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 consumers' adoption of FinTech lending, which amplifies the effects of a monetary stimulus. I provide causal estimates of the network effect on FinTech adoption using county-level data. To quantify the role of FinTech lending and network spillovers in the transmission of monetary policy shocks, I build a heterogeneous-agent model with social learning. The model shows that the consumption response to a monetary stimulus is 13% higher in the presence of FinTech lending and network spillovers, and that about half of this improvement is accounted for by network spillovers.

Keywords: FinTech, network effect, monetary policy, mortgage, consumption, refinancing

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

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1 Introduction

One of the most important channels through which monetary policy affects the real economy is mortgage borrowing. Lower mortgage rates resulting from expansionary monetary policies reduce long-term borrowing costs, generate liquidity for refinancing borrowers, and stimulate household spending. This channel, however, 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, which slow their responses to surging demand during periods of low 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 a loan officer.[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 the features of their products, it has not studied the spillovers of FinTech lending across consumers' social networks. Social interactions play a key role in consumers' acquisition of information and decision-making, so it stands to reason that FinTech adoption is affected by peers. To the extent that this effect is strong, the transmission of a monetary stimulus in the FinTech era will be further amplified. A rigorous analysis of the role of FinTech lending

[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 origination 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).

in the monetary transmission has to take into account both FinTech product features and the amplification through social network spillovers. Using two alternative identification strategies, I provide causal estimates of the network spillover effect on FinTech adoption. To quantify the effects of monetary policy shocks on household consumption and borrowing in the presence of FinTech lending, I develop a heterogeneous-agent model with social learning. The model allows counterfactual analysis to assess separately the role of FinTech lending features, network spillovers, and mortgage market frictions in the monetary transmission.

I start by providing empirical evidence on the effect of social network spillovers on FinTech market penetration at the county level. The identification of causal effects involves two major challenges. First, how to measure social networks and network spillovers across U.S. counties? Second, how to solve the identification problem arising from the existence of unobserved common shocks that drive FinTech lending to grow simultaneously in multiple markets without market-to-market spillovers?[3] For example, socially connected counties are likely to share similar borrower characteristics and be exposed to common economic shocks, which could affect FinTech adoption through channels other than social interactions, confounding the identification of the network effect.

To overcome the first challenge, I employ the novel social connectedness index (SCI) developed by Bailey et al. (2018b), who use granular data on social networks of U.S. Facebook users, aggregate this information to the county level, and measure the relative intensity of social interactions for every pair of counties. Using this index, I measure network spillovers as the weighted change in the FinTech market share in a county's socially connected markets, with the largest weights assigned to counties that are most socially connected to this county. Unlike conventional approaches that focus on a few neighboring markets to study market spillovers (e.g., DeFusco et al. (2018)), this approach allows many counties (not necessarily just neighboring counties) to affect a given county, based on a continuous measure of social connectedness.

To overcome the second challenge, I employ two alternative instrumental-variable (IV) strategies. The first strategy leverages the panel nature of county-level data, making it

[3]The identification of the causal spillover 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.

possible to include a rich array of controls that account for both demand-side confounding factors (e.g., demographics, borrower characteristics, and labor- and housing-market conditions) and supply-side spillovers (e.g., advertising), as well as region-by-quarter fixed effects that soak up all shocks affecting counties in a census division within a quarter. Nevertheless, it is possible that some unobserved shocks that affect a narrower geographical area are not captured by these fixed effects. More generally, economic activities in neighboring markets tend to comove strongly in response to unobserved regional shocks, which are hard to control for. I therefore use instruments to further strengthen the identification. Specifically, I adapt the IV strategy of Bailey et al. (2018a) to the panel setting, exploiting exogenous variation in the FinTech growth in a county's socially connected but geographically distant markets.

This strategy reveals a sizable network spillover effect. A county's FinTech market share increases by about 0.3 percentage points (pps) in a year, when the FinTech market share in its socially connected markets increases by 1 pp. This effect is stronger at longer horizons. A breakdown by loan purpose suggests that the spillover effect is larger for FinTech refinancing than for FinTech home purchases. Moreover, I find that counties with higher social and economic mobility, such as those located in metropolitan areas, those with higher shares of college graduates, and those having experienced larger migration flows in the past, are more responsive to the network shock. This heterogeneity adds further credence to the propagation of FinTech lending across consumers' social networks.

While the panel IV strategy exploits all sources of variation in the FinTech growth in a county's distant but socially connected markets, it is agnostic about the underlying structural causes of FinTech growth. An alternative approach to identification is to exploit a specific source of exogenous variation. This strategy is motivated by the finding in the banking literature that an important driver of fast FinTech growth after the financial crisis was a shift in U.S. banking regulations that effectively reduced banks' presence in the mortgage market (Buchak et al. (2018)). At the county level, the exposure to the regulatory shift depends on the pre-crisis capital structure of the banks operating in a 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 socially connected markets to the regulatory change may serve as the instrument for the FinTech growth in these markets, which then helps identify the spillover effect. This cross-sectional IV strategy reveals a strong network spillover effect in the long run, corroborating the findings from the panel IV strategy.

Motivated by these empirical findings, I develop a structural heterogeneous-agent model to quantify the role of FinTech lending and network spillovers in the transmission of monetary policy shocks to households. The model incorporates three key empirical features of FinTech lending. First, FinTech lenders offer more convenient services to consumers, increasing the likelihood of refinancing (Buchak et al. (2018)). Second, FinTech lenders respond more elastically to surging demand, facilitating the pass-through of policy shocks (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 (this paper).

The model has rich heterogeneity on the household side characterized by idiosyncratic income shocks, balance-sheet conditions, and household-specific mortgage rates, all of which matter for consumption and refinancing decisions. While refinancing amid a monetary stimulus benefits most households, two types of frictions in the model may prevent households from taking this action. One is the non-pecuniary cost of refinancing (e.g., the time and effort spent on talking to the agent, visiting the lender's office and completing the paperwork). The other is capacity constraints faced by traditional lenders. 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 social networks and/or non-network sources (e.g., advertisements or search engines) with some probabilities, which in turn determines the market share of FinTech lenders.

Model simulations show that, when FinTech market penetration and social network intensity are calibrated to data from 2017, a monetary stimulus that lowers the mortgage rate by 1 pp increases the refinancing propensity (i.e., the share of borrowers refinancing their mortgage in a year) by 11.1 pps. In an otherwise identical economy without FinTech lending and network spillovers, the refinancing propensity only increases by 9.9 pps upon the policy shock, suggesting a 1.2 pps (or a 12%) improvement in the effect of the monetary stimulus on refinancing. When the network spillover is shut down, the refinancing propensity only increases by 10.6 pps (or 7%), suggesting that almost half of the improved monetary-policy effect on refinancing is due to the amplification of network spillovers. Quantitatively similar results are obtained for the consumption response: Network spillovers contribute slightly more than half (55%) to the overall 13% increase in the consumption response.

As FinTech lending continues to expand in the U.S. mortgage market, it will likely become more important in the monetary transmission. A counterfactual analysis based on the model helps understand how the effects of a monetary stimulus would change, if social networks played an even more important role in spreading information. As the probability of learning from peers increases, the FinTech market share rises, even if FinTech lenders do not actively expand their business, and consumption and refinancing are more responsive to the policy stimulus. A rise of the FinTech market share from 20% to 80% due to stronger network spillovers, for example, would increase the consumption and refinancing responses by 56% and 51%, respectively.

Relation to the literature. This paper 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)). This literature so far 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. My paper incorporates FinTech lending within the analysis of the household problem, providing a new perspective on the state-dependence of the effects of monetary policy shocks. Conventional models with standard calibration may underestimate the changing responsiveness of the household sector, as FinTech lending continues to expand in the U.S. mortgage market.

This paper also adds to a growing literature on 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 in the FinTech era, calling further attention from policy makers to the broad implications of technology innovations.

In addition, this paper also contributes to the microeconomic literature studying social interactions and household financial decision-making.[4] This literature has offered extensive evidence on peer effects in other contexts, for example, 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 do not inform us about the magnitude of the peer effects in FinTech mortgage adoption. While the related studies by Maturana and Nickerson (2019) and McCartney and Shah (2021) provide peer-effect estimates for mortgage refinancing and lender choices, they focus on a specific setting (interactions between Texas school teachers) or a small geographic area (Los Angeles) over the period before FinTech emerged. There are reasons to believe that (and indeed, I show that) the network effect on FinTech refinancing is stronger than that on other refinancing due to the highly standardized online application systems designed by FinTech lenders. This paper's main contribution to the literature is to provide estimates of causal network effects in the FinTech mortgage setting, 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, my work is connected to the literature on how shadow banks affect the transmission of monetary policy. Xiao (2020), focusing on upstream shadow banks that take deposits from households, shows that deposits flow out of the banking system and into 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 changing the consequences of aggregate policies such as quantitative easing (QE). Unlike these studies, I focus on the role of consumers' social

[4]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.

networks in expanding the FinTech footprint, which amplifies the transmission of monetary policy through the refinancing channel.

The remainder of the paper is organized as follows. Section 2 describes the main proprietary datasets used in the empirical analysis and highlights the trends in the mortgage lender advertising data. Section 3 presents empirical evidence on the network spillover effect of FinTech lending based on two alternative IV strategies. Sections 4 and 5 describe the structural model and its calibration. Section 6 presents model simulations and counterfactual analysis that quantify the role of FinTech lending features and the role of social network spillovers in changing the effects of monetary policy shocks. Section 7 concludes.

2 Data

The empirical analysis in this paper draws on loan-level, bank-level, county-level and national-level economic and financial data. This section describes two main proprietary datasets used: the confidential-version HMDA data and Mintel-Comperemedia advertising data. To conserve space, the description of other datasets is provided in Appendix B.

Home Mortgage Disclosure Act (HMDA). This dataset contains nearly the universe of residential mortgage application and approval records in the U.S. It has detailed loan-level information and borrower-level characteristics, as well as the lender identifier, making it the most suitable source for studying FinTech lending in the U.S. national and regional mortgage markets. The public version of the data can be obtained from the Consumer Financial Protection Bureau (CFPB).

The confidential version of the data, accessible from the Federal Reserve Board, has additional information on the exact date of origination, rather than just the year as in the public version. This information allows me to construct county-level panel data at quarterly frequency to study the dynamics of FinTech spillovers, and to strengthen the identification by including region-by-quarter fixed effects in my regressions. Moreover, the confidential HMDA data have higher precision, because they are continuously updated and corrected for 18 months after the original submission, whereas the public version is not. I use the confidential HMDA data to implement the panel IV strategy.

Mintel-Comperemedia Direct Mail and Print Advertising Data. Since the empirical analysis of this paper aims to identify the spillover of FinTech lending across consumers' social networks, the supply-side spillovers must be controlled for. For example, one concern is that a FinTech lender earning the market share in one county may expand its business to socially connected 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 issue using a new dataset on mortgage lenders' advertising. If the estimated network effect reflects cross-region spillovers arising from lenders' business strategy, we would expect such spillovers to be also reflected in their advertising strategy.

The data, obtained through a customized contract between the Federal Reserve Bank of Dallas and Mintel Comperemedia Inc., contain information on the volume of advertisements (offers) sent by individual mortgage lenders to households by mail at the zip-code level. The dataset includes all major mortgage lenders—both FinTech and non-FinTech—and has a number of advantages: a geographically representative coverage, a long sample period (since 2007), and its high frequency (monthly).[5] In all my empirical specifications, I include changes in FinTech advertising volumes in a county and in the county's socially connected markets as control variables, so that any supply-side spillovers through advertising are accounted for.

To understand the trends in U.S. mortgage lenders' advertising, panel (a) of Figure C1 in the Appendix plots the time series of mortgage-offer volumes. Mortgage advertising experienced a boom-bust circle in the mid and late 2000s, as did mortgage originations. The spike in 2012-13, driven by refinancing advertisements, coincided with a mortgage refinancing boom over this period. Panel (b) plots the share of mortgage offers sent by FinTech lenders. Similar to the patterns in the HMDA data, FinTech advertising was essentially non-existent before 2011 and increased dramatically in subsequent years, accounting for a large share of the refinancing offers. These patterns suggest that FinTech lenders are active in advertising and that the advertising trends resemble those in the actual originations data. Panels (c)

[5] The underlying microdata used to construct this dataset consist of a panel of 70,000 households who regularly share the direct mails and print advertisements they received with the Mintel team on a weekly basis. The sampling of these 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 advertising volume at the zip-code level can be reliably estimated with appropriate weighting.

and (d) plot the advertising shares of two largest FinTech lenders, Quicken Loans and Loan Depot. The former sent the most offers among FinTech lenders (and originated the most loans), dwarfing the share of Loan Depot.

One may be concerned that these data cover only direct mails and print advertising, not capturing trends in other forms of advertising, such as email offers (for which no suitable data exist). One way to address this concern is to cross-check online search statistics, which are likely to reflect the volume of information consumers received online or electronically. The lower panel of Figure C1 shows the Google search trends indices for Quicken Loans and Loan Depot (as mortgage companies). These indices moved closely with the advertising shares in panel (c), with correlations as high as 0.85 (for Quicken loans) and 0.86 (for Loan Depot). This comparison provides further support to the usefulness of the Mintel data in capturing lender advertising patterns.

3 Empirical Evidence

This section discusses two measures of social interactions at the county level and how they may be used to estimate the network spillover effect. To overcome the identification challenge to causal inference, I implement two alternative IV strategies: a panel IV strategy that exploits variation in FinTech growth in a county's socially connected but geographically distant markets and a cross-sectional IV strategy that exploits variation in the market exposure to post-crisis banking regulations. Additional evidence from examining the heterogeneity in the network effect, external survey evidence, and a battery of robustness checks provides further support to a sizeable network effect of FinTech lending. I conclude this section by discussing the aggregate implications of network spillovers and how my empirical evidence motivates the structural model in Section 4.

3.1 Measuring Network Spillovers

At the individual level, the network spillover effect (or peer effect) on FinTech adoption refers to the change in a person's probability of adopting FinTech, if the probability of FinTech adoption increases among the set of people whom the person connects to through social relationships. With county-level data, this interpretation naturally extends to the change in a county's FinTech market share, given an exogenous increase in the FinTech market share in the county's socially connected markets.

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

I construct the network-spillover variable, which is the key RHS variable in my regressions, as the weighted change in the FinTech market share in a county's socially connected markets.[7] Using the SCI-based measure, for example, the spillover from county c's socially connected areas (SCAs) is

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

where the weight, $\omega_{j,c}^{SCA} \equiv \frac{s_{j,c}}{\sum_{k \in J_c^{SCA}} s_{k,c}}$, increases in the SCI between counties j and c ($s_{j,c}$), so that the largest weights are assigned to the counties that are most socially connected to county c. $\Delta FinTech_{j,t}$ is the change in the FinTech market share in county j at time t. J_c^{SCA} denotes the set of counties that are socially connected to county c.

Alternatively, using the more traditional distance-based measure, the FinTech spillover from county c's geographically connected areas (GCAs) is

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

where the weight, $\omega_{j,c}^{GCA} \equiv \frac{1}{1+d_{j,c}}$, is inversely related to the distance, $d_{j,c}$, between counties

[6]See Bailey et al. (2018b) for a detailed description of the construction of the SCI and its correlations with distance and trade flows. 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 in the county over this period accounted for by FinTech lenders. The loan-level HMDA data are used to construct FinTech market shares.

j and c. J_c^{GCA} denotes the set of counties that are geographically close to county c.

Given the large dimensionality of the dataset, J_c^{SCA} and J_c^{GCA} are chosen to include markets that have non-trivial social interactions with county c. In the main analysis, I include counties ranked as the top 200 socially connected counties to county c (according to the SCI) in J_c^{SCA} and counties within 200 miles of county c in J_c^{GCA}. Increasing these thresholds has little impact on the estimated network spillover effect (see Appendix Table C1). The reason is that the weights ($\omega_{j,c}^{SCA}$ and $\omega_{j,c}^{GCA}$) are essentially zero for markets excluded by these thresholds, and that the spillovers from these markets are statistically and economically insignificant (see Section 3.2.2). An example of the differences between GCAs and SCAs is provided in Appendix Figure C2 for Cook county, IL, where Chicago is located.

To estimate the network spillover effect, one may attempt to regress the change in the FinTech market share in county c, $\Delta FinTech_{c,t}$, on $\Delta FinTech_{c,t}^{SCA}$ (or $\Delta FinTech_{c,t}^{GCA}$). The identification of the causal effect, however, is threatened by the existence of unobserved common shocks, both on the demand and the supply side, that cause FinTech to grow simultaneously in socially connected markets without market-to-market spillovers. On the demand side, consumers in socially connected counties are likely to share similar characteristics (e.g., demographics, educational attainment, and credit worthiness) or be exposed to common economic shocks (e.g., housing- and labor-market shocks) that directly affect their mortgage choices. On the supply side, lenders may advertise their products to multiple markets simultaneously, or deliberately expand their business to socially connected markets. In the next two subsections, I introduce two alternative empirical strategies, as well as a number of robustness checks and additional evidence, to deal with these concerns.

3.2 The Panel IV Approach

My first empirical strategy leverages the panel nature of county-level data, which allows the inclusion of a rich set of time-varying controls and fixed effects to mitigate the endogeneity concerns. First, to account for correlated consumer characteristics, I include time-varying shares of the young population, minority population, college graduates, and subprime borrowers in the county and in its socially connected counties, as well as the interactions between demographics and year dummies to account for the possibility that different demographic groups face different economic shocks that are common across regions. Second, to account for the impact of housing and labor market conditions, I include the growth rates of house prices, employment, and population in the county and in its socially connected markets. Third, to account for supply-side spillovers, I control for the growth rates of mortgage advertising sent by FinTech lenders to the county and to its socially connected markets. Fourth, I include county fixed effects and region-by-time fixed effects to control for unobserved heterogeneity and regional-specific time trends that could affect both loan demand and supply across counties in a given census division within a quarter.

Despite this comprehensive list of controls, it is possible that some unobserved shocks may affect a narrower geographical area and hence are not captured by the fixed effects. More generally, economic activities in neighboring markets tend to comove strongly in response to regional shocks, which are hard to control for due to their wide scope and unobserved nature. I therefore use instruments to abstract from this concern. Note that the SCI-based measure of connectedness can identify counties that are socially connected to but geographically distant from a county. Utilizing this feature, the instrument is constructed as the weighted change in the FinTech market share in a county's socially connected but geographically distant markets,

$$\Delta FinTech_{c,t}^{SCA,Out} \equiv \sum_{j \in J_c^{SCA,Out}} \omega_{j,c}^{SCA,Out} \Delta FinTech_{j,t}. \tag{3}$$

A similar instrument was proposed by Bailey et al. (2018a) to isolate exogenous house price changes experienced by an individual's friends and to study the network effect of beliefs on housing investment. In essence, this instrument exploits exogenous variation in the network formation between faraway counties, for example, historical migration patterns that shaped the social connectedness between Cook County in Illinois and Holmes County in Mississippi, interacted with idiosyncratic shocks that drive local FinTech growth. Since these counties are distant, it is less likely that they are hit by unobserved common shocks that typically affect neighboring markets, especially conditional on the many controls discussed above.

Equation (4) formalizes this panel IV strategy:

$$\begin{aligned} \textit{1st stage: } \Delta FinTech_{c,t}^{SCA} &= \delta_c + \delta_{d,t} + \alpha_1 \Delta FinTech_{c,t}^{SCA,Out} + \alpha_2 \mathbf{x}_{c,t} + \alpha_3 \bar{\mathbf{x}}_{c,t}^{SCA} + \nu_{c,t}^{SCA} \\ \textit{2nd stage: } \Delta FinTech_{c,t} &= \gamma_c + \gamma_{d,t} + \beta_1 \Delta \widehat{FinTech}_{c,t}^{SCA} + \beta_2 \mathbf{x}_{c,t} + \beta_3 \bar{\mathbf{x}}_{c,t}^{SCA} + \varepsilon_{c,t}, \end{aligned} \tag{4}$$

where $\Delta FinTech_{c,t}$ is the four-quarter change in county c's FinTech market share, $\Delta FinTech_{c,t}^{SCA}$ the weighted four-quarter change in the FinTech market share in county c's SCAs (as defined in equation 3), and $\Delta FinTech_{c,t}^{SCA,Out}$ the weighted four-quarter change in the FinTech market share in county c's socially connected but geographically distant markets. As in Bailey et al. (2018a), I use counties outside county c's commuting zone to construct the instrument. As shown in the robustness (Section 3.2.3), using alternative distance thresholds (e.g., at least 100 or 200 miles away) gives similar estimates. δ_c and γ_c denote the county fixed effects, $\delta_{d,t}$ and $\gamma_{d,t}$ the region-by-quarter fixed effects, $\mathbf{x}_{c,t}$ the set of controls for county c, and $\bar{\mathbf{x}}_{c,t}^{SCA}$ the set of controls for county c's SCAs.[8] The standard errors are clustered at the county level.[9]

3.2.1 Baseline Results

Panel I of Table 1 presents the OLS estimates of the network spillover effect using the SCI-based measure of connectedness. The estimates are stable across specifications: A 1 pp increase in SCAs' FinTech market share raises a county's FinTech market share by 0.33-0.34 pps over a one-year horizon. The estimates in panel II using the distance-based measure of connectedness are similar. A 1 pp increase in GCAs' FinTech market share raises a county's FinTech market share by 0.33-0.37 pps. Panel III shows the IV estimates using the FinTech growth in a county's out-of-commuting-zone SCAs as the instrument. With the full set of controls, the baseline IV estimate in the third column, 0.33, is similar to the OLS estimate, suggesting that the inclusion of a rich set controls and fixed effects is effective in addressing the endogeneity concern. These estimates imply a sizable network spillover effect:

[8]The control variables for the county's SCAs, $\bar{\mathbf{x}}_{c,t}^{SCA}$, take the linear-in-mean form (as standard in the peer effects literature). It means that each of the variables in this set (e.g., house price growth) is a weighted average of the same variable across the county's SCAs (using $\omega_{j,c}^{SCA}$ as the weight).

[9]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.

If SCAs' or GCAs' FinTech market-share growth moves from the 10^{th} to 90^{th} percentile of the distribution, a county's FinTech market share will increase by 1.8 pps, a 31% increase relative to the unconditional mean (about 6 pps).

So far, the network spillover effect is estimated for all types of FinTech originations (i.e., refinancing and home purchases). To answer the question of which type of lending is more responsive to network spillovers, I estimate the IV specification with the change in county c's FinTech market share of refinancing or home-purchasing mortgages, respectively, as the second-stage dependent variable. Columns 2 and 3 of Table 2 show a stronger effect on refinancing than home-purchasing. A 1 pp increase in SCAs' FinTech market share raises a county's FinTech refinancing share by 0.38 pps, about twice as much as the effect on FinTech home purchases. This pattern is consistent with the fact that refinancing is easier to automate, unlike home-purchasing mortgages that require coordination with other parties.

In addition, Table 2 shows that the rising FinTech market share caused by network spillovers is associated with a growing volume of FinTech lending, rather than a decline in the non-FinTech lending volume. Column 4 shows that a county's FinTech lending volume (normalized by prior-year total originations) increases by 0.4 pps in response to network spillovers. Given the 6% FinTech market share, this implies a 7% increase in the county's FinTech lending volume. Both refinancing and home-purchasing volumes grow (columns 5 and 6), with higher growth observed for FinTech refinancing. Finally, column 7 shows no change in the volume of non-FinTech lending in response to FinTech spillovers.

3.2.2 Heterogeneity in FinTech Spillover Effect

The results in Section 3.2.1 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 most responsive to network spillovers.

I start by testing whether a gravity relationship holds for the spillover effect, i.e., whether a county's most socially connected markets exert the greatest impact on the county's FinTech lending. For this purpose, I reconstruct $\Delta FinTech_{c,t}^{SCA}$ such that it includes only a subset of connected markets. The instrument is reconstructed accordingly using counties in this subset but geographically faraway from county c. Table 3 presents the IV estimates, which show a clear 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. Zooming in on individual counties, Figure 1 shows the network spillover effects of a county's top 10 SCAs and top 10 GCAs on the county's FinTech market share, using the OLS specification. Even within this small set of connected counties, a declining pattern of the network effect is observed for relatively less connected counties (regardless of the connectedness measure), consistent with a gravity relationship.

Which counties are more responsive to network spillovers? A natural conjecture is that counties more connected to the outside world and more socially and economically mobile should be more responsive. To evaluate this hypothesis, I interact $\Delta FinTech_{c,t}^{SCA}$ with each of the four county characteristics in Table 4 one at a time. The instruments are constructed accordingly by interacting $\Delta FinTech_{c,t}^{SCA,Out}$ with these characteristics. The results show that, the spillover effect is larger for counties located in metropolitan areas with a larger population (column 1), for counties with higher (above-the-median) shares of college graduates (column 2), for counties with higher shares of African Americans (column 3), and for counties having experienced larger migration flows in the previous year (column 4), reinforcing the earlier results.

3.2.3 Additional Evidence and Robustness

Refinancing spillovers vs. FinTech refinancing spillovers. Previous studies focusing on the pre-FinTech era provided evidence that peer effects exist in consumers' refinancing decisions (e.g., Maturana and Nickerson (2019); McCartney and Shah (2021)). An important question is whether the FinTech refinancing spillover effect I estimated earlier merely reflects peer effects common to all forms of refinancing. There is reason to believe, however, that peer effects in refinancing are stronger with FinTech, given the widespread internet access and highly standardized online application systems designed by FinTech lenders.

One way to address this question is to estimate the refinancing spillover effect by lender segment. Table 5 shows the estimates for overall refinancing, FinTech refinancing, non-bank refinancing, and bank refinancing. These effects are estimated using IV specifications similar to equation (4), with the LHS, RHS and IV constructed accordingly for a given lender segment. In addition, for the effects to be comparable across specifications, I rescale the regression variables so that the coefficient in each column represents the percent change relative to the unconditional mean, caused by a 1 s.d. increase in the explanatory variable (as in Maturana and Nickerson (2019)). Column (1) shows that the overall refinancing share increases by 15.7% in a county (relative to the unconditional mean), following a 1 s.d. increase in SCAs' overall refinancing share. Column (2) shows that the FinTech refinancing share increases by almost 20% in a county, following a 1 s.d. increase in SCAs' FinTech refinancing share. This effect is significantly higher than that in column (1), based on a bootstrap test of equal coefficients.

A closely related question is whether the FinTech spillover effect merely reflects the spillover effect of non-bank lending. Column (3) shows that the network spillover effect of non-bank refinancing is only 14.5%, significantly lower than the FinTech network effect. Finally, column (4) estimates the spillover effect of bank refinancing, showing a even weaker effect of 7%. These results suggest that, while network effects exist in mortgage refinancing in general, the FinTech network effect is the most pronounced.

Instruments using alternative distance thresholds. To see if the baseline IV estimate is robustness to alternative criteria for defining counties' socially connected but geographically distant markets, columns (1)-(2) of Appendix Table C2 present the estimates using FinTech growth in a county's SCAs that are at least 100 miles and 200 miles away from the county as the instruments. The estimates (0.34 and 0.42) are similar to the baseline estimate.

Spillovers measured by FinTech refinancing shares. One concern about using $\Delta FinTech_{c,t}^{SCA}$ as the key RHS variable for estimating equation (4) is that it reflects both FinTech refinancing and home-purchasing activities. The latter are know to be volatile and display seasonality, likely resulting in unstable estimates. To address this concern, I use the change in SCAs' FinTech refinancing market share as the RHS and rescale this variable to account for its mean difference from $\Delta FinTech_{c,t}^{SCA}$. The instrument is constructed accordingly using the weighted change in the FinTech refinancing market share in a county's distant SCAs. Column (3) of Table C2 in the Appendix shows that the overall effect, 0.28, is similar to the baseline. Columns (4) and (5) estimate the effect by loan purpose and again show a stronger network effect for FinTech refinancing, consistent with the pattern documented earlier.

Big-city effects. One concern about the identification in the panel IV strategy is that some unobserved shocks may affect socially connected counties simultaneously even if they are faraway. For example, a FinTech product may be first launched in a few major cities. Demand shocks, such as tech-sector layoffs, may affect geographically distant markets that have a similar employment composition (although the educational attainment-by-time fixed effects should account for this kind of shock). This issue is more prominent for counties in big cities (e.g., New York and San Francisco). To address this concern, I drop counties in the largest metropolitan areas (MSAs), not only in the main regression but also for constructing the IVs, and re-estimate the IV specification to obtain the spillover effect. Column (6) of Appendix Table C2 shows that the baseline estimate is essentially unchanged when counties in the largest 10 MSAs are excluded. Even if counties in the largest 30 MSAs are excluded (accounting for half of the MSA population), column (7) shows an estimate similar to the baseline IV estimate.

Dynamic spillover effects. The origination-date information in the confidential HMDA data allows me to examine the network spillover effect at a higher frequency and its dynamics over time. Figure 2 plots the cumulative network spillover effect at different horizons (1-quarter, 2-quarter, etc.), using the IV strategy in equation (4). The 4-quarter effect is the same as in the baseline. The left panel shows a rising network effect over time, from 0.1 after one quarter to about 0.4 after eight quarters. The right panel shows the effect by loan purpose. Both FinTech refinancing and home-purchasing display stronger network effects over time, and, consistent with the earlier results, the effect is larger for FinTech refinancing at all horizons.

Survey evidence on network spillovers. Since mortgage loan-level data do not reveal borrower-level relationships, it is difficult to provide direct evidence that it is chats with friends and family that lead to FinTech adoption. My analysis hence has relied on social-connectedness measures at the county level and empirical strategies for causal inference. External survey data provide direct evidence for this narrative. The PricewaterhouseCoopers (PwC) consumer-finance group conducted a national survey in 2015 to study consumer preferences for loan origination.[10] Two results from this survey shed light on the role of technology and social interactions in mortgage origination. First, whereas most consumers preferred completing mortgage applications by traditional methods and interacting with lenders in 2013, most consumers in 2015 preferred completing this task online, suggesting a shift in preferences toward technology-based lending. Second, as shown in Appendix Figure C3, consumers ranked "friends and family" as the second most influential referral source for mortgages (27%). The most influential source is "existing banking relation" (29%), which does not apply to FinTech lenders, because they specialize in mortgage originations and do not take household deposits. Interestingly, social media itself (e.g., social media campaigns) are not an important referral source. It is friends and family whom consumers may interact with through social media that matter for their decisions.

3.3 The Cross-Sectional IV Approach

While the panel IV strategy essentially exploits all sources of variation in the FinTech growth in a county's socially connected but geographically distant markets, it is agnostic about the underlying structural causes of FinTech growth in regional markets. I now consider an alternative IV strategy that isolates a specific source of the differential growth of FinTech in county markets—shifts in U.S. banking regulations after the financial crisis.

After the financial crisis, traditional banks faced numerous regulatory shocks such as the Dodd Frank Act and Basel III measures (Buchak et al. (2018)). One significant change was increased capital requirements. As shown in the left panel of Figure 3, banks' tier 1 (T1) capital ratio—the core measure of a bank's financial strength from a regulator's point of view—rose drastically in the years after the crisis. Building up regulatory capital, however, comes at the cost of reducing banks' balance-sheet lending and mortgage originations. This created opportunities for FinTech lenders, who did not face these regulatory burdens, to gain

[10] 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.

market shares.

At the county level, the exposure of a specific county to the regulatory tightening depends on the pre-crisis capital structure of the banks operating in that county, which varies substantially and is plausibly unrelated to post-crisis loan demand. This suggests that the exposure of a county's socially connected markets to regulatory shocks may serve as the instrument for the post-crisis FinTech growth in these markets, which then helps identify the causal spillover effect. Since the nature of the shock is cross-sectional and it took several years for banks to adapt to the new regulatory environment, my analysis focuses on FinTech growth in the period of 2008-2015.

The design of the instrument is motivated by the finding in Buchak et al. (2018) that counties where banks increased their T1 capital ratios the most after the crisis experienced the highest growth in FinTech lending.[11] To avoid the concern that changes in T1 capital ratios after the crisis may reflect, to some extent, rising demand for FinTech loans over the same period, I use banks' T1 capital ratios at the beginning of 2008 to construct the instrument. Variation in this ratio comes from capital decreases before the crisis under loose financial supervision, which cannot be possibly driven by post-crisis loan demand. In fact, banks had the lowest capital ratios in 2008 were those reducing capital the most before the crisis. These banks also experienced the largest capital increases after the crisis (see Figure 3, right panel).

The instrument has two layers of aggregation. The first layer measures the exposure of a specific county, say, county j (in county c's network), to the regulatory shock. The second layer aggregates the exposure of a set of counties in county c's network, using the social-connectedness weight, $\omega_{j,c}^{SCA}$. The following expression defines the IV,

$$T1Ratio_{c,2008}^{SCA} \equiv \sum_{j \in J_c^{SCA}} \omega_{j,c}^{SCA} \underbrace{\left(\sum_{b \in B^j} s_{b,j} T1Ratio_{b,2008} \right)}_{\text{county } j\text{'s exposure}}. \tag{5}$$

[11] Buchak et al. (2018) presented the result that counties where banks increased their T1 capital ratios the most after the crisis experienced the highest growth in the market share of nonbank lending. I ran the same specification using county-level data and confirmed that this result also holds for the FinTech market share.

The exposure of county j to the regulatory shock is measured by origination share-weighted T1 capital ratios. $s_{b,j}$ in expression (5) denotes bank b's origination share in county j in 2008, and $T1Ratio_{b,2008}$ denotes bank b's T1 capital ratio at the beginning of 2008.

Equation (6) formalizes this cross-sectional IV strategy:

$$\begin{aligned} &\textit{1st Stage:} \quad \Delta FinTech^{SCA}_{c,2008-2015} = \delta_s + \alpha_1 T1Ratio^{SCA}_{c,2008} + \alpha_2 \mathbf{x}_c + \alpha_3 \bar{\mathbf{x}}^{SCA}_c + \nu^{SCA}_c \\ &\textit{2nd Stage:} \quad \Delta FinTech_{c,2008-2015} = \gamma_s + \beta_1 \Delta \widehat{FinTech}^{SCA}_{c,2008-2015} + \beta_2 \mathbf{x}_c + \beta_3 \bar{\mathbf{x}}^{SCA}_c + \varepsilon_c. \end{aligned} \tag{6}$$

The control variables include those discussed earlier (adapted here to the cross-sectional setting) and the bank share of originations in 2008. More importantly, I include the exposure of the county itself to the regulatory shocks ($T1Ratio_{c,2008}$), so that any direct impact due to the county's exposure to these shocks on its FinTech market share is accounted for. State fixed effects, δ_s and γ_s, ensure that the estimation compares counties within a state. The main identifying assumption is that, conditional on the county's exposure to regulatory shifts and a rich set of controls for loan demand, the regulatory shocks experienced by the county's socially connected markets only affect its FinTech lending indirectly through the impact on these connected markets' FinTech growth. As shown later, the IV estimate from this strategy is robust to a refined instrument using the exposure of a county's socially connected but geographically distant markets, and to a different exposure measure based on county-specific market shares of the four largest banks (Big4) at the onset of the crisis.

3.3.1 Results

In the first stage of equation (6), $\hat{\alpha}_1$ is expected to be negative, because counties where banks had low capital ratios in early 2008 were more likely to experience capital rebuilding after the crisis, which depressed balance-sheeting lending and encouraged FinTech lending. The bin scatter plot of FinTech growth in SCAs against the instrument (residualized using other control variables) in panel (a) of Figure 4 shows this negative relationship. This is confirmed by the first-stage estimate, -0.37, in panel I of Table 6, column (1), which also shows a high relevance of the IV.

The second-stage IV estimate shows that a 1 pp increase in SCAs' FinTech market share raises the county's FinTech market share by 1.5 pps, indicating a strong network spillover effect. This estimate is larger than the panel IV estimate in Section 3.2, likely due to the longer estimation horizon in this case. This can also be seen by comparing the OLS estimates: At the one-year horizon, the effect is 0.33 pps (Table 1), while at the cross-sectional seven-year horizon, the OLS estimate is 1 pp (column 5, Table 6).

One may raise the concern that the exposure to the regulatory tightening is likely to be correlated across neighboring counties, since smaller banks typically operate within a limited geographic area, resulting in a similar bank composition in these markets. This issue itself does not introduce bias, because I already controlled for the county's exposure. It may, however, introduce multicolinearity that inflates the coefficients and standard errors. To address this issue, I refine the instrument using the exposure of the county's socially connected but geographically distant markets, $T1Ratio^{SCA,Out}_{c,2008}$. Columns (3) and (4) in panel I of Table 6 show the results. The first stage has a negative sign (as expected) and a high relevance. The network spillover effect in the second stage, 1.3 pps, is only slightly lower than that in column 2.[12]

3.3.2 The Role of Big4 Banks

While the U.S. banking sector as a whole faced numerous regulatory shocks following the financial crisis, the burden fell particularly hard on the largest four banks (Bank of America, Citi, JP Morgan and Wells Fargo), as documented by Begley and Srinivasan (2022). For example, these banks started their regulatory capital from the lowest level at the onset of the crisis and had to increase capital ratios the most after the crisis. This implies that the exposure of a county to regulatory shocks should be largely captured by its exposure to Big4 lending. To provide further support to the regulatory channel, I construct an IV using Big4 origination shares in county markets, as shown below, and run 2SLS as in equation (6),

$$Big4Share^{SCA}_{c,2008} \equiv \sum_{j \in J^{SCA}_c} \omega^{SCA}_{j,c} Big4Share_{j,2008}, \tag{7}$$

[12] I also reestimate the IV specification using T1 capital ratios and the market-share distribution in an earlier year to construct the instrument. This lagged instrument helps purge demand shocks that are correlated with bank balance-sheet conditions in 2008 and post-crisis FinTech growth, since it is less likely that unobserved local demand shocks correlated with balance-sheet conditions in the early 2000s can explain FinTech growth in the far future in 2015. I found similar estimates to those in Table 6.

where $Big4Share_{j,2008}$ represents the origination share of the Big4 banks in county j in 2008.

The first-stage coefficient, $\hat{\alpha}_1$, is expected to be positive, because counties where Big4 had the highest market shares before the crisis were most likely to experience severe regulatory adjustments, a withdrawal of the Big4 banks, and FinTech entry. The bin scatter plot in panel (b) of Figure 4 shows the positive relationship between the 2008 Big4 share in SCAs and the post-crisis FinTech growth in SCAs. The strongly positive estimate in the lower panel of Table 6 (column 1) confirms this relationship. The second-stage network spillover effect is 1.3. Using a refined version of the IV based on the exposure of socially connected but geographically distant markets to Big4 lending, I obtain a similar spillover effect, 1.2 (column 4, panel II). These results support the view that regulatory changes were a main driver of FinTech growth, which in turn was amplified by network spillovers.

3.4 Implications for the Monetary Transmission

To summarize, my empirical analysis establishes that network spillovers play an important role in the penetration of FinTech lending in county markets. At the aggregate level, higher FinTech market penetration helps ease mortgage market frictions, facilitates loan originations, and enhances the pass-through of monetary policy stimulus. The important questions are how to quantify this effect of FinTech lending and how important the network spillovers are in driving this effect. Answering these questions requires a structural model and counterfactual analysis, which I explore in Sections 4-6.

Before we can design such a structural model, we need to know more about how FinTech lending affects the monetary transmission. First, does FinTech market penetration affect monetary transmission mainly through the refinancing channel or the home-purchasing channel? Second, does FinTech market penetration affect monetary transmission mainly through the quantity channel (i.e., by originating more loans) or the price channel (i.e., by offering lower rates)?

Evidence in Fuster et al. (2019) provides some answers to these questions. Specifically, they show that the refinancing propensity increases significantly for counties with higher FinTech market penetration. Moreover, using Ginnie Mae loan-level data, which capture a riskier segment of the U.S. mortgage market, they document that FinTech lenders offer slightly lower rates to home-purchasing mortgages, while no differences in the refinancing rates are found. Their evidence, however, does not tell us about the effect of FinTech market penetration on home purchases, nor the effect on the rate for a typical new mortgage.

I therefore extend Fuster et al.'s county-level evidence to additional outcome variables, the home-purchasing propensity and the average rate on newly originated mortgages, using mortgage servicing data, McDash. The data, regression specification and estimation results are detailed in Appendix D. The key findings can be summarized as follows. First, unlike the refinancing propensity, the home-purchasing propensity does not change for counties with higher FinTech market penetration. Second, the average rate on newly originated mortgages does not differ across counties with different FinTech market penetration. Together, these findings suggest that FinTech market penetration facilitates monetary transmission mainly through the refinancing-quantity channel, which will be the focus of the structural model in the next section.

4 Model

Motivated by these empirical findings, I develop a quantitative macroeconomic model of heterogeneous agents to assess the role of FinTech lending and network spillovers in the transmission of monetary policy shocks to households. The model helps us understand how consumers make decisions given their income and wealth conditions and how these decisions are affected by various shocks and institutional features. The model incorporates three key empirical features of FinTech lending. First, FinTech lenders offer more convenient services that are valued by the average consumer.[13] Second, FinTech lenders respond more elastically to demand shocks, facilitating the pass-through of policy stimulus. 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

[13]For supporting evidence, see Buchak et al. (2018) and Fuster et al. (2019). Evidence from customer reviews and industry ratings also supports this point. 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 (see Section 6.3).

and policy experiments, I quantify the change in the monetary policy effects due to the introduction of FinTech lending, with a particular focus on the role of network spillovers.

Preferences. The economy is populated by a continuum of infinitely-lived households indexed by i. Households maximize their expected life-time utility

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

where $c_{i,t}$ denotes consumption of household i 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.[14]

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

$$\log(y_{i,t}) = (1-\rho^y)\mu^y + \rho^y \log(y_{i,t-1}) + \varepsilon^y_{i,t}, \quad \varepsilon^y_{i,t} \sim^{\text{i.i.d.}} (0, \sigma^2_y), \tag{8}$$

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

$$\log(p_t) = (1-\rho^p)\mu^p + \rho^p \log(p_{t-1}) + \varepsilon^p_t, \quad \varepsilon^p_t \sim^{\text{i.i.d.}} (0, \sigma^2_p), \tag{9}$$

with unconditional mean μ^p, persistence ρ^p, and an idiosyncratic shock ε^p_t.

Mortgage debt, refinancing, and liquid savings. Mortgage debt is long-term. It requires a recurring fixed payment, $r^b_{t_0} b_{i,t_0}$, 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 balance b_{i,t_1} at the current market rate, $r^b_{t_1}$. The resulting new payment is $r^b_{t_1} b_{i,t_1}$. Upon refinancing, households cash out available home

[14] 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-purchasing originations. The role of FinTech lending remains important even if housing investments are modeled as endogenous.

equity, if any. If they are underwater, they have to pay back the amount that meets the loan-to-value (LTV) requirement. This implies that the collateral constraint binds at the time of refinancing,

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

where γ is the maximum LTV ratio set by the lender.

Refinancing involves two types of costs. One is a closing cost that is proportional to the new borrowing amount, $\phi b_{i,t_1}$. The other is non-pecuniary, reflecting the time and effort spent on refinancing-related activities, such as talking to the loan agent, visiting the lender's office, and completing the paperwork. This non-pecuniary cost, $f_{i,t}$, is drawn from an i.i.d. process with the cumulative distribution function F_f. Households have access to liquid assets, $a_{i,t}$, which pay a rate of return $r^a < r^b$. Moreover, households face the liquidity constraint every period, $a_{i,t} \geq 0$.

FinTech lending and network spillovers. One important feature of FinTech lending is improved services (e.g., reduced paperwork, at-home origination, and faster loan processing).[15] I model this feature as a utility gain, q, when consumers refinance their mortgage with a FinTech lender. For the baseline model, I assume that q is a positive constant (calibrated from data). Of course, in reality, some consumers may not perceive FinTech services as more convenient and may prefer traditional lending. In Section 6.3, I relax this assumption by allowing heterogeneity in q and in the choice between FinTech and traditional lenders even after the consumer learns about FinTech, and I examine how the distribution of q affects my baseline model results.

Although FinTech services in the baseline model raise utility, not every consumer uses these services, because consumers are not fully informed. There are two ways to learn about FinTech lending. First, FinTech information may arrive from a non-network source (e.g., advertising and search engines). Let the arrival of information from this source be a random variable, $Q_{i,t}$, drawn from an i.i.d. Bernoulli process. With probability p^q, information arrives ($Q_{i,t} = 1$), and the consumer chooses whether to refinance her mortgage. If she

[15] My model assumes that FinTech lenders and traditional lenders charge the same closing fees 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 Appendix D.

chooses to refinance, she will do so with a FinTech lender because of the utility gain. If she chooses not to refinance, she makes the mortgage payment according to the existing contract. With probability $1 - p^q$, the information does not arrive ($Q_{i,t} = 0$). In this case, she decides whether to refinance with a traditional lender (assuming no learning from the other source).

The second source of FinTech information is social networks. Let the arrival of FinTech information from this source be a random variable, $E_{i,t}$, drawn from an i.i.d. Bernoulli process, which is also independent from $Q_{i,t}$. With probability p^e, information arrives from social interactions ($E_{i,t} = 1$). If the consumer chooses to refinance with a FinTech lender, she receives a utility gain $e > q$. The inequality captures the additional benefits from personal experience and extra information shared by friends. This assumption will also be relaxed in Section 6.3. With probability $1 - p^e$, the consumer does not learn about FinTech from her social network, but she may still learn it from the non-network source.[16]

Since information may arrive from two independent sources, there are different paths that lead to a refinancing decision. To summarize, first, with probability $(1 - p^q)(1 - p^e)$, the consumer does not learn about FinTech from either source ($Q_{i,t} = E_{i,t} = 0$) and decides whether to refinance with a traditional lender. Second, with probability $p^q(1 - p^e)$, the consumer learns about FinTech only from the non-network source ($Q_{i,t} = 1$, $E_{i,t} = 0$) and decides whether to refinance with a FinTech lender. Third, with probability p^e, the consumer learns about FinTech through social interactions ($E_{i,t} = 1$), which may or may not be coincident with non-network learning, and decides whether to refinance with a FinTech lender. The overall utility gain from refinancing with a FinTech lender, therefore, is $\max\{qQ_{i,t}, eE_{i,t}\}$.[17]

Monetary policy stimulus and capacity constraints. As extensively documented in the literature, another type of friction that weakens the pass-through of low policy rates to borrowers is the slow response of traditional lenders to surging demand (Fuster et al. (2019); Fuster et al. (2021)). This results from capacity constraints and operational bottlenecks (e.g.,

[16] 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.

[17] In the model, the draws of $Q_{i,t}$ and $E_{i,t}$ are independent across time. Allowing draws to be persistent has a similar effect to feeding rising paths of p^q and p^e into the model. In Section 6.2, I use counterfactual analysis to show how the efficacy of monetary policy would change if p^e increases.

rising training costs, hiring difficulties and staffing issues) that are more likely to be binding during periods of low rates, especially for lenders who rely on traditional, labor-intensive underwriting. Consumers are negatively impacted by delayed processing and credit rationing.

I model the implications of this friction as a utility toll on consumers who refinance their mortgage with a traditional lender after a stimulative monetary policy shock. Specifically, in response to an unexpected permanent decline in the mortgage rate in period T, the utility loss of these consumers is

$$\chi(r^b_{T-1}, r^b_{T+\tau}) \equiv \mathbb{I}(r^b_{T+\tau} < r^b_{T-1})(r^b_{T-1} - r^b_{T+\tau})[\chi(\tau+1)^{-\alpha}], \quad \tau = 0, 1, 2, ... \tag{10}$$

where $r^b_{T-1} - r^b_{T+\tau}$ is the rate change, τ the number of periods since the rate change, and $\chi > 0$ and $\alpha > 0$ parameters to be calibrated. This specification captures several key features of the capacity-constraint-induced cost: (i) it appears only when the rate falls, (ii) it is proportional to the size of the rate shock, and (iii) it diminishes over time.[18] FinTech lending eases this type of friction. Without loss of generality, I assume that FinTech lenders do not face capacity constraints, so their consumers do not incur this utility loss.

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 network 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)).

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

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)). 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 (9), which gives $\sigma_p = 0.95$ and $\rho_p = 0.05$.

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.[19] The maximum LTV 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 LTV 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.[20] 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).

[19] For example, Quicken Loans 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.

[20] 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 experimented with alternative values of f^H satisfying these restrictions and found that the quantitative results are robust.

There are four key parameters related to FinTech lending: the probabilities of FinTech information arriving from network and non-network sources, p^e and p^q, and FinTech utility gains with and without social interactions, e and q. The first two parameters determine the FinTech market share, while the latter two parameters are related to the likelihood of refinancing conditional on receiving FinTech information. 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 10% 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.[21] This calibration yields $p^q = 7\%$ and $p^e = 6\%$. Third, the refinancing propensity in the no-FinTech-spillover economy is 6% higher than in the no-FinTech economy before the policy shock. Fourth, the refinancing propensity in the baseline economy is 18% higher than in the no-FinTech economy before the policy shock.

The latter two moments are set by estimating the equation of the county-level refinancing propensity:

$$Refi_{c,t} = \gamma_c + \gamma_{d,t} + \beta_1 \Delta FinTech_{c,t} + \beta_2 \Delta FinTech^{SCA}_{c,t} + \beta_3 \mathbf{x}_{c,t} + \beta_4 \bar{\mathbf{x}}^{SCA}_{c,t} + \varepsilon_{c,t}. \tag{11}$$

In equation (11), the effects of FinTech lending and network spillovers on a county's refinancing propensity are estimated simultaneously. The estimates, $\hat{\beta}_1 = 0.011$ and $\hat{\beta}_2 = 0.021$ (both significant at the 1% level), imply that a 10 pp increase in the county's own FinTech lending (equivalent to moving from the 10th to 90th percentile) is associated with a 6% higher refinancing propensity. In addition, if FinTech lending in the county's SCAs also increases by 10 pps, the refinancing propensity would be 18% higher.[22]

[21] The counterfactual is calculated as follows. Table 1 shows that a 1 pp increase in the FinTech market share in a county's network raises the county's FinTech market share by about 0.3 pps. The increase of the explanatory variable from its smallest value to its mean is about 10 pps, implying a 3 pp increase in the county's FinTech market share due to spillovers. This effect accounts for 50% 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 10% (=20%*[1-50%]).

[22] 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 (0.33). The effect of a 1 pp increase in $\Delta FinTech^{SCA}_{c,t}$ 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+ (0.021+0.011*0.33)*10]/2=18%.

6 Quantitative Results

In this section, I use the calibrated model to address two key questions. First, to what extent have FinTech lending and its network spillovers changed consumption and refinancing responses to a stimulative monetary policy shock? Second, how would consumption and refinancing responses, as well as the FinTech market share, change if social networks played an even more important role in spreading information? Answering these questions using a structural model avoids the empirical challenges to the identification of monetary policy shocks, especially given the short time span for which FinTech has existed. Moreover, counterfactual analysis helps isolate the role of network spillovers in the monetary transmission. The baseline model is then extended to allow for heterogeneity in the utility gain from FinTech services.

6.1 How Has FinTech Lending Changed Monetary Transmission?

Consider the effects of a monetary policy shock that lowers the mortgage rate by 1 pp permanently in three economies: the no-FinTech economy, the economy with FinTech lending but without network spillovers, and the economy with FinTech and network spillovers (baseline). Comparing the consumption and refinancing responses across the three economies allows me to isolate the role of technology itself and the role of network spillovers in changing the efficacy of a monetary stimulus. Note that the calibration reflects the FinTech market penetration in 2017, so the quantitative results are specific to that baseline. In Section 6.2, I consider alternative states of FinTech presence and assess the change in the monetary policy effects.

Panel (a) of Figure 5 plots the refinancing propensity (i.e., the percent of borrowers who refinance their mortgage in a year) before and after the monetary policy shock in the three economies. Before the shock, this propensity is 2.1% in the no-FinTech economy, 2.2% in the no-FinTech-spillover economy, and 2.4% in the baseline economy, reflecting a small fraction of households who extract home equity to smooth consumption without changing the mortgage rate. Upon the shock, the borrowing cost is lower and the refinancing propensity rises across the board to 12%, 12.8% and 13.5%, respectively. Panel (b) plots the refinancing response to the monetary stimulus (i.e., the change in the refinancing propensity) for each economy, which is 9.9 pps, 10.6 pps, and 11.1 pps, respectively. This means that, compared to the no-FinTech economy, the refinancing response to the policy shock is 1.2 pps (or 12%) higher in the economy with FinTech and network spillovers. Shutting down network spillovers would increase the refinancing response only by 0.7 pps (or 7%), implying that almost half (41%) of the total improvement in the monetary policy effect on refinancing is accounted for by the amplification of network spillovers.

Quantitatively similar results are obtained for the consumption responses. As shown in panel (d) of Figure 5, consumption increases by 1.11%, 1.16% and 1.24%, respectively, in response to the shock in three economies. In the economy with FinTech and network spillovers, consumption is 13% more responsive to the policy shock than in the no-FinTech economy. Shutting down network spillovers would only increase the consumption responsiveness by 6%, implying that slightly more than half (55%) of the total improvement in the monetary policy effect on consumption is accounted for by network spillovers.

To understand which households are the main driver behind these responses, Figure 6 plots the refinancing propensity conditional on the household type. The upper panel shows that, in the no-FinTech economy, only households with low non-pecuniary refinancing costs are able to refinance their mortgage, and that their response to the policy shock explains the overall refinancing and consumption responses. With FinTech lending (the middle panel), the utility gain from more convenient services and greater lender resilience increase the refinancing propensity for those with low non-pecuniary costs (yellow bars). More importantly, some households who otherwise would not refinance due to high non-pecuniary costs are able to respond to the policy shock, thanks to FinTech lending (blue bar). Finally, the lower panel highlights the role of network spillovers. Households who obtain FinTech information from social networks are more likely to refinance their mortgage than otherwise identical households, which contributes to the higher responsiveness of the refinancing and consumption to the policy shock.

The role of market frictions. Standard macroeconomic models usually incorporate two explanations for why a consumer may not refinance her mortgage when the policy stimulus hits the mortgage market. First, the present discounted value of the future interest savings (i.e., the accounting benefit) may be lower than the refinancing closing cost. Second, the consumer may be ineligible for refinancing due to a high LTV ratio. My model highlights two additional explanations arising from mortgage market frictions: non-pecuniary costs associated with refinancing (the consumer-side friction) and capacity-constraint-induced utility loss (the lender-side friction). Without these frictions, every eligible consumer would have refinanced her mortgage as long as the accounting benefit exceeds the closing cost.

I assess the role of market frictions in weakening the monetary stimulus through counterfactual analysis. Figure 7 shows the refinancing propensity in the period of the policy shock in each of the six scenarios. First, in the economy without these two types of frictions, the refinancing propensity conditional on eligibility is 100%, suggesting that the policy stimulus is large enough to make every eligible consumer benefit financially from refinancing. The unconditional refinancing propensity is lower, 80%, reflecting the fraction of eligible consumers. Second, in the economy with the lender-side friction, the refinancing propensity conditional on eligibility falls to 55%, and the unconditional refinancing propensity is lower (44%). Third, in the economy with consumer-side frictions, the conditional and unconditional refinancing propensities are even lower, 28% and 22%. Fourth, with both types of frictions, only 15% of eligible consumers and 12% of all consumers refinance their mortgage, severely limiting the pass-through of the policy stimulus.

FinTech lending and network spillovers help ease these frictions. The baseline calibration shows that the conditional and unconditional refinancing propensities are 17% and 14% on impact. With stronger network spillovers, for example, p^e=0.6, the refinancing propensities could reach 26% (conditional) and 21% (unconditional).

6.2 Policy Experiments

As FinTech lending continues to expand in the U.S. mortgage market, it will likely become more important in easing market frictions and facilitating the pass-through of future interest rate cuts. My empirical analysis has stressed the role of social networks in FinTech market penetration. This motivates a counterfactual analysis for understanding how the effects of monetary policy shocks would change, if social networks play an even more important role in spreading information (e.g., through technologies that allow consumers to be more connected with their peers).

The key parameter governing the strength of social interactions in the model is p^e, the probability that a consumer learns about FinTech from her social network. Figure 8 plots for different values of p^e the FinTech market share and the refinancing and consumption responses to a stimulative monetary policy shock, holding other parameters fixed. The left panel shows that, as the probability of learning from peers increases, the market share of FinTech rises, even if FinTech lenders do not actively expand their business (e.g., through advertising that increases p^q). When p^e increases from the baseline 6% to 60%, for example, the FinTech market share in refinancing would increase from 20% to 80%. The middle and right panels show that refinancing and consumption are more responsive to the monetary policy shock, as the FinTech market share rises. When the FinTech market share increases from 20% to 80%, the effect of the monetary policy shock on refinancing increases from 11.1 pps to 16.8 pps, which is a 51% increase in the responsiveness. The effect on consumption increases from 1.2% to 1.9%, which is a 56% increase in the responsiveness. This result shows that FinTech lending in conjunction with social network spillovers can be an important determinant of the effects of monetary policy shocks.

6.3 Model Extension

To account for the possibility that FinTech lending may not benefit consumers equally and that some consumers may even view it as burdensome (perhaps because they are not adept at operating mobile apps or prefer personal interactions), I extend the baseline model to allow for heterogeneity in the utility consumers receive when using FinTech, $q \sim F_q$. The purpose of this exercise is to examine how parameters governing the distribution of q affect the baseline model results.

To illustrate the point, I add to the baseline model a binary probability distribution for q. Specifically, conditional on learning about FinTech, a fraction p^{qL} of consumers perceive FinTech services to be inconvenient and experience a utility loss ($q^L < 0$), if they refinance with a FinTech lender. The remaining consumers, as in the baseline model, view FinTech services as more convenient and obtain a utility gain ($q^H > 0$) from a FinTech refinance. Social interactions help mitigate the utility loss of the former group of consumers. If a consumer learns about FinTech from social networks, the overall utility gain from FinTech services is $\max\{qQ_{i,t}, e\}$ (which cannot be negative), whereas it is q (which can be negative), if the consumer does not learn about FinTech from social networks.

As a starting point, I set p^{qL}=10% to match the fraction of the U.S. population who had less than a high school diploma or equivalent in the 2010s, given the evidence that FinTech adoption is increasing in educational attainment (see Fuster et al. (2019)). I set $q^H = 0.06$, which is a small deviation from the value of q in the baseline model (0.05). Setting the mean of q to 0.05 implies $q^L = -0.04$. This parametrization yields quantitative results similar to the baseline model. I then conduct two experiments: (i) changing the mean of q by changing the fraction of consumers who would be worse off with FinTech (p^{qL}), and (ii) changing the dispersion of q by enlarging the gap between q^H and q^L, while keeping the mean fixed at 0.05.

Figure E1 in the Appendix shows the mean of q, the FinTech market share in the period of the policy shock, and the refinancing and consumption responses, as p^{qL} increases from 10% to 90%. As more consumers are made worse off by using FinTech services, the expected utility gain from FinTech refinancing diminishes, which pushes down the FinTech market share and reduces the responsiveness of refinancing and consumption to the policy stimulus. However, since consumers can always resort to traditional lenders for refinancing, the effects of the policy stimulus on refinancing and consumption will be larger than in the no-FinTech economy, as long as some consumers are better off from FinTech services.

Figure E2 in the Appendix shows the standard deviation of q, together with other aggregate outcomes, for different values of q^H. To keep p^{qL} and the mean of q constant, as q^H increases, q^L has to fall. The FinTech market share increases, because, as q^H increases, consumers receiving q^H are more likely to refinance with a FinTech lender, whereas consumers receiving (more negative) q^L are unaffected— they would choose traditional lenders or would not refinance even for a smaller loss. On the other hand, the refinancing and consumption responses are weakened, because those who receive q^H would be more likely to refinance with FinTech lenders even before the policy shock. This lowers the sensitivity of refinancing and consumption to the policy shock.

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, typically through mortgage refinancing. This refinancing channel of monetary policy, however, has been weakened by various frictions, such as the complicated loan origination process that discouraged consumers and capacity constrains that slow lenders' responses in periods of low rates. The rapid growth of financial technology in the mortgage industry is expected to ease these frictions, given the more convenient services brought in by this new lending model and the greater lender resilience.

This is only part of the story, however, because consumers' social networks can propagate FinTech adoption, further amplifying the impact of monetary policy shocks. 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 in areas with higher social and economic mobility and for refinancing mortgages as opposed to home-purchasing mortgages.

I develop a structural model to quantify the importance of FinTech lending features and network spillovers in the transmission of stimulative monetary policy shocks. The consumption response to a 1 pp decline in the mortgage rate is 13% higher with FinTech lending. About half of this improvement is due to FinTech amplification 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. I use counterfactual analysis to assess the effects of a monetary policy stimulus, were social interactions become more effective in spreading information. I show that an increase in the FinTech market share to 80% resulting from more effective social learning, for example, would raise the consumption and refinancing responses by 50%-60% compared to the economy in 2017, when the FinTech refinancing market share was 20%.

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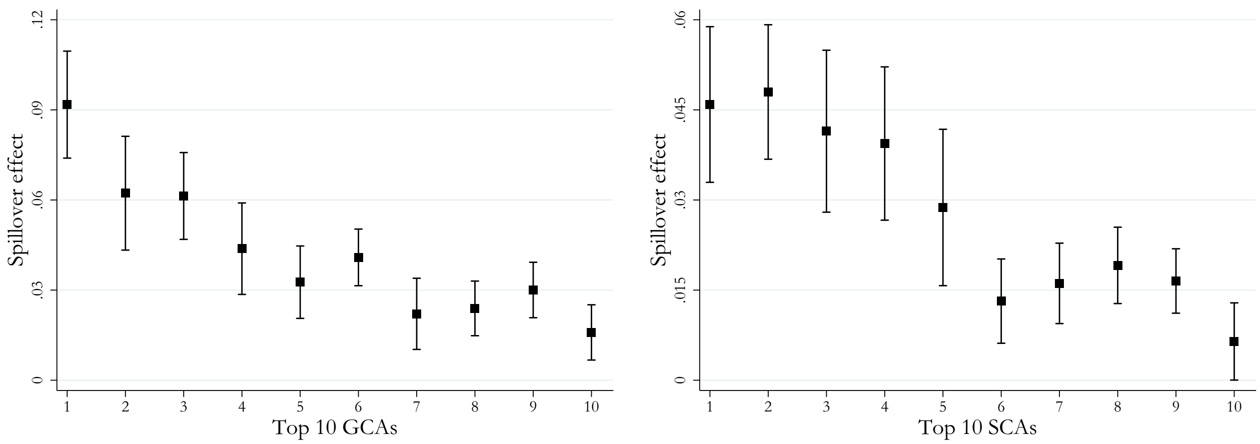
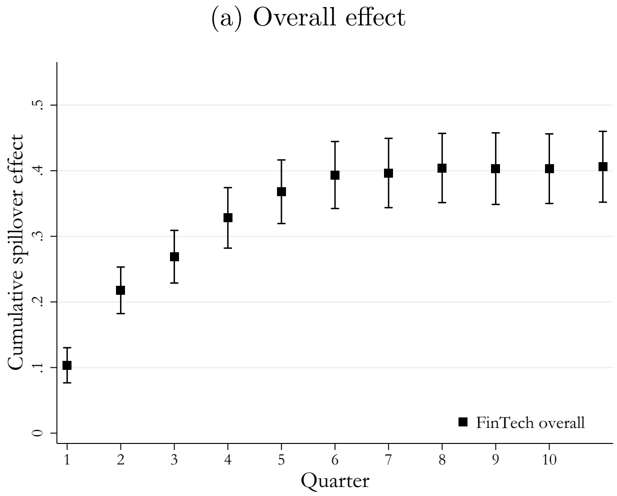
Figure 1: FinTech spillover effects from the socially most connected counties

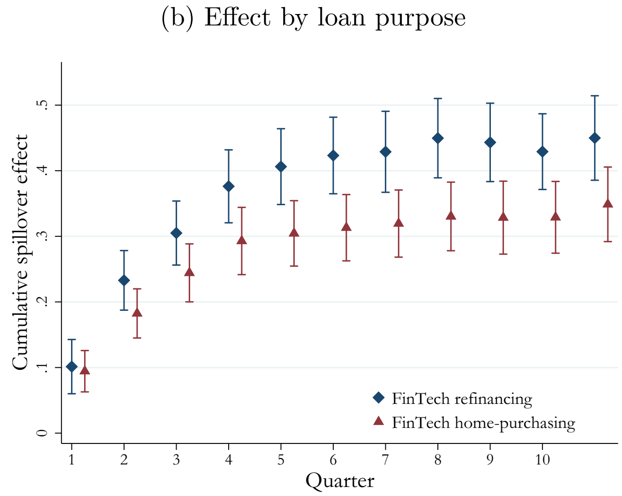
(a) Top 10 GCAs (b) Top 10 SCAs



Notes: Point estimates and the 95% confidence intervals are obtained by estimating the OLS specification in the third column of Table 1 for each of the top 10 geographically connected areas (GCAs) and top 10 socially connected areas (SCAs). Standard errors are clustered at the county level. See text for the description of the control variables.

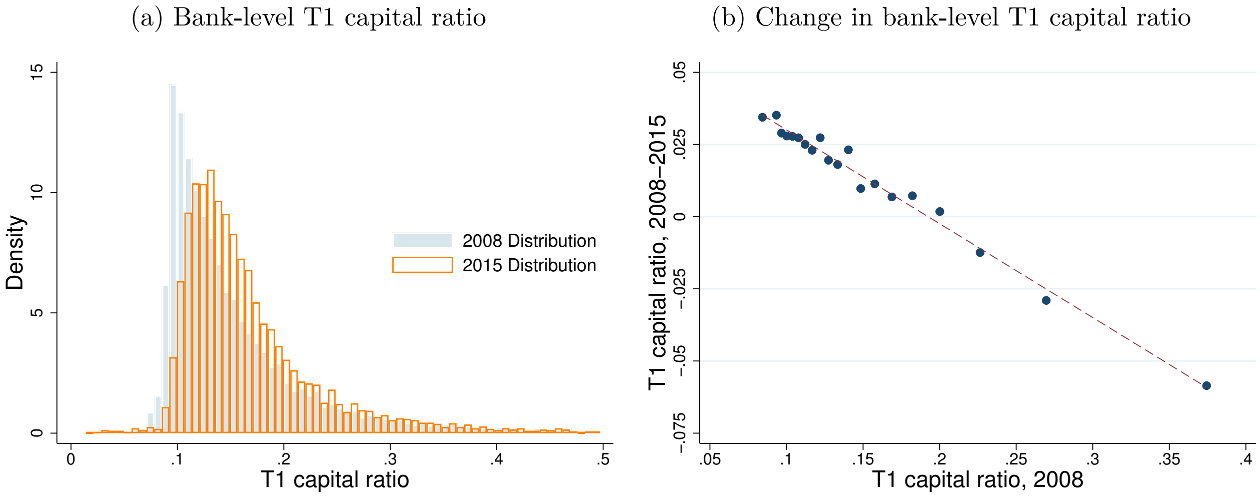
Figure 2: Dynamic effects of FinTech spillovers





Notes: Point estimates and the 95% confidence intervals are obtained by estimating the IV specifications in the third column of Table 1 for each horizon and by loan purpose. Standard errors are clustered at the county level. See text for the description of the control variables.

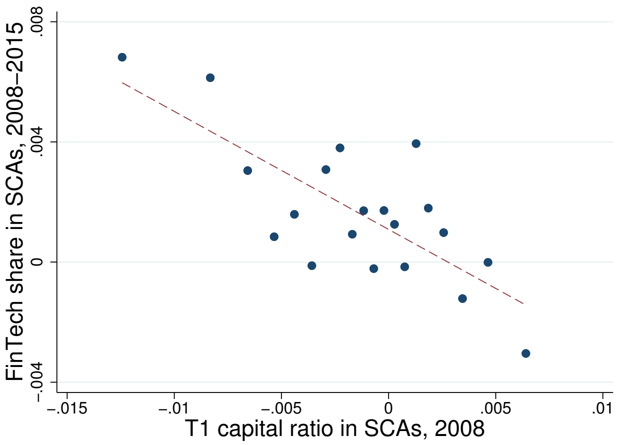
Figure 3: Rising capital ratios after the financial crisis



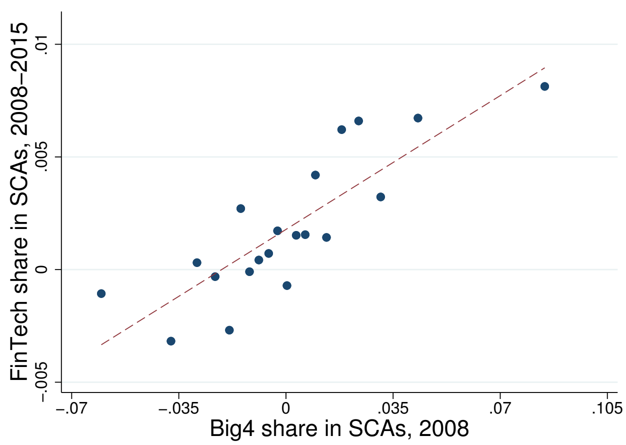
Notes: Panel (a) plots the distribution of the bank-level T1 capital ratio in 2008 and 2015. For visual presentation, the upper 2% extreme values are winsorized. Panel (b) shows a bin scatter plot of the bank-level T1 capital ratio growth from 2008 to 2015 (y-axis) against the 2008 bank-level T1 capital ratio (x-axis).

Figure 4: Instruments for FinTech growth in socially connected markets

(a) T1 capital ratio in SCAs

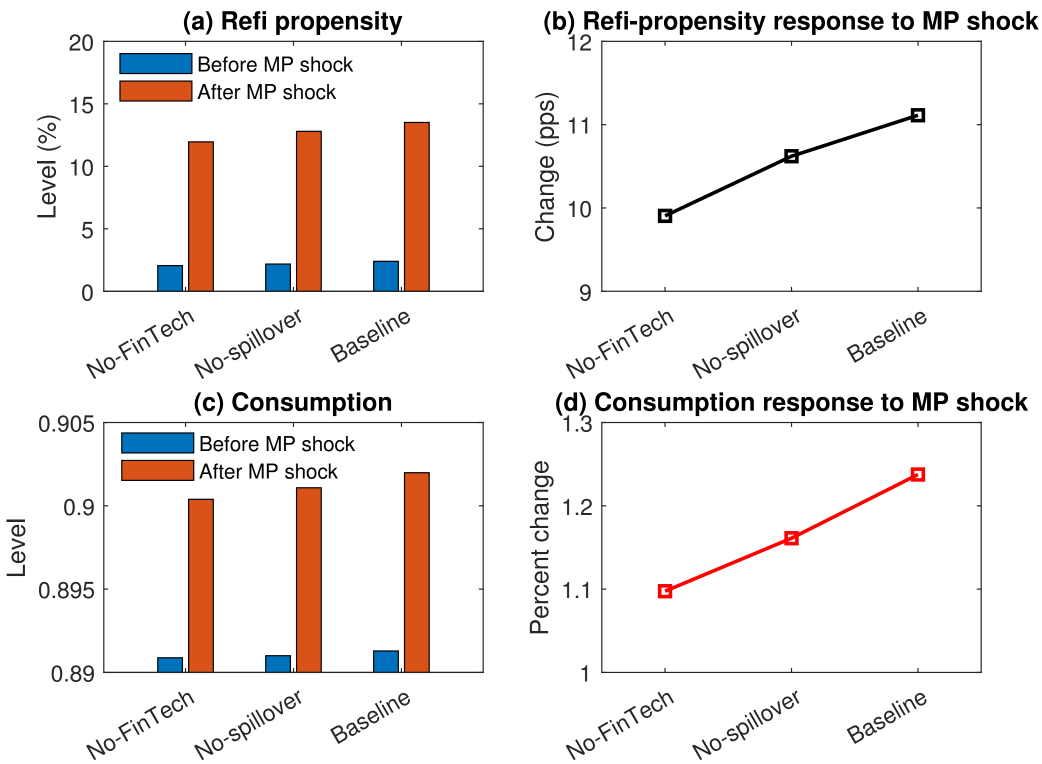


(b) Big4 share in SCAs



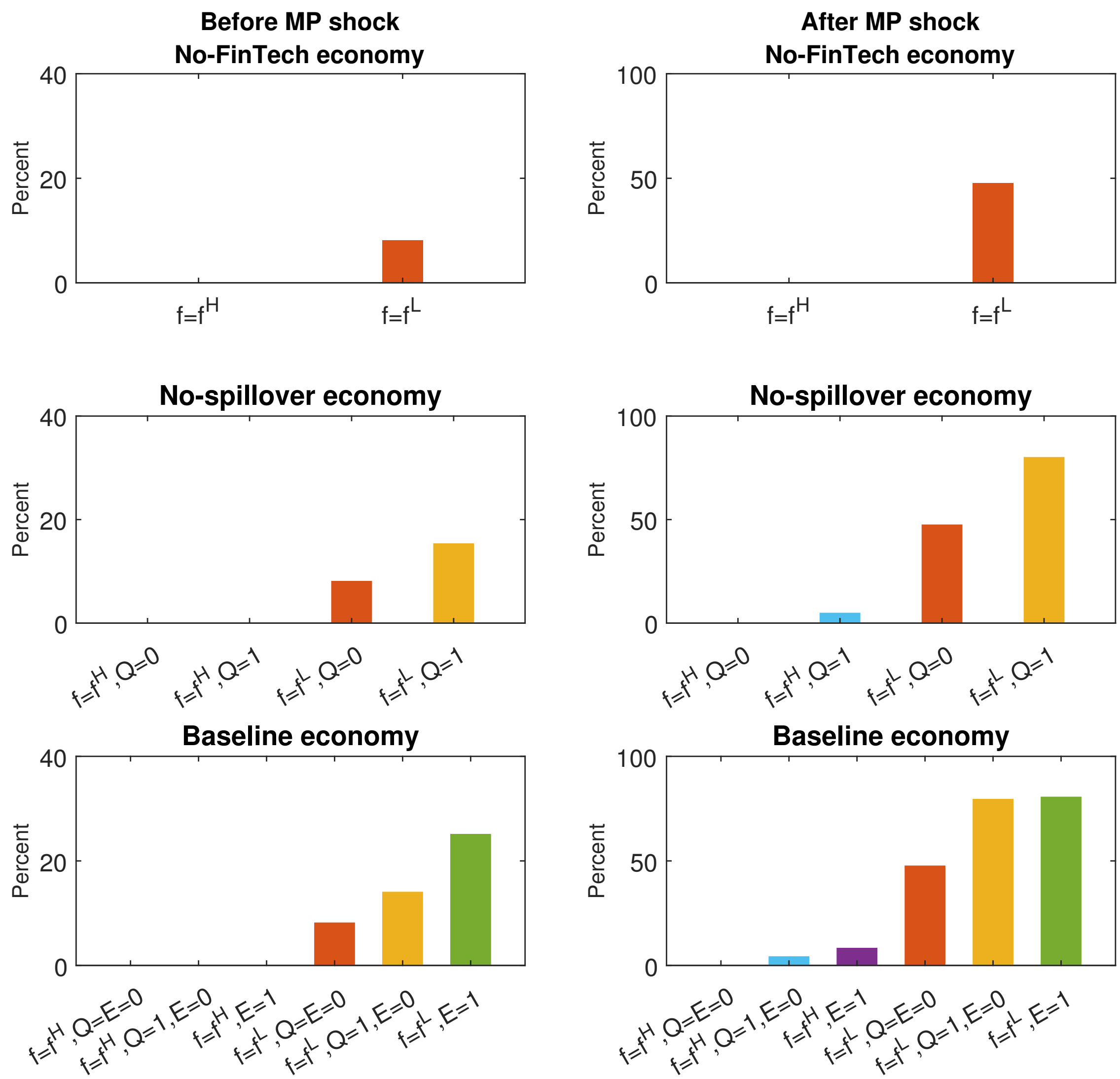
Notes: This figure shows the bin scatter plots for the first stage of the IV strategy in equation (6). Note that these variables are residualized using other control variables to reflect the first-stage regression coefficients. Panel (a) plots the change in SCAs' FinTech market share from 2008 to 2015 (y-axis) against the instrument (x-axis): origination-share-weighted 2008 T1 capital ratios in SCAs. Panel (b) plots the change in SCAs' FinTech market share from 2008 to 2015 (y-axis) against an alternative instrument (x-axis): 2008 Big4 market shares in SCAs.

Figure 5: Effects of a stimulative monetary policy shock on refinancing and consumption



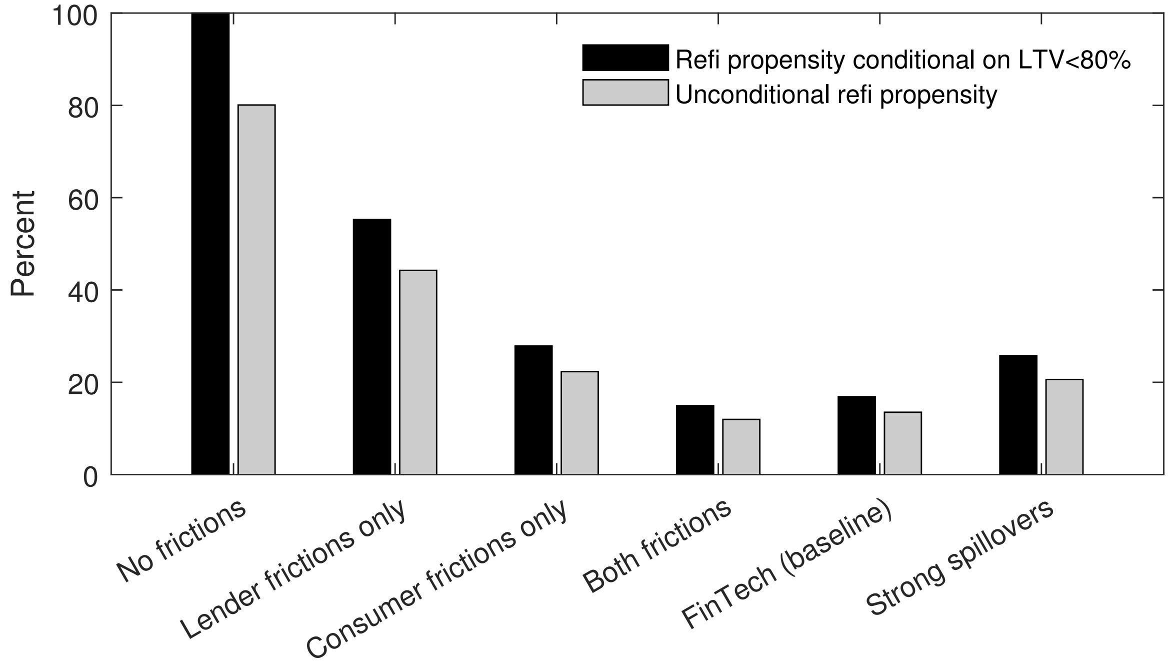
Notes: Model simulations. Panel (a) plots the levels of the refinancing propensity (i.e., the fraction of borrowers who refinance their mortgage in a year) under different scenarios (no-FinTech, no-spillover, baseline) before and after a monetary-policy (MP) shock that lowers the mortgage rate by 1 pp. Panel (b) plots the changes in the refinancing propensity in response to the MP shock under these scenarios (in percentage points). Panel (c) plots the levels of consumption (in numeraire) before and after the MP shock under these scenarios. Panel (d) plots the percent changes in consumption in response to the MP shock under these scenarios.

Figure 6: Conditional refinancing propensities



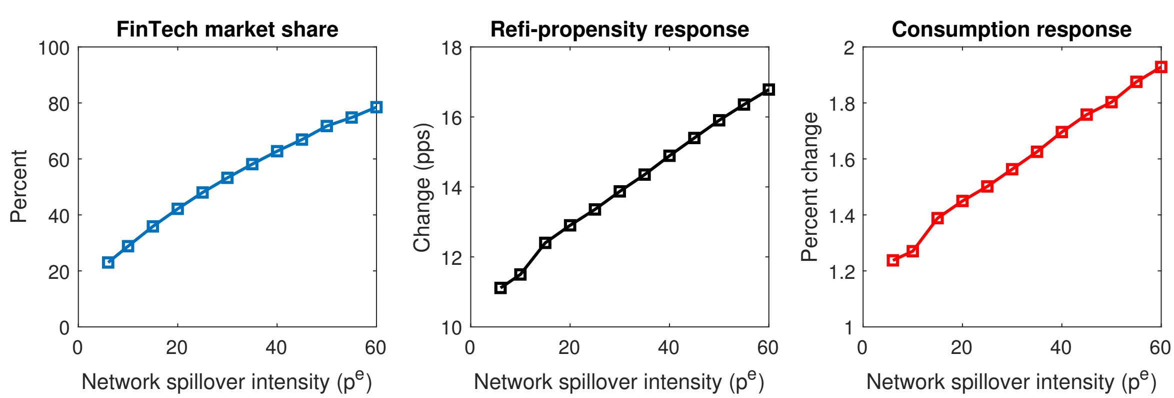
Notes: Model simulations. The colored bars in the left column show the refinancing propensity for each type of consumers (conditional on their realizations of f, Q and E) under each scenario (no-FinTech, no-spillover, baseline) before a monetary-policy (MP) shock that lowers the mortgage rate by 1 pp. The colored bars in the right column indicate the conditional refinancing propensity for each type of consumers in each scenario after the MP shock.

Figure 7: Counterfactual analysis: The role of frictions and FinTech in explaining the refinancing propensity after a monetary policy shock



Notes: Model simulations. The gray bars indicate the refinancing propensity (the percent of consumers who refinance their mortgage in the year) after a stimulative monetary-policy (MP) shock that lowers the mortgage rate by 1 pp. The black bars indicate the refinancing propensity conditional on eligibility (the LTV ratio less than 80%) after the MP shock. There are two types of market frictions: the non-pecuniary refinancing cost faced by consumers and the capacity constraints faced by traditional lenders. This figure shows how each friction reduces the refinancing propensity (relative to the no-frictions case) and how FinTech lending and network spillovers help ease the impact of these frictions.

Figure 8: Social network intensity and monetary policy effects



Notes: Model simulations. This figure depicts the changes in the FinTech market share and the refinancing and consumption responses to a stimulative monetary-policy (MP) shock that lowers the mortgage rate by 1 pp, as the network spillover becomes stronger (p^e increases).

Table 1: FinTech spillover effect: Panel estimates

Panel I. SCA spillovers	Dep. variable: ΔFinTech share$_c$		
OLS estimates	(1)	(2)	(3)
ΔFinTech^{SCA}	0.342***	0.337***	0.329***
	(0.022)	(0.022)	(0.022)
County FE	x	x	x
Region-by-quarter FE	x	x	x
County controls		x	x
SCA controls			x
R-squared	0.363	0.367	0.371
# Obs.	122,350	122,314	122,314
Panel II. GCA spillovers			
OLS estimates	(1)	(2)	(3)
ΔFinTech^{GCA}	0.333***	0.338***	0.370***
	(0.024)	(0.025)	(0.027)
County FE	x	x	x
Region-by-quarter FE	x	x	x
County controls		x	x
GCA controls			x
R-squared	0.356	0.361	0.367
# Obs.	122,384	122,325	122,325
Panel III. SCA spillovers			
IV estimates	(1)	(2)	(3)
$\Delta\widehat{FinTech}^{SCA}$	0.343***	0.338***	0.328***
	(0.024)	(0.024)	(0.024)
County FE	x	x	x
Region-by-quarter FE	x	x	x
County controls		x	x
SCA controls			x
1st stage coef. on ΔFinTech^{SCA,Out}	0.788***	0.786***	0.784***
F-stat of excluded instruments	9,139	9,330	9,322
# Obs.	122,350	122,314	122,314

Notes: SCA denotes socially connected area and GCA denotes geographically connected area. *, ** and *** denote significance at the 10%, 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^{SCA,Out} is the social connectedness-weighted change in the FinTech market share in a county's socially connected but geographically distant areas, i.e., outside of this county's commuting zone (see Table C2 for IVs with alternative distance thresholds).

Table 2: FinTech spillover effect by loan purpose: Panel IV estimates

	ΔFinTech share (1)	ΔFinTech refi share (2)	ΔFinTech purchase share (3)	ΔFinTech volume (4)	ΔFinTech refi volume (5)	ΔFinTech purchase volume (6)	ΔNonFin volume (7)
$\Delta\widehat{FinTech}^{SCA}$	0.328***	0.376***	0.167***	0.397***	0.303***	0.094***	-0.133
	(0.024)	(0.028)	(0.020)	(0.031)	(0.027)	(0.012)	(0.109)
County FE	x	x	x	x	x	x	x
Region-by-quarter FE	x	x	x	x	x	x	x
County controls	x	x	x	x	x	x	x
SCA controls	x	x	x	x	x	x	x
# Obs.	122,314	119,718	119,663	122,314	122,314	122,314	122,314

Notes: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the county level. See Table 1 for further information on the instrument.

Table 3: FinTech spillover effect by connectedness: Panel IV estimates

	Spillover effect from				
	Top 50 SCAs	Top 51-100	Top 101-150	Top151-200	Top 201-500
$\Delta\widehat{FinTech}^{SCA}$	0.245***	0.095***	0.060***	0.016	0.035
	(0.019)	(0.013)	(0.013)	(0.011)	(0.040)
County FE	x	x	x	x	x
Region-by-quarter FE	x	x	x	x	x
County controls	x	x	x	x	x
SCA controls	x	x	x	x	x
# Obs.	122,314	122,314	122,314	122,314	122,314

Notes: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the county level. See Table 1 for further information on the instrument.

Table 4: Heterogeneity in FinTech spillover effect: Panel IV estimates

Dep. variable: ΔFinTech share$_c$	(1)	(2)	(3)	(4)
$\Delta \widehat{FinTech}^{SCA}$	0.201***	0.273***	0.242***	0.199***
	(0.046)	(0.030)	(0.031)	(0.022)
$\times$Nonmetro, urban pop$\geq$2.5K	0.048			
	(0.051)			
$\times$Metro, pop $<$ 1 Million	0.105*			
	(0.055)			
$\times$Metro, pop $\geq$ 1 Million	0.216***			
	(0.057)			
$\times$High share of Bachelor's degree		0.069*		
		(0.037)		
$\times$High share of black			0.123***	
			(0.041)	
$\times$High prior-year migration flow				0.152***
				(0.030)
County FE	x	x	x	x
Region-by-quarter FE	x	x	x	x
County controls	x	x	x	x
SCA controls	x	x	x	x
# Obs.	122,314	122,314	122,314	109,835

Notes: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the county level. See Table 1 for further information on the instrument. All interaction terms are also instrumented by interacting the IV with the county characteristics.

Table 5: Refinancing spillover effect by lender segment: Panel IV estimates

	ΔRefi share$_c$	ΔFinTech Refi share$_c$	ΔNonbank Refi share$_c$	ΔBank Refi share$_c$
	(1)	(2)	(3)	(4)
ΔRefi share^{SCA}	15.70***			
	(1.036)			
ΔFinTech Refi share^{SCA}		19.28***		
		(1.420)		
ΔNonbank Refi share^{SCA}			14.52***	
			(0.733)	
ΔBank Refi share^{SCA}				7.22***
				(0.381)
County FE	x	x	x	x
Region-by-quarter FE	x	x	x	x
County controls	x	x	x	x
SCA controls	x	x	x	x
# Obs.	122,314	119,718	119,718	119,718

Notes: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the county level. The dependent variables and the key explanatory variables shown in the table are scaled such that the coefficient represents the percent change relative to the unconditional mean of the level variable (i.e., refi share, FinTech refi share, non-bank refi share and bank refi share) for a 1 s.d. increase in the explanatory variable. The instrument in column (1) is the weighted changed in the refinancing share in a county's out-of-commuting-zone socially connected areas (out-CZ SCAs). The instrument in column (2) is the weighted changed in the FinTech market share (of refinancing mortgages) in a county's out-CZ SCAs. The instrument in column (3) is the weighted changed in the non-bank market share (of refinancing mortgages) in a county's out-CZ SCAs. The instrument in column (4) is the weighted changed in banks' market share (of refinancing mortgages) in a county's out-CZ SCAs.

Table 6: Instrumenting FinTech spillovers with regulatory exposure

Panel I	(1)	(2)	(3)	(4)	(5)
T1-ratio-based IV	1st stage	2nd stage	1st stage	2nd stage	OLS
$\Delta \widehat{FinTech}^{SCA}$		1.542***		1.312***	1.009***
		(0.296)		(0.349)	(0.038)
$\text{T1Ratio}_{2008}^{SCA}$	-0.370***				
	(0.050)				
$\text{T1Ratio}_{2008}^{SCA,Out}$			-0.318***		
			(0.052)		
State FE	x	x	x	x	x
County controls	x	x	x	x	x
SCA controls	x	x	x	x	x
F-stat of excluded instruments	55	-	37	-	-
# Obs.	3,094	3,094	3,094	3,094	3,094

Panel II	(1)	(2)	(3)	(4)
Big4-share-based IV	1st stage	2nd stage	1st stage	2nd stage
$\Delta \widehat{FinTech}^{SCA}$		1.301***		1.235***
		(0.185)		(0.287)
$\text{Big4share}_{2008}^{SCA}$	0.097***			
	(0.008)			
$\text{Big4share}_{2008}^{SCA,Out}$			0.078***	
			(0.010)	
State FE	x	x	x	x
County controls	x	x	x	x
SCA controls	x	x	x	x
F-stat of excluded instruments	137	-	55	-
# Obs.	3,094	3,094	3,094	3,094

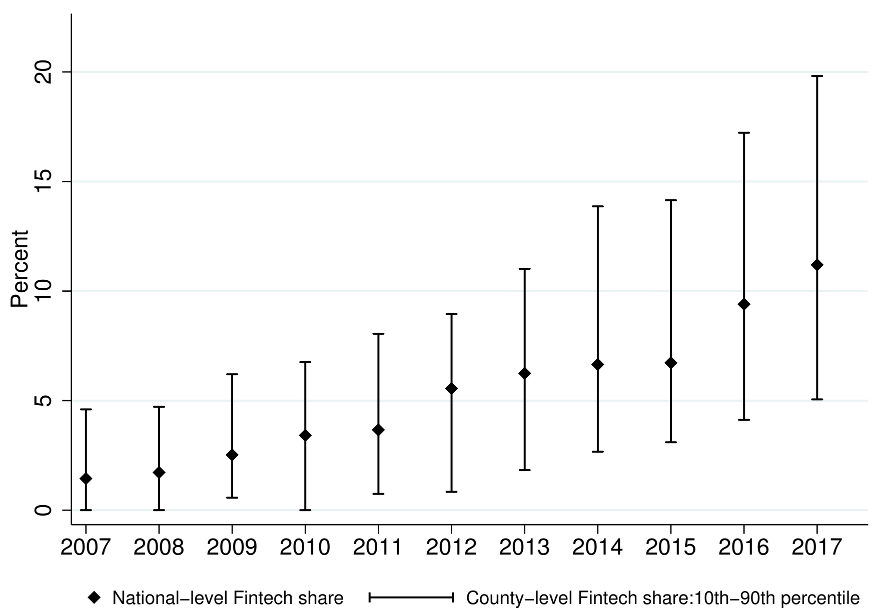
Notes: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Columns (1) and (2) of panel I use $T1Ratio_{2008}^{SCA}$ as the instrument for estimating the IV specification in equation (6). Columns (3) and (4) of panel I use $T1Ratio_{2008}^{SCA,Out}$ as the instrument with the superscript SCA, Out denoting socially connected counties outside the county's commuting zone. Columns (1) and (2) of panel II use $Big4share_{2008}^{SCA}$ as the instrument for estimating the IV specification in equation (6). Columns (3) and (4) of panel II use $Big4share_{2008}^{SCA,Out}$ as the instrument with the superscript SCA, Out denoting socially connected counties outside the county's commuting zone.

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.[23] 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.

[23] 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 Appendix

This appendix describes the data used in my empirical analysis that are not discussed in Section 2.

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).[24] 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

$$SCI_{i,j} = \frac{FB\ Connections_{i,j}}{FB\ Users_i \times FB\ Users_j}, \tag{12}$$

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.[25] 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)).

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).[26] 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

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

[25] 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.

[26] 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 a 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.

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.

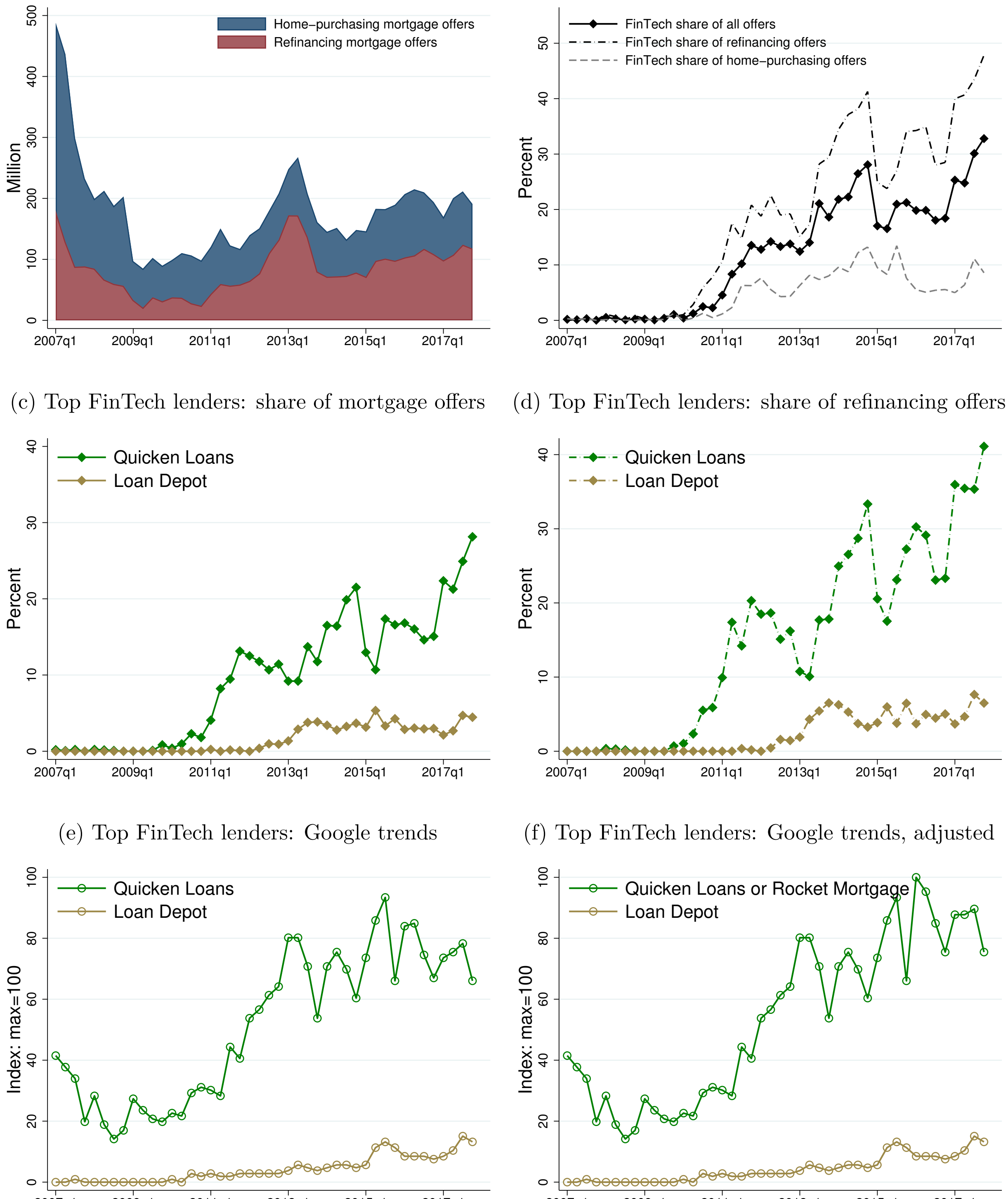
Bank Balance Sheet Data. Tier 1 capital ratios are constructed using bank call reports accessed through the Federal Financial Institutions Examination Council's (FFIEC) Central Data Repository. This information is then merged with the HMDA dataset using the Avery file.[27]

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 extension of Fuster et al. (2019) analysis in Appendix D at the county level: the refinancing propensity, the home purchasing propensity, the average rate of newly refinanced mortgages, the average rate of new home-purchasing mortgages, 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).

C Additional Evidence and Robustness

[27]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.

Figure C1: U.S. mortgage lenders' advertising



(a) Aggregate volume of mortgage offers

(b) FinTech share of mortgage offers

(c) Top FinTech lenders: share of mortgage offers

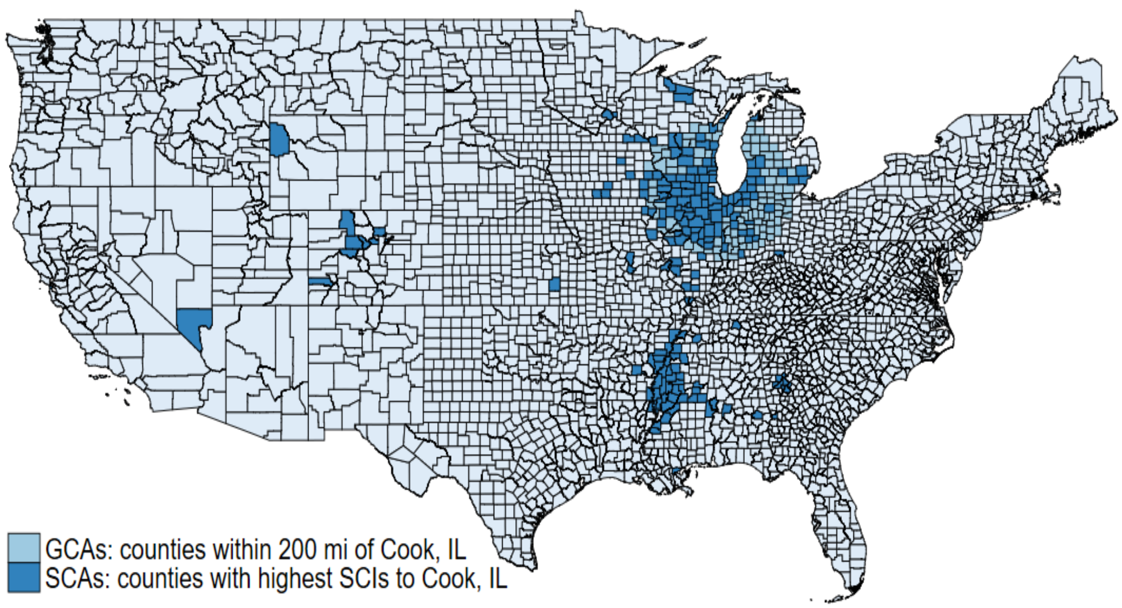
(d) Top FinTech lenders: share of refinancing offers

(e) Top FinTech lenders: Google trends

(f) Top FinTech lenders: Google trends, adjusted

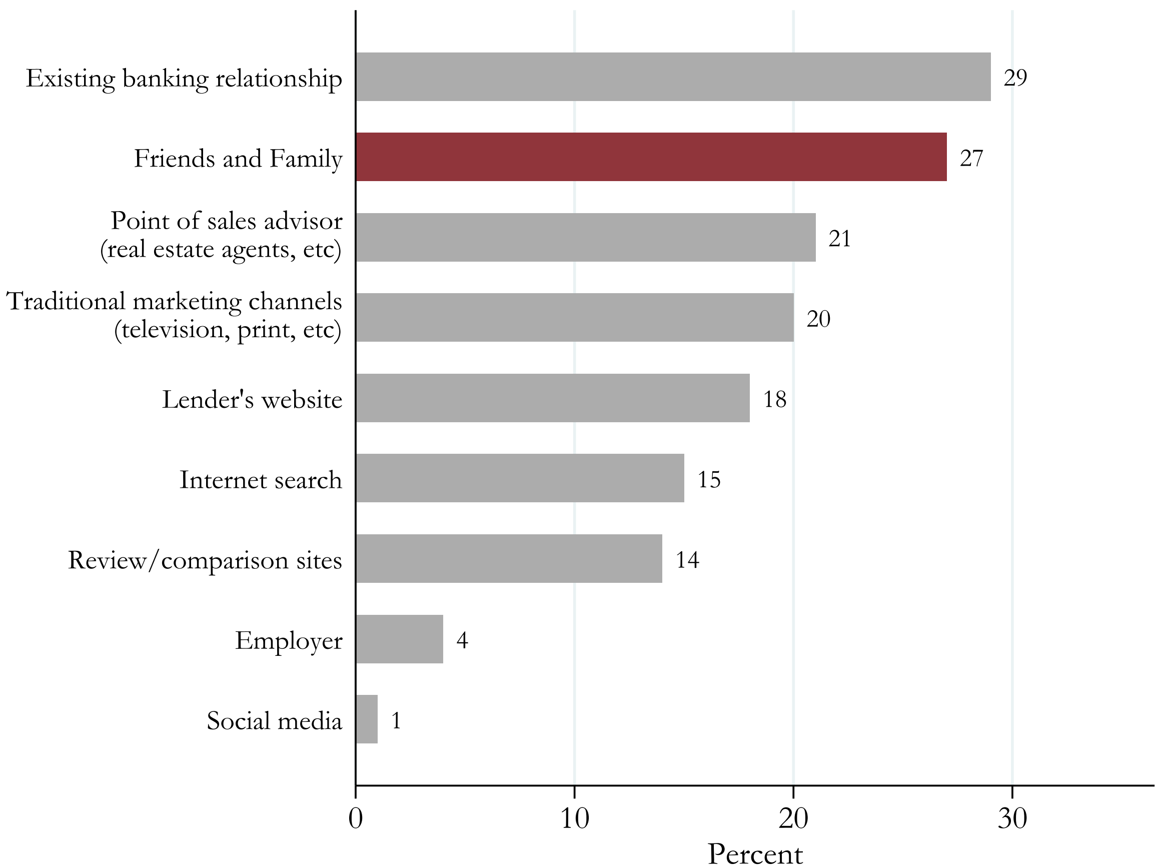
Source: Mintel-Comperemedia Direct Mail and Print Advertising Dataset; Google Trends. Notes: Panel (e) plots quarterly Google Trends statistics for the terms "Quicken Loans" and "Loan Depot" (both identified by Google as mortgage loan companies). Panel (f) plots the adjusted Quicken Loan series by adding the Trends statistics for "Quicken Loans" and for "Rocket Mortgage" to account for the fact that Rocket Mortgage is Quicken Loan's online retail lending platform.

Figure C2: 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 C3: 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%. URL: https://www.pwc.com/mx/es/servicios-consultoria/archivo/experience-radar-prestamos-a-consumo-entendiendo-al-prestatario-empoderado-de-hoy.pdf

Table C1: Panel IV estimates: Robustness to changing SCA thresholds

	Spillover effect from					
	Top 200 SCAs	Top 250 SCAs	Top 300 SCAs	Top 500 SCAs	Top 1000 SCAs	All counties
$\Delta \widehat{FinTech}^{SCA}$	0.328***	0.342***	0.348***	0.361***	0.368***	0.354***
	(0.024)	(0.025)	(0.026)	(0.028)	(0.029)	(0.029)
County FE	x	x	x	x	x	x
Region-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.	122,314	122,314	122,314	122,314	122,314	122,314

Notes: See notes for Table 1.

Table C2: Panel IV estimates: Robustness to alternative specifications

	Alternative instruments		Alternative RHS: ΔFinTech Refi^{SCA}			Excl. counties in largest	
	SCAs>100mi	SCAs>200mi	Total effect	Refinancing	Purchases	10 MSAs	30 MSAs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta \widehat{FinTech}^{SCA}$	0.344***	0.417***	0.281***	0.418***	0.090***	0.311***	0.258***
	(0.035)	(0.061)	(0.022)	(0.031)	(0.016)	(0.025)	(0.023)
County FE	x	x	x	x	x	x	x
Region-by-quarter FE	x	x	x	x	x	x	x
County controls	x	x	x	x	x	x	x
SCA controls	x	x	x	x	x	x	x
1st stage coef. on IV	0.514***	0.146***	0.453***	0.453***	0.453***	0.762***	0.731***
F-stat of excluded instruments	1,082	226	9,122	9,071	9,074	8,268	6,921
# Obs.	122,314	122,314	122,314	119,718	119,663	118,154	114,114

Notes: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the county level. The first two columns estimate IV specification (4) with alternative instruments using SCAs that are 100 or 200 miles away from the county of interest. Columns (3)-(5) use the weighted change in SCAs' FinTech refinancing share (as opposed to the weighted change in SCAs' overall FinTech share) as the key RHS variable to estimate IV specification (4) by loan purpose. Columns (6) and (7) show the IV estimates excluding counties in the largest MSAs.

D Extension to Fuster et al. (2019)

To inform the structural modeling choices, I extend the county-level evidence in Fuster et al. (2019) by examining the effects of FinTech market penetration on (i) the home-purchasing propensity, and (ii) the average interest rate of newly originated mortgages (excluding jumbo loans). The sample period is 2007Q1-2017Q4. The regression specification and the measure of FinTech market penetration closely follow those in Fuster et al. (2019):

$$y_{c,t} = \gamma_c + \gamma_t + \beta_1 FinPenetration_{c,t-1} + \beta_2 \mathbf{x}_{c,t} + \varepsilon_{c,t}, \tag{13}$$

where the measure of FinTech market penetration, $FinPenetration_{c,t-1}$, is the one-quarter lagged four-quarter moving-average FinTech market share in county c at quarter t. The regression includes county and quarter fixed effects, as well as the controls for the loan-market composition and demand shifters (e.g., the average FICO score, house prices growth, lagged average rates and demographics). Standard errors are clustered at the county level.

The dependent variables are constructed using quarterly loan-level mortgage servicing data (McDash), which cover the majority of existing mortgages in the U.S. (see Appendix B for the data description). The home-purchasing propensity is the share of newly originated home-purchasing mortgages among all existing mortgages. The average interest rates on new refinancing mortgages and on new home-purchasing mortgages are straightforward to construct using the McDash data.

Table D1 shows the estimation results. Column (1) confirms the finding in Fuster et al. (2019) that the refinancing propensity is significantly higher for counties with higher FinTech market penetration. In contrast, column (2) shows no significant change in the home-purchasing propensity. Columns (3) and (4) show no significant differences in the average rate of new mortgages, either refinancing or home-purchasing, for counties with higher FinTech market penetration. These results together suggest that higher FinTech market penetration facilitates the transmission of monetary stimulus mainly through the refinancing quantity channel.

Table D1: Effects of FinTech market penetration on mortgage originations and rates

	Refi propensity	Purchasing propensity	Avg. refi rate	Avg. purchasing rate
	(1)	(2)	(3)	(4)
FinTech Penetration	0.038***	0.006	-0.006	0.180
	(0.010)	(0.009)	(0.072)	(0.143)
County FE	x	x	x	x
Quarter FE	x	x	x	x
County controls	x	x	x	x
# Obs.	119,073	119,073	101,254	102,485

Notes: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. Standard errors are clustered at the county level. See text for the description of control variables.

E Model Appendix: 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 $V = \max\{V^R, V^N\}$, where

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

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

with $\log(y')$ and $\log(p')$ evolving according to equations (8) and (9).

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 (8) and (9).

The baseline model. In this model, FinTech information can be obtained from both network and non-network 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 (8) and (9).

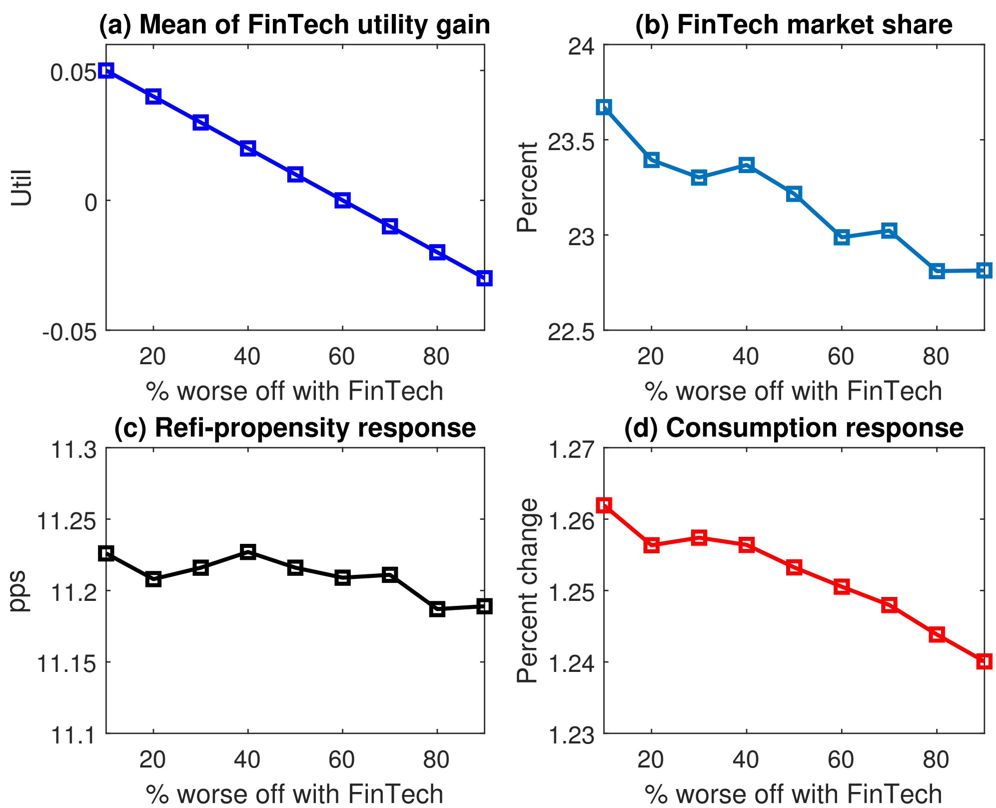
Solution methods. The baseline model is characterized by a large number of state variables. One way to reduce the state space is to define a new random variable that combines information in f, Q and E. Let $Z = -f + \max\{qQ, eE\}$ with cumulative density function F_Z. The value of refinancing, V^R,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

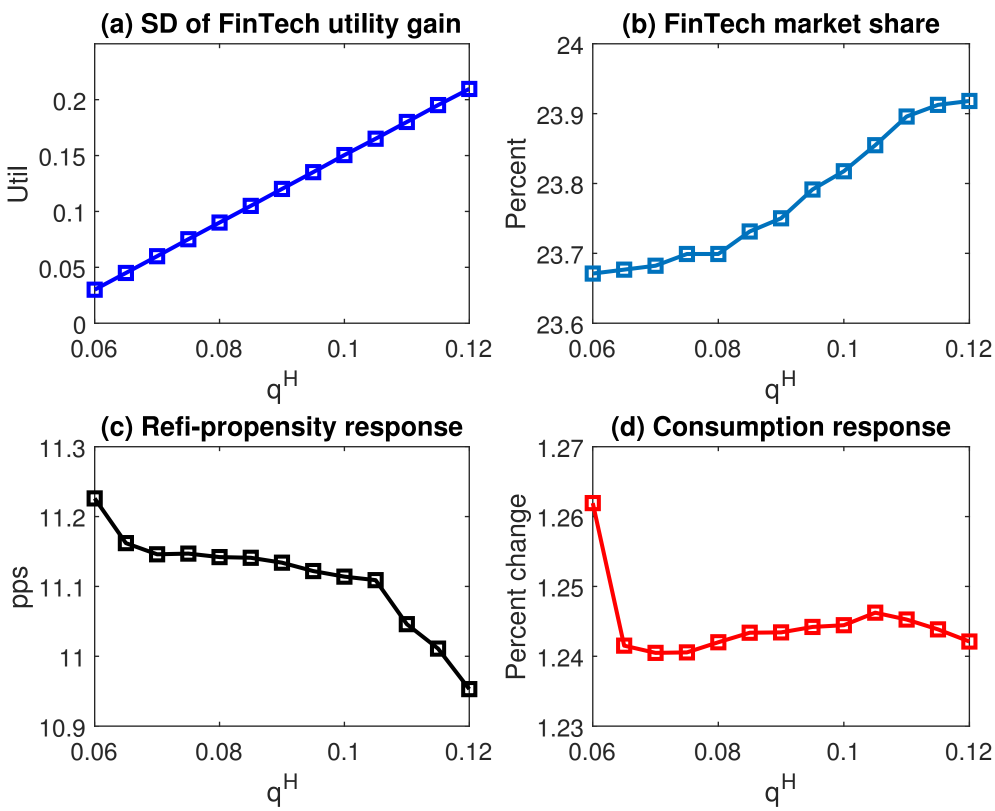
The model is solved numerically using a value function iteration method. In the first step, the state space is discretized and the value functions are solved over fixed grids of the state space. In the second step, the policy functions are obtained by solving the maximization problem over finer grids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

Figure E1: Average FinTech utility gain and monetary policy effects



Notes: Model simulations. This figure depicts how the FinTech market share, the refinancing response, and the consumption response change (panels b-d), when the average utility gain from FinTech refinancing decreases (panel a) due to a rising share of consumers who are worse off with FinTech lending.

Figure E2: Dispersion in FinTech utility gain and monetary policy effects



Notes: Model simulations. This figure depicts how the FinTech market share, the refinancing response, and the consumption response change (panels b-d), when the average utility gain from FinTech refinancing is fixed but the dispersion increases (panel a) due to the increasing dispersion in the realized FinTech utility gain.