FinTech lenders. In the baseline economy (lower panels), the refinancing propensity is higher for households receiving FinTech information, and is the highest among those with $E = 1$. This composition means that the overall refinancing propensity is higher in this economy both before and after the policy shock. In this exercise, the probabilities of receiving FinTech information, p^q and p^e, are held constant. As shown in Section 6.2, rising p^q and p^e contributes to higher refinancing and consumption responses at the extensive margin.

6.2 Policy Experiments

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 specific 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 technologies, and that make consumers more informed about FinTech lending. These policies increase the probability that FinTech lending directly reaches consumers, implying a higher p^q in the model. Panel (a) of Figure 8 plots refinancing responses for different values of p^q, holding other parameter values fixed. A moderate increase in p^q from 0.07 (baseline) to 0.25 would raise the refinancing propensity by 1.8 pps, a 16% increase relative to the baseline and 31% relative to the no-FinTech economy.

A more dramatic increase in p^q to 0.5 (implying a 70% FinTech market share) would raise the refinancing propensity by 4.3 pps, almost a 40% increase from the baseline and 56% from the no-FinTech economy. The effect on consumption is of a similar magnitude.

Next, consider policies that expand consumers' networks and their ability to share information. These changes are mapped to a higher probability of FinTech information being acquired from social interactions, p^e. Panel (b) of Figure 8 plots refinancing responses for different values of p^e, holding other parameter values fixed. As p^e increases from 0.06 in the baseline to 0.5 (implying a 71% FinTech market share), the refinancing propensity would be 15.9%, a 41% increase from the baseline and 60% from the no-FinTech scenario.

Panel (c) of Figure 8 considers the case when both p^q and p^e rise. The refinancing response is substantially higher than when only one parameter is changed. If both p^q and p^e increase from their baseline values to 0.5 (implying a 85% FinTech market share), the refinancing response would increase by 60% relative to the baseline and 81% relative to the no-FinTech scenario.

Lastly, consider policies that ease capacity constraints faced by traditional lenders. This corresponds to a lower value of χ in the model. In Figure 9, I compare refinancing responses given different values of χ in the three economies. In each economy, easing capacity constraints helps boost refinancing and facilitate the monetary transmission. With FinTech lending and network spillovers, for example, reducing the capacity-constraint-induced cost by one third, i.e., χ falling from 0.75 to 0.5, would boost the refinancing response by 72%, 63% and 56%, respectively, in the no FinTech economy, the no-FinTech-spillover economy and the baseline economy. Since the presence of traditional lenders remains high in the current U.S. mortgage market, policies easing capacity constraints of these lenders may serve as an important alternative tool to enhance the monetary transmission.

6.3 Monetary Stimulus and Regional Inequality: Can FinTech Lending Help?

The success of FinTech lending and network spillovers in boosting refinancing responses raises the question of whether they may also reduce regional inequality arising from unintended consequences of monetary policy. As documented in Beraja et al. (2018), after the financial crisis, accommodative monetary policies provided unintentionally less stimulus to economically depressed regions, because homeowners in these regions were less likely to satisfy underwriting criteria for refinancing and had little home equity to cash out.

This is unlikely to change with FinTech lending, as shown in Figure 10. The refinancing propensity is the lowest in the economically depressed region, whether or not FinTech lending exists (panel a). Although the policy shock stimulates refinancing in all regions (panel b), the change in this propensity is the smallest in the depressed regions (panel c); if anything, FinTech lending and network spillovers tend to widen the refinancing gap between booming and depressed regions, according to the model. This result is not surprising, because FinTech lenders rely heavily on GSE securitization and they cannot help borrowers who do not have enough home equity to meet GSE underwriting criteria.

While FinTech lending is unlikely to alter rising regional inequality in the face of aggregate monetary stimulus, it does help economically depressed regions to better take advantage of the stimulus. After all, many households in these regions do not refinance their mortgages, not because they are not qualified, but because of market frictions. Appendix Table E1 presents the model simulation and shows that 40% of households in the depressed region are qualified for refinancing when the policy stimulus arrives, but only 11% of them take the action because of various market frictions. The presence of FinTech lending and network spillovers can help these households refinance.

7 Conclusion

In the U.S., the vast majority of borrowers hold long-term fixed-rate mortgages. This institutional feature implies that the pass-through of lower policy rates to the household sector depends on households' ability and willingness to change their rates, for example, through refinancing. This refinancing channel of monetary policy, however, has been weakened by various frictions, such as the complicated loan origination process that deters consumers and the capacity constrains that slow lenders' responses in periods of low interest rates. The rapid growth of FinTech lending is expected to ease these frictions, given the convenient and flexible services brought in by this new lending model and FinTec lenders' greater resilience to surging demand.

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 new financial technology. Using U.S. county-level data, I show that FinTech lending displays a sizable spillover effect across social networks, and that this effect is particularly strong for refinancing and in areas with higher social and economic mobility.

I develop a structural model to quantify the importance of FinTech propagation relative to FinTech product features and lender resilience for the transmission of monetary policy. Consumption and refinancing responses to a 1 pp decline in the mortgage rate are 13% higher with FinTech lending. Almost half of this improvement is due to FinTech propagation through social networks, and the rest is accounted for by FinTech product features and lender resilience.

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 monetary policy effects when FinTech market penetration is higher and when social interactions are more informative. I show that an increase in the FinTech market share to 70%, for example, would raise consumption and refinancing responses by 50%-60% compared to the same economy without FinTech lending.

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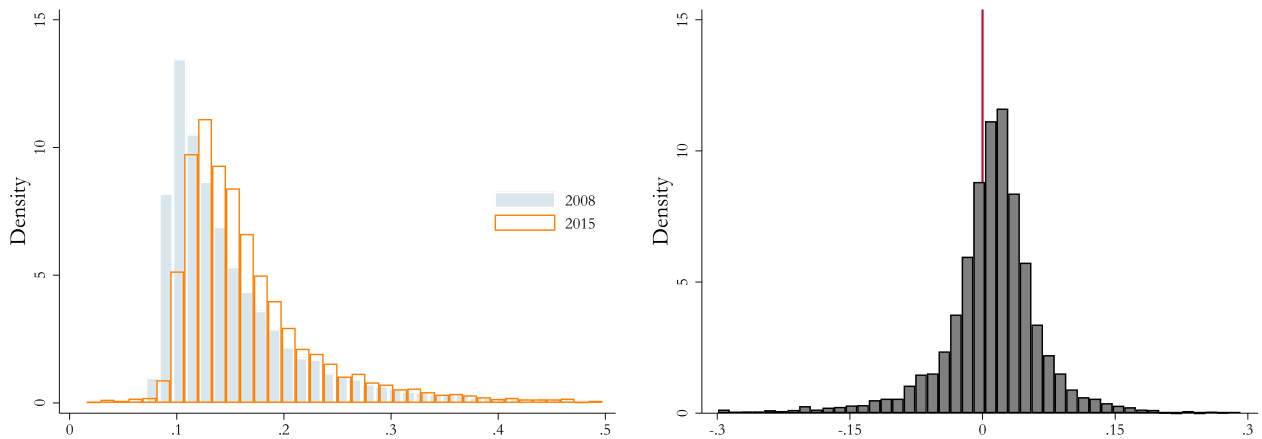
Figure 1: Distribution of bank tier 1 (T1) capital ratio

(a) Level of T1 ratio

(b) Change in T1 ratio, 2008-2015

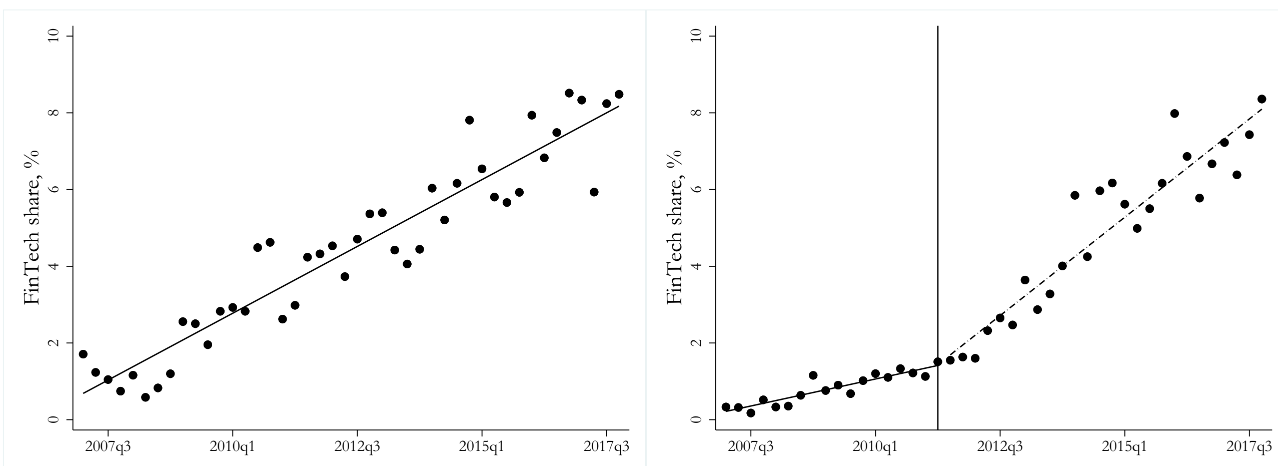


Sources: Bank call reports obtained from FFIEC.

Figure 2: Structural break in FinTech lending growth

(a) No break: Fairfax county, VA

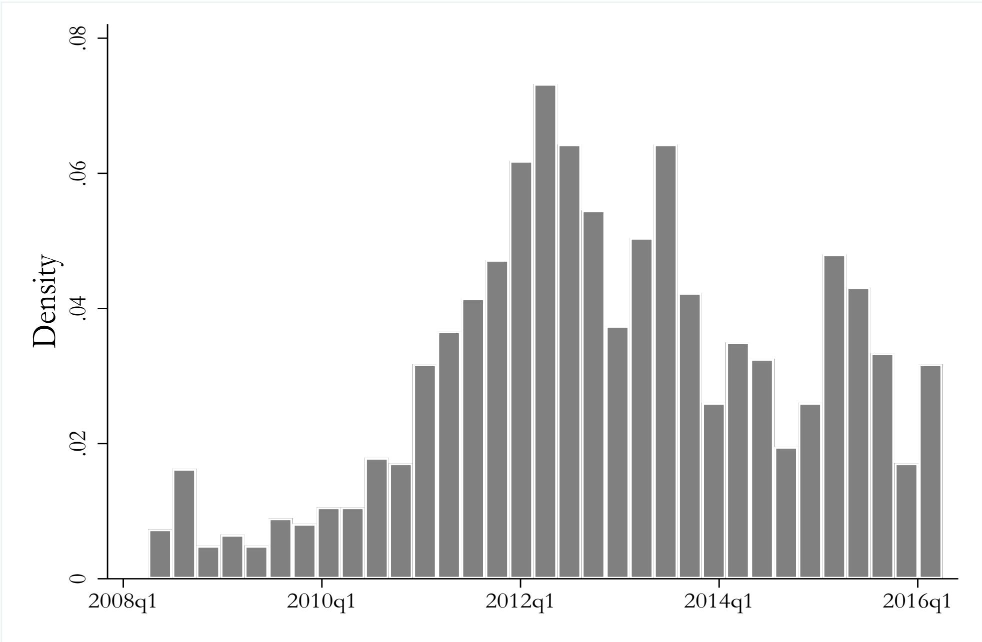
(b) One break: Salt Lake county, UT



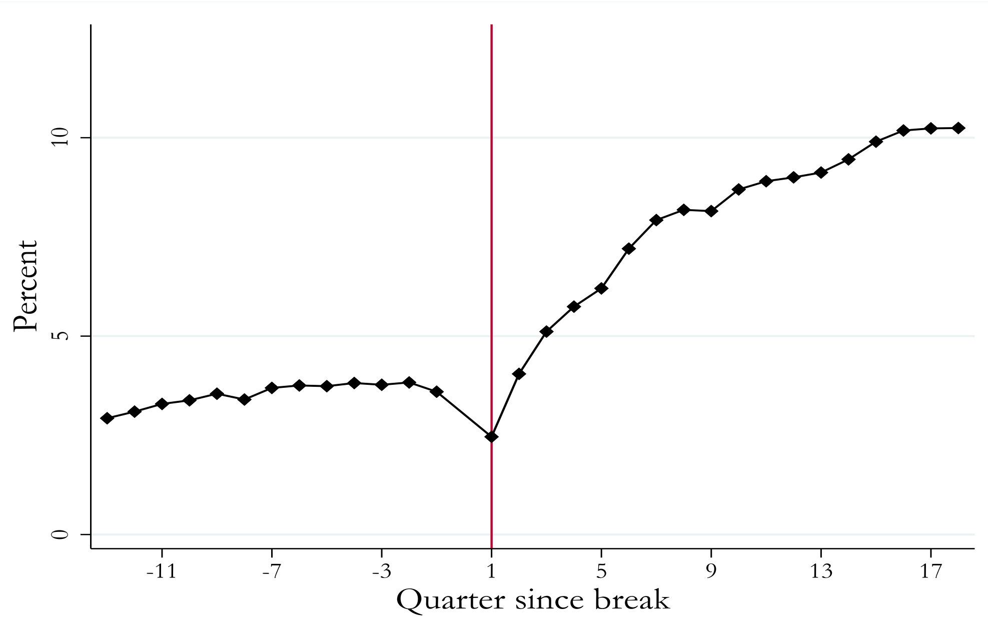
Source: HMDA non-public data, 2007-2017. Notes: The dots in each panel are the quarterly FinTech market share in the county. The solid vertical line in panel (b) indicates the timing of the structural break. The fitted regression lines are obtained by estimating equation (7) using data on FinTech market shares before and after the break.

Figure 3: Timing of the structure break and FinTech share around the break

(a) Distribution of the timing of the structural break



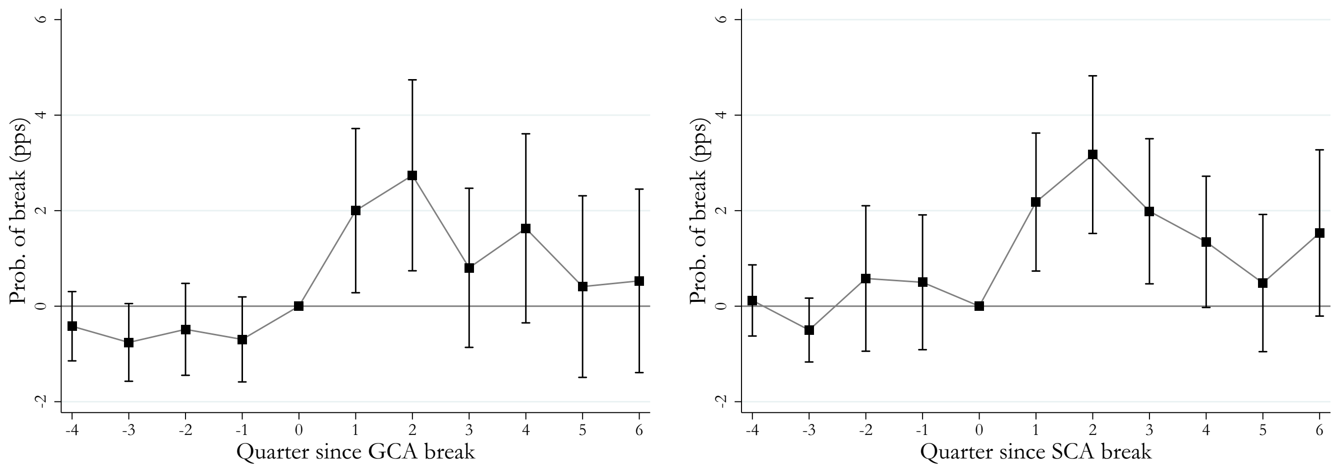
(b) FinTech market share around the structural break



Notes: The structural break point for a given county is estimated using equation (7) with quarterly data from 2007 to 2017.

Figure 4: Dynamics of FinTech spillover

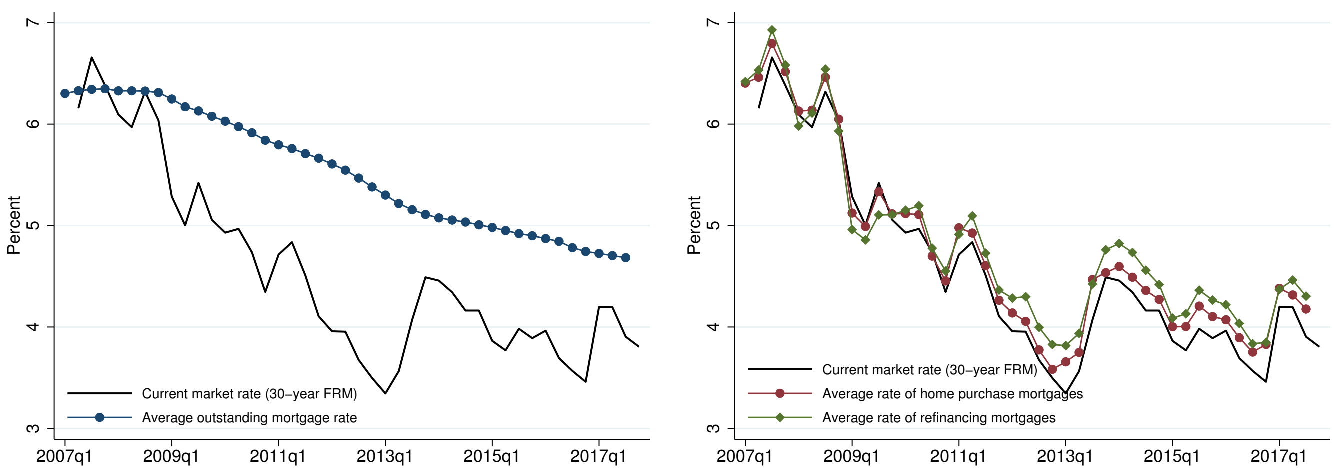
(a) Response to GCA break (b) Response to SCA break



Notes: Point estimates and the 95% confidence intervals are obtained by estimating a quarterly version of the event-study specification in equation (8).

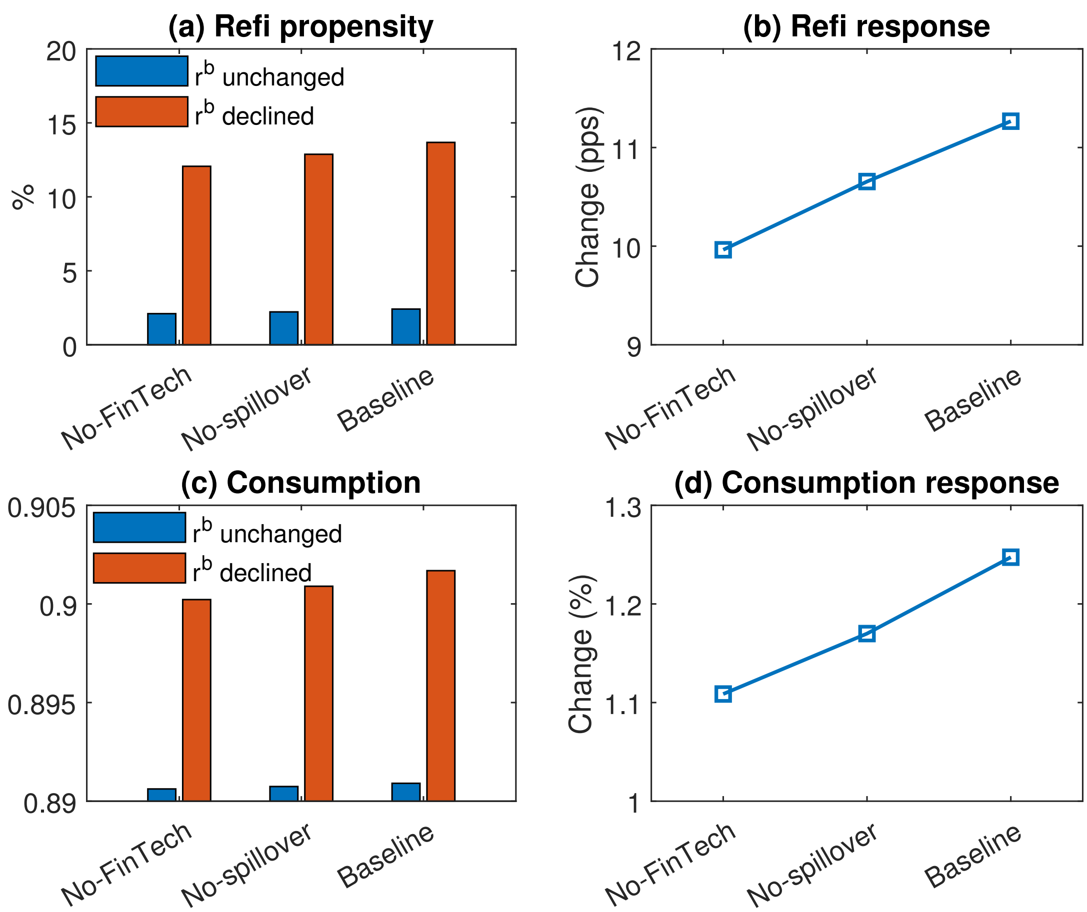
Figure 5: Average outstanding mortgage rate and current market rate

(a) The mortgage rate gap (b) Rates on new mortgages



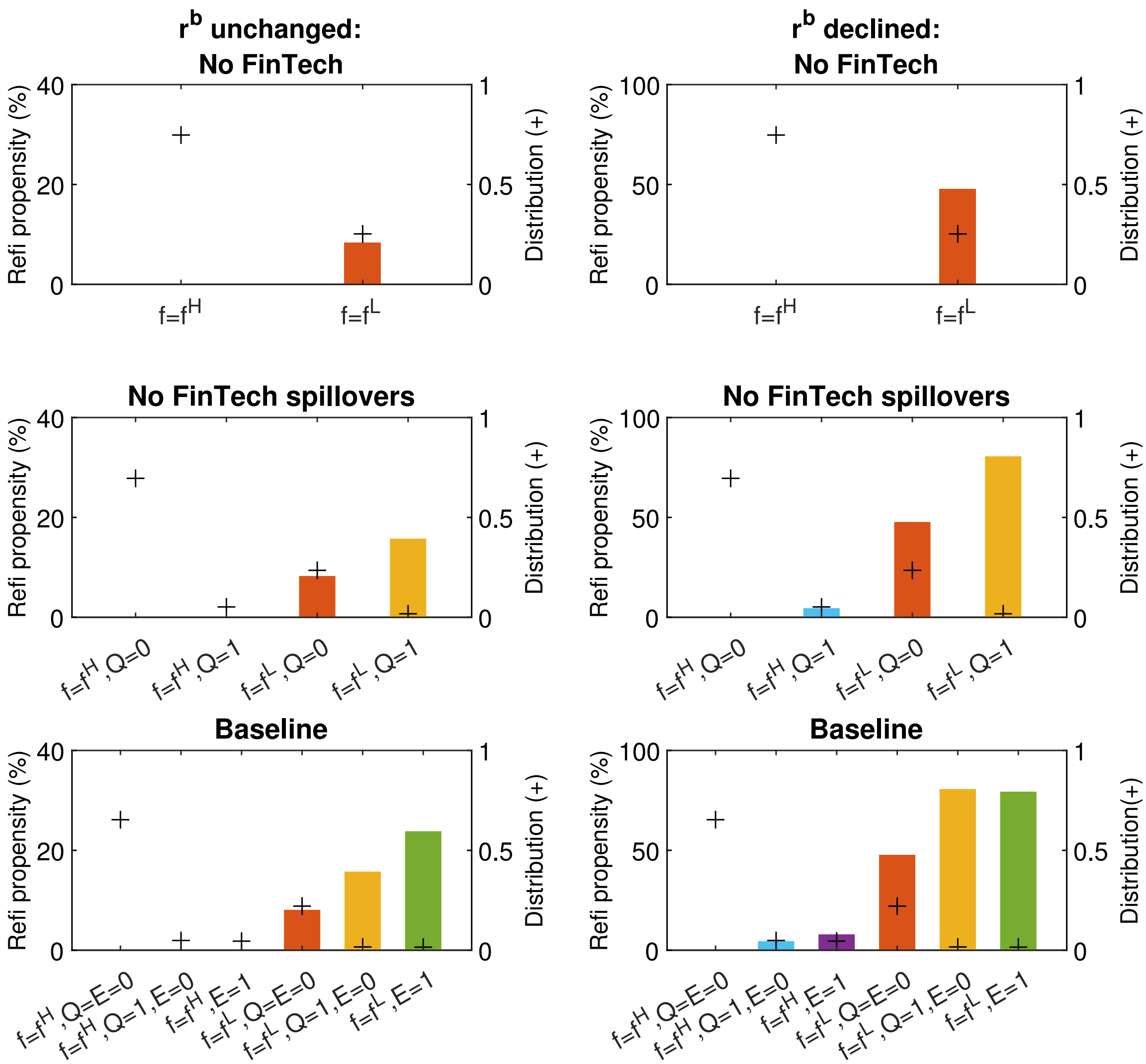
Sources: FRED; Black Knight McDash. Notes: The current market rate is the 30-year FRM rate obtained from FRED. All other series of average rates are constructed using the Black Knight McDash loan-level data.

Figure 6: Responses to a monetary policy shock that lowers the mortgage rate by 1 pp



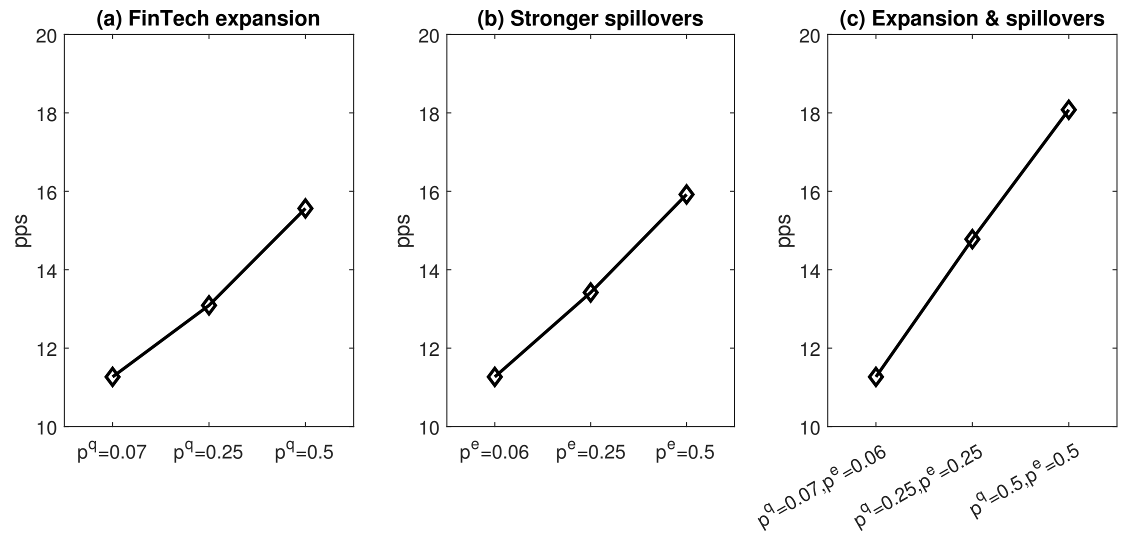
Notes: Simulations from the calibrated model (impact-period responses). The refinancing response in panel (b) is the change in the refinancing propensity (in percentage points). The consumption response in panel (d) is the log change in consumption (in percent).

Figure 7: Household type-specific refinancing propensities



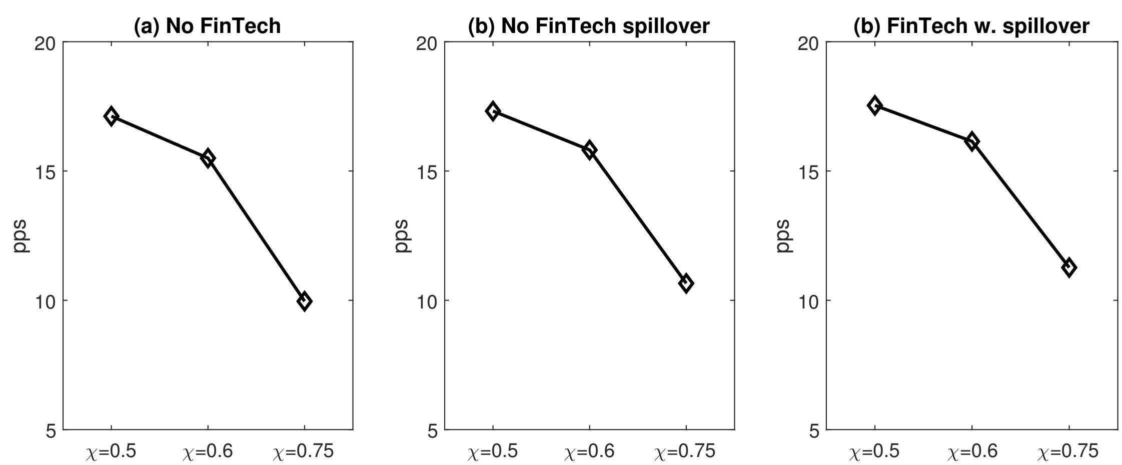
Notes: Household type-specific refinancing propensities (colored bars) and the distribution of household types (+ signs) are simulated from the calibrated model for the impact period.

Figure 8: Policy experiments: Expanding FinTech lending and network spillovers



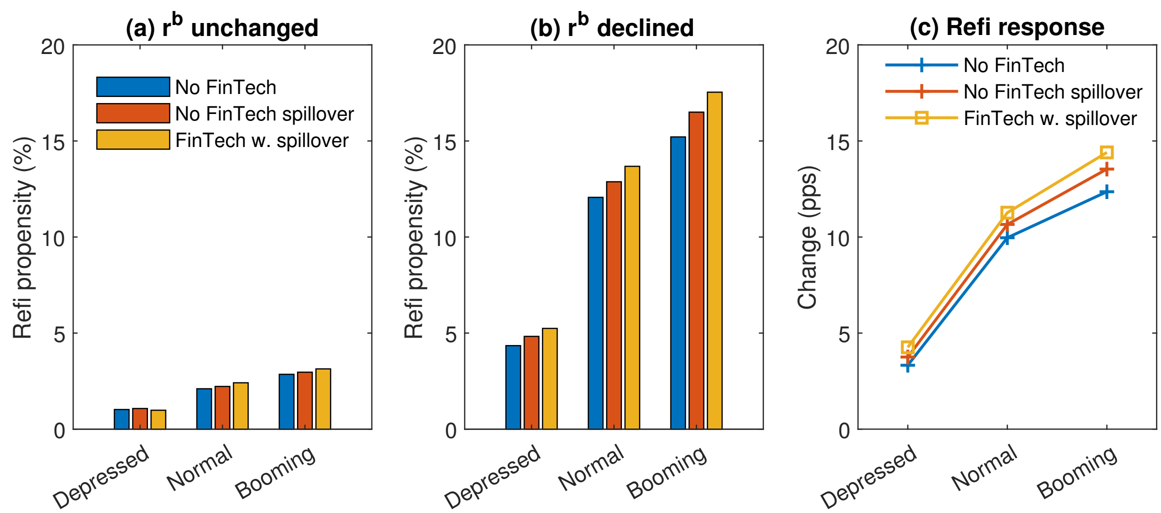
Notes: Simulated refinancing responses to the monetary policy stimulus in the impact period.

Figure 9: Policy experiments: Easing capacity constraints



Notes: Simulated refinancing responses to the monetary policy stimulus in the impact period.

Figure 10: Refinancing responses and regional economic conditions



Notes: Simulated refinancing responses to the monetary policy stimulus in the impact period for the economically depressed, normal and booming regions.

Table 1: FinTech spillover effect: Panel estimates

Panel I. GCA spillovers	Dep. variable: ΔFinTech share$_c$		
OLS estimates	(1)	(2)	(3)
ΔFinTech share$_{-1}^{GCA}$	0.247***	0.249***	0.257***
	(0.020)	(0.021)	(0.020)
County FE	x	x	x
Division-by-quarter FE	x	x	x
County controls		x	x
GCA controls			x
R-squared	0.345	0.346	0.348
# Obs.	118,482	118,426	118,426
Panel II. SCA spillovers			
OLS estimates	(1)	(2)	(3)
ΔFinTech share$_{-1}^{SCA}$	0.236***	0.234***	0.232***
	(0.017)	(0.017)	(0.017)
County FE	x	x	x
Division-by-quarter FE	x	x	x
County controls		x	x
SCA controls			x
R-squared	0.346	0.347	0.349
# Obs.	118,455	118,419	118,419
Panel III. SCA spillovers			
IV estimates	(1)	(2)	(3)
ΔFinTech share$_{-1}^{SCA}$	0.228***	0.226***	0.226***
	(0.020)	(0.020)	(0.020)
County FE	x	x	x
Division-by-quarter FE	x	x	x
County controls		x	x
SCA controls			x
1st stage coef on ΔFinTech share$_{-1}^{SCA,Out}$	0.786***	0.786***	0.786***
1st stage F-stat	9,024	1,384	779
# Obs.	118,455	118,419	118,419

Notes: GCA denotes geographically connected area and SCA denotes socially connected area. ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of the control variables. The instrument in panel III, ΔFinTech share$_{-1}^{SCA,Out}$ is the social connectedness-weighted change in the FinTech market shares in a county's socially connected but geographically distant areas, i.e., outside of the county's commuting zone (see Table D2 for IVs with alternative distance thresholds).

Table 2: FinTech spillover by loan purpose: Panel estimates

	ΔFinTech refi share (1)	ΔFinTech purchase share (2)	ΔFinTech volume (3)	ΔFinTech refi volume (4)	ΔFinTech purchase volume (5)
Panel I. SCA spillovers, OLS estimates					
ΔFinTech share$^{SCA}_{-1}$	0.242***	0.168***	0.280***	0.182***	0.099***
	(0.019)	(0.017)	(0.020)	(0.015)	(0.010)
County FE	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x
County controls	x	x	x	x	x
SCA controls	x	x	x	x	x
# Obs.	116,262	116,238	118,419	118,419	118,419
Panel II. SCA spillovers, IV estimates					
ΔFinTech share$^{SCA}_{-1}$	0.248***	0.134***	0.272***	0.195***	0.077***
	(0.026)	(0.019)	(0.024)	(0.020)	(0.012)
County FE	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x
County controls	x	x	x	x	x
SCA controls	x	x	x	x	x
# Obs.	116,262	116,238	118,419	118,419	118,419

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See notes in Table 1 for the instrument.

Table 3: FinTech spillover by connectedness: Panel IV estimates

	Spillover effect of				
	Top 50 SCAs	Top 51-100	Top 101-150	Top151-200	Top 201-500
ΔFinTech share$^{SCA}_{-1}$	0.178***	0.043***	0.029***	0.018	0.002
	(0.016)	(0.012)	(0.010)	(0.014)	(0.042)
County FE	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x
County controls	x	x	x	x	x
SCA controls	x	x	x	x	x
# Obs.	118,419	118,419	118,419	118,419	118,419

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See notes in Table 1 for the instrument.

Table 4: Heterogeneity in FinTech spillover: Panel IV estimates

Dep. variable: ΔFinTech share$_c$	(1)	(2)	(3)	(4)
ΔFinTech share$^{SCA}_{-1}$	0.089	0.172***	0.136***	0.129***
	(0.046)	(0.024)	(0.025)	(0.021)
ΔFinTech share$^{SCA}_{-1}$	0.059			
$\times$ Nonmetro, urban pop$\geq$2.5K	(0.050)			
ΔFinTech share$^{SCA}_{-1}$	0.088			
$\times$ Metro, pop<250K	(0.053)			
ΔFinTech share$^{SCA}_{-1}$	0.128**			
$\times$ Metro, pop$\in$[250K,1M)	(0.054)			
ΔFinTech share$^{SCA}_{-1}$	0.218***			
$\times$ Metro, pop$\geq$ 1M	(0.052)			
ΔFinTech share$^{SCA}_{-1}$		0.067**		
$\times$ High share of Bachelor's degree		(0.028)		
ΔFinTech share$^{SCA}_{-1}$			0.126***	
$\times$ High share of black			(0.032)	
ΔFinTech share$^{SCA}_{-1}$				0.114***
$\times$ High migration flow$_{-1}$				(0.028)
County FE	x	x	x	x
Division-by-quarter FE	x	x	x	x
County controls	x	x	x	x
SCA controls	x	x	x	x
# Obs.	118,419	118,419	118,419	118,290

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See notes in Table 1 for the instrument. All interaction terms are also instrumented by interacting the IV with the county characteristics.

Table 5: Instrumenting FinTech spillovers with banking regulation shocks

	GCA spillover		SCA spillover	
	1st stage	2nd stage	1st stage	2nd stage
$\Delta \widehat{FinTech\ share}^M$		0.767***		1.768***
		(0.192)		(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
County controls	x	x	x	x
GCA/SCA controls	x	x	x	x
1st stage F-stat	80.2	-	146	-
# Obs.	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 the control variables. ΔRegulation^M is the origination share-weighted change in banks' T1 ratios from 2008 to 2015 in a county's connected markets (GCAs or SCAs), further weighted by the social connectedness measure. Bank share^M is banks' origination shares in 2008 in a county's connected markets weighted by the social connectedness measure.

Table 6: Dynamics of FinTech spillover: Event-study estimates

Dep. variable:	GCA spillover				SCA spillover			
$\mathbb{I}(Break)_c$	25 GCAs	50 GCAs	75 GCAs	100 GCAs	25 SCAs	50 SCAs	75 SCAs	100 SCAs
Two years before	-0.265	-0.072	-0.181	-0.146	-0.144	-0.530	-0.505	-0.455
	(0.456)	(0.291)	(0.359)	(0.362)	(0.440)	(0.311)	(0.346)	(0.282)
One year before	-0.533	0.282	0.257	0.138	0.119	0.047	-0.081	-0.242
	(0.399)	(0.305)	(0.370)	(0.419)	(0.424)	(0.323)	(0.336)	(0.182)
One year after	1.858**	1.432***	0.887	0.607	2.232***	1.411***	1.201**	0.850
	(0.762)	(0.544)	(0.630)	(0.682)	(0.543)	(0.522)	(0.550)	(0.495)
Two years after	0.335	0.103	-0.167	0.063	1.269	1.534	0.149	-0.195
	(0.862)	(0.808)	(0.811)	(0.876)	(0.804)	(0.808)	(0.629)	(0.647)
Three years after	-0.293	-0.129	-0.108	0.015	0.686	0.834	-0.018	-0.721
	(0.879)	(0.693)	(0.749)	(0.774)	(0.732)	(0.790)	(0.631)	(0.792)
County FE	x	x	x	x	x	x	x	x
Division-by-quarter 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
# Obs.	49,301	52,612	53,890	54,450	49,101	52,527	53,684	54,359
Prob(GCA/SCA 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. The structural break point for a given county is estimated using equation (7) with quarterly data between 2007 and 2017. Equation (8) is then estimated to obtain the event-study estimates.

Table 7: No evidence for supply-side spillovers: Panel estimates

Panel I. **FinTech marketing spillover**	GCA spillover OLS	SCA spillover OLS	SCA spillover IV
ΔFinTech Ads$^{M}_{-1}$	0.031	0.020	0.004
	(0.033)	(0.032)	(0.004)
County FE	x	x	x
Division-by-quarter FE	x	x	x
County controls	x	x	x
GCA/SCA controls	x	x	x
# Obs.	118,426	118,419	118,419

Panel II. **Accounting for marketing effect**	GCA spillover OLS	SCA spillover OLS	SCA spillover IV
ΔFinTech share$^{M}_{-1}$	0.257***	0.234***	0.226***
	(0.020)	(0.017)	(0.020)
ΔFinTech Ads	0.000	-0.001	-0.001
	(0.003)	(0.003)	(0.003)
ΔFinTech Ads^{M}	0.003	-0.008**	-0.008**
	(0.006)	(0.004)	(0.004)
County FE	x	x	x
Division-by-quarter FE	x	x	x
County controls	x	x	x
GCA/SCA controls	x	x	x
# Obs.	118,426	118,419	118,419

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. The IV in column (3) of panel I is the social connectedness-weighted change in the log FinTech advertising volumes in a county's out-of-CZ SCAs. See notes in Table 1 for the instrument in panel II.

Table 8: Effect of FinTech market 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. Composition 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

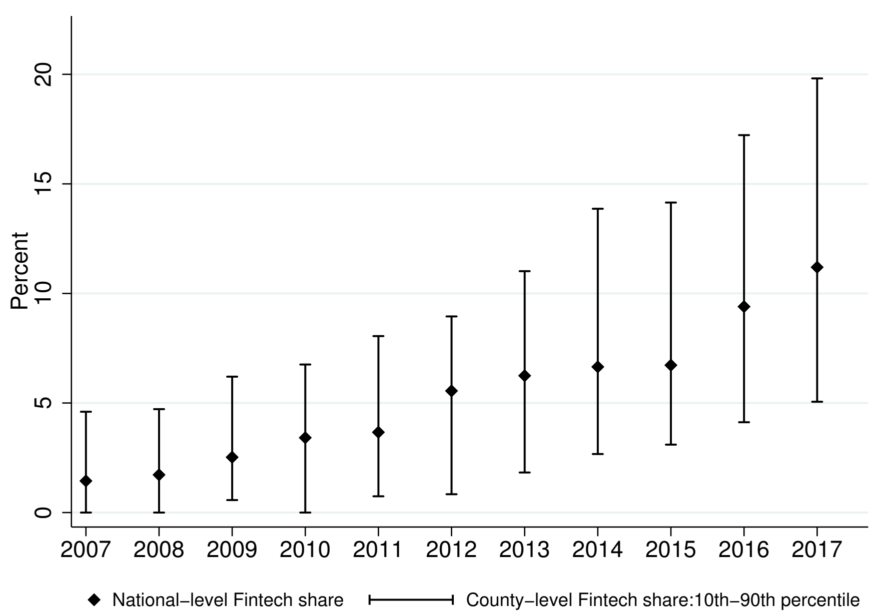
Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of control variables.

Appendices to "Financial Technology and the Transmission of Monetary Policy: The Role of Social Networks"

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 enabling a mortgage applicant to obtain a preapproval online. The two classification schemes 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.[28] I use the combined list of FinTech lenders from these two studies, as in Jagtiani et al. (2020). Similar empirical results are obtained when using either one of these classifications. 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 market shares in the 2017 HMDA data.

Figure A1: FinTech market share in mortgage originations



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

[28] While both studies consider the possibility of "FinTech bank lenders", they do not classify any bank as a FinTech lender as of 2017. This is because the prevalence of existing business models and legacy systems in traditional banks has hindered their ability to adopt new technologies.

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 data, 2017. Notes: FinTech market shares are computed using the volume of mortgage originations.

B Data Description

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

Home Mortgage Disclosure Act (HMDA). This dataset contains the vast majority of home-mortgage application and approval records in the United States. It provides detailed loan-level information and borrowers' 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, which is accessible to Federal Reserve System employees, has additional information on the exact date when an action is taken (e.g., origination, denial or withdrawal), rather than just the year as in the public version. Since this information is crucial for implementing my empirical strategies, I use the confidential version of the HMDA data for most of my analysis.

Black Knight McDash Dataset (McDash). This dataset consists of servicing portfolios of the largest mortgage servicers in the U.S., covering two-thirds of installment-type loans in the residential mortgage servicing market. The data contain loan-level information at origination and monthly updates on the performance. Unlike the HMDA dataset that measures the flow into mortgage debt, the McDash data measures the stock of mortgages. I use these data to construct several key variables for the analysis in Section 3 at the county-quarter level: the average outstanding mortgage rate, the average rate of newly originated mortgages, the share of newly originated mortgages in the mortgage stock, and the average FICO score. I restrict the sample to conventional first-lien 30-year FRMs below the jumbo cutoff. The dataset 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 the geographical distance between two counties, obtained from the NBER County Distance Database. The other is based on novel social network data developed by Bailey et al. (2018b), including the county-pair-level social connectedness index (SCI).[29] This index uses an anonymized snapshot of active Facebook users and their friendship links as of August 2020 to capture the intensity of social interactions between any two counties. The SCI between counties i and j is constructed as

$$SCI_{i,j} = \frac{FB\ Connections_{i,j}}{FB\ Users_i \times FB\ Users_j}, \tag{14}$$

where $FB\ Users_i$ and $FB\ Users_j$ are the numbers of Facebook users in counties i and j, and $FB\ Connections_{i,j}$ is the total number of friendship links between individuals in the two counties.[30] Bailey et al. (2018b) show that the index is strongly negatively correlated with distance and is positively correlated with bilateral social and economic activities. The index has been increasingly used by researchers to study the role of social interactions in economic outcomes at the individual, neighborhood, regional and national levels (see Kuchler and Stroebel (2021)).

Mintel-Comperemedia Direct Mail and Print Advertising Volume. This dataset contains information on the volume of advertisements sent by each mortgage lender to households at the zip-code-month 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 estimated with appropriate weighting.

To get a sense of the aggregate trend in mortgage advertising, panel (a) of Figure B1

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

[30] The public SCI data are scaled to have a maximum value of 10^9 and a 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.

plots the aggregate volume of mortgage offers since 2007 and by loan purpose. It shows that, while home-purchasing and refinancing offers each accounted for about half of the overall advertising, refinancing offers surged particularly during the refinancing boom of 2012-2013. Panel (b) plots the shares of advertisements made by FinTech lenders as a share of total advertisements made by all lenders. FinTech offers have grown rapidly since 2011, which has been mainly driven by refinancing offers, consistent with the trend in the HMDA data.

Bank Balance Sheet Data. 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.[31]

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 Bureau of Labor Statistics' Quarterly Census of Employment and Wages. The share of subprime borrowers is constructed using the New York Fed (FRBNY) Consumer Credit Panel/Equifax Data (accessed through FRS-RADAR-DW).[32] It is 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 as in FHFA data) and available at relatively high frequency. The disadvantage is that the index does not have the full geographical coverage at the county level. To address this issue, for counties where the HPI data are not available, I use house price growth in their respective MSAs. If a county is missing the HPI data and is not located in an MSA, I use house price growth in its state. Using alternative FHFA county-level HPI data does not affect my empirical results.

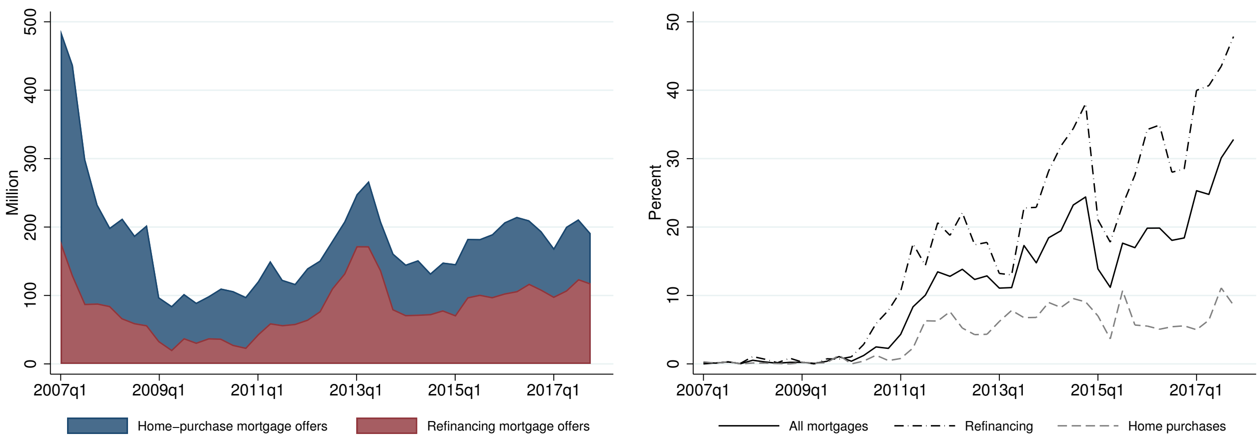
[31] Constructed by Robert Avery, the Avery file contains matching information for all lenders in the HMDA data and the FFIEC Call reports in each filing year. I downloaded the Stata version of this file made available by Neil Bhutta on his homepage: https://sites.google.com/site/neilbhutta/data.

[32] 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: U.S. mortgage lenders' advertising

(a) Aggregate volume of mortgage offers

(b) Offers made by FinTech lenders



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

C Decomposing the Mortgage Rate Gap

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

$$\bar{r}_{c,t} \equiv \frac{\sum_{i=1}^{N_{c,t}} r_{i,c,t}}{N_{c,t}} = \frac{N_{c,t}^{refi}\bar{r}_{c,t}^{refi} + N_{c,t}^{pur}\bar{r}_{c,t}^{pur} + (N_{c,t} - N_{c,t}^{refi} - N_{c,t}^{pur})\bar{r}_{c,t-1}^{ex}}{N_{c,t}}, \tag{15}$$

where $N_{c,t}^{refi}$ and $N_{c,t}^{pur}$ denote the numbers of newly refinanced mortgages and newly originated home-purchasing mortgages 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-purchasing mortgages, and existing mortgages originated at $t-1$ or earlier. Rewrite equation (15) as

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

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

The county-level mortgage rate gap, $RateGap_{c,t}$, is the difference between the average outstanding mortgage rate and the prevailing market rate, $\bar{r}_{c,t} - R_t$. Using equation (16),

$$RateGap_{c,t} = s_{c,t}^{refi}\left(\bar{r}_{c,t}^{refi} - R_t\right) + s_{c,t}^{pur}\left(\bar{r}_{c,t}^{pur} - R_t\right) + (1 - s_{c,t}^{refi} - s_{c,t}^{pur})\left(\bar{r}_{c,t-1}^{ex} - R_t\right). \tag{17}$$

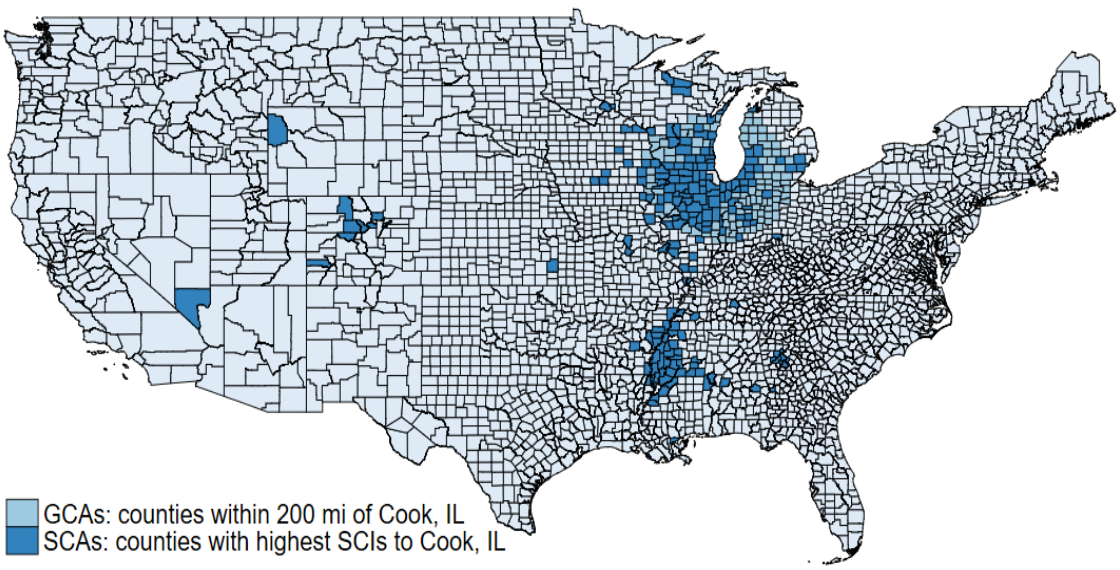
Equation (17) shows that, controlling for $\bar{r}_{c,t-1}^{ex}$, higher FinTech market penetration may reduce the mortgage rate gap through two effects:

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

2. **The composition effect.** Suppose that all lenders offer the same rates at the market level, i.e., $\bar{r}^{refi}_{c,t} = \bar{r}^{pur}_{c,t} = R_t$. Since $\bar{r}^{ex}_{c,t-1} > R_t$, the rate gap falls if $s^{refi}_{c,t}$ or $s^{pur}_{c,t}$ increase. In other words, if more new mortgages are originated at the current market rate (either for refinancing or home purchasing) in counties where FinTech market penetration is higher, all else equal, the rate gap shrinks. The equal-rate condition, $\bar{r}^{refi}_{c,t} = \bar{r}^{pur}_{c,t} = R_t$, can be relaxed. In fact, as long as $\bar{r}^{ex}_{c,t-1} > \bar{r}^{refi}_{c,t}$ and $\bar{r}^{ex}_{c,t-1} > \bar{r}^{pur}_{c,t}$, which holds over my sample period, originating more new mortgages will always reduce the rate gap.

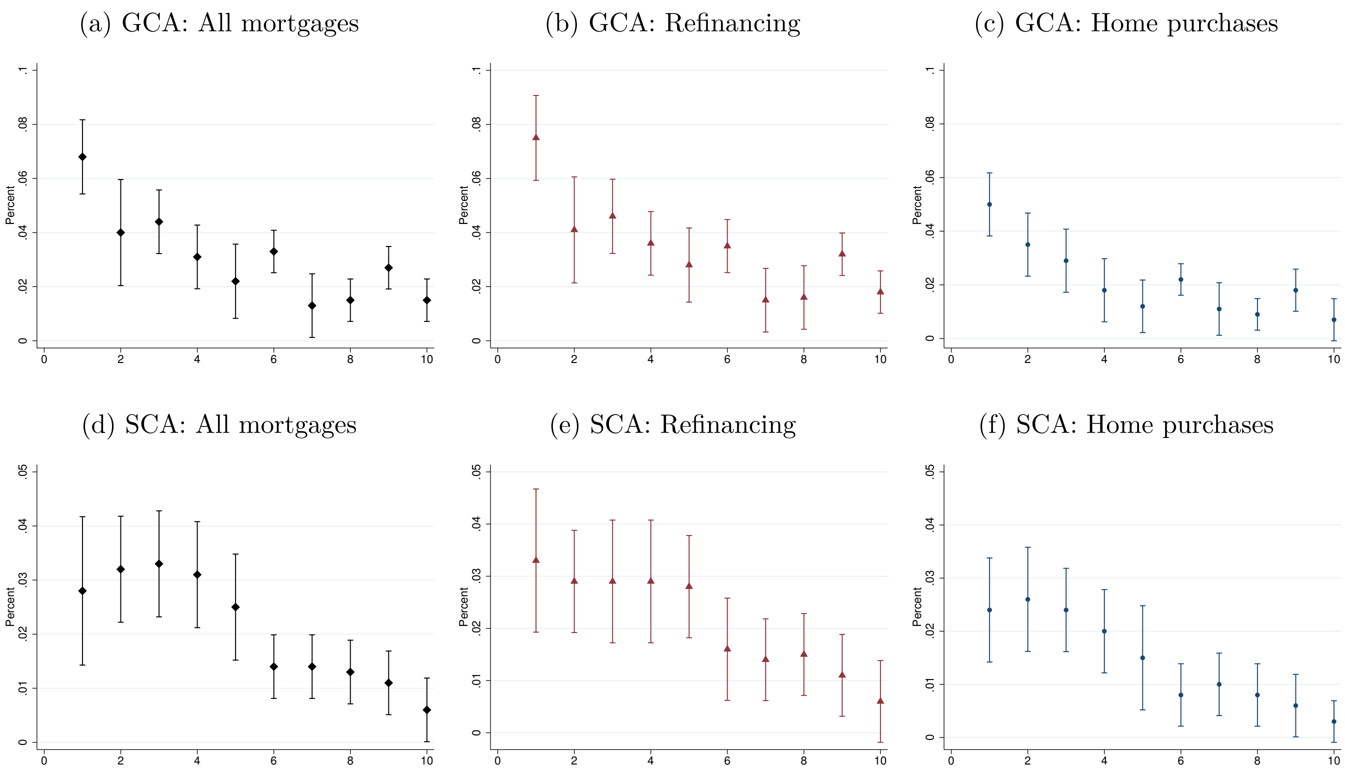
D Additional Empirical Results

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



Notes: This figure depicts the GCAs (light blue) and the SCAs (dark blue) of Cook county, IL. While a large number of counties are both geographically and socially connected to Cook, many counties in Michigan are only geographically connected to it. On the other hand, many counties in Mississippi, Arkansas and Louisiana are far away from Cook but are socially connected to it, which is likely explained by migration of African Americans from the South to the urban North during the Great Migration period.

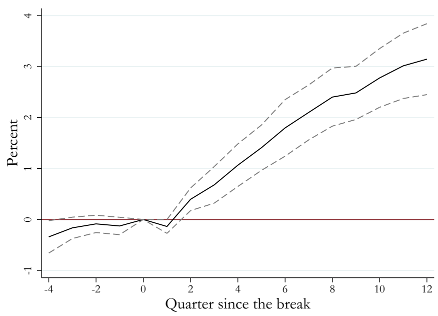
Figure D2: FinTech spillovers from top 10 GCAs (top panel) and top 10 SCAs (bottom panel)



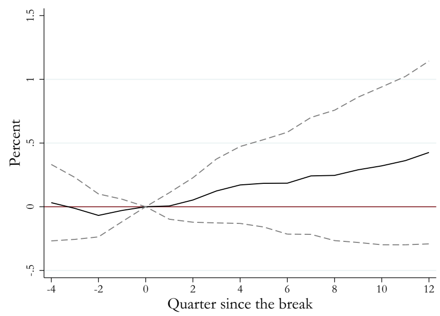
Notes: Point estimates and the 95% confidence intervals are obtained by estimating the OLS specifications in the third column of Table 1 for each of the 10 closest GCAs and 10 closets SCAs. Standard errors are clustered at the county level. See text for the description of the control variables.

Figure D3: County economic conditions around the structural break

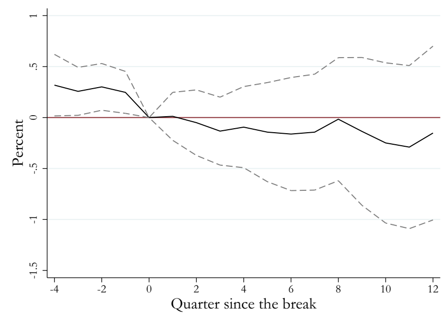
(a) FinTech market share



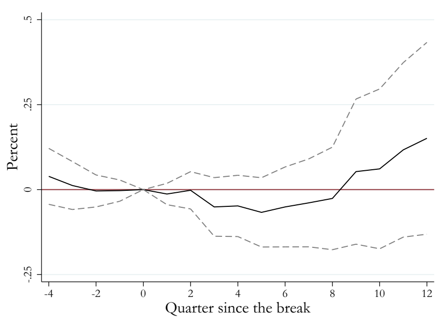
(b) Employment growth



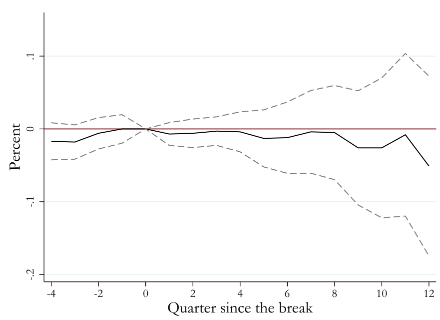
(c) House price growth



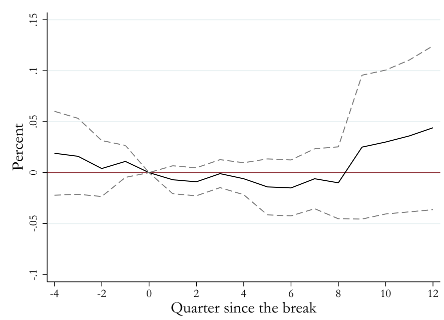
(d) Share of subprime borrowers



(e) Share of young population

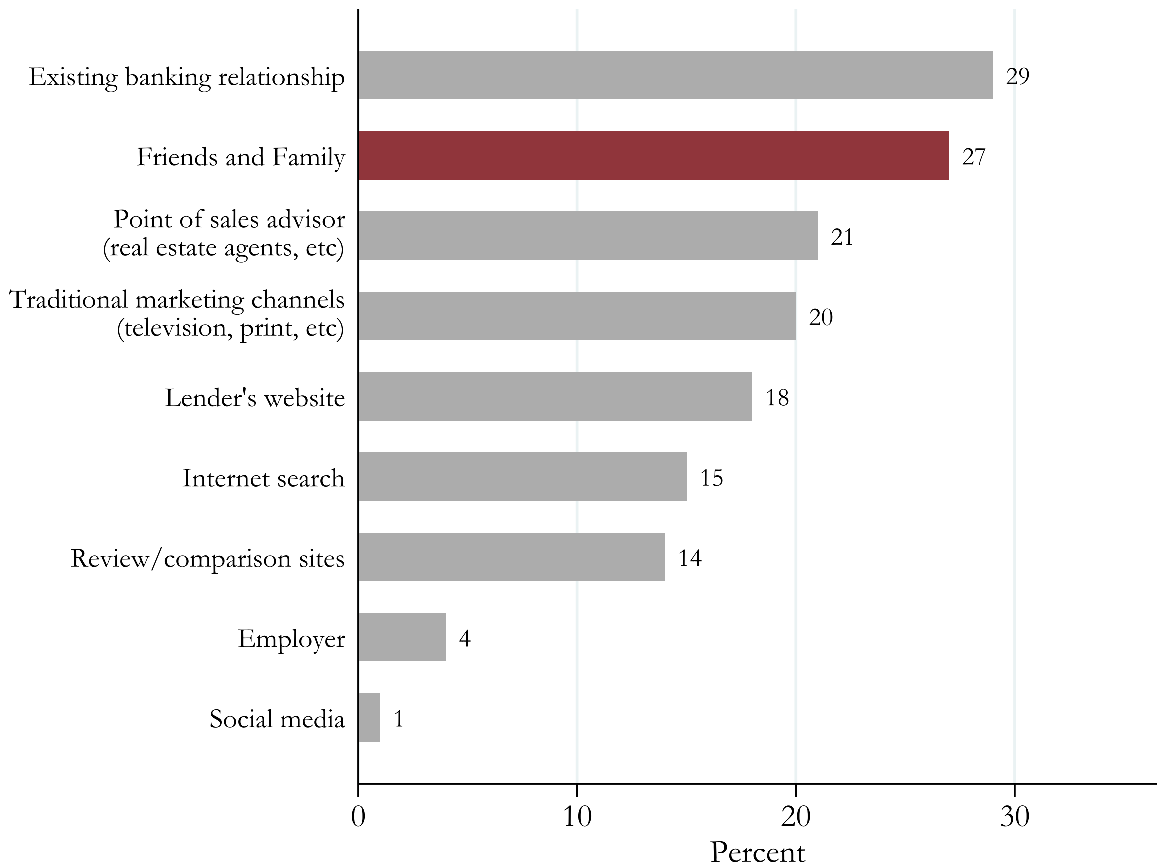


(f) Share of African Americans



Notes: Point estimates and the 95% confidence intervals are obtained by estimating an event-study specification for each of the six outcome variables. The key RHS variables are quarterly dummies that indicate the timing of the county's structural break. Each regression includes county and division-by-quarter fixed effects with standard errors clustered at the county level.

Figure D4: Referral sources for home mortgages, 2015



Source: PwC report "Consumer lending: Understanding today's empowered borrower", 2015. Notes: The report is based on a national survey of 2,000 consumers conducted by PwC in June 2015 using a population targeting approach. The percentages indicate how many respondents ranked the option in their top 3 referral sources. Thus, percentages will not sum to 100%. https://www.pwc.com/mx/es/servicios-consultoria/archivo/experience-radar-prestamos-a-consumo-entendiendo-al-prestatario-empoderado-de-hoy.pdf

Table D1: Robustness to changing GCA and SCA thresholds

Panel I. GCA spillovers	Dependent variable: ΔFinTech share$_c$					
OLS estimates	Within 200 miles	Within 250 miles	Within 300 miles	Within 500 miles	Within 1000 miles	All counties
ΔFinTech share$_{-1}^{GCA}$	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
Division-by-quarter FE	x	x	x	x	x	x
County controls	x	x	x	x	x	x
GCA controls	x	x	x	x	x	x
# Obs.	118,426	118,426	118,426	118,426	118,426	118,426

Panel II. SCA spillovers						
OLS estimates	Top 200 SCAs	Top 250 SCAs	Top 300 SCAs	Top 500 SCAs	Top 1000 SCAs	All counties
ΔFinTech share$_{-1}^{SCA}$	0.232***	0.241***	0.245***	0.254***	0.261***	0.257***
	(0.017)	(0.018)	(0.018)	(0.019)	(0.020)	(0.021)
County FE	x	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x	x
County controls	x	x	x	x	x	x
SCA controls	x	x	x	x	x	x
# Obs.	118,419	118,419	118,419	118,419	118,419	118,419

Panel III. SCA spillovers						
IV estimates	Top 200 SCAs	Top 250 SCAs	Top 300 SCAs	Top 500 SCAs	Top 1000 SCAs	All counties
ΔFinTech share$_{-1}^{SCA}$	0.226***	0.234***	0.239***	0.248***	0.256***	0.245***
	(0.020)	(0.020)	(0.021)	(0.023)	(0.024)	(0.024)
County FE	x	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x	x
County controls	x	x	x	x	x	x
SCA controls	x	x	x	x	x	x
# Obs.	118,419	118,419	118,419	118,419	118,419	118,419

Notes: See notes for Table 1.

Table D2: Robustness to alternative specifications

	Alt. instrument		Alt. $\Delta FinTech^{M}_{c,t-1}$			Alt. dynamic structure		
	SCAs≥100mi	SCAs≥200mi	GCA-OLS	SCA-OLS	SCA-IV	GCA-OLS	SCA-OLS	SCA-IV
ΔFinTech share$^{M}_{-1}$	0.214***	0.221***	0.202***	0.182***	0.197***			
	(0.032)	(0.050)	(0.016)	(0.015)	(0.021)			
ΔFinTech share$^{M}_{0Q}$						0.162***	0.143***	0.129***
						(0.013)	(0.013)	(0.015)
ΔFinTech share$^{M}_{-1Q}$						0.068***	0.063***	0.051***
						(0.011)	(0.009)	(0.012)
ΔFinTech share$^{M}_{-2Q}$						0.012	0.011	-0.003
						(0.009)	(0.009)	(0.011)
ΔFinTech share$^{M}_{-3Q}$						0.024	-0.005	(-0.003)
						(0.010)	(0.011)	(0.013)
ΔFinTech share$^{M}_{-4Q}$						-0.004	0.001	0.011
						(0.011)	(0.009)	(0.011)
County FE	x	x	x	x	x	x	x	x
Division-by-quarter FE	x	x	x	x	x	x	x	x
County controls	x	x	x	x	x	x	x	x
SCA/GCA controls	x	x	x	x	x	x	x	x
1st stage F-stat	117	25	-	-	771	-	-	≥575
# Obs.	118,419	118,419	118,426	118,419	118,419	117,915	117,908	117,908

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. The first two columns estimate the specification in column (3), panel III of Table 1 with alternative instruments using SCAs that are 100 or 200 miles away from the county of interest. The middle three columns use the weighted change in SCAs' or GCAs' FinTech refinancing shares (as opposed to overall FinTech shares) as the key RHS variable. The last three columns present the dynamic quarterly responses with the LHS variable being the quarterly change in the FinTech market share in the focal county. All lagged variables are instrumented in the IV specification.

Table D3: Alternative IV strategies exploiting banking regulation shifts

Dep. variable:	Alternative 1		Alternative 2		Alternative 3	
ΔFinTech share$_c$	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
$\Delta \widehat{FinTech\ share}^{SCA}$		1.108***		0.977***		1.402***
		(0.325)		(0.154)		(0.517)
ΔT1 ratio$^{SCA}_{2006-2008}$	-0.762***					
	(0.135)					
Big4 exposure$^{SCA}_{2008}$			0.092***			
			(0.008)			
MSR$^{SCA}_{2008}$					0.052**	
					(0.024)	
State FE	x	x	x	x	x	x
County controls	x	x	x	x	x	x
SCA controls	x	x	x	x	x	x
1st stage F-stat	146	-	155	-	144	-
# Obs.	3,095	3,095	3,095	3,095	3,095	3,095

Notes: ** and *** denote significance at the 5% and 1% level, respectively. The first two columns present the IV estimate using the origination share-weighted change in banks' T1 ratios from 2006 to 2008 in each SCA (further weighted by the SCA conectedness) as the instrument. The middle two columns show the IV estimate using the origination share of Big4 in 2008 in each SCA (weighted by the SCA connectedness) as the instrument. The last two columns show the IV estimate using the origination share-weighted MSR ratio in 2008 in each SCA (weighted by the SCA connectedness) as the instrument.

Table D4: Observables do not explain the timing of a structural break

Dependent variable: $\mathbb{I}(Break)_{c,t}$	Coefficient	Clustered S.E.	P-value
Employment growth	-0.080	0.064	0.21
House price growth	-0.025	0.082	0.76
Share of subprime borrowers	-0.186	0.103	0.07
Share of young population	0.080	0.223	0.72
Share of African Americans	-0.117	0.337	0.73
Population growth	-0.217	0.224	0.34

Notes: Results from estimating a panel linear probability model. The regression includes the above variables, county fixed effects and division-by-quarter fixed effects. Standard errors are clustered at the county level. The sample is restricted to counties that have an identified structural break.

Table D5: Heterogeneous effect of FinTech market penetration

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

Notes: ** and *** denote significance at the 5% and 1% level, respectively. Standard errors are clustered at the county level. $\Delta R_{t,t-8}$ is the change in the prevailing market rate over eight quarters with the sign normalized such that $\Delta R_{t,t-8} > 0$ represents a fall in the market rate. $Gap_{-1} \in (75, 125]$ is the indicator for the one-quarter lagged rate gap between 75 and 125 basis points.

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 baseline model. In this model, 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 baseline 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 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

Table E1: Refinancing propensity condition on LTV<80%

	% Households with LTV<80% (1)	No frictions (2)	Lender frictions (3)	Consumer frictions (4)	Both frictions (5)	FinTech baseline (6)	FinTech $p^q = p^e = 0.5$ (7)
Depressed region	40	100%	42.5%	27.0%	10.8%	13.1%	23.5%
Normal region	80	100%	55.2%	28.2%	15.1%	17.1%	27.2%
Booming region	94	100%	63.3%	34.3%	16.2%	18.7%	30.9%

Notes: Simulations from the calibrated model for the impact period of a monetary stimulus. Column (1) shows the share of households having positive home equity. Columns (2)-(5) report the refinancing propensities in economies without FinTech lending. Column (6) follows the baseline calibration and column (7) follows the policy experiment in Section 6.2. Lender frictions refer to capacity constraints; consumer frictions refer to non-pecuniary costs associated with refinancing.