Local lending specialization and monetary policy*

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Abstract

We provide evidence that bank loan supply reactions to monetary policy changes are market-specific, emphasizing the importance of banks' local specialization. We analyze the U.S. mortgage market and find that, when monetary policy eases banks increase new mortgage lending growth more in markets in which they are geographically specialized relative to other markets and banks. This holds after controlling for local lending opportunities and (unobservable) bank differences. Further empirical findings, supported by a simple model, suggest that banks face market-specific differences in lending advantages, related to market-specific information, leading them to exhibit different reactions to monetary policy adjustments. We document the aggregate effects of this geographical specialization channel both at the county level on mortgage supply and house price growth, as well as at the bank level on average specialization growth. Our study underscores the relevance of banks' local specialization in shaping the transmission of monetary policy.

Keywords: Bank Lending; Federal Funds Rate; Geographical Specialization; Information Asymmetries; Market Structure; Monetary Policy; Mortgage Market.
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1 Introduction

Banks are key agents in the transmission of monetary policy to the real economy (Kashyap and Stein, 1995; Kishan and Opiela, 2000; Drechsler et al., 2017). One relevant characteristic of banks is their heterogeneous presence across different local markets, which we refer to as local or geographical specialization. Banks that concentrate their lending activities in specific markets may develop expertise, skills, or technologies in screening or monitoring borrowers, which can lead to market-specific lending advantages (Loutskina and Strahan, 2011; Berger et al., 2017b; Paravisini et al., 2023; Blickle et al., 2023) and influence their responses to shocks. Moreover, geographical specialization can also determine their exposure to idiosyncratic local shocks, thereby impacting their resilience (Goetz et al., 2016). In this study, we propose and test the relevance of banks' local specialization in lending markets for the transmission of monetary policy to the economy and to banks' geographical diversification.

We first measure a bank's local specialization based on its lending shares within a given market, relative to the bank's total amount lent. We then employ this measure to assess whether bank loan supply reactions to monetary policy changes are market-specific, contingent on this characteristic. Our findings reveal that following a monetary policy easing, banks increase new mortgage lending growth by more in counties where they are more specialized, compared to other markets and other banks.[1] What we call the local specialization channel. We illustrate how this local specialization channel, by affecting new mortgage lending at the county level, induces relevant regional effects. It affects house price growth, which has been shown to be important for households and financial stability (Cloyne et al., 2019; Mian and Sufi, 2009), as well as, in a milder way, wage and employment growth. Moreover, we also illustrate that the local specialization channel affects banks' overall geographical diversification, potentially influencing their resilience to local economic shocks. Finally, we provide theoretical and empirical evidence suggesting that our findings are consistent with differences in bank-market-specific lending advantages related to informational differences, that may lead to heterogeneous bank lending costs in each market.

Our results are important for three reasons. First, to the best of the authors' knowledge, we are the first paper to provide evidence, and a simple theoretical setup, in line with banks' local market specialization being a relevant channel for the transmission of monetary policy to regional mortgage lending, house prices, and economic activity. Our results are robust and the economic effects are large. Second, we provide evidence in line with monetary policy

[1] Although our main results present average effects, we interpret our results in the context of interest rate decreases as subsequent analysis reported in the appendix reveals that the identified channel is particularly prominent after a monetary policy easing.

being a determinant of how banks are geographically specialized (or diversified) in local mortgage markets. Lower monetary policy rates increase banks' incentives for specialization, influencing their exposure to undiversifiable negative shocks in local markets which can affect banks' resilience to local shocks. Third, we contribute to a deeper understanding of how bank loan supply reactions to shocks may exhibit market-specific patterns, potentially attributable to lending advantages conferred by local specialization.

As previously argued, bank local specialization is a relevant feature of the bank lending market. We observe a consistent pattern where the majority of banks specialize geographically by concentrating their lending disproportionately in specific local markets. Regardless of bank type or location, most banks in our sample rank in the top quartile of the share distribution of lending in certain local markets throughout the sample period. Furthermore, we report that the bank specialization measure is stable over time. These stylized facts support the notion that most banks tend to lend disproportionately to certain local markets where they might develop greater expertise.[2].

Our analyses are subject to two common identification challenges in the empirical banking literature: demand shocks and other bank level supply effects. Specifically, results might be driven by changes in local lending opportunities and/or bank-year level heterogeneity and not by changes in bank's loan supply. If monetary policy changes affect local lending opportunities and/or the liability side of banks, attributing changes in loan quantities to variations in loan supply due to local market specialization becomes challenging. As explained below, our data and estimation procedures are designed to address these concerns.

We analyze the mortgage market using origination data collected under the Home Mortgage Disclosure Act (HMDA) from the Federal Financial Institutions Examination Council (FFIEC) for the years 1994 to 2019. At the bank-county-year level, we measure growth in new mortgage lending and construct a measure of bank specialization. This measure captures the relative importance of each county for a given bank, defining a bank as more specialized in a given market if the relative amount of new mortgage lending originated in that market is higher. The granularity of our data allows us to absorb potential confounding demand effects at the county level by incorporating county-time fixed effects, and to account for bank-wide factors by incorporating bank-time fixed effects. When including this set of fixed effects, we ensure that our results using the specialization measure account for the size of the local market or bank-wide lending advantages due to factors such as a technological advantage in lending to all markets.

In our most saturated specification, we are effectively comparing at the same time new

[2]These stylized facts resemble those found in studies such as (Paravisini et al., 2023; Blickle et al., 2023) which focus on banks' sectorial specialization in firm loans.

mortgage lending growth originated by different banks having different levels of local specialization in the same market and year, and new mortgage lending growth originated by the same bank in different markets where it has different levels of local specialization. The identifying assumptions for our estimates capturing supply effects are: (i) banks can allocate funds internally, and (ii) banks granting mortgages in the same market face the same change in local lending opportunities. Both assumptions are standard in the empirical banking literature addressing related issues (e.g., Gilje et al. (2016); Cortés et al. (2020))

Our interest in the mortgage market is based on the fact that mortgage lending is one of the most relevant credit markets for banks and households, and has also been shown to be at the core of important economic fluctuations like the recent financial crisis (Mian and Sufi, 2009; Favara and Imbs, 2015; Cortés and Strahan, 2017; Demyanyk and Loutskina, 2016). Hence, while analyzing the mortgage market helps in ameliorating some identification challenges we face, it is in itself a very important market to analyze.

Our initial finding shows that bank loan supply reactions to monetary policy changes exhibit market specificity, contingent on the degree of a bank's local specialization. This result holds when we control for potential changes in local lending opportunities, lending market size, and bank-year heterogeneity. Specifically, we document how following a 100 basis points (bps) decline in the Fed funds rate, a one standard deviation increase in bank's local mortgage market specialization increases new mortgage lending growth by 54.3 bps.

A potential concern regarding this finding is that it could be driven by other banks' local market structure characteristics, which might impact the transmission of monetary policy to loan supply and could be correlated with local market specialization. Some of these characteristics include banks' local loan market share (Favara and Giannetti, 2017; Giannetti and Saidi, 2019) or banks' exposure to local deposit market concentration (Drechsler et al., 2017).[3] To ameliorate this concern, we show that bank's local mortgage market specialization remains both economically and statistically significant when controlling for the effects of local loan market share and bank exposure to local deposit market concentration.

To verify the consistency of our first finding, we perform several additional robustness tests: (i) alternative measures of our specialization variable, (ii) alternative measures of monetary policy stance, (iii) alternative measures of our dependant variable, and (iv) different sample periods.

First, given that we lack information on mortgage stocks disaggregated by markets, we proxy a bank's local mortgage market specialization using different measures. These include

[3]It is important to note that in our primary specification, where we control for bank-year level heterogeneity by including bank-year fixed effects, the effect of bank exposure to local deposit market concentration is absorbed. Therefore, to include the effect of bank exposure to concentrated deposit markets as a control, we need to omit the bank-year fixed effects.

a two-period lag, an average across the entire sample period, an average over the previous five years and specialization computed for the period 1994 to 2004, with subsequent testing for its influence post-2005.[4] Moreover, while the inclusion of county-year fixed effects addresses concerns related to county heterogeneity, we also construct the specialization variable as quartile dummies for each county and year in the spirit of Paravisini et al. (2023) and as excess specialization taking into account the relative importance of each geographical market in the spirit of Blickle et al. (2023). Notably, our findings are robust to these alternative measures of specialization.[5]

Second, we verify the robustness of our results to employing different measures of monetary policy, such as using the average instead of the end-of-period aggregation method. We also use monetary policy shocks, as in Jarociński and Karadi (2020), to disentangle the effect of changes in the Fed funds rate from central bank information shocks. In order to better capture changes during periods of a flat Fed funds target rate, we also use shadow rates as an alternative monetary policy measure. We find that our results are robust to using these alternative measures of monetary policy stance.

Third, we further assess the robustness of our results to examining alternative dependent variables, including log-differences in new lending (Favara and Imbs, 2015) and the growth in the number of new mortgage loans originated, instead of the dollar amount. To provide additional evidence of a supply mechanism at play, we conducted two further robustness tests. These involved analyzing differences in approval ratios and comparing lending originated by different banks to the same customer types in the same market, thus controlling for changes in lending opportunities arising from different borrowers based on their income. In both cases, the results suggest the presence of a supply bank-market-specific mechanism at play.

Finally, we investigate whether specific sample periods are driving our results. Drechsler et al. (2022) show that monetary policy impacted the U.S. housing boom, Gelman et al. (2023) demonstrate how bank's geographic diversification influences credit supply during crisis periods, and Altavilla et al. (2018) show that under a low-interest rate environment, monetary policy does not work as intended. We provide evidence that our results are not driven by these specific sample periods. They hold when excluding or specifically focusing on the U.S. housing boom period, excluding the Great Recession years, or narrowing the sample to 1994 to 2013, excluding the low-interest rate period.[6]

[4]This latter specification suggests that endogeneity issues of the specialization variable may not be a fundamental driver of our results.

[5]Additionally, our results are also robust when considering the extensive margin effect, accounting for entries and exits into local markets. While monetary easing might encourage new market entries, quantitatively, this effect is smaller than the increase in pre-existing markets.

[6]In the appendix, we provide additional robustness tests. These include controlling for lagged new mortgage lending growth, accounting for time-invariant bank-county heterogeneity, focusing on an alternative

We then turn to analyze plausible underlying mechanisms shaping our results. We find evidence consistent with market specialization being related to informational lending advantages. Specifically, we find that: (i) bank specialization is correlated with proxies related to bank informational advantages, (ii) the economic relevance of the bank specialization channel decreases (but is still significant) when controlling for informational proxies, and (iii) the bank specialization channel is more prevalent in more information-sensitive markets.

We argue that if bank specialization relates to market-specific lending advantages, this can translate to banks effectively having heterogeneous market specific lending costs that can shape the transmission of monetary policy. We present a simple theoretical model in which a bank faces different marginal lending costs across markets and funds itself at the monetary policy rate. We assume that the bank has an exogenous market-specific lending cost function that is increasing and convex. Crucially, the convexity of the function differs across markets, leading the bank to have lower lending costs in certain markets, characterized by a lower convex cost function. We characterize how the bank tends to lend more, i.e. is more specialized, in markets where the lending cost function is less convex. Moreover, in line with our empirical results, we characterize how the bank exhibits a stronger increase in lending in such markets in response to monetary policy decreases.

We then turn to provide empirical evidence relating specialization to informational lending advantages. Given the nature of the lending market we argue that one relevant aspect of lending advantages can be related to market specific information. Market specialization may confer enhanced information about the market (as well as expertise and monitoring capabilities) thereby leading to a lending advantage (Berger et al., 2017b; Paravisini et al., 2023; Blickle et al., 2023). To provide empirical evidence relating bank specialization and information lending advantages we use different proxies of bank information.

Building upon the arguments of Petersen and Rajan (1994), Mester et al. (2007), Bolton et al. (2016), and Botsch and Vanasco (2019), among others, we posit that banks may possess greater market-specific information, and lending advantages (such as reduced marginal lending costs associated with borrower screening and monitoring), in markets where they have a lengthy history of lending, where their headquarters are located, in close geographic proximity to their headquarters, where they own a larger number of branches, or in markets where they exhibit a high degree of deposit specialization. Our empirical findings reveal that

boom period, adopting different definitions of the mortgage market, considering new small business lending, and including both depository and non-depository institutions in the analysis. Notably, our findings in the latter test provide evidence that the loan supply originated from any financial institution, regardless of its deposit insurance condition, is affected by monetary policy changes heterogeneously depending on its degree of local specialization. Furthermore, we observe an amplification of this effect for non-depository institutions, suggesting that monetary policy changes may exert a more pronounced impact on their funding costs.

banks exhibit a higher degree of local lending specialization in such markets, consistent with the presence of greater information based lending advantages.

Furthermore, when controlling for such proxies, that are plausibly related to information and lending advantages for a given bank within a local market, the impact of local specialization on the transmission of monetary policy to loan supply is attenuated. This aligns with the notion that information based lending advantages may be a plausible underlying driver of our proposed channel. However, while loosing around 35 percent of its relevance, local specialization maintains economic relevance, both in terms of significance and magnitude, suggesting that it encompasses expertise and lending advantages that are not fully captured by these other bank-market-specific proxies.

To provide further insights into our proposed relation between bank market specialization and information we exploit two distinct cross-sectional variations differentiating between more and less information-sensitive markets. If local lending specialization is related to market-specific information and lending advantages for a given bank, its impact on the transmission of monetary policy to lending growth should be stronger within information-sensitive segments of the mortgage market, such as jumbo mortgages, and in local markets where information asymmetry is expected to be more acute, as proxied by higher loan size dispersion. Our analyses reveal that the local specialization channel exhibits greater relevance in both the jumbo information-intensive segment of the mortgage market and in markets with higher loan dispersion.

We also empirically investigate whether risk-taking could be a plausible mechanism underlying our results. Our analysis reveals that, following a monetary policy easing, mortgages originated in markets where the bank specializes do not demonstrate differences in their ex-ante riskiness, as measured by the loan-to-income (LTI) ratio, compared to those originated in other markets. Moreover, leveraging additional measures of ex-ante riskiness and ex-post performance for a subset of mortgages originated to sell to government-sponsored enterprises (GSEs), we show that these mortgages do not display significant differences in terms of LTI ratio, FICO score, and interest rates.[7] However, these mortgages exhibit higher ex-post default rates compared to those originated in other markets. Hence, while there is no evidence supporting ex-ante riskiness as a relevant driver of our results, nor evidence of a worsening in balance sheet non-performing mortgage ratios, our findings suggest that banks are able to sell mortgages to GSEs that perform less favorably ex-post. This suggests they may capitalize on the information advantage plausibly conferred by bank specialization.

[7] Risk-taking does not appear to be the underlying driver of the results, as additional findings presented in the appendix indicate that our proposed channel is not driven by factors such as low-income borrowers, ex-ante riskier local markets, or banks with lower capital ratios, reduced liquidity ratios, or elevated non-performing loan (NPL) ratios.

We end our study by analyzing the aggregate implications of the channel we have documented, both at the county level and at the bank level. To do so, we first compute the county level exposure to local specialized banks in the mortgage market and examine its impact on the transmission of monetary policy to regional new mortgage lending, house prices, and economic activity (wage and employment) growth. Consistent with our previous results, we find that, following a monetary policy easing, counties exposed to banks with higher specialization in that mortgage market experience a higher increase in aggregate new mortgage lending, house price, wage, and employment growth relative to other counties. These results hold when accounting for relevant local market characteristics and additional county controls. Specifically, we estimate that a one standard deviation increase in county level exposure to specialized banks is associated with a 138.24 bps increase in new mortgage lending growth, a 14.4 bps increase in house price growth, a 8.69 bps increase in wage growth, and a 1.66 bps increase in employment growth per 100 bps decrease in the Fed funds rate. We also document how these results hold when, as in our previous robustness analysis, using monetary policy shocks, constructing the dependent variables with the log difference, and focusing on the period from 1994 to 2013.

Finally, we investigate the aggregate effects at the bank level to analyze if, as suggested by our previous results, monetary policy affects banks' geographical specialization. We compute the average bank's local specialization, which is the opposite of banks' geographical diversification, to examine the impact of monetary policy on aggregate bank specialization (diversification) growth. We find that banks experience an increase in their aggregate local specialization growth, i.e. reduction in geographic diversification, following a monetary policy easing. This result holds even when controlling for time-invariant bank heterogeneity and time-variant bank characteristics. We estimate that for a 100 bps decrease in the Fed funds rate, bank specialization growth increases by 47.4 bps. As in our previous analyses, we document the robustness of this result when using monetary policy shocks, constructing dependent variable with the log difference, and focusing on the period from 1994 to 2013.

Taken together, our novel findings underscore the significant role of bank local specialization decisions in influencing the transmission of monetary policy to the real economy. Importantly, these decisions are not only relevant but are also shaped by monetary policy, thereby carrying substantial implications for understanding the overall effects of monetary policy on the economy. This novel insight not only contributes to inform the conduct of monetary policy but also aids in anticipating its heterogeneous effects, thereby leading to more informed monetary policy decisions.

1.1 Literature Review

This paper contributes to several strands of the literature. Our article relates to long-standing literature on the transmission of monetary policy to the real economy through bank lending, the bank lending channel. The focus of this literature has primarily been on the effect of Federal funds rate changes on commercial banks (Bernanke and Blinder, 1988; Bernanke, 1992; Kashyap et al., 1993; Kashyap and Stein, 2000; Jiménez et al., 2012). Within this literature, emphasis has been placed on the diverse characteristics of banks influencing the transmission of monetary policy, including size, liquidity, leverage, capital, exposure to interest rate risk, and online banking (Kashyap and Stein, 1995, 2000; Kishan and Opiela, 2000; Kashyap and Stein, 2000; Jiménez et al., 2012; Dell'Ariccia et al., 2017; Gomez et al., 2021; Erel et al., 2023).[8] To this literature we contribute by providing evidence that the response of bank supply to Fed funds changes is market-specific, depending on the degree of the bank's geographical lending specialization.

On this strand of literature, our article is most closely related to studies examining the impact of banking market structure characteristics on the transmission of monetary policy to the economy. Imperfect competition in the banking market has been theoretically (Dell'Ariccia et al., 2014; Drechsler et al., 2017; Martinez-Miera and Repullo, 2020) and empirically (Scharfstein and Sunderam, 2016; Drechsler et al., 2017; Li et al., 2023) examined as a relevant friction affecting the transmission of monetary policy.[9] While prior research focuses on imperfect competition in the deposit or loan market for the pass-through of monetary policy to lending, our focus diverges.[10] We present evidence and a simple theoretical framework for a novel market structure characteristic, bank's local lending specialization, influencing this transmission. To the best of our knowledge, we are the first to show how bank's local specialization affects the transmission of monetary policy to the economy, with monetary policy itself being one determinant of how banks specialize their lending activities

[8]Similar to these studies, some papers studied the role of non-insured financial institutions dampening the impact of monetary policy (Xiao, 2020; Cucic and Gorea, 2022; Elliott et al., 2023), how the transmission of monetary policy during the U.S. housing boom affected differently bank and nonbank lenders (Drechsler et al., 2022), and how the housing boom impacted the real economy (Mian and Sufi, 2009; Justiniano et al., 2019). We provide evidence suggesting that local market specialization is relevant for the transmission of monetary policy to new mortgage lending growth for boom and bust periods, and it is even moreso, when including nonbank lenders and during the U.S. housing boom period.

[9]Notably, Drechsler et al. (2017) provides a theoretical setup and empirical findings, showing how a tightening of monetary policy exerts a more pronounced impact on the reduction of deposit quantities in concentrated markets compared to competitive deposit markets. This is the so called deposits channel of monetary policy that works through bank market power in the deposit market, ultimately resulting in implications on bank lending and economic activity.

[10]Related to this strand of the literature, the study by Ruzzier (2024) examines the impact of banks' sectoral specialization on the transmission of monetary policy shocks to syndicated commercial and industrial business loans in the US.

in local markets.

Our paper also contributes to the literature on the real effects of bank specialization and diversification. Existing studies show that banks often specialize, i.e., concentrate their lending activities in specific industries and markets (Loutskina and Strahan, 2011; Berger et al., 2017b; Giometti and Pietrosanti, 2022; Saidi and Streitz, 2021; Chu et al., 2021; Paravisini et al., 2023; Blickle et al., 2023).[11] Specialized banks, as revealed by existing research, seem to possess the capacity to offer more favorable loan conditions, including less restrictive covenants and lower spreads. Moreover, they tend to invest more in information collection, fostering a range of outcomes such as the reduction of zombie lending, the utilization of spillovers from industry specialization to influence its mortgage lending allocation, and the imposition of reduced requirements for audited financial statements in industries and markets where they specialize.[12]

This literature also focuses on analyzing the advantages and disadvantages associated with bank diversification, emphasizing the ongoing debate on whether diversification ultimately enhances or diminishes bank stability. On one hand, poses the risk of diminishing monitoring incentives, prompting banks to allocate fewer resources to information collection. This, in turn, can elevate default risks, amplify systemic vulnerabilities, and result in diminished performance (Acharya et al., 2006; Berger et al., 2010; Loutskina and Strahan, 2011; Tabak et al., 2011; Goetz et al., 2013; Berger et al., 2017a; Chu et al., 2020).[13] On the other hand, diversification may mitigate banks' exposure to idiosyncratic local risks and can offer improved access to funding, particularly during crisis periods. This positive aspect of diversification manifests in influencing lending origination positively and generating beneficial spillover effects on the real economy (Favara and Imbs, 2015; Goetz et al., 2016; Doerr and Schaz, 2021; Bord et al., 2021; Levine et al., 2021; Gelman et al., 2023).[14] Overall, we contribute to this literature on bank specialization by showing that Fed funds rate changes

[11] Related to this line of research, Blickle et al. (2024) recently introduced a theoretical framework that concentrates on the private information banks gather from borrowers to analyze bank lending specialization and borrower screening.

[12] In line with this, Duquerroy et al. (2022) also find that bank branches specialize by industry affecting lending to small businesses in France. Additionally, Di and Pattison (2023) analyze the growing tendency among small business lenders to specialize in specific industries and its consequent impact on credit and competition.

[13] Aguirregabiria et al. (2016) provide evidence that the deregulation of the U.S. banking sector enabled banks to enhance their geographical risk diversification, with only certain major banks strategically capitalizing on this opportunity.

[14] Gilje et al. (2016) highlight the relevance of geographical diversification for banks, allowing them to internally allocate funds from markets with excess capital to those with more lending opportunities. Additionally, Traversa and Vuillemey (2019) use branch-level data to empirically study how banks expand or contract to local markets. Their findings reveal that banks tend to expand in counties with similar industry compositions to their existing locations, and contraction is more likely in areas with greater similarity.

are key determinants of how bank geographical specialization (diversification) is determined. Specifically, we illustrate how a decrease in the Fed funds rate is related to an increase (reduction) in the growth of banks' local market specialization (diversification).

Our paper builds on empirical work in the banking literature emphasizing how shocks affecting banks and firms are transmitted to the economy depending on banking market structure characteristics.[15] Various characteristics have been identified as influential in shaping the transmission of shocks to lending and sector activity. These include market shares (Giannetti and Saidi, 2019; De Jonghe et al., 2020; Giannetti and Jang, 2021), industry, export market, and geographical specialization (De Jonghe et al., 2020; Karakaya et al., 2022; De Jonghe et al., 2021; Iyer et al., 2022; Duquerroy et al., 2022; Paravisini et al., 2023; Izadi and Saadi, 2023; Dursun-de Neef, 2023), and, more specifically in the mortgage market, the proportion of outstanding mortgages on banks' balance sheets (Favara and Giannetti, 2017; Gupta, 2022).[16] We depart from these previous studies by showing how the transmission of monetary policy to lending supply is bank-market-specific depending on the degree of local specialization and by analyzing how monetary policy affects bank's local specialization decisions.[17]

Our article is also linked to papers examining bank relationship lending and the plausible role of information in industry and market specialization. The facets of relationship lending encompassing prior borrowing history, repeated interactions, and duration (Petersen and Rajan, 1994; Berger and Udell, 1995; Sufi, 2007; Bharath et al., 2011; López-Espinosa et al., 2017; Botsch and Vanasco, 2019; Berger et al., 2021), as well as considerations like distance (Degryse and Ongena, 2005; Liberti and Mian, 2009; Bolton et al., 2016; Hollander and Verriest, 2016; Granja et al., 2022), a bank's business model centered on relationship lending (Beck et al., 2018), concentration of borrowing (Jiménez et al., 2022), and the acquisition of alternative financial services such as checking and savings accounts (Berlin and Mester, 1999; Mester et al., 2007), have all been established as factors influencing lending outcomes.[18] In the context of portfolio concentration, if bank specialization is associated with enhanced expertise, technological development, or skills in evaluating projects within a particular sector or geographical market, banks may obtain a sector- or market-specific advantage where they specialize (Berger et al., 2017b; De Jonghe et al., 2020; Giometti and Pietrosanti, 2022;

[15] Kundu et al. (2021) exploit natural disasters to argue that geographically concentrated bank deposits play a pivotal role in influencing economic growth.

[16] While the approach by Gupta (2022) is theoretical, their model posits that lenders with a substantial number of outstanding mortgages have incentives to extend risky credit to prop up house prices.

[17] In Section 3, we show the robustness of our results when we include a control for the effect of local bank market shares in the transmission of monetary policy to loan supply.

[18] The literature even explores how social connectedness between bank and borrower regions can impact bank lending, as shown in Rehbein and Rother (2022).

Chu et al., 2021; Paravisini et al., 2023; Blickle et al., 2023; Izadi and Saadi, 2023).[19] While existing literature predominantly focuses on how banks specialize their lending activities in specific sectors and how it influences lending outcomes. However, our focus on geographical portfolio specialization adds a distinct dimension. We contribute by providing evidence that the transmission of monetary policy to bank lending is bank-market-specific, potentially related to the lending advantages conferred by geographical specialization.

Our article also relates to studies investigating both the ex-ante riskiness and ex-post performance in the mortgage market following the implementation of new laws (Saadi, 2020), the consequences of specific shocks (Karimli, 2022), and variations attributed to distinct bank, borrower, and local characteristics (Jiang et al., 2014; Adelino et al., 2016; Hurst et al., 2016; Bhutta et al., 2017; Chu et al., 2022, 2021; Fuster et al., 2022; Ganong and Noel, 2023; Gerardi et al., 2023).[20] Our distinctive contribution to this body of work lies in revealing that the observed effect extends to mortgages originated and sold to GSEs. Despite exhibiting similar ex-ante characteristics, these mortgages demonstrate a more unfavorable ex-post performance. This pattern aligns with the notion of timely selling of mortgages to third parties such as Fannie Mae and Freddie Mac. This observed pattern could potentially be attributed to banks holding an information advantage in markets where they specialize, given the absence of evidence suggesting ex-ante risk-taking behavior or deterioration in balance sheet metrics like non-performing mortgage ratios.

Finally, our paper ties into the body of literature that documents the impact of credit supply on aggregate economic activity and the price of assets. Prior studies have illustrated that shifts in credit supply through various lending channels have significant effects on real economic outcomes, as evidenced by changes in employment and wage growth (Chodorow-Reich, 2014; Drechsler et al., 2017; Lin, 2020; Luck and Zimmermann, 2020). Abundant theoretical and empirical evidence further attests to the influence of credit supply changes on asset prices (Favara and Imbs, 2015; Favara and Giannetti, 2017; Favilukis et al., 2017; Di Maggio and Kermani, 2017; Blickle, 2022). Our contribution to this literature is distinctive, emphasizing the crucial role of a novel characteristic in the transmission of monetary policy changes, banks' geographical specialization, which exerts an impact on house prices and regional economic activity.

In the remainder of the paper, Section 2 describes the data, Section 3 delves into our empirical methods, presenting micro evidence on lending along with theoretical and empirical evidence supporting the plausible mechanisms underlying the main result, Section 4 examines

[19] In line with this, Chu et al. (2021) highlight positive spillovers from industry specialization into the mortgage market, enhancing banks' capability to assess borrowers' risk.

[20] In line with this vein of literature, Davis et al. (2023) provides a comprehensive overview of the default risk history in the US mortgage market over the past quarter-century.

the regional aggregate implications on lending, house prices, and economic activity, Section 5 reports the aggregate implications on bank specialization, and Section 6 concludes.

2 Data

2.1 Data Sources

For our study, we need information on bank loans extended to borrowers in a wide range of local markets. Given the absence of comprehensive data on all bank credit segmented by local markets, we focus on the mortgage market, given its substantial size and significance for banks.[21] Our approach aligns with numerous empirical studies that have analyzed varied lending origination across markets in the United States, as evident in works such as Favara and Imbs (2015); Gilje et al. (2016); Favara and Giannetti (2017); Cortés and Strahan (2017); Doerr et al. (2022). To conduct our analysis, we use data from the FFIEC HMDA database.

The HMDA database covers the vast majority of mortgage activity conducted by commercial banks, thrifts, credit unions, and mortgage companies (Mian and Sufi, 2009; Favara and Imbs, 2015; Favara and Giannetti, 2017).[22] This database contains crucial information on various aspects, including the size, type, and purpose of loans. It also indicates whether a loan was approved, denied, or purchased. Additionally, it offers details on the county and state location of the property acquired through the mortgage. Furthermore, the HMDA database provides insights into borrower characteristics such as self-reported income, race, and gender.

Our sample, constructed at the bank-county-year level, quantifies the volume of total housing-related loans originated, including mortgages for home purchase, refinancing, and improvement, from depository institutions (i.e., banks), consistent with Gilje et al. (2016).[23] To distinguish between depository and non-depository institutions, we employ the "HMDA Lender file," compiled by Robert Avery for most lenders who have reported mortgage originations in HMDA, following Demyanyk and Loutskina (2016) and Agarwal et al. (2023).

[21] This decision is supported by Figure A1 in the appendix, illustrating that outstanding mortgages constitute between 49% and 65% of total outstanding loans of U.S. banks from 1994 to 2019.

[22] Inclusion in the HMDA database is contingent upon factors such as the lender's size, the scope of its activity in a Central Business Statistical Area (CBSA), and the significance of mortgage lending within its portfolio. For a more detailed description of HMDA data, refer to Gilje et al. (2016) and Cortés and Strahan (2017).

[23] From now on, we refer to this data structure, where we observe lending amounts originated by each bank in each county (i.e., market) and year, as bank-county-year level data. To ensure comparability across the sample period, we deflate the amount of new mortgage lending using the consumer price index, as outlined in Drechsler et al. (2017). In our preferred specification (column 1 of Table 2), we present mortgage lending growth information for 12,082 unique depository institutions.

While our primary analyses focus on banks, we include non-depository institutions in some robustness tests.[24] Our focus is on mortgages originated to hold and sell, as our interest lies in the originated amount rather than whether banks retain lending on their balance sheet.[25] Counties serve as our definition for local banking markets, aligning with standard practices in the empirical banking literature (see, for example, Gilje et al. (2016), Drechsler et al. (2017) and Lin (2020)).[26] Our sample spans from 1994 to 2019.[27]

We obtain the Fed funds target rate as our primary measure of monetary policy rates from the Federal Reserve Economic Data (FRED), following the approach outlined in Drechsler et al. (2017). We use the end of period aggregation method and, after the introduction of a target corridor in 2008, compute the average of the upper and lower Fed funds target rate. Specifically, we rely on annual data corresponding to the last quarter of each year.[28]

Given the limitations of the HMDA data, which lacks information on mortgage performance, interest rates, and comprehensive measures of ex-ante risk, we augment this dataset by incorporating information from the Fannie Mae and Freddie Mac single-family loan-level datasets. These datasets encompass fully amortizing, 30-year fixed-rate, fully documented mortgages acquired by the two institutions.[29] The performance datasets from Freddie Mac and Fannie Mae start in 1999 and 2000, respectively. Although these datasets offer detailed information on mortgage characteristics, they do not entirely disclose lender originators. To address this, we match these datasets with HMDA data from 2000 to 2017. This matching

[24] We use the variable ENTITYyy, which takes the Federal Reserve Board Entity number (RSSD9001) for commercial banks, thrifts, or credit unions. For subsidiaries of BHC, it corresponds to the entity number of the lead bank or thrift in the holding company, constituting our main sample for this research. For independent mortgage companies classified as nonbanks in our sample, the variable takes a value of zero unless additional information indicates it is a subsidiary of a commercial bank or thrift. In cases where the independent mortgage company is a subsidiary of a holding company, its mortgage lending is attributed to the lead bank in the holding company. Our results, as shown in Table A4 in the appendix, remain robust when including non-depository institutions in the analysis.

[25] Robustness tests demonstrate that our findings are stronger for mortgages originated to sell to GSEs and that they persist even when excluding mortgages originated for sale. Additionally, we exclude Federal Housing Administration (FHA) insured, Veterans Administration (VA) guaranteed, Farm Service Agency (FSA), and Rural Housing Service (RHS) mortgages, in line with Loutskina and Strahan (2009).

[26] Consistent with Cortés et al. (2020), we limit our sample to markets where a given bank made at least five loans in the previous period to eliminate noise from counties with an insignificant amount of loans originated by a given bank. Table 4 shows that our results remain robust when analyzing the entire sample of bank-counties.

[27] To avoid potential distortions from COVID-19-related issues, our sample concludes in December 2019, as it is beyond the scope of this study.

[28] We also use the estimated monetary policy shocks following Jarociński and Karadi (2020) to disentangle the effect of interest rate changes from central bank information shocks, and our results hold. Additionally, our results are robust to use the average aggregation method of the Fed funds target rate and to use the shadow rates to exploit monetary policy variation in the zero lower bound environments.

[29] It is important to note that these databases exclude certain mortgage types, such as Home Affordable Refinance Program (HARP) mortgages, loans with a loan-to-value (LTV) greater than 97%, adjustable-rate mortgages, balloon mortgages, and government-insured mortgages, among others.

process results in a substantial sample of mortgages sold to Fannie Mae and Freddie Mac, comprising approximately 2 million mortgages. The dataset includes information on the originator, interest rate, ex-ante riskiness, and ex-post mortgage performance, tracked until the end of 2023.[30]

We collect county-level data on house prices from the Federal Housing Finance Agency (FHFA) following Chakraborty et al. (2018), Lin (2020), and Doerr et al. (2022). The series are calibrated using appraisal values and sales prices for mortgages bought or guaranteed by Fannie Mae and Freddie Mac.[31] Our dataset encompasses information on total wages and employment at the county level, serving as indicators of local economic activity. We derive this data from the Quarterly Census of Employment and Wages (QCEW) and the Local Area Unemployment Statistics (LAUS) programs provided by the Bureau of Labor Statistics (BLS). The dataset includes county-level information on house prices, wages, and employment spanning from 1994 to 2019. Additionally, we incorporate county-level controls, specifically the natural logarithm of population and the natural logarithm of income per capita, obtained from the Bureau of Economic Analysis (BEA). We also include the proportion of securitized mortgages from HMDA as additional controls.

To account for the influence of local deposit market concentration on the transmission of monetary policy to bank loan supply, a phenomenon established in prior research (Drechsler et al., 2017), we use deposit market data. This data, obtained from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits (SOD) database, provides comprehensive information on U.S. bank branches. Collected annually since June 1994, the dataset encompasses details on branch characteristics, including deposit quantities, parent bank, and geographic location.

We collect bank-level data on bank characteristics and headquarters location from the U.S. Call Reports provided by the FDIC. We use data corresponding to the last quarter of each year, spanning from 1994 to 2019. While the U.S. Call Reports data is available at the quarterly level, we opt to use end-of-year data to facilitate seamless integration with mortgage market data. We match bank-level data from the U.S. Call Reports with the HMDA bank-county level data, employing the unique identifier assigned by the Federal Reserve Board entity.

[30]For a more detailed understanding of the Fannie Mae and Freddie Mac performance data, as well as the matching procedure with the HMDA data, refer to Adelino et al. (2016) and Saadi (2020). Additional details about the matching procedure are provided in Section 3.

[31]See Bogin et al. (2019) for a more detailed description of house price index data.

2.2 Variable Definitions

We adopt the definition of the growth of new mortgage lending proposed by Cortés et al. (2020) as our main measure of mortgage lending growth to alleviate the impact of outliers, often stemming from a small denominator. This involves normalizing the year-to-year change in the new mortgage lending amount by the midpoint of new mortgage lending between the two years as follows:

$$Growth_{bct} = \frac{A_{bct} - A_{bct-1}}{(A_{bct} + A_{bct-1})/2} \tag{1}$$

where A represents the amount of new mortgage lending, b denotes the bank, c represents the county, and t denotes the year. This definition constrains the growth variable between +2 and -2, reaching zero for banks in counties that show no variation in new mortgage lending.[32] This growth definition has been widely employed in related studies by Berton et al. (2018), Luck and Zimmermann (2020), and Doerr et al. (2022), among others, to calculate employment, lending, and/or deposit growth.[33]

We define bank's specialization, denoted as $Spec_{bct}$ for bank b in county c and year t, as the proportion of new mortgage lending originated by the bank b in county c during year t, divided by the total amount of new mortgage lending originated by bank b during year t.[34] This variable is defined in equation 2:

$$Spec_{bct} = \frac{A_{bct}}{A_{bt}} \tag{2}$$

Higher values of bank's specialization in a given local market and year imply that the specified local market is more important for the overall allocation of new mortgage lending by the bank during that specific year. Our estimation strategy relies on a within-bank and within-county comparison, effectively accounting for both bank- and county-wide factors such as lower cost of funds or larger market size. This approach enables us to capture the bank-market-specific reactions in loan supply to changes in monetary policy, attributable to local specialization.

[32] The boundaries of this variable serve to measure entries and exits of banks in local markets. Although entries and exits are not included in our main specification, we show in Table 4 that our primary results remain robust even when considering them.

[33] As alternative measures of new mortgage lending growth, we also employ the log-difference, akin to Favara and Imbs (2015), who uses the log-difference of county-level activity in the mortgage market. Our robustness tests, presented in Table 4 and Table A13, confirm the stability of our results when using this alternative dependent variable at the bank-county and county levels, respectively.

[34] We opt for new mortgage lending to construct bank specialization due to the absence of information on the stock of loans disaggregated by local markets. However, our results are consistent when using alternative specifications of the specialization variable (refer to Table 4 and Table A4).

We report in Table A1 that the specialization variable is stable over time, exhibiting high serial correlation throughout the sample period. Additionally, we observe that the majority of banks exhibit local specialization by concentrating their lending into specific local markets. Specifically, out of 12,082 banks in our main sample in column (1) of Table 2, 11,996 banks rank in the top quartile of the share distribution of lending in certain local markets at any given point throughout the sample period. These patterns are consistent with the notion that banks specialize their lending activities in markets where they may possess a market-specific lending advantage (Loutskina and Strahan, 2011; Berger et al., 2017b; Paravisini et al., 2023; Blickle et al., 2023).

To examine the broader regional and bank-level implications of our findings, we compute two specialization measures—one at the county level and another at the bank level. We measure the county-level exposure to banks that are specialized in that market, calculated as the weighted average of $Spec_{bct}$ across all banks originating new mortgage loans, using the amount of new mortgage loans originated as weights. We denote this variable as $CSpec_{ct}$, and it is defined in equation 3:

$$CSpec_{ct} = \sum_{b=1}^{n} \frac{Spec_{bct} \times A_{bct}}{A_{ct}} \tag{3}$$

Following this definition, the variable $CSpec_{ct}$ captures the extent to which new mortgage lending of a local market (i.e., county) during a given year is originated by banks specialized in that specific market and year.

To assess the aggregate average specialization of banks, we calculate the weighted average of $Spec_{bct}$ across all markets, using the amount of new mortgage loans originated in each county as weights. We denote this variable as $BSpec_{bt}$ and it is defined in equation 4:

$$BSpec_{bt} = \sum_{c=1}^{n} \frac{Spec_{bct} \times A_{bct}}{A_{bt}} \tag{4}$$

A high value for the bank's average specialization indicates that a significant portion of new mortgage lending originated by a particular bank in a given year is concentrated in markets where the bank is specialized.

2.3 Summary Statistics

Panel A of Table 1 presents summary statistics at the bank-county-year level for the mortgage market using HMDA and FDIC data. On average, a bank-county originates 89 new mortgages, amounting to an average of $17.3 million in new mortgages per year. The growth of new mortgage lending exhibits a mean of -11.5 bps with a standard deviation of 71 bps. The average bank-county has a level of specialization equal to 7.9 bps.[35]

Panel B provides county-level summary statistics for the HMDA, FHFA, and BLS data. In the average county, banks originate \$376 million in new mortgage lending, representing a growth of 8 bps. The average county hosts a total employed population of 45 thousand, with total wages amounting to \$1.8 billion and a house price index of 242.[36] The average county-level growth in employment, total wage bill, and house price index are 0.4, 3.5, and 2.7 basis points, respectively. There are around 37 banks on average originating mortgage lending in each U.S. county. The average county is exposed to a level of $CSpec$ of 6.8 bps.

Panel C presents summary statistics at the bank level for the HMDA and FDIC data. On average, a bank originates mortgage lending in around 28 markets and holds total assets amounting to \$758 million, with a deposit ratio of 83%, liquidity ratio of 6%, and leverage ratio of 90%. We compute the deposit, liquidity, and leverage ratio as the total deposits over total assets, total cash and balances due from depository institutions over total assets, and total liabilities over total assets, respectively.[37] The average bank also exhibits an average local specialization of 48.5 bps and an average growth in local specialization of -2.8 bps.

Our empirical analysis uses variation in local market exposure to specialized banks to explore the regional aggregate implications of the presented channel. As precisely defined earlier, we measure county exposure to specialized banks in a given year using $CSpec_{ct}$.

Figure 1 presents a map depicting the average county exposure in the United States over the sample period from 1994 to 2019. A higher numerical value indicates that new mortgage lending is originated by banks that are more specialized in that market. The observed variation across counties is substantial, ranging from a minimum average county exposure of 0.0001 to a maximum of 0.63. This significant variability allows us to explore the aggregate regional effects of monetary policy transmission through county exposure to specialized banks.

[35] It's important to note that these summary statistics are based on our main sample of bank-county-year observations, where banks originate at least five loans in a given market during the previous period.

[36] It is worth noting that publicly available data on the house price index from the FHFA covers around 2,755 counties between 1994 and 2019, which does not encompass all counties in our mortgage market sample (approximately 3,227 counties).

[37] These bank characteristics are measured from the U.S. Call Reports provided by the FDIC, focusing on information from domestic offices.

3 Results on Bank Lending: Micro Evidence

3.1 Baseline Empirical Strategy

In this section, we examine how banks' monetary policy transmission can be market-specific, emphasizing the role of a given bank's local market specialization in such transmission. The main identification challenge arises from potential omitted variables, notably changes in local lending opportunities (i.e., local loan demand) and bank-year level heterogeneity (e.g., deposit outflows from a specific bank). If fluctuations in the Fed funds rate influence local lending opportunities, changes in loan quantities may be caused by loan demand and not by loan supply, which is an acknowledged concern in the banking literature (Khwaja and Mian, 2008; Degryse et al., 2019). Furthermore, if changes in the Fed funds rate affect the liability side of banks differently (Dell'Ariccia et al., 2017; Drechsler et al., 2017; Heider et al., 2019), variations in loan supply could be attributed to alterations in bank financing rather than their specialization in the local loan market.

To address these identification challenges, we employ a within-bank-county estimation strategy, comparing lending originated by different banks within the same market and year (see, for example, Gilje et al. (2016); Drechsler et al. (2017); Cortés et al. (2020)), and lending originated by the same bank across different markets with varying levels of specialization (see, for example, Cortés et al. (2020)).[38] This strategy further addresses concerns regarding the specialization variable, including bank-wide factors that may confer advantages for a given bank across all markets and the size of the local market.

The main identifying assumptions for our specifications to be controlling for changes in local lending opportunities and bank-specific shocks are that banks located in the same market face the same change in lending opportunities and that banks can allocate deposits across branches.[39] The assumption that banks can allocate deposits across branches implies a separation between their decisions on raising deposits and originating loans. In other words, overall bank-specific shocks due to monetary policy changes are transmitted uniformly to lending decisions across markets. If a bank experiences huge deposit outflows in a given year and cannot perfectly substitute those deposits with alternative financing sources, the

[38] Cortés et al. (2020) uses at the same time a within-county and within-bank estimation including county-time and bank-time fixed effects to reduce the potential for credit demand to drive their results and to absorb all sources of bank-year-level heterogeneity, respectively. We refer to it as a within-bank-county estimation strategy.

[39] Under these assumptions, when we compare lending originated by the same bank in different markets, we control for changes coming from the liability side of banks each period. Specifically, we absorb any possible effect related to bank size, liquidity, capital, deposit ratio, and bank exposure to local deposit market specialization and concentration - factors that may impact loan supply following monetary policy changes.

resultant reduction in lending origination is expected to be homogeneous across markets. This assumption is supported by Gilje et al. (2016), who provide evidence that banks facing liquidity inflows after shale booms increased loan origination in markets beyond those one experiencing the liquidity windfall.[40]

We apply our within-bank-county estimation strategy to study whether the transmission of monetary policy to bank loan supply is market-specific, depending on the bank's local specialization in the loan market, using information from the mortgage market.[41] As previously explained, we control for the change in local lending opportunities and bank-year level heterogeneity by running the following panel regression including bank-time and county-time fixed effects:

$$\Delta y_{bct} = \omega_{bt} + \gamma_{ct} + \beta_1 \Delta FF_t \times Spec_{bct-1} + \beta_2 Spec_{bct-1} + \epsilon_{bct}, \tag{5}$$

where Δy_{bct} represents the growth of the amount of new mortgage lending originated by bank b in county c at year t, $Spec_{bct-1}$ denotes the specialization of bank b in county c at year $t-1$, and ΔFF_t is the difference in the Fed funds target rate from year $t-1$ to t. We include ω_{bt} and γ_{ct} as bank-time and county-time fixed effects, respectively.[42] We double-cluster standard errors at the bank and county levels.

County-time fixed effects are the main control variables that absorb changes in local loan demand under the identifying assumption that banks located in the same market face the same change in local lending opportunities.[43]

We include bank-time fixed effects to absorb all sources of bank-year level heterogeneity, alleviating the possibility that changes in bank deposit quantities or the liability structure

[40] This aligns with findings from Cortés and Strahan (2017) and Brown et al. (2021), which provide evidence consistent with banks reallocating funds across markets after natural disasters and emphasize the importance of controlling for credit demand, as it can significantly influence loan conditions, respectively.

[41] We limit our analysis to bank-county-year observations with positive values on the amount of newly originated mortgages.

[42] We do not include the difference in the Fed funds target rate in the regression, as it is absorbed by bank-time, county-time, or time fixed effects across all columns of our tables.

[43] If different banks that originate loans in the same market have heterogeneous changes in loan opportunities (i.e. different changes in loan demand), the inclusion of county-time fixed effects would not solve this issue. In such a case, our results could be driven by loan demand rather than loan supply. To address the concern that our results might be driven by heterogeneous changes in loan demand rather than loan supply, we employ two approaches. First, we use the difference in the approval ratio as the dependent variable in Table 4 and demonstrate that the main result holds. Additionally, we utilize self-reported income data from HMDA to compare lending originated by different banks to the same type of borrower in a given market. We categorize borrowers into four income brackets based on the 25^{th}, 50^{th}, and 75^{th} percentiles, corresponding to $\$59,000$, $\$90,000$, and $\$137,000$, respectively, as of 2010 U.S. dollars. Subsequently, we include county-year-income fixed effects to control for the change in local lending opportunities (demand) arising from different types of borrowers based on their income. The results presented in Table A5 of the appendix confirm the robustness of our main finding.

are driving the results. In certain specifications without county-time fixed effects, we interact county fixed effects with a dummy variable taking the value of one from 2009 to 2014, and zero otherwise, to accommodate the flat Fed funds target rate period.[44] Additionally, in specifications without bank-year fixed effects, we introduce bank fixed effects. Finally, when both county-year and bank-year fixed effects are omitted, we include year fixed effects.

We focus on the sample of banks originating mortgages in at least two counties and in counties where at least two banks originate mortgages. This selection is made because the coefficient of interest, β_1, lacks identification for single-county banks and counties with only one bank when both bank-time and county-time fixed effects are included. To facilitate comparison, we also provide estimates without the inclusion of bank-time and county-time fixed effects.

3.2 Baseline Results

Table 2 presents the results of estimating equation (5) using banks' local specialization in each market from 1994 to 2019. Column (1) contains our preferred specification with the full set of fixed effects. It documents that after a decrease in the Fed funds rate, banks exhibit a greater increase in new mortgage lending growth in markets where they are more specialized relative to markets where they are less specialized, controlling for the change in aggregate local lending opportunities (i.e., local loan demand). A one standard deviation increase in *Spec* (0.192) corresponds to a 54.3 bps increase in lending per 100 bps decrease in the Fed funds target rate (54.3 bps = 0.543% = 0.192 × (-0.0283) × (-1) × 100).[45] This result is statistically significant at the 1% level. As previously explained in Section 2, our data does not include information on the stock of mortgages held on banks' balance sheets. Therefore, this estimate captures the growth of new mortgage lending, not the growth of outstanding mortgage lending on banks' balance sheets.

This estimate strongly supports the idea that a local bank's specialization in the mortgage market plays a crucial role in shaping how changes in monetary policy impact the growth of new mortgage lending. Therefore, this result suggests that bank supply reactions to monetary policy changes are market-specific. We refer to this phenomenon as the specialization channel. This result can also be interpreted in the following way: after a decrease in the Fed funds rate, more locally specialized banks increase new mortgage lending growth by more, relative to other banks in the same market. In doing so, we compare two different

[44] We follow the approach of Drechsler et al. (2017) for the inclusion of these fixed effects, denoted as fipszero, in lending specifications covering the flat Fed funds target rate period.

[45] We focus our interpretation on the aftermath of a decrease in the Fed funds rate, as our results are stronger following monetary easing rather than tightening, as shown in the appendix.

banks originating new mortgage lending in the same market and controlling for bank-year level heterogeneity.[46]

Column (2) omits the county-year fixed effects. The coefficient of interest (β_1) is almost unchanged from column (1) and remains statistically significant at the 1% level. Column (3) shows how our coefficient of interest remains negative and significant, but the magnitude nearly doubles when we omit the bank-year fixed effects. This finding suggests that accounting for bank-year level heterogeneity is important when examining the impact of a bank's local specialization on the transmission of monetary policy changes to new mortgage lending growth. Bank-year fixed effects control for various factors, including changes in the liability side of banks induced by fluctuations in the Fed funds rate.[47]

Column (4) drops county-year and bank-year fixed effects. The main coefficient of interest (β_1) remains statistically significant at the 1% level and almost unchanged from column (3), suggesting that the main control for our coefficient to be accurately estimated is bank-year level heterogeneity. These results show that the impact of local bank's specialization in the mortgage market on the sensitivity of local new mortgage lending growth to monetary policy remains present when we do not control for the change in local lending opportunities and bank-year level heterogeneity.

The estimates presented in Table 2 align with the idea of differential behavior exhibited by banks with differing levels of specialization in response to a monetary policy change. We posit that this divergent sensitivity may stem from banks encountering heterogeneous lending costs across markets, potentially associated with lending advantages conferred by local specialization. This interpretation aligns with empirical evidence and the simplified theoretical framework outlined in Subsection 3.4.

Moreover, these results provide empirical support for monetary policy being a key determinant of banks' decisions regarding local mortgage market specialization. Banks specializing in few local lending markets (i.e., low geographical diversification) would be more

[46]In our main specification, we do not include bank-county fixed effects as we are comparing the growth of new mortgage lending for a given bank in a county. This approach is consistent with Gilje et al. (2016), Cortés et al. (2020), and Granja et al. (2022). However, to absorb all sources of time-invariant characteristics of a given bank in a county, such as local brand effects (Drechsler et al., 2017), we include bank-county fixed effects in Table A4 of the appendix. The results indicate that our main finding remains robust even with the inclusion of bank-county fixed effects.

[47]Previous studies, such as Dell'Ariccia et al. (2017), provide evidence that banks tend to increase risk-taking after decreases in short-term interest rates, with a more pronounced effect for banks with relatively high capital. Additionally, Drechsler et al. (2017) show that after a rise (reduction) in the Fed funds rate, banks that raise deposits in more concentrated markets reduce (increase) lending relative to banks that raise deposits in less concentrated markets. Heider et al. (2019) explore how negative interest rates may impact the funding cost of high-deposit banks relative to low-deposit banks, thereby influencing bank risk-taking and lending behavior. Columns (1) and (2), with the inclusion of bank-year fixed effects, provide control for these effects, among others.

exposed to negative local market shocks (Goetz et al., 2016). Consequently, our findings suggest that monetary policy influences the exposure of banks to shocks in specific local loan markets. Section 5 conducts a detailed analysis of this result at the bank level

3.3 Robustness

3.3.1 Other Relevant Market Structure Characteristics

Having established the impact of a bank's local mortgage market specialization on the transmission of monetary policy to mortgage lending supply, we explore whether this relationship persists when controlling for alternative local market structure mechanisms. Notably, lenders with high market shares are more likely to internalize negative spillovers and provide liquidity to distressed industries (Giannetti and Saidi, 2019). Therefore, a bank's local mortgage market shares may also influence the transmission of monetary policy to loan supply. As bank specialization and bank market share may be correlated, it is important to account for its influence for the transmission of monetary policy.

Following the approach of Giannetti and Saidi (2019), we construct the variable $MktSh_{bct}$, representing a bank's local mortgage market share. This variable is defined as the share of new mortgage lending originated in a market by a bank and year, divided by the total amount of new mortgage lending originated by all banks in that market and year. In Figure 2, we present a scatter plot illustrating the relationship between local specialization and local market share.[48]

Bank exposure to local deposit market concentration has also been documented as a factor influencing the transmission of monetary policy to bank's loan supply (Drechsler et al., 2017). To capture this effect, we follow the methodology of Drechsler et al. (2017) and construct two variables. The first variable, C-HHI-Dep$_c$, measures local deposit market concentration using a standard Herfindahl index. It is computed by summing the squared deposit-market shares of all banks with branches in a given county and year, then averaging across all years from 1994 to 2019. The second variable, Bank-HHI-Dep$_{bt}$, is a bank-level measure indicating the extent to which banks raise deposits in concentrated deposit markets. This is obtained by averaging C-HHI-Dep$c$ at the bank level, using lagged deposit shares across branches as weights.[49]

[48]It is calculated as follows:

$$MktSh_{bct} = \frac{A_{bct}}{A_{ct}}$$

where A represents the amount of new mortgage lending, b represents the bank, c represents county, and t represents year.

[49]We report in Table A2 of the appendix a correlation matrix between bank's local mortgage market specialization, banks' local mortgage market share, bank-level exposure to local deposit market concentration,

Table 3 presents the results estimating equation 5 with additional controls for relevant bank market structure characteristics that may influence the transmission of monetary policy to loan supply. Column (1) is similar to column (1) of Table 2 but we control for the effect of bank's loan market share for the transmission of monetary policy to mortgage loan supply.[50] The result provides evidence that our specialization channel ($\Delta FF \times Spec$) remains robust even when accounting for the effect of the bank's local market share on the transmission of monetary policy ($\Delta FF \times MktSh$). As column (1) shows, after a 100 bps decrease in the Fed funds rate, a one standard deviation increase in $Spec$ (0.192) increases lending by 36.5 bps, while a one standard deviation increase in $MktSh$ (0.070) increases lending by 65.6 bps.[51] The results are statistically significant at the 1% level.[52] This finding suggests that the bank's local loan market share is also a relevant characteristic influencing the transmission of monetary policy to new mortgage lending.[53]

Column (2) drops the bank-year fixed effects and controls for the effect of bank exposure to concentrated deposit markets for the transmission of monetary policy ($\Delta FF \times$Bank-HHI-Dep). This analysis confirms the robustness of the result regarding bank's local specialization even after accounting for the effect of bank exposure to concentrated deposit markets. The main coefficient of interest, representing the interaction between changes in the Fed funds rate and specialization, remains large and statistically significant at the 1% level. Interestingly, while the effect of bank exposure to concentrated deposit markets on the transmission of monetary policy to new mortgage lending growth is not statistically significant at the 10% level, the effect of the bank's local loan market share remains statistically significant at the 1% level. It's important to note that, in comparison with our main specifications, these estimates might be influenced by the presence of bank-year level heterogeneity. This potential bias could explain the sharp increase in the coefficients' magnitude for the effects of the bank's local specialization and market share for the transmission of monetary policy.

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and county-level local deposit market concentration. We show that the correlations between our main measure of specialization and other relevant market structure characteristics do not pose concerns for our analysis.

[50]Note that we cannot control for the effect of bank exposure to concentrated deposit markets because its effect is absorbed when we include bank-year fixed effects.

[51]We emphasize our interpretation on the consequences of a decrease in the Fed funds rate, as our findings exhibit greater robustness following monetary easing compared to tightening measures. This pattern is illustrated in Table A3 in the appendix.

[52]As bank's local specialization could be also closely tied to its past new mortgage lending growth, there might be concerns that the transmission of monetary policy to new mortgage lending is influenced by past growth rather than local specialization. To address this concern, we control for the effect of lagged new mortgage lending growth on the transmission of monetary policy to contemporaneous new mortgage lending growth. Table A4 demonstrates that our result remains robust even after accounting for the impact of past growth, providing further support for the validity of our findings.

[53]Although interesting, given our study's focus on the effect of a bank's local specialization on the transmission of monetary policy, further analysis of this finding is left for future research.

Finally, column (3) drops the county-year fixed effects and controls for the direct effect of local deposit market concentration for the transmission of monetary policy ($\Delta FF \times$C-HHI-Dep). The main coefficient of interest representing the effect of specialization remains nearly unchanged from column (2) and remains statistically significant at the 1% level. The effect of local market shares on the transmission of monetary policy remains unaltered. Additionally, we observe that local deposit market concentration positively affects the transmission of the Fed funds rate to new mortgage lending growth, and this result is statistically significant at the 10% level. However, bank exposure to concentrated deposit markets still shows no statistically significant effect on the transmission of the Fed funds rate to new mortgage lending growth at conventional significance levels.

Overall, the results presented in Table 3 affirm the robustness of our findings to the inclusion of additional controls for relevant local market structure characteristics. These controls account for potential influences on the transmission of monetary policy to new lending growth in the mortgage market.

3.3.2 Further Robustness

Building on our previous findings highlighting the importance of bank's geographical specialization in the transmission of monetary policy to mortgage lending supply, Table 4 presents additional robustness tests. These tests are conducted on our preferred specification, which includes both bank-time and county-time fixed effects, while also controlling for the direct effect of local bank market shares on the transmission of monetary policy. The objective is to examine the consistency of the impact of bank's local market specialization across various computations of the specialization variable, alternative monetary policy measures, different dependent variables, and diverse sample periods.

To address concerns regarding the unavailability of information on the stock of mortgage lending on bank balance sheets disaggregated by markets, we explore alternative definitions of the specialization variable in columns (1) to (3) of Panel A. Specifically, we consider the two-period lag, the average over the entire sample period from 1994 to 2019, and the average for the five previous years. Results from these alternative specifications align with our baseline findings, indicating that our variable *Spec* (lagged one period) serves as a presumably good measure of a given bank's local market specialization.[54]

[54] While the inclusion of county-year fixed effects addresses concerns related to county heterogeneity, Table A4 of the appendix demonstrates consistent results when constructing the specialization variable using quartile dummies for each county and year, in the spirit of Paravisini et al. (2023), and when using the excess specialization in the spirit of Blickle et al. (2023) as deviations of a bank specialization to the share of new mortgage lending originated by all banks in a given county and year. The first approach also enables us to capture nonlinearities, allowing the effect of specialization for the transmission of monetary policy to

To address concerns about the construction of the specialization variable using the same sample period for testing, we examine an alternative in column (4) of Panel A. Here, we construct the specialization variable as the average for the period from 1994 to 2004 and assess the relevance of the specialization channel from 2005 to 2019, a sample period not included in the variable construction. The result remains robust to this alternative specification.

To address concerns about the interpretation of results tied to the specific choice of the monetary policy variable, we explore alternative measures in Panel B. In column (1), we employ the average aggregation method to compute the yearly measure of the Fed funds target rate. In column (2), following Jarociński and Karadi (2020), we disentangle the effect of changes in the Fed funds rate from central bank information shocks. Lastly, in column (3), we use shadow rates to capture monetary policy movements during the flat Fed funds target rate. Remarkably, the results remain consistent across these alternative monetary policy measures.

To address concerns about potential differential reactions to entering and exiting local markets, we incorporate entries and exits of banks in different local markets. Given the bounded nature of the dependent variable, where the upper limit corresponds to entries (+2) and the lower limit to exits (-2), column (4) of Panel B demonstrates that not only does our estimate remain robust, but the point estimate of the interaction term even increases.

In Panel C, we investigate the robustness of our results by employing alternative measures of the outcome variable. In column (1), we use the log-difference of new mortgage lending originated, following Favara and Imbs (2015), which utilizes the log-difference of county-level activity in the mortgage market.[55] Column (2) calculates the growth of the number of new mortgages, column (3) examines the average loan amount growth, and column (4) reports the results using the difference in the approval ratio. Our result holds when we use the log difference instead of growth, the number instead of amount, and the approval ratio to further avoid issues that demand may be driving the results. Furthermore, they indicate that after an easing of monetary policy, banks adjust loan supply decisions based on the level of local specialization by modifying the number of loans rather than the dollar amount of the loans granted.[56]

To address concerns about the influence of specific sample periods on our main result, as

be nonlinear in the degree of local specialization. Additionally, the results hold when using the three-period lag of the specialization variable.

[55] In Table A4 of the appendix, we show the robustness of our result by employing the non-symmetrical growth rate of new mortgage lending, winsorized at the 5% level to mitigate the influence of outliers, as the dependent variable. The consistent finding further supports the reliability of our result.

[56] We acknowledge that one of the underlying assumptions of our empirical strategy may be strong, as different banks located in the same market may face different lending opportunities, serving to different type of customers. To address this concern, we disaggregate lending by a given bank in a given market.

highlighted by Mian and Sufi (2009), Justiniano et al. (2019), and Drechsler et al. (2022), we conduct additional tests in columns (1) to (4) of Panel D. These tests assess whether the result holds during the U.S. housing boom period from 2003 to 2006 (column (1)), when excluding the four years corresponding to the housing boom (column (2)), when excluding the years from 2007 to 2009 to avoid the impact of the Great Recession (column (3)), and when focusing on the subsample period from 1994 to 2013 (column (4)). The results remain robust across these various sample periods, even amplifying during the U.S. housing boom.[57] Column (4) demonstrates that our result holds when focusing on the sample period from 1994 to 2013, alleviating concerns that under a low Fed funds rate, monetary policy may not work as intended (Heider et al., 2019; Abadi et al., 2023; Altavilla et al., 2018). This consistency provides reassurance about the generalizability of our findings.[58]

We also extend our sample to include depository and non-depository institutions, related to prior research providing evidence that the transmission of monetary policy to financial institutions may be different depending on their type of financing (Xiao, 2020; Drechsler et al., 2022; Elliott et al., 2023; Cucic and Gorea, 2022). Non-depository institutions are also called independent mortgage companies (IMC) in the U.S. mortgage market and originate a substantial amount of mortgage lending in the U.S. mortgage market as shown in Figure A2 of the appendix. The results confirm that loan supply originated by any type of financial institution (banks and non-depository institutions) is affected by the specialization channel and that the sensitivity of mortgage loan supply to this channel is amplified for

[57] Consistent results are obtained when considering the years 2002 to 2005 as the U.S. housing boom period, as detailed in Table A4 of the appendix. Moreover, non-depository institutions, also known as independent mortgage companies (IMC) in the U.S. mortgage market, originate a substantial amount of mortgage lending, as illustrated in Figure A2 of the appendix. Given the significance of nonbank originators in the mortgage market and in light of previous research suggesting variations in the transmission of monetary policy to financial institutions based on their financing structure (Xiao, 2020; Drechsler et al., 2022; Elliott et al., 2023; Cucic and Gorea, 2022), we present evidence in Table A5 of the appendix, demonstrating that our result remains robust when including nonbanks. Notably, the effect is even more pronounced for nonbank lenders.

[58] To address concerns regarding the specificity of our results to the sample selection in the mortgage market, we conduct additional tests in Table A5 of the appendix. Our findings remain robsut when we include also all mortgage markets where a given bank made less than 5 loans in the previous period, when we consider only mortgage lending originated to hold, and when we focus on the most illiquid mortgages that cannot be purchased or helped to securitize by Fannie Mae and Freddie Mac (GSEs) (Loutskina and Strahan, 2009; Cortés and Strahan, 2017). This result demonstrates the robustness of our findings across alternative sample selections in the mortgage market. Additionally, we exploit information from 1997 to 2019 from the FFIEC Community Reinvestment Act (CRA) on an alternative lending market, bank loans to small businesses. We compute total new small business lending as the total amount of new loans of less than $1 million. As shown in Table A5 of the appendix, bank's local specialization in the small business lending market also affects the transmission of monetary policy to new small business lending growth. Despite new small business lending possibly being more influenced by other market characteristics, such as sector specialization (Berger et al., 2017b; Blickle et al., 2023), this finding provides further evidence supporting the relevance of local lending specialization for the transmission of monetary policy.

non-depository institutions, relative to banks.

3.4 Mechanism

To strengthen the interpretation of our findings, in this subsection, we delve into the potential mechanisms underlying the specialization channel. We begin by presenting a simple theoretical model, based on heterogeneous market-specific lending costs. The main hypotheses of the model align with our empirical findings. Subsequently, we provide empirical evidence supporting the notion of heterogeneous market-specific lending costs for a given bank, particularly related to lending advantages, which could serve as a significant driver of our main result. Finally, we present evidence indicating that while banks are better able to sell mortgages to the GSEs that perform worse in the future, our results do not suggest that ex-ante risk-taking and in-balance sheet riskiness are the primary underlying drivers.

3.4.1 Theoretical Model

We provide a simple theoretical setup aimed at providing a foundation for the empirical findings observed in our main analysis concerning the interplay of monetary policy, banks' lending specialization, and loan supply.

Let's consider a one-period, risk-neutral economy with two types of agents: borrowers and a monopolistic financial intermediary referred to as a bank. The bank invests in lending to borrowers and funds itself in a perfectly competitive market that requires an expected return R_0 per unit of funding. We take this return as a proxy for the monetary policy rate. Borrowers are located in two different markets, denoted as A and B. If nothing is explicitly stated, both markets are symmetrical.

In each market, there exists a continuum of penniless borrowers, denoted by the index i. Each borrower needs L units to invest in an asset that generates Y units. Borrowers differ in a borrower-specific observable characteristic x_i, which determines the cost of lending to such entrepreneur.[59] In order to lend to a borrower with characteristic x_i, the bank has to undergo a cost $c(x_i)$.[60] The lending cost can be rationalized by considering that the bank needs to screen or monitor the borrower, and in the absence of such screening or monitoring, the loan has a negative net present value (NPV). Following Hauswald and Marquez (2003) we can assume that monitoring cost is borrower-specific and increases with higher values of

[59] This characteristic could signify various factors such as the physical distance between a bank's branch and a borrower, dissimilarities in core knowledge between the bank's core knowledge of an industry and the borrower's operations, or differences in bank characteristics and borrower preferences

[60] For simplicity, we assume that $x_i > 1$.

x_i.[61]

Specifically, we assume that the lending cost function takes the form

$$c(x_i) = x_i^{\beta_j} \tag{6}$$

with $\beta_j > 1$. This increasing and convex cost function captures that lending is more costly, and increasingly so, for higher x_i.

The only difference that we assume between the two markets is that the bank incurs a higher marginal cost of lending in market B than in market A, which we capture by assuming $\beta_A < \beta_B$. This dissimilarity can be attributed to variations in the bank's familiarity and lending advantages in each market. Banks may develop expertise, technologies, and skills in evaluating or monitoring projects in specific markets that could lead to market-specific lending advantages (Paravisini et al., 2023).[62] Consequently, the marginal lending cost may be lower in markets where banks specialize (market A), under the assumption that bank specialization is related to lending advantages and expertise in specific markets.[63]

The bank, being a monopolist, sets a lending rate equal to the success return (utility of the borrower). Consequently, the profits of the bank from serving a borrower with characteristics x_i in market j is equal to:

$$Y - LR_0 - x_i^{\beta_j} \tag{7}$$

This formulation allows us to identify the threshold borrower $\hat{x}_j$, which represents the last borrower a bank serves. The threshold borrower is determined by the following equation:

$$\begin{aligned} Y - LR_0 - x^{\beta_j} &= 0. \\ \hat{x}_j &= (Y - LR_0)^{\frac{1}{\beta_j}} \end{aligned} \tag{8}$$

[61] See also Vives and Ye (2021) for similar assumptions. An alternative interpretation is that the bank incurs costs to approach the borrower, making its existence known (e.g., through focused marketing techniques), and reaching borrowers with higher x_i is more costly for the bank.

[62] At least part of such differences may arise from the challenges in transmitting soft information from branches located farther away from the bank's headquarters (Bolton et al., 2016). Moreover, variations in the bank's knowledge of local markets, acquired through repeated lending or other interactions such as deposit services (Petersen and Rajan, 1994; Mester et al., 2007; Bharath et al., 2011), could contribute to this difference.

[63] This micro foundation of the heterogeneous cost function finds further support in empirical evidence presented in subsection 3.4.2, underscoring the correlation between bank specialization and observable factors that may be associated with market-specific expertise and information. Moreover, the reduction in the impact of specialization on the transmission of monetary policy to market-specific loan supply, when controlling for these observable factors, further reinforces this interpretation.

Given that the supply of loans in each market, $L\hat{x}_j$, is determined by the threshold borrower, $\hat{x}_j$, we can derive the following two results.

1. *Specialization result.* The bank is more specialized in market A, $\hat{x}_A > \hat{x}_B$

Given that $\hat{x}_A = (Y - LR_0)^{\frac{1}{\beta_A}}$ and $\hat{x}_B = (Y - LR_0)^{\frac{1}{\beta_B}}$ it is direct to show that $\frac{L\hat{x}_A}{L\hat{x}_A + L\hat{x}_B} > \frac{L\hat{x}_B}{L\hat{x}_A + L\hat{x}_B}$ follows from $\beta_A < \beta_B$ .This result states that the bank lends more, i.e. is more specialized, in the market where it faces lower marginal lending costs.

2.*Differential response to R_0.* A decrease in R_0 leads to a higher relative increase in loan supply by the bank in market A than in market B $\frac{\frac{dL\hat{x}_A}{dR_0}}{L\hat{x}_A} < \frac{\frac{dL\hat{x}_B}{dR_0}}{L\hat{x}_B} < 0$. This result states that the bank experiences a greater relative increase in lending in response to lower safe rates in the market where it has a larger presence.

Proof:

$$
\begin{gathered}
\frac{\frac{dL\hat{x}_A}{dR_0}}{L\hat{x}_A} = -\frac{\frac{L^2}{\beta_A}(Y - LR_0)^{\frac{1}{\beta_A}-1}}{L(Y - LR_0)^{\frac{1}{\beta_A}}} < -\frac{\frac{L^2}{\beta_B}(Y - LR_0)^{\frac{1}{\beta_B}-1}}{L(Y - LR_0)^{\frac{1}{\beta_B}}} = \frac{\frac{dL\hat{x}_B}{dR_0}}{L\hat{x}_B} \\
-\frac{1}{\beta_A}\left(\frac{L}{Y - LR_0}\right) < -\frac{1}{\beta_B}\left(\frac{L}{Y - LR_0}\right) \\
\beta_B > \beta_{A.}
\end{gathered}
\tag{9}
$$

Results 1 and 2, the primary testable hypotheses of our stylized setup, align with our empirical findings. The underlying intuition is as follows: The bank exhibits greater specialization in market A due to the lower marginal cost of lending (attributed to lower monitoring or screening costs). Additionally, the bank responds to a reduction in the safe (monetary policy) rate, R_0, by expanding relatively more in the market where the marginal cost of increasing lending is lower, namely market A.

3.4.2 Lending Advantage and Information

While our methodology indicates so far that bank loan supply responses to changes in monetary policy are market-specific, contingent on the level of local specialization, we now empirically explore whether bank expertise and lending advantages could be a potential driver of these results. First, we investigate the relationship between geographical specialization and bank-market-specific measures that may serve as plausible proxies for lending costs and advantages. Second, we assess the potential role of such proxies in shaping the observed effects on the significance of a bank's local specialization for the transmission of monetary policy to loan supply. This analysis is motivated by existing research highlighting the relevance of industry and market specialization, which is consistent with enhanced information acquisition, skills, expertise, technology, and monitoring capabilities (Loutskina and Strahan, 2011; Berger et al., 2017b; Paravisini et al., 2023; Blickle et al., 2023; Izadi and Saadi, 2023). Such specialization may lead to lower marginal lending costs, in line with our simple theoretical framework.

For instance, we use the following variables as bank-market-specific proxies for information and lending advantages. Initially, we focus on the relatively new entrance of banks into specific local markets, potentially serving as a proxy for low information, given the limited knowledge regarding market-specific borrower characteristics (Petersen and Rajan, 1994; Bharath et al., 2011; López-Espinosa et al., 2017; Botsch and Vanasco, 2019).[64] Specifically, we define the variable $Newt-1$ ($Newt-5$) as a dummy variable that equals one if a bank entered a particular local market within the preceding two (six) years, and zero if the bank entered more than two (five) years ago. Both variables serve as proxies for low bank-market-specific information.

Subsequently, we focus on the geographic location of banks' headquarters. The transmission of soft information from bank branches to the central headquarters may be difficult, particularly for branches situated distantly from the headquarters as argued by Bolton et al. (2016) and Liberti and Mian (2009).[65] Accordingly, we construct the indicator variable $SameMkt$ that equals one for the market where the bank is headquartered in the preceding period, and zero otherwise, likely reflecting augmented bank-market-specific information. Additionally, to capture the differences between markets where the bank is not headquartered, we compute the variable $Dist$ as the natural logarithm of the distance in miles from a given local market to the bank's headquarters.[66] This variable serves as a proxy for low bank-market-specific information.[67]

Furthermore, our analysis incorporates the number of physical branches and the extent

[64]While these papers have established the relevance of repeated lending interactions with individual borrowers for shaping lending outcomes, we argue that the phenomenon of repeated lending within a local market may also be related with the market-specific information banks accrue over time.

[65]In line with this explanation, Hollander and Verriest (2016) also analyzes the effect of information asymmetry, measured as geographical distance between lenders and borrowers, on loan contracts. They find that the higher the distance between the headquarters of lenders and borrowers, the stronger the covenant tightness of loan contracts.

[66]Jean Roth created this data of U.S. county distances in miles for all combinations of U.S. counties using the Haversine formula based on internal points in the geographic area.

[67]While we focus on physical distance, Rehbein and Rother (2022) use social connections as a proxy for soft information between banks and borrowers. Our rationale aligns with Berger et al. (2017b) that finds evidence that banks are less likely to collect audited financial statements from firms in industries and local markets where they are more specialized. This is consistent with banks having expertise, hence facing lower marginal costs of monitoring/screening in some industries and markets where they do not need to demand detailed and verified borrower information.

of local specialization in deposits, as potential proxies for augmented bank-market-specific information. Banks can enhance their market-specific information, particularly concerning screening and monitoring capabilities, through alternative sources such as checking and savings accounts (Berlin and Mester, 1999; Mester et al., 2007). We define $NBranches$ as the number of branches of a given bank operating within a local market during the preceding year, while $SpecD$ denotes the degree of deposit specialization in the previous year, computed utilizing the formula described in equation 2 based on the deposit stock instead of the volume of new lending. Both variables serve as proxies for heightened bank-market-specific information.

We first evaluate the correlation between our measure of bank lending specialization within a local market and these proxies of low and high bank-market-specific information. Table 5 underscores a positive (negative) correlation between local specialization and $SameMkt$, $NBranches$, and $SpecD$ ($Newt-1$, $Newt-5$, and $Dist$), indicative of high (low) bank-market-specific information. These correlations are statistically significant at the 1% level, implying a discernible connection between bank local specialization and bank-market-specific information. Banks are more likely to specialize their mortgage lending activities within local markets where they started to lend some years ago, are headquartered, are closer to their headquarters, own a greater number of physical branches, and possess a higher degree of specialization in deposits.

We then investigate whether bank local specialization undergoes alteration and continues to influence the transmission of monetary policy to new mortgage lending when we control for these proxies for bank-market-specific information. We estimate our baseline regression in equation 5, incorporating the defined information proxies and their interactions with monetary policy changes, alongside controls for the effect of local market shares. Table 6 presents the results. Columns (1) to (6) indicate that following a decrease in the Fed funds rate, banks increase new mortgage lending growth in markets characterized by richer bank-market-specific information, with this effect achieving statistical significance at conventional levels for most information proxies.

More importantly, columns (1) to (6) show that the effect of the interaction between local specialization and the change in the Fed funds rate on new mortgage lending growth is reduced in magnitude, compared with the results reported in Table A6 of the appendix, where we report identical regressions without controlling for the information proxies.[68] While

[68] It is important to compare the results in Table 6 with their corresponding columns in Table A6 of the appendix as both use the same sample sets for the estimations. Columns (1) and (2) of both tables rely on data from 1996 and 2000, as we need to compute the variables $Newt-1$ and $Newt-5$ using information from the two and six preceding years, respectively. Columns (3) incorporate data on the geographical location of bank's headquarters, sourced from the U.S. Call Reports provided by the FDIC. It is noteworthy that the

this reduction in magnitude suggests a relationship with bank-market-specific information, as part of the effect is presumably captured by these proxies, the interaction remains statistically significant. This further suggests that local specialization entails lending advantages that are not fully captured by the employed information proxies.

Lastly, despite the high correlation among the information proxies, column (7) encapsulates simultaneous control for $Newt-1$, $SameMkt$, $NBranches$, and $SpecD$.[69] Again, the magnitude of the interaction between specialization and changes in the Fed funds target rate diminishes in comparison to column (7) of Table A6 in the appendix. Specifically, following a 100 basis points decrease in the Fed funds rate, the increase in new mortgage lending growth associated with a one standard deviation increase in $Spec$ (0.192) amounts to 26.69 basis points when controlling for these information proxies. In contrast, it rises to 42.62 basis points when not accounting for them. Hence, although the relevance of specialization for this transmission decreases, it is still consistent with specialization potentially linked to lending advantages that are not captured by the utilized market-specific information proxies.

The findings presented in Tables 5 and 6 indicate that our results are consistent with bank-market-specific information and lending advantages serving as a plausible underlying mechanism for our proposed channel. The results suggest a relationship between local specialization and bank-market-specific lending advantages, as evidenced by their correlation with proxies potentially capturing such information advantage. Moreover, while the observed attenuation in the impact of specialization on the transmission of monetary policy when controlling for these proxies reinforces this proposition, the results also suggest that local specialization retains distinct bank-market-specific lending advantages that extend beyond the scope of these information proxies.

3.4.3 Cross-Section

To provide additional evidence on our proposed mechanism, we explore two distinct scenarios where the geographical specialization of banks is expected to wield heightened relevance. If indeed local lending specialization is related to bank-market-specific information and lending

number of observations diminishes compared to Table 2, attributed to the exclusion of banks not featured in the U.S. Call Reports from the FDIC. Notably, this exclusion primarily affects Federal and State Credit Unions, which furnish data to HMDA but are absent from the FDIC's U.S. Call Reports dataset. Column (4) focuses on markets where the bank was not headquartered in the previous period. Columns (5) and (6) focus on the sub-samples with information on $NBranches$ and $SpecD$, respectively. At last, column (7) focuses on the sub-sample with information on the information proxies $Newt-1$, $SameMkt$, $NBranches$, and $SpecD$, from 1996.

[69] When we simultaneously control for various information proxies in column (7), the reduction in the impact of specialization on the transmission of monetary policy remains consistent across different information proxies. These proxies include $Dist$, which concentrates on non-headquarter markets, and $Newt-5$, which focuses on the sample period from the year 2000.

advantages, we would expect the local specialization channel to be more pronounced within segments of the mortgage market characterized by heightened information intensity and in local markets where information asymmetry is acute. Accordingly, we empirically exploit cross-sectional variation within two segments of the mortgage market, jumbo and non-jumbo mortgages, as well as heterogeneity in mortgage loan sizes.

First, as information is more relevant in the jumbo segment of the mortgage market (Loutskina and Strahan, 2011), banks have greater incentives to collect private information on jumbo mortgages, partly due to their heterogeneity and the infeasibility of (GSEs) to provide subsidies for such mortgages. Thus, if our proposed channel is related to information, it may be more relevant in this segment of the mortgage market. To test this implication, we construct an indicator variable for mortgages falling within the jumbo category.[70] We then test the differential impact of bank specialization on the transmission of monetary policy changes to new mortgage lending growth in the jumbo and non-jumbo segments.

Second, the dispersion in mortgage sizes within a local market may engender heightened informational asymmetries (Berger et al., 2017b; Chu et al., 2021), potentially amplifying adverse selection concerns.[71] Therefore, local markets characterized by pronounced diversity in mortgage sizes may accentuate banks' exposure to heterogeneous borrower profiles, thereby exacerbating information asymmetry problems. Consequently, if specialization is related to market-specific information and expertise, its effect is expected to be more pronounced within settings characterized by heightened information asymmetries. To examine this proposition, we construct an indicator denoting local markets exhibiting loan amount dispersion above the 75$^{\text{th}}$ percentile threshold to be compared with local markets exhibiting loan amount dispersion below the 25$^{\text{th}}$ percentile.[72] We then test the differential impact of specialization on the transmission of monetary policy changes to new mortgage lending growth between local markets characterized by high and low loan size dispersion.

Table 7 presents the results derived from estimating equation 5 across various sub-samples categorized by the jumbo status and local market loan size dispersion. Columns (1) and (2)

[70] As explained in Loutskina and Strahan (2009) and Cortés and Strahan (2017), the presence of Fannie Mae and Freddie Mac (GSEs) created a segmentation of the U.S. mortgage market into two types of mortgages depending on its size. GSEs can purchase or help to securitize by selling credit protection mortgages that are below the jumbo cutoff threshold (i.e., non-jumbo mortgages). Yet by regulation, jumbo mortgages that are bigger than the jumbo cutoff threshold are out of the scope of GSEs. This limitation was designed to promote access to mortgage credit for low- and moderate-income households. Using data from the FHFA, we can identify the jumbo cutoff threshold for each year to separate new mortgage lending into two different categories.

[71] While Berger et al. (2017b) focus on commercial lending, they argue that the performance dispersion of firms in an industry may reflect settings with a more pronounce adverse selection.

[72] Loan size dispersion is defined as the interquartile range of loan amount in a given local market during the previous year. Our results remain robust, although they exhibit less significance when alternative thresholds of the loan amount dispersion are considered.

confirm that the effect of specialization for the transmission of monetary policy changes to new mortgage lending growth is stronger for jumbo relative to non-jumbo mortgages. Specifically, a one standard deviation increase in *Spec* (0.192) corresponds to a 100.6 bps and a 37.3 bps increase in new lending growth per 100 bps decrease in the Fed funds target rate for the jumbo and non-jumbo segments of the mortgage market, respectively. These effects, along with the difference between them, are statistically significant at the 1% level.

Columns (3) and (4) document that specialization is more relevant for the transmission of monetary policy to new mortgage lending growth in local markets characterized by higher loan size dispersion. Specifically, a one standard deviation increase in *Spec* (0.192) increases new mortgage lending growth by 66.1 bps per 100 bps decrease in the Fed funds target rate within local markets exhibiting high loan size dispersion. This effect is statistically significant at the 1% level. While the impact in local markets characterized by low loan size dispersion goes in the same direction, statistical significance is not attained at conventional levels. Notably, the difference between these effects is statistically significant at the 5% level.

In sum, these cross-sectional examinations underscore the heightened relevance of local specialization for the transmission of monetary policy to lending for both, the information-intensive segment of the mortgage market and in local markets where information asymmetry is anticipated to be more acute. This is consistent with bank-market-specific information and lending advantages being a plausible underlying driver of our results.[73]

3.4.4 Ex-Ante Riskiness and Ex-Post Performance

In this subsection, we explore the connection between the specialization channel and the ex-ante riskiness, loan interest rates, and ex-post mortgage performance.[74] We assess whether mortgages originated by banks in markets with higher local specialization differ from those in other markets, focusing on the LTI ratio, FICO score, and interest rates at origination. Additionally, we investigate the non-performing status of these mortgages throughout their history, focusing on the subsample of mortgages sold to GSEs.

The analysis in this subsection is at the mortgage level and we use data from Fannie Mae and Freddie Mac's Single Family Loan-Level Data Sets as in Hurst et al. (2016), Saadi (2020), and Karimli (2022), among others. These datasets include publicly available information on

[73]To mitigate potential concerns that our results are driven by small banks specializing their lending activities due to size constraints rather than lending advantages (Blickle et al., 2023), we find in Table A7 of the appendix that the specialization channel is stronger for larger banks, those with a presence in a larger number of local markets, and more diversified banks.

[74]While Blickle et al. (2023) show that commercial and industrial (C&I) loans originated in sectors where the bank has higher degree of specialization are less likely to become non-performing, we study whether, following a monetary policy change, mortgage loans sold to GSEs originated in geographical markets where the bank is specialized exhibit different ex-post performance, relative to those originated in other markets.

fully amortizing, 30-year fixed-rate mortgages sold to these two institutions. We match these data from 2000 to 2017 with the mortgage data in HMDA to obtain information on the lender originating the mortgage, using the 3-digit zip-code where the residence is located, the size of the mortgage, the occupancy, and the purpose of the mortgage. As the variables used for the matching procedure are not enough to uniquely identify mortgages in both datasets, our approach involves keeping only those mortgages where we can be confident that the ex-ante riskiness and ex-post performance information aligns accurately with each respective mortgage. We end up with around 2 million mortgages from a total population of around 7 million mortgages available in the Fannie Mae and Freddie Mac's data.[75]

We assess whether, following a reduction in the Fed funds rate, mortgages originated in markets where the bank is specialized have different ex-ante characteristics, price, and ex-post performance, relative to mortgages originated in other markets.[76] Consistent with previous analyses, we absorb for changes in local lending opportunities and bank-year level heterogeneity, while also controlling for the impact of local bank market shares. Additionally, as we do not compute the dependent variable as changes from the previous period, we include bank-county fixed effects.[77] We use as dependent variables the LTI ratio, borrower's FICO score, mortgage interest rate, and a binary indicator for non-performing status, taking the value of one if the mortgage falls at least 90 days behind on monthly payments, enters foreclosure, or becomes real estate owned.

Table 8 presents the results. Given the availability of the LTI ratio for the majority of mortgages originated in HMDA, we examine the impact of the specialization channel on this ex-ante riskiness characteristic across the entire HMDA mortgage sample akin to the approach in Loutskina and Strahan (2011) and Chu et al. (2021). Column (1) shows that following a decrease in the Fed funds rate, the LTI ratio of borrowers does not exhibit

[75] Table A8 of the appendix provides evidence that the mortgage population in Fannie Mae and Freddie Mac's data is similar to the matched sample with HMDA in terms of both ex-ante riskiness and ex-post performance, where information on the originating lender is available.

[76] While comprehensive evidence on ex-ante riskiness and ex-post performance is available only for a subset of mortgages originated and sold to GSEs, this mechanism is still relevant due to the substantial securitization of loans in the US mortgage market by the GSEs (see Hurst et al. (2016), among others). In our sample of approximately 90 million mortgages originated by banks between 2000 and 2017, over 35 million mortgages are sold to GSEs, as detailed in columns (1) and (2) of Table 8. Furthermore, as shown in column (2) of Table A9 of the appendix, the specialization channel is still important for mortgages originated to sell to GSEs.

[77] This decision aligns with the methodology employed in previous studies such as Drechsler et al. (2017), Doerr and Schaz (2021), Iyer et al. (2022), Duquerroy et al. (2022), and Paravisini et al. (2023). These papers do not compute the dependent variable as changes from the preceding period and adopt a similar approach by adding the same or an equivalent set of fixed effects to their analyses. However, we provide a robustness test in Table A10 of the appendix, showing that most of the results on ex-ante riskiness and ex-post performance remain robust when we use data at the bank-county level, computing the dependent variable as changes relative to the previous period and omitting bank-county fixed effects.

statistically significant differences depending on the level of bank specialization in the local market. The result is similar when we focus on the subsample of mortgages originated to sell to GSEs (column (2)) and the matched sample of mortgages from Fannie Mae, Freddie Mac and HMDA (column (3)). Additionally, focusing on the matched sample of mortgages, we find similar results for the borrower's FICO score (column (4)) and the interest rate of the mortgage (column (5)).[78]

Column (6) focuses on the non-performing status using information from the matched sample of mortgages and reports the estimate for the linear probability model.[79] It shows that following a decrease in the Fed funds rate, mortgages originated by banks in markets where they have a higher degree of specialization that are sold afterwards to GSEs face higher probabilities of becoming non-performing throughout their history. This result is statistically significant at the 1% level. Columns (7) to (9) provide evidence that this effect remains robust even after controlling for the mortgage size, interest rate, FICO score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio. The estimate in column (9) implies that the semielasticity from a one standard deviation increase in *Spec* (0.192) corresponds to a 2.1 bps higher probability of delinquency per 100 bps decrease in the Fed funds target rate (2.1 bps = 0.021% = 0.192 × (-0.00569) × (-1) / 0.053), at the mean of the dependent variable (0.053).[80]

[78] Table A11 of the appendix provides additional evidence to rule out the alternative explanation that ex-ante riskiness may be the underlying factor driving the observed results. The concern is that banks in specialized markets might disproportionately increase lending to borrowers with lower income levels or in perceived riskier markets, as indicated by the average LTI level within the local market. Alternatively, the specialization channel could be driven by banks with a greater appetite for risk, which can be proxied by bank balance-sheet strength/weakness. To investigate whether the specialization channel holds more sway for borrowers within specific income categories, we adopt the methodology of Doerr et al. (2022). For bank balance-sheet strength, we employ liquidity and capital ratios following Jiménez et al. (2012). To measure loan performance on the balance sheet, we use the NPL ratio. The results indicate that banks do not disproportionately expand lending to the lowest income category in markets where they specialize relative to other markets. Instead, the specialization channel appears to be more relevant for lending to borrowers in the two highest income categories. Additionally, we focus on the triple interaction between the change in the Fed funds rate, the degree of specialization, and the risk measurement at either the county or bank level. The results suggest that the specialization channel does not predominate in riskier local markets, nor does it for banks with lower liquidity ratios, reduced capital ratios, or elevated NPL ratios. These findings suggest that ex-ante riskiness is not the predominant mechanism driving our main result.

[79] We employ a linear probability model in columns (6) to (9) of Table 8 in the spirit of Jiménez et al. (2012), Jiménez et al. (2014), Basten and Juelsrud (2023), among others.

[80] This result remains robust when extending the analysis to the bank-county level, as outlined in Table A10 of the appendix. We focus on the subsample of bank-counties with information on at least 4 mortgages to calculate average ex-ante riskiness, loan pricing, and ex-post performance measures. This approach includes approximately 25% of bank-county-year observations. Additionally, Table A9 of the appendix provides additional robustness for the main result presented in column (1) of Table 3. In this case, we focus on the period spanning from 2000 to 2017, during which information on ex-ante riskiness and ex-post performance is available. Additionally, we consider different samples, including the entire set of originated mortgages, mortgages originated to sell to GSEs, and the matched sample of mortgages from Fannie Mae, Freddie Mac,

This increase in ex-post performance of mortgages may not be exclusive to those originating for sale to GSEs, but could also extend to mortgages retained in banks' balance sheets, amplifying the overall riskiness of banks' portfolios. Although detailed information regarding the ex-post performance of newly originated mortgages held in balance sheets is unavailable, Table A12 of the appendix presents aggregated bank-level evidence on the ratio of non-performing outstanding mortgages from the U.S. Call Reports. Our results indicate that banks with a higher geographical specialization experience a reduction in their non-performing mortgage ratios relative to other banks following a monetary policy easing. This suggests that banks do not intensify their on-balance sheet risk-taking due to the specialization channel.[81] This aligns with the findings in Blickle et al. (2023), who find that loans originated in industries where a bank specializes are less likely to become non-performing relative to other loans due to the informational advantage in screening and/or monitoring such loans.

Overall, the findings in this section do not yield statistically significant evidence suggesting that the ex-ante riskiness of mortgage loans is influenced by the specialization channel. However, it is observed that mortgages originated by banks in markets where they specialize exhibit a disproportionately higher default rate ex-post. This evidence on ex-post performance is derived from a sample of mortgages sold to GSEs and is estimated while controlling for ex-ante riskiness, loan amount, and interest rate. This suggests that, after a decrease in the Fed funds rate, banks may possess the capacity to expand loan supply more substantially in specialized markets and mitigate the adverse effects of defaults by expeditiously selling mortgages to GSEs. This strategic approach may capitalize on the plausible information and lending advantage they hold in these specialized markets, with no apparent detrimental impact on the quality of the mortgages retained in banks' balance sheets. This lends support to the notion that risk-taking is not the primary underlying driver of our proposed channel.

and HMDA. Again, we include bank-counties with at least 4 mortgages originated.

[81] It's noteworthy that the ex-post performance data from U.S. Call Reports computed using the ratio of outstanding non-performing mortgages in the fourth quarter of a given year differ from those in the matched sample of mortgages sourced from HMDA, Fannie Mae, and Freddie Mac computed using the ratio of mortgages originated and sold to GSEs in a given year that have a non-performing status throughout the history of the loan. Despite this discrepancy, Table A12 of the appendix also reveals that, at the aggregate bank level, mortgages sold to GSEs that are originated by geographically specialized banks exhibit worse ex-post performance throughout their history after a monetary policy easing.

4 County Level Results on Lending, House Prices, and Economic Activity

4.1 Baseline Specifications

In our core set of tests, we isolate the supply effect of banks by comparing at the same time bank's new mortgage lending growth originated by the same bank-year in different counties, and new mortgage lending growth originated by different banks in the same county-year. The inclusion of bank-year effects absorbs time-variant bank heterogeneity. County-year effects absorb changes in credit demand, but they also absorb any potential aggregate effect of credit supply. We expect aggregate mortgage credit supply to be affected by the specialization channel. However, variations in new mortgage lending growth following monetary policy changes could potentially be compensated within a given market between specialized and non-specialized banks. In such cases, credit reallocation between banks may occur within a market, but the overall aggregate mortgage credit supply would remain unaffected.

In this section, we analyze the aggregate effects at the county level stemming from the channel we have identified. To do so, we aggregate our loan market data on mortgage lending at the county-year level and study whether specialization influences the transmission of monetary policy to aggregate growth in mortgage lending, house prices, and economic activity, measured by employment and wages.

Our previous results suggest that markets with a higher exposure to specialized banks may experience a rise in aggregate new mortgage lending growth compared to other markets following a monetary policy easing. If this hypothesis holds at the aggregate (county) level, it implies an increased supply of new mortgage lending by banks, consequently easing household restrictions on accessing mortgage credit. As a result, house prices may witness a more pronounced increase in markets exposed to specialized banks relative to other markets after a monetary policy easing.[82] Finally, the expansion in new mortgage lending growth may have a direct effect on the growth of economic activity, as measured by employment and wages, or an indirect effect through the rise in house price growth, which can influence the collateral value of entrepreneurs (Cloyne et al., 2019).

We construct a county-level variable, denoted as $CSpec_{ct}$, to measure the degree to which new mortgage lending in a county is originated by banks specialized in that specific market. This variable is constructed by computing the weighted average of $Spec_{bct}$ across all banks originating mortgages, using the amount of new mortgage lending originated as weights. A

[82] This aligns with findings in Blickle (2022), that investigate the impact of mortgage supply on house prices.

more detailed definition of this variable is provided in Section 2.

To account for the impact of local bank market shares (Giannetti and Saidi, 2019) in the transmission of monetary policy to aggregate mortgage lending, house prices, wage, and employment growth at the county level, we construct the variable $CMktSh_{ct}$. This variable measures local mortgage market concentration, representing the county's exposure to banks with high mortgage market shares, calculated as a standard Herfindahl index. The index is computed by summing the squared mortgage-market shares of all banks in a given county and year.

Additionally, we create the variable C-HHI-Expo$_{ct}$ to capture the extent to which new lending in a market is originated by banks raising deposits in concentrated deposit markets (Drechsler et al., 2017).[83]

To investigate the impact of county specialization on the transmission of monetary policy to regional outcomes, we estimate the following regression:

$$\begin{aligned} \Delta y_{ct} = & \alpha_c + \omega_t + \beta_1 \Delta FF_t \times CSpec_{ct-1} + \beta_2 CSpec_{ct-1} + \\ & + \beta_3 \Delta FF_t \times CMktSh_{ct-1} + \beta_4 CMktSh_{ct-1} + CountyControls + \epsilon_{ct}, \end{aligned} \tag{10}$$

where Δy_{ct} represents either the new mortgage lending growth, house price growth, total wage growth, or total employment growth in county c from year $t-1$ to t. ΔFF_t is the difference in the Fed funds target rate from $t-1$ to t. $CSpec_{ct-1}$ is the lagged county exposure to bank specialization in that local market using new mortgage lending shares as weights, while $CMktSh_{ct-1}$ is the lagged local mortgage market concentration, α_c and ω_t denote county and time fixed effects, respectively.[84] $CountyControls$ includes a set of controls such as the lagged log of population, the lagged log of income per capita, the lagged proportion of securitized mortgages, C-HHI-Dep, C-HHI-Expo, and their interactions with the difference in the Fed funds rate. We cluster standard errors at the county level.

Table 9 presents the results. Column (1) reports the specification using new mortgage lending growth as the outcome variable, while column (2) includes relevant controls. These findings indicate that counties more exposed to banks that are specialized in that specific local market experience an increase in new mortgage lending growth compared to other markets following a monetary policy easing. Specifically, column (2) shows that a one standard deviation increase in $CSpec$ (0.096) increases new mortgage lending growth by 138.24 bps per 100 bps decrease in the Fed funds rate. The result is statistically significant at the 1%

[83] Given our focus on the mortgage market, we use new mortgage lending shares as weights for this variable.

[84] We do not include the difference in the Fed funds target rate in the regression because it is absorbed across all columns of our tables by time fixed effects.

level.

Columns (3) and (4) present the results for regional house price growth. As shown in column (4), we find that per 100 bps decrease in the Fed funds rate, a one standard deviation increase in $CSpec$ (0.096) increases house price index growth by 14.4 bps. This result is statistically significant at the 1% level.

Columns (5) and (6) show the results for wage growth. In particular, column (6) documents that a one standard deviation increase in $CSpec$ (0.096) increases wage growth by 8.69 bps, per 100 bps decrease in the Fed funds rate. This result is statistically significant at the 1% level. Columns (7) and (8) present the results for employment growth. More specifically, column (8) indicates that a one standard deviation increase in $CSpec$ (0.096) increases employment growth by 1.66 bps, per 100 bps decrease in the Fed funds rate. The result is statistically significant at the 10% level.

Overall, the findings in Table 9 provide strong evidence that the specialization channel gives rise to aggregate regional implications. The level of county exposure to local specialized banks in the mortgage market significantly influences the responsiveness of new mortgage lending, house prices, wage, and employment growth to changes in monetary policy. These results suggest that the surge in new mortgage lending growth, driven by the diverse exposure to local bank specialization in the mortgage market following a monetary policy easing, not only contributes to increased regional house price growth but also exerts a direct and/or indirect impact on wage and employment growth.

4.2 Robustness

We document in Table A13 of the appendix how our results withstand a wide set of additional robustness tests for the specifications in columns (2), (4), (6), and (8) of Table 9. In Panel A, we address the potential concern that our findings might be influenced by information shocks on economic conditions rather than changes in interest rates. To explore this, we replace the change in the Fed funds rate with annual monetary policy shocks, constructed following Jarociński and Karadi (2020). Importantly, our results remain robust under the use of this alternative monetary policy measure.

In Panel B, we explore the robustness of our results by employing an alternative specification for the four outcome variables: new mortgage lending, house price index, wage, and employment growth. Specifically, we use the log difference of new mortgage lending as in Favara and Imbs (2015), the log difference of house price index as in Favara and Imbs (2015), Favara and Giannetti (2017), Cloyne et al. (2019) and Doerr et al. (2022) and the log difference in wage and employment as in Drechsler et al. (2017).

In Panel C, we narrow our focus to the sample period from 1994 to 2013. We aim to mitigate the potential impact of the low Fed funds rate environment, a period when the transmission of monetary policy may deviate from its intended effects (Heider et al., 2019). We observe consistent results for new mortgage lending, house price, and wage growth. However, the result on employment growth, while consistent with the previous findings, does not attain statistical significance at the standard levels.

5 Bank Level Results on Bank Specialization

Our estimates so far provide evidence that banks exhibit heterogeneous reactions to changes in monetary policy based on their level of specialization, even when accounting for variations in local lending opportunities and bank-year level heterogeneity. Moreover, this differential response to monetary policy generates aggregate implications at the county level, impacting mortgage lending, house prices, total wages, and total employment. This heterogeneous reaction to monetary policy within a given bank also affects its overall specialization by construction. Specifically, if following a decrease in the Fed funds rate, banks increase new mortgage lending growth by more in markets where they are specialized, the average specialization growth of the bank would increase. However, it's worth noting that a reduction in the Fed funds rate could also prompt banks to enter local markets, potentially diminishing their specialization growth. In this section, we provide a detailed examination at the aggregate bank level of how changes in the Fed funds rate impact the average specialization growth of banks.

We start by calculating banks' average specialization for each bank and year. This measure, denoted as $BSpec_{bt}$ and precisely defined in Section 2, is computed as the weighted average of $Spec_{bct}$ across all markets. The weights are determined by the amount of new mortgage loans originated in each county. Essentially, $BSpec_{bt}$ reflects the degree to which a bank, on average, specializes in local mortgage markets within the U.S. for a specific year.

Under the specialization channel we present, decreases in the Fed funds rate should predict increases in bank's specialization growth. To investigate this, we calculate the growth of $BSpec_{bt}$ and offer visual evidence illustrating how changes in the Fed funds rate impact a bank's average specialization growth.[85] The approach involves sorting all years into 12 bins based on their changes in the Fed funds target rate.[86] Subsequently, we calculate the

[85] Consistent with prior analyses, we measure the growth of a bank's average specialization as outlined in equation 1.

[86] There are 12 different changes in the Fed funds target rate across the entire sample period, allowing for the computation of the growth in the bank's average specialization. The first bin corresponds to the most substantial easing of monetary policy (-475 bps), and the last corresponds to the most significant tightening

average growth of a bank's average specialization within each bin.

Figure 3 plots the result. It suggests that decreases in the Fed funds rate are associated with smaller average declines in a bank's specialization growth. Specifically, the graph illustrates a decrease in bank's average specialization growth from -0.6 basis points in the most significant easing to -2.9 basis points in the strongest tightening of monetary policy. Notably, the most notable decrease in bank's average specialization growth is observed at -6.4 basis points, corresponding to the second-largest tightening of monetary policy.

One potential concern might be the influence of extreme values of bank's average specialization growth or the specific construction of the outcome variable on this result. In order to alleviate these concerns, we develop two robustness tests. Firstly, we compute the median of bank's average specialization growth within each bin. Secondly, we calculate the growth of bank's average specialization using log differences. The graphical evidence presented in Figure A3 of the appendix substantiates that the result remains consistent with these modifications.

We should be cautious when interpreting this evidence, recognizing the limitation in our ability to control for changes in loan demand or bank-year level heterogeneity at the aggregate bank level. The most comprehensive control we employ is accounting for bank-level heterogeneity. This is achieved by incorporating bank fixed effects and time-variant bank controls in the following regression:

$$\Delta y_{bt} = \alpha_b + \beta_1 \Delta FF_t + BankControls + \epsilon_{bt}, \tag{11}$$

where y_{bt} is bank's average specialization growth of bank b from year $t-1$ to t, ΔFF_t is the difference in the Fed funds target rate from $t-1$ to t, α_b are bank fixed effects, and $BankControls$ is a set of lagged controls, including the deposit ratio, liquidity ratio, leverage ratio, and the logarithm of total assets. We cluster standard errors at the bank level.

Table 10 presents the result. Columns (1) and (2) report the specifications using bank's average specialization growth as the outcome variable. Column (2) is our preferred specification where we include bank fixed effects and lagged bank characteristics as controls. It documents that a reduction in the Fed funds rate is associated with increases in bank's average specialization growth. Per 100 bps decrease in the Fed funds rate, bank's average specialization growth increases by 47.4 bps. The result is statistically significant at the 1% level.

We show in Table A14 of the appendix that our findings withstand an additional set of robustness tests. As in the robustness tests conducted in previous sections, we substitute the

(200 bps).

change in the Fed funds rate for the monetary policy shocks constructed following Jarociński and Karadi (2020). This substitution aims to address any potential concern that our results might be driven by information shocks. Importantly, our results remain robust even when using this alternative monetary policy measure.

We further enhance the robustness of our findings by employing the log difference of bank's average specialization as the outcome variable. This adjustment is made to allay any concerns that our main result might be influenced by the specific computation of the growth variable. Importantly, the result remains virtually unaltered.

Additionally, to address potential concerns related to the low Fed funds rate period affecting our results, we narrow our focus to the sample period from 1994 to 2013, excluding the period close to the zero lower bound. The result remains consistent.

While recognizing the limitations in controlling for changes in loan demand or bank-year level heterogeneity, our results suggest that a monetary policy easing is associated with increases in a bank's average local specialization growth. Consequently, following a monetary policy easing, the banking system appears to become relatively more exposed to local market shocks.

6 Conclusion

This paper provides evidence supporting the idea that the transmission of monetary policy changes to bank loan supply is market-specific, particularly depending on the extent of bank geographical specialization. By analyzing U.S. mortgage market data from 1994 to 2019, we measure the degree of market-specific bank geographical specialization for each bank and local market and show its significance in influencing the transmission of monetary policy to lending. Importantly, our estimation strategy effectively accounts for both bank- and county-wide factors, mitigating potential concerns regarding the influence of variations in local lending opportunities, differences in local market sizes, and bank-year differences on our results.

Our primary finding reveals that, following a decrease in the Fed funds rate, banks experience a more pronounced increase in new mortgage lending growth in markets where they exhibit higher specialization compared to other markets. When banks concentrate their lending activities disproportionately on a specific market, they may acquire expertise, technology, or skills that can provide them with market-specific lending advantages over other lenders. Our empirical findings, supported by our theoretical framework, suggest that our results may stem from the diverse marginal costs of lending that banks encounter across different markets, potentially arising from such disparities in bank-market-specific lending advantages. Additionally, our findings suggest that while the lending advantage possibly gained through banks' specialization may enable them to promptly sell mortgages characterized by a higher likelihood of default to GSEs, factors related to ex-ante risk-taking and in-balance riskiness are not be the primary drivers of the proposed channel.

Our findings provide evidence that the specialization channel we document gives rise to aggregate regional and bank-level implications. Specifically, we document how aggregate regional new mortgage lending is affected by market exposure to locally specialized banks after monetary policy changes. Given the direct impact of bank mortgage lending supply on household funds for home purchases, our results show that, following a reduction in the Fed funds rate, markets with higher exposure to locally specialized banks exhibit greater increases in aggregate new mortgage lending growth. Consequently, these markets also experience more pronounced growth in house price index compared to other markets. The observed changes in new mortgage lending and house price growth, in turn, may have consequential effects on real economic activity at the regional level. Our results indicate that wage and employment growth are weakly affected by the local specialization channel, aligning with the notion that an expansion in aggregate new mortgage lending growth and/or house price index growth contributes to increased real economic activity.

By construction, our results imply that monetary policy changes affect how banks specialize in local markets. We extend our analysis to the aggregate bank level to offer additional evidence of this connection. Our findings suggest that the easing of monetary policy spurs bank's specialization growth in local mortgage markets. This surge in specialization amplifies their exposure to local market shocks, leading to reduced geographic diversification. Consequently, our results contribute to the understanding of a novel channel through which monetary policy can influence banks' strategic decisions regarding specialization or diversification in local markets.

Our results are important for three key reasons. Firstly, we contribute to the understanding of how monetary policy influences lending, house prices, and economic activity through a novel banking market structure characteristic, geographical specialization. Secondly, our findings bear substantial policy implications. Monetary policy impacts the diversification decisions of banks in local mortgage markets. Consequently, decreases in interest rate levels may spur bank risk-taking in the form of banks being more exposed to adverse local shocks. Thirdly, our results have significant implications for understanding how bank loan supply responses to shocks are specific to individual markets, potentially attributable to the information and lending advantages conferred by specialization.

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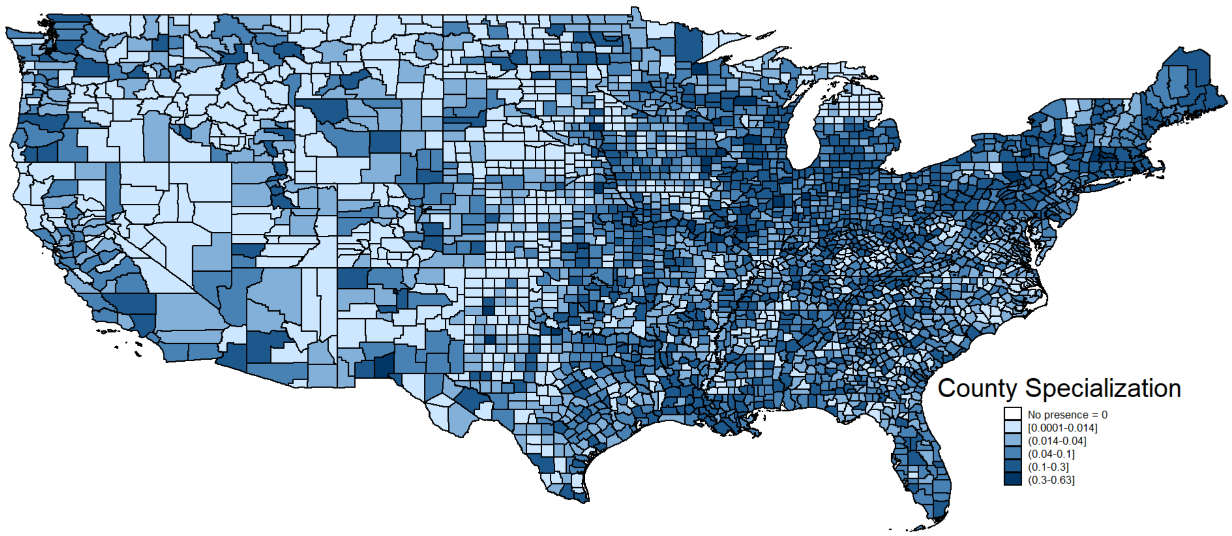
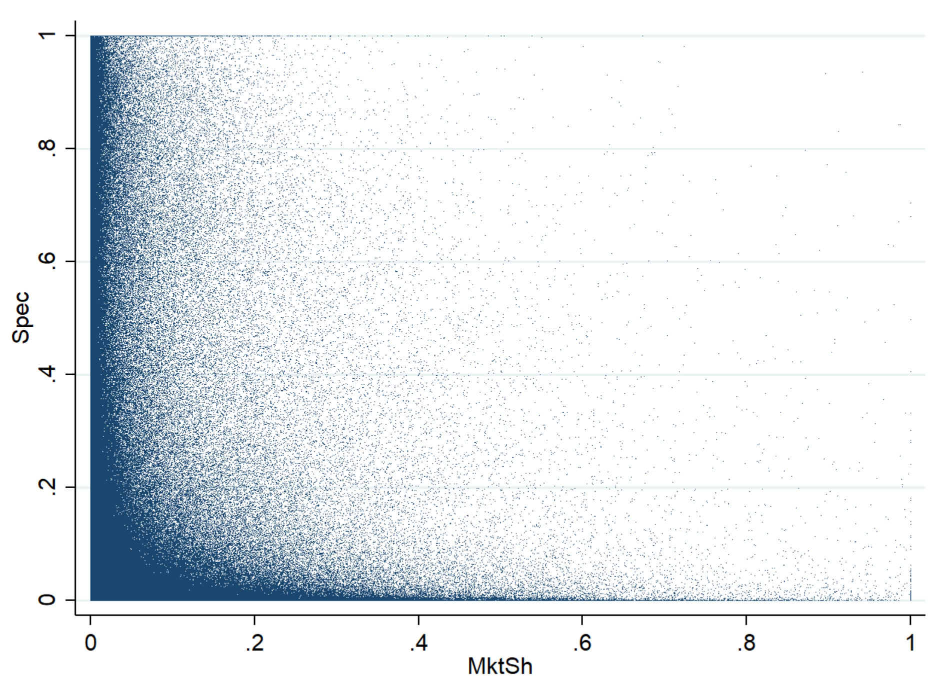
Figure 1: County Exposure to Specialization in Local Lending Markets



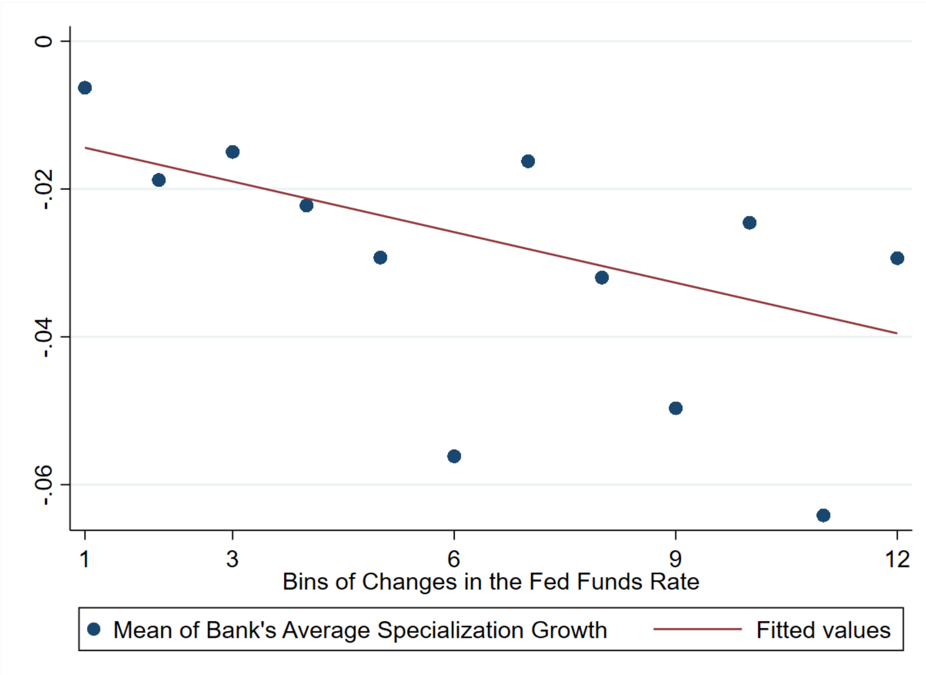
Notes. This map shows the average county-level exposure to banks' local mortgage market specialization for each U.S. county during the sample period from 1994 to 2019. The underlying data is from the FFIEC.

Figure 2: Scatter Plot Specialization and Market Share



Notes. This figure shows the scatter plot of banks' local lending specialization and local lending market share. The figure is constructed using data at the bank-county-year level. The underlying data are from the FFIEC covering 1994 to 2019.

Figure 3: Aggregate Bank Specialization and Monetary Policy: Bins



Notes. This figure shows the relationship between the mean of bank's average specialization growth and changes in the Fed funds rate. The figure is constructed in two steps. The first is to sort all years into 12 bins according to their change in the Fed funds rate. The second is to compute the mean of bank's average specialization growth for each bin. The underlying data are from HMDA and the FRED covering 1994 to 2019.

Table 1: Summary Statistics

	N	mean	sd
Panel A: Bank-county-level mortgage lending (HMDA and FDIC)			
New mortgage lending (mill. $)	1,600,174	17.298	126.663
New mortgage lending growth	1,600,174	-0.115	0.710
Number of new mortgages	1,600,174	89.169	405.981
ΔFF (%)	1,600,174	-0.154	1.534
Spec	1,600,174	0.079	0.192
MktSh	1,600,174	0.035	0.070
Bank-HHI-Dep	1,025,741	0.226	0.083
C-HHI-Dep	1,599,973	0.239	0.131
New t-1	1,600,174	0.104	0.305
SameMkt	1,392,091	0.070	0.255
Dist (log)	1,294,491	5.518	1.457
NBranches	1,600,174	1.001	4.316
Spec-Dep	1,600,174	0.054	0.193
Panel B: County-level (HMDA, FHFA and BLS)			
New mortgage lending (mill. $)	79,619	376.276	2,080.451
New mortgage lending growth	79,619	0.080	0.449
Total employment (thousand)	79,531	44.635	143.978
Employment growth	79,524	0.004	0.042
HPI	65,071	241.844	155.881
HPI growth	64,261	0.027	0.052
Total wages (bill. $)	79,580	1.766	8.264
Wage growth	79,571	0.035	0.060
ΔFF (%)	79,619	-0.156	1.439
CSpec	78,558	0.068	0.096
CMktSh	79,619	0.169	0.162
C-HHI-Expo	79,516	0.243	0.044
C-HHI-Dep	79,323	0.354	0.211
Population (thousand)	76,296	97.101	311.732
Population (log)	76,296	10.271	1.435
Income per capita (thousand $)	76,296	31.822	11.894
Income per capita (log)	76,296	10.308	0.342
Securitized mortgages (%)	79,619	51.089	17.907
Banks (number)	78,558	36.954	39.596
Panel C: Bank-level (HMDA and FDIC)			
BSpec	151,713	0.485	0.270
BSpec growth	151,713	-0.028	0.307
ΔFF (%)	151,713	-0.168	1.440
Mkts (number)	151,713	27.537	137.298
Size (bill. $)	106,401	0.758	2.013
Size (log)	106,401	12.404	1.279
Deposit ratio (%)	106,400	82.6	8.7
Liquidity ratio (%)	106,400	5.9	5.3
Leverage ratio (%)	106,400	89.7	3.5

Notes. This table provides summary statistics at the bank-county, county, and bank levels. Panel A presents mortgage lending data at the bank-county level. The underlying data are from the FFIEC, FDIC, and FRED for the years 1994 to 2019. Panel B presents data on mortgage lending, house prices, employment, and wages at the county level. The underlying data are from the FFIEC, FDIC, FHFA, FRED, and BLS for the years 1994 to 2019. Panel C presents data on mortgage bank specialization at the bank level. The underlying data are from the FFIEC, FDIC, and FRED for the years 1994 to 2019.

Table 2: Lending, Local Specialization, and Monetary Policy

	New mortgage lending growth			
	(1)	(2)	(3)	(4)
ΔFF$\times$Spec	-0.0283***	-0.0323***	-0.0692***	-0.0749***
	(0.00293)	(0.00253)	(0.0136)	(0.0148)
Spec	-0.0465***	-0.0545***	0.0412***	0.0363***
	(0.00632)	(0.00666)	(0.00932)	(0.00960)
Observations	1,557,766	1,562,955	1,594,588	1,599,605
R-squared	0.424	0.383	0.177	0.131
Bank-Year FE	Y	Y	N	N
County-Year FE	Y	N	Y	N
Bank FE	N	N	Y	Y
County FE	N	N	N	Y
Year FE	N	N	N	Y
Fipszero FE	N	Y	N	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to new mortgage lending growth. The data are at the bank-county-year level from 1994 to 2019. New mortgage lending growth is the growth of new mortgage lending originated by a given bank in a given county and year. Spec is the bank's local specialization in a given county and year, lagged one period. ΔFF is the difference in the Fed funds target rate. Fipszero is the interaction between a county identifier and a dummy variable that takes the value of one from 2009 to 2014, and zero otherwise. The data are from the FFIEC and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *** indicates significance at the 0.01 level.

Table 3: Lending, Specialization, and Monetary Policy: Market Structure Controls

	New mortgage lending growth		
	(1)	(2)	(3)
ΔFF×Spec	-0.0190***	-0.0638***	-0.0708***
	(0.00415)	(0.0184)	(0.0195)
Spec	0.00419	0.0704***	0.0473***
	(0.00834)	(0.0108)	(0.0114)
ΔFF×MktSh	-0.0937***	-0.272***	-0.216***
	(0.0312)	(0.0389)	(0.0432)
MktSh	-0.466***	-0.698***	-0.587***
	(0.0602)	(0.0724)	(0.0617)
ΔFF×Bank-HHI-Dep		-0.0328	-0.0239
		(0.0814)	(0.0796)
Bank-HHI-Dep		-0.320	-0.263
		(0.251)	(0.244)
ΔFF×C-HHI-Dep			0.0272**
			(0.0118)
C-HHI-Dep			0.0272**
			(0.0118)
Observations	1,557,766	1,019,762	1,025,192
R-squared	0.424	0.196	0.134
Bank-Year FE	Y	N	N
County-Year FE	Y	Y	N
Bank FE	N	Y	Y
County FE	N	N	Y
Year FE	N	N	Y
Fipszero FE	N	N	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to new mortgage lending growth controlling for the effect of other relevant bank's local market characteristics. The data are at the bank-county-year level from 1994 to 2019. MktSh is the bank's local market share in a given county and year, lagged one period. C-HHI-Dep is the county level HHI of the deposit market. Bank-HHI-Dep is the bank level average of C-HHI-Dep using lagged deposit shares across branches as weights. All other variables are explained in Table 2. The data are from the FFIEC, the FDIC, and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 4: Lending, Specialization, and Monetary Policy: Robustness

	New mortgage lending growth			
	Spec t-2	Spec Avg	Spec Avg 5y	Spec Prev. Sample
	(1)	(2)	(3)	(4)
Panel A: Alternative measures of specialization				
ΔFF×Spec	-0.0208***	-0.0245***	-0.0233***	-0.0157***
	(0.00387)	(0.00412)	(0.00389)	(0.00379)
Spec	0.226***	0.340***	0.181***	0.232***
	(0.00679)	(0.00788)	(0.00670)	(0.00741)
ΔFF×MktSh	-0.0908***	-0.0942***	-0.0905***	-0.0247
	(0.0316)	(0.0305)	(0.0310)	(0.0364)
MktSh	-0.625***	-0.642***	-0.569***	-0.650***
	(0.0549)	(0.0489)	(0.0530)	(0.0652)
Observations	1,395,035	1,557,766	1,557,766	793,781
R-squared	0.433	0.427	0.425	0.412
Bank-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County

	New mortgage lending growth			
	FF avg	JK Shocks	Shadow Rate	Exit & Entry
	(1)	(2)	(3)	(4)
Panel B: Alternative monetary policy measures and including exits & entries				
MP×Spec	-0.0236***	-0.114***	-0.0155***	-0.0249***
	(0.00428)	(0.0315)	(0.00362)	(0.00415)
Spec	0.00502	9.37e-05	0.00320	-0.580***
	(0.00835)	(0.00846)	(0.00839)	(0.0164)
MP×MktSh	-0.106***	-0.699***	-0.0717***	-0.109***
	(0.0285)	(0.205)	(0.0255)	(0.0417)
MktSh	-0.470***	-0.497***	-0.467***	-3.341***
	(0.0600)	(0.0620)	(0.0605)	(0.168)
Observations	1,557,766	1,557,766	1,557,766	5,965,916
R-squared	0.424	0.424	0.424	0.273
Bank-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County

	New mortgage lending growth			
	Logdifference	New # Loans	Avg Amount	Approval Ratio
	(1)	(2)	(3)	(4)
Panel C: Alternative dependent variables				
ΔFF×Spec	-0.0238***	-0.0187***	0.00131	-0.235**
	(0.00394)	(0.00353)	(0.00233)	(0.113)
Spec	-0.0228***	0.0970***	-0.0778***	-0.109
	(0.00818)	(0.00787)	(0.00456)	(0.111)
ΔFF×MktSh	-0.103***	-0.101***	0.0213	3.048***
	(0.0288)	(0.0271)	(0.0170)	(1.043)
MktSh	-0.534***	-0.0892	-0.362***	-4.066***
	(0.0576)	(0.0610)	(0.0234)	(0.798)
Observations	1,557,766	1,557,766	1,557,766	1,557,766
R-squared	0.419	0.462	0.247	0.234
Bank-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County

	New mortgage lending growth			
	Boom	Non-Boom	Without Crisis	1994-2013
	(1)	(2)	(3)	(4)
Panel D: Alternative sample periods				
ΔFF×Spec	-0.0413***	-0.0190***	-0.0199***	-0.0201***
	(0.0120)	(0.00492)	(0.00535)	(0.00430)
Spec	0.0350*	0.00158	-0.00173	0.00971
	(0.0188)	(0.00803)	(0.00820)	(0.00865)
ΔFF×MktSh	-0.204**	-0.0687*	-0.136***	-0.0984***
	(0.0824)	(0.0358)	(0.0400)	(0.0329)
MktSh	-0.479***	-0.435***	-0.451***	-0.496***
	(0.143)	(0.0547)	(0.0563)	(0.0684)
Observations	349,281	1,208,485	1,339,333	1,234,411
R-squared	0.398	0.431	0.413	0.442
Bank-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to new mortgage lending growth using different specifications for robustness. The data are at the bank-county-year level from 1994 to 2019. If nothing is explicitly stated, new mortgage lending growth is the growth of new mortgage lending originated by a given bank in a given county and year. Panel A examines other measures of specialization. Columns (1)-(3) report the results for *Spec* lagged two periods, average for the whole sample period from 1994 to 2019, and average from t-1 to t-5, respectively. Column (4) uses the specialization average from 1994 to 2004 and 2005 to 2019 as the sample for the analysis. Panel B examines whether the result holds for alternative monetary policy measures and including exits and entries in local markets. Columns (1)-(3) report the results for the difference in the Fed funds using the average aggregation method, monetary policy shocks following Jarociński and Karadi (2020), and the difference in shadow rates, respectively. Column 4 includes entries and exits in local markets. Panel C examines alternative dependent variables. Columns (1)-(4) use the log difference of new lending winsorized at the 10% level, the growth of the number of new mortgages, the growth of the average amount of new lending, and the difference in the approval ratio, respectively. Panel D examines alternative sample periods. Columns (1)-(4) focus on the U.S. housing boom period from 2003 to 2006, excluding on the U.S. housing boom period (2003 to 2006), excluding the three years related to the Great Recession (2007-2009), and focus on the years from 1994 to 2013, respectively. All other variables are explained in Tables 2 and 3. The data are from the FFIEC and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 5: Bank Specialization and Information

	Spec					
	(1)	(2)	(3)	(4)	(5)	(6)
Newt-1	-0.0189***					
	(0.00187)					
Newt-5		-0.0323***				
		(0.00286)				
SameMkt			0.309***			
			(0.00571)			
Dist				-0.00438***		
				(0.000458)		
NBranches					0.00229***	
					(0.000885)	
SpecD						0.470***
						(0.00595)
MktSh	0.559***	0.538***	0.209***	0.175***	0.531***	0.263***
	(0.0670)	(0.0766)	(0.0300)	(0.0277)	(0.0590)	(0.0357)
Observations	1,529,159	1,333,918	1,362,781	1,266,627	1,557,766	1,557,766
R-squared	0.571	0.571	0.759	0.601	0.576	0.726
Bank-Year FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County

Notes. This table estimates the relationship between local specialization and the information proxies used to study the underlying mechanism of the main result. The data are at the bank-county-year level from 1994 to 2019. $Newt-1$ ($Newt-5$) is an indicator variable for the markets where the bank originates new mortgage lending only since last year (since five years ago). $SameMkt$ is an indicator variable for the market where the bank is headquartered. $Dist$ is the natural logarithm of the distance in miles from each market to bank's headquarters. $NBranches$ is the number of physical branches the bank has in a local market. $SpecD$ is the deposit specialization of the bank in a local market. All other variables are explained in Tables 2 and 3. The data are from the FFIEC and the FDIC. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *** indicates significance at the 0.01 level.

Table 6: Lending, Specialization, Information, and Monetary Policy

	New mortgage lending growth						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔFF×Spec	-0.0180***	-0.0130***	-0.0167***	-0.0363***	-0.0153***	-0.0112**	-0.0139**
	(0.00425)	(0.00417)	(0.00557)	(0.0121)	(0.00405)	(0.00439)	(0.00637)
Spec	0.000668	-0.0327***	-0.303***	-0.392***	-0.00526	-0.209***	-0.501***
	(0.00842)	(0.00979)	(0.0105)	(0.0243)	(0.0105)	(0.0112)	(0.0153)
ΔFF×Newt-1	0.0179***						0.0193***
	(0.00463)						(0.00477)
Newt-1	-0.0812***						-0.0653***
	(0.00796)						(0.00829)
ΔFF×Newt-5		0.0112***					
		(0.00302)					
Newt-5		-0.127***					
		(0.00668)					
ΔFF×SameMkt			-0.00296				-0.00261
			(0.00205)				(0.00211)
SameMkt			0.210***				0.0791***
			(0.00477)				(0.00489)
ΔFF×Dist				0.00723***			
				(0.00225)			
Dist				-0.0566***			
				(0.00395)			
ΔFF×NBranches					-0.000901***		-0.000860***
					(0.000248)		(0.000261)
NBranches					0.00270***		0.00169***
					(0.000858)		(0.000612)
ΔFF×SpecD						-0.00755***	0.00314
						(0.00290)	(0.00394)
SpecD						0.279***	0.331***
						(0.00799)	(0.0112)
ΔFF×MktSh	-0.0865***	-0.0673**	-0.0977***	-0.0820**	-0.0798***	-0.0928***	-0.0785**
	(0.0311)	(0.0294)	(0.0320)	(0.0339)	(0.0299)	(0.0313)	(0.0305)
MktSh	-0.484***	-0.551***	-0.550***	-0.754***	-0.509***	-0.527***	-0.597***
	(0.0607)	(0.0628)	(0.0601)	(0.0668)	(0.0563)	(0.0579)	(0.0588)
Observations	1,529,159	1,333,918	1,362,781	1,266,627	1,557,766	1,557,766	1,337,718
R-squared	0.423	0.420	0.421	0.419	0.425	0.426	0.421
Bank-Year FE	Y	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County

Notes. This table estimates the effect of both banks' local specialization and the proxies for informational asymmetries on the transmission of monetary policy to new mortgage lending growth. The data are at the bank-county-year level from 1994 to 2019. In columns (1) and (7) the sample spans from 1996 to 2019 and in column (2) from 2000 to 2019. New mortgage lending growth is the growth of new mortgage lending originated by a given bank in a given county and year. All variables are explained in Tables 2, 3 and 5. The data are from the FFIEC, FDIC, and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. **, *** indicate significance at the 0.05, and 0.01 levels, respectively.

Table 7: Lending, Specialization, and Monetary Policy: Cross-Sectional Differences

	New mortgage lending growth			
	(1)	(2)	(3)	(4)
ΔFF$\times$Spec	-0.0524***	-0.0194***	-0.0344***	-0.00729
	(0.00793)	(0.00368)	(0.00607)	(0.0125)
Spec	-0.206***	0.0655***	-0.0219	0.0877***
	(0.0169)	(0.00770)	(0.0140)	(0.0173)
ΔFF$\times$MktSh	-0.182***	-0.106***	-0.134*	-0.0507
	(0.0464)	(0.0273)	(0.0805)	(0.0337)
MktSh	-1.628***	-0.289***	-1.494***	-0.418***
	(0.115)	(0.0589)	(0.164)	(0.0514)
Observations	476,205	1,547,004	375,403	382,422
R-squared	0.324	0.448	0.509	0.422
Bank-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County
Sample	Jumbo	Non-Jumbo	High Dispersion	Low Dispersion
Difference ΔFF$\times$Spec: (Jumbo=1-Jumbo=0)	-0.330***			
Difference ΔFF$\times$Spec: (HighDis=1-HighDis=0)			-0.027**	
Difference: P-Value	0.000		0.050	

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to new mortgage lending growth, after splitting the sample on different sub-samples. The data are at the bank-county-year level from 1994 to 2019. Column (1) reports the result for the sub-sample of jumbo mortgages and column (2) for the sub-sample of non-jumbo mortgages. Column (3) reports the result for the sub-sample of counties with a high degree of loan amount dispersion and column (4) for the sub-sample of counties with low degree of loan amount dispersion. All variables are explained in Tables 2 and 3. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 8: Ex-Ante Riskiness, Ex-Post Performance, Specialization, and Monetary Policy

	LTI (1)	LTI (2)	LTI (3)	FICO (4)	Rate (5)	NP (6)	NP (7)	NP (8)	NP (9)
ΔFF×Spec	-0.00328	0.00166	0.00293	0.220	0.00373	-0.00571***	-0.00569**	-0.00536***	-0.00569***
	(0.00302)	(0.00366)	(0.0124)	(0.523)	(0.00539)	(0.00221)	(0.00221)	(0.00207)	(0.00210)
Spec	-0.00337	-0.0302	0.0372	0.0338	0.0456**	0.00233	0.00235	0.00102	-0.000747
	(0.0218)	(0.0534)	(0.0641)	(2.070)	(0.0227)	(0.00850)	(0.00850)	(0.00811)	(0.00795)
ΔFF×MktSh	0.0297	0.00811	0.00531	-1.275**	0.0220**	0.00873***	0.00873***	0.00722***	0.00799***
	(0.0182)	(0.0124)	(0.0155)	(0.634)	(0.00938)	(0.00319)	(0.00319)	(0.00275)	(0.00294)
MktSh	-0.0456	0.0390	0.0466	-0.455	0.0193	0.0149**	0.0151**	0.0139**	0.00953
	(0.0531)	(0.0552)	(0.0493)	(1.889)	(0.0214)	(0.00622)	(0.00628)	(0.00588)	(0.00641)
MortgageSize	0.792***	0.675***	0.632***	0.917*	-0.0549***		-0.00113	0.00102	-0.0105***
	(0.0232)	(0.0147)	(0.0113)	(0.544)	(0.0101)		(0.00146)	(0.00137)	(0.000621)
Rate								0.0246***	0.0141***
								(0.00143)	(0.000992)
FICO								-0.000810***	-0.000752***
								(0.00004)	(0.00005)
LTV									0.000752***
									(0.00007)
DTI									0.000886***
									(0.00005)
Observations	91,114,474	35,888,086	1,942,262	2,004,302	2,010,054	2,010,054	2,010,054	2,004,302	1,861,301
R-squared	0.048	0.104	0.171	0.182	0.873	0.112	0.112	0.146	0.155
Bank-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank-County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County
Sample	HMDA	HMDA-SoldGSEs	HMDA-FF	HMDA-FF	HMDA-FF	HMDA-FF	HMDA-FF	HMDA-FF	HMDA-FF

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to ex-ante measures of riskiness, interest rate charged on the mortgage, and ex-post performance. The data are at the mortgage level from 2000 to 2017. LTI, FICO, and Rate are the loan-to-income ratio, FICO score, and interest rate of the mortgage originated and sold to Fannie Mae or Freddie Mac by a given bank in a given county and year. NP is a dummy variable that indicates whether or not the mortgage is at least 90 days past due on their monthly payments, is in foreclosure, or is real estate owned through the history of the loan. Columns (1)-(3) report the results for the LTI for the full sample of mortgages in HMDA, the subsample of mortgages originated to sell to GSEs in HMDA, and the matched sample from HMDA, Fannie Mae, and Freddie Mac, respectively. Columns (4) and (5) report the results for the FICO score and interest rate charged on the mortgage for the matched HMDA, Fannie Mae, and Freddie Mac sample. Columns (6)-(9) report the results for the delinquency status of mortgages for the matched HMDA, Fannie Mae, and Freddie Mac sample including different controls. MortgageSize, LTV, and DTI are the $ amount, loan-to-value, and debt-to-income of the mortgage originated and sold to Fannie Mae or Freddie Mac by a given bank in a given county and year. All other variables are explained in Tables 2 and 3. The data are from the FFIEC, the FRED, the Fannie Mae loan performance data, and the Freddie Mac loan performance data. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 9: Aggregate County Implications, Specialization, and Monetary Policy

	New mortgage lending growth		HPI growth		Wage growth		Employment growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFF×CSpec	-0.129***	-0.144***	-0.00902***	-0.0150***	-0.00266	-0.00905***	-0.000105	-0.00173*
	(0.00941)	(0.0104)	(0.00127)	(0.00159)	(0.00163)	(0.00175)	(0.000868)	(0.000938)
CSpec	-1.160***	-1.193***	-0.00478*	-0.00555*	0.00946***	0.00334	0.00238	0.000251
	(0.0299)	(0.0297)	(0.00288)	(0.00305)	(0.00307)	(0.00319)	(0.00199)	(0.00210)
ΔFF×CMktSh		-0.0183		0.000428		-0.00248		-0.00477***
		(0.0182)		(0.00247)		(0.00281)		(0.00141)
CMktSh		0.357***		0.0173***		0.000239		-0.00150
		(0.0266)		(0.00279)		(0.00269)		(0.00177)
Observations	78,545	75,029	64,111	62,828	78,500	75,011	78,457	75,008
R-squared	0.475	0.500	0.401	0.411	0.222	0.232	0.214	0.218
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Fipszero FE	Y	Y	Y	Y	Y	Y	Y	Y
County Controls	N	Y	N	Y	N	Y	N	Y
Cluster s.e.	County	County	County	County	County	County	County	County

Notes. This table estimates the effect of county exposure to local specialized banks for the transmission of monetary policy to aggregate new mortgage lending, house price, wage, and employment growth. The data are at the county-year level covering the years from 1994 to 2019. New mortgage lending growth is the growth of new mortgage lending in a given county and year. HPI growth is the growth of the house price index in a given county and year. Employment and wage growth are the growth in total employment and wages in a given county and year, respectively. $CSpec$ is the county-level average of $Spec$ using mortgage lending shares across banks as weights, lagged one period. $CMktSh$ is the county-level local mortgage market concentration calculated as a standard HHI, lagged one period. County (not reported) controls are the lagged log of the population, the lagged log of income per capita, the lagged proportion of securitized mortgages, C-HHI-Dep, C-HHI-Expo, and the interactions between these variables and the difference in the Fed funds rate. All other variables are defined in Table 2. The data are from the FFIEC, the FRED, the FHFA, and the BLS. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by county. *, *** indicate significance at the 0.1, and 0.01 levels, respectively.

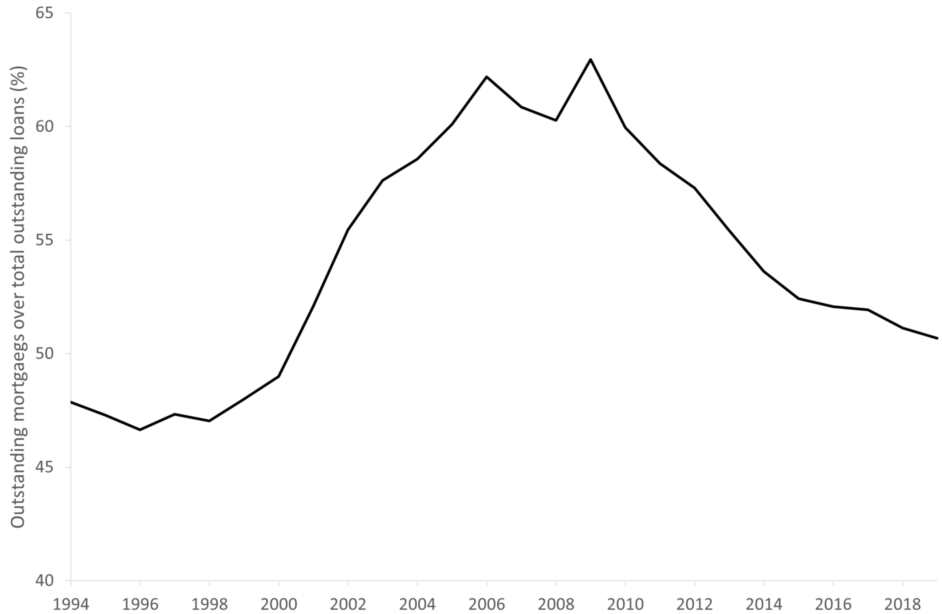
Table 10: Aggregate Bank Specialization and Monetary Policy

	Bank's average specialization growth	
	(1)	(2)
ΔFF	-0.00412***	-0.00474***
	(0.000561)	(0.000689)
Observations	150,863	105,717
R-squared	0.040	0.048
Bank FE	Y	Y
Bank Controls	N	Y
Cluster s.e.	Bank	Bank

Notes. This table estimates the effect of monetary policy changes on bank's average specialization growth. The data are at the bank-year level covering the years from 1994 to 2019. Bank's average specialization growth is the growth of bank's average specialization for a given bank and year. Bank (not reported) controls are the lagged deposit ratio, lagged liquidity ratio, lagged leverage ratio, and lagged log of total assets. All other variables are defined in Table 2. The data are from the FFIEC, the FDIC, and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank. *** indicates significance at the 0.01 level.

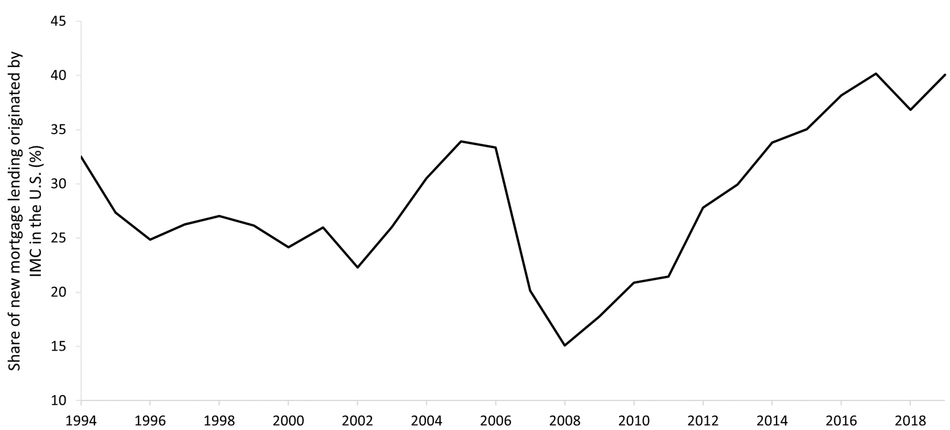
A Appendix

Figure A1: Mortgage Market Relevance



Notes. This figure shows the relevance of outstanding mortgage lending over total outstanding loans of U.S. banks. The figure is constructed using data from the last quarter of each year. The underlying data are from the FDIC (U.S. Call Reports) covering 1994 to 2019.

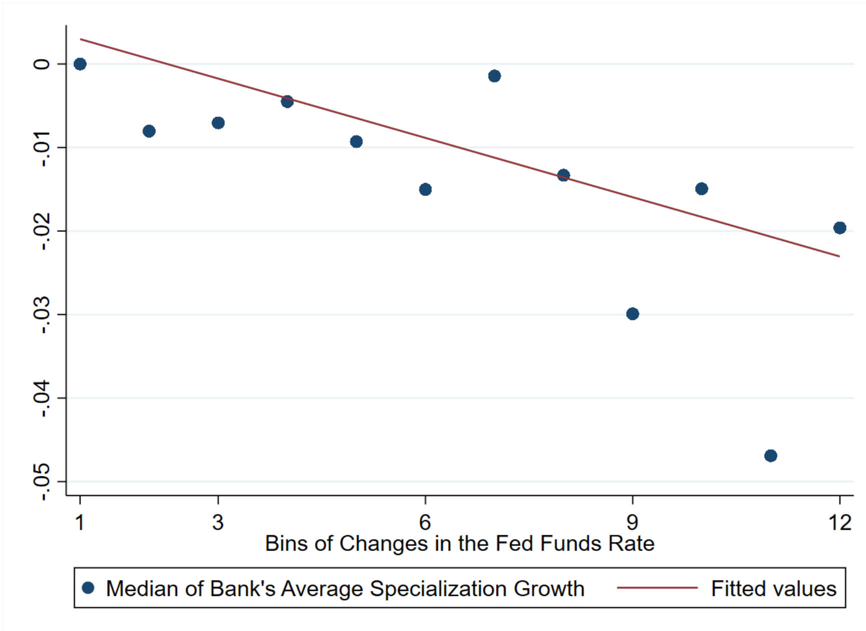
Figure A2: Non-Depository Institutions Relevance



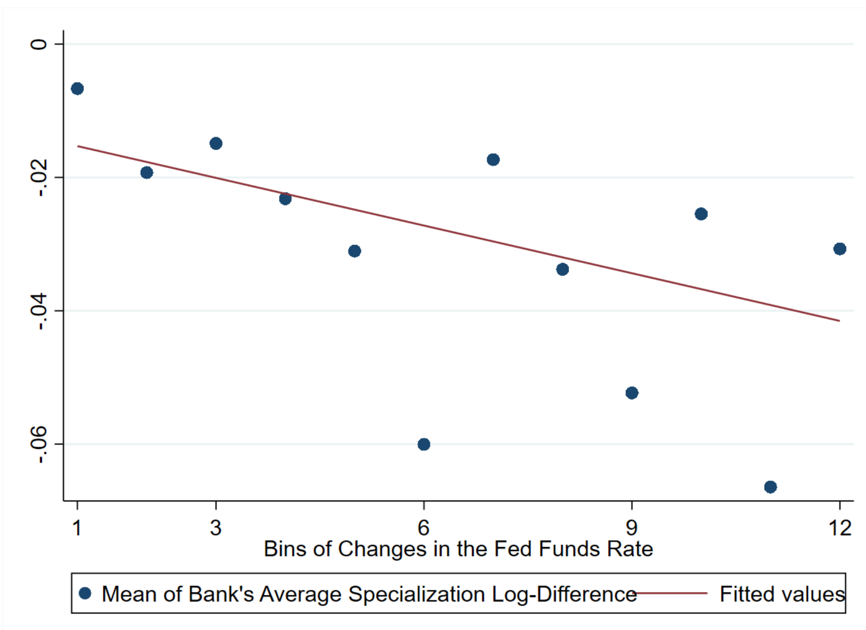
Notes. This figure shows the relevance of non-depository institutions (IMC) in the U.S. mortgage market. The underlying data are from the FFIEC covering 1994 to 2019.

Figure A3: Aggregate Bank Specialization and Monetary Policy: Bins Robustness

Panel A: Median of Average Specialization and Monetary Policy



Panel B: Log-Difference of Average Specialization and Monetary Policy



Notes. This figure shows the relationship between the median of the growth of bank's average specialization or the average of the log-difference of bank's average specialization and changes in the Fed funds rate. The figure is constructed in two steps. The first is to sort all years into 12 bins according to their change in the Fed funds rate. The second is to compute the median or average of the growth or log-difference of bank's average specialization for each bin. Panel A shows the results for the median of bank's average specialization growth. Panel B shows the results for the mean of bank's average specialization log-difference. The underlying data are from HMDA and the FRED covering 1994 to 2019.

Table A1: Serial Correlation Specialization Variable

	Spec t		
	(1)	(2)	(3)
Spec t-1	0.936***		
	(0.000174)		
Spec t-5		0.866***	
		(0.00356)	
Spec t-10			0.797***
			(0.00577)
Observations	2,903,057	1,254,409	586,308
R-squared	0.903	0.862	0.822
Year FE	Yes	Yes	Yes
Cluster s.e.	Bank&County	Bank&County	Bank&County

Notes. This table reports the serial correlation of the bank's local mortgage market specialization variable for different periods. The data are at the bank-county-year level from 1994 to 2019. $Spect$, $Spect-1$, $Spect-5$, and $Spect-10$ correspond to the specialization of bank b in a given county and year, in the contemporaneous period, lagged one period, lagged five periods and lagged ten periods, respectively. The data are from the FFIEC. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *** indicates significance at the 0.01 level.

Table A2: Correlation Matrix: Market Structure Characteristics

Variables	Spec	MktSh	Bank-HHI-Dep	C-HHI-Dep
Spec	1.000			
MktSh	0.063	1.000		
Bank-HHI-Dep	-0.062	0.118	1.000	
C-HHI-Dep	-0.100	0.233	0.124	1.000

Notes. This table reports the correlation matrix between bank's local mortgage market specialization, banks' local mortgage market share, bank-level exposure to local deposit market concentration, and county-level local deposit market concentration. The data are at the bank-county-year level from 1994 to 2019. All variables are defined in Tables 2 and 3. The data are from the FFIEC and the FDIC.

Table A3: Lending, Specialization, and Monetary Policy: Tightening and Easing

	New mortgage lending growth			
	ΔFF<0	ΔFF>0	JK Shocks< 0	JK Shocks> 0
	(1)	(2)	(3)	(4)
ΔFF×Spec	-0.0102*	-0.00155	-0.118***	-0.162
	(0.00551)	(0.0141)	(0.0395)	(0.143)
Spec	0.0296**	-0.0241	-0.00175	0.00491
	(0.0122)	(0.0161)	(0.0105)	(0.0164)
ΔFF×MktSh	-0.0381	-0.209**	-0.611**	0.523
	(0.0390)	(0.0894)	(0.281)	(0.844)
MktSh	-0.376***	-0.448***	-0.461***	-0.627***
	(0.0765)	(0.0868)	(0.0664)	(0.112)
Observations	525,876	652,887	844,558	713,208
R-squared	0.444	0.367	0.450	0.390
Bank-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County

Notes. This table estimates the differential effect of banks' local specialization for the transmission of monetary policy to new mortgage lending growth separately for tightening and easing periods. The data are at the bank-county-year level from 1994 to 2019. New mortgage lending growth is the growth of new mortgage lending originated by a given bank in a given county and year. Columns (1) and (2) report the results for decreases and increases in the Fed funds rate, respectively. Columns (3) and (4) report the results for decreases and increases in the monetary policy shocks (Jarociński and Karadi, 2020), respectively. All variables are explained in Tables 2, 3, and 4. The data are from the FFIEC and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A4: Lending, Specialization, and Monetary Policy: Additional Robustness

	New mortgage lending growth							
	Growth Control	Spec t-3	Spec Quartiles	Spec Excess	Non-Sym. Growth	BC F.E.	Alt. Boom	Alt. Non-Boom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFF×Spec	-0.0173***	-0.0207***		-0.019***	-0.0213***	-0.0275***	-0.0416***	-0.0174***
	(0.00384)	(0.00378)		(0.00416)	(0.00448)	(0.00402)	(0.0101)	(0.00482)
Spec	-0.0224***	0.215***		0.0042	-0.271***	-1.804***	0.0263*	0.00272
	(0.00761)	(0.00676)		(0.0083)	(0.0107)	(0.0319)	(0.0150)	(0.00840)
ΔFF×MktSh	-0.112***	-0.0696**	-0.0793***	-0.0937***	-0.0726**	-0.0585**	-0.223***	-0.0749**
	(0.0314)	(0.0350)	(0.0251)	(0.0312)	(0.0287)	(0.0293)	(0.0822)	(0.0339)
MktSh	-0.473***	-0.676***	-0.0373	-0.4663	-1.293***	-4.151***	-0.429***	-0.454***
	(0.0544)	(0.0560)	(0.0303)	(0.0602)	(0.0690)	(0.171)	(0.120)	(0.0578)
ΔFF×Growth	0.00184							
	(0.00185)							
Growth	-0.238***							
	(0.00555)							
ΔFF×SpecQ4			-0.0216***					
			(0.00562)					
SpecQ4			-0.291***					
			(0.0139)					
ΔFF×SpecQ3			-0.0149***					
			(0.00543)					
SpecQ3			-0.236***					
			(0.0132)					
ΔFF×SpecQ2			-0.00392					
			(0.00391)					
SpecQ2			-0.165***					
			(0.00861)					
Observations	1,395,035	1,223,720	1,557,766	1,557,766	1,557,766	1,487,343	339,808	1,217,958
R-squared	0.467	0.444	0.431	0.424	0.403	0.548	0.395	0.432
Bank-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank-County FE	N	N	N	N	N	Y	N	N
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to new mortgage lending growth using additional specifications for robustness. The data are at the bank-county-year level from 1994 to 2019. New mortgage lending growth is the growth of new mortgage lending originated by a given bank in a given county and year. Column (1) includes a control for the effect of lagged new mortgage lending growth. Column (2) replaces specialization lagged one period with specialization lagged three periods. Column (3) replaces specialization lagged one period with dummies of specialization constructed per county and year, being the Q4 is an indicator variable for the highest quartile and Q1 for the smallest, in the spirit of Paravisini et al. (2023). Column (4) replaces specialization lagged one period with the excess specialization in the spirit of Blickle et al. (2023). Column (5) uses as the dependent variable the growth rate at the bank-county level winsorized at the 10% level. Column (6) includes bank-county fixed effects. Columns (7)-(8) focus on an alternative boom period from 2002 to 2005 and exclude such periods, respectively. All other variables are explained in Tables 2 and 3. The data are from the FFIEC, the FDIC, and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A5: Lending, Specialization, and Monetary Policy: Alternative Mortgage and Lending Samples

	New mortgage lending growth						
	Without Filter	To Hold	All Institutions	All Institutions	Income B.	SBL	SBL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔFF×Spec	-0.0398***	-0.0186***	-0.0248***	-0.0217***	-0.0159***	-0.0233***	-0.0197*
	(0.00344)	(0.00637)	(0.00378)	(0.00390)	(0.00466)	(0.00602)	(0.0101)
Spec	-0.275***	-0.0264***	-0.0127	-0.00904	0.182***	-0.0455***	0.139***
	(0.0121)	(0.00968)	(0.00786)	(0.00834)	(0.00902)	(0.0128)	(0.0211)
ΔFF×MktSh	-0.103***	-0.0401	-0.104***	-0.101***	-0.119***		-0.00895
	(0.0291)	(0.0383)	(0.0351)	(0.0373)	(0.0305)		(0.0200)
MktSh	-1.789***	-0.556***	-0.615***	-0.489***	0.308***		-0.543***
	(0.0868)	(0.0485)	(0.0696)	(0.0775)	(0.0579)		(0.0522)
ΔFF×Spec×Nonbank				-0.0290***			
				(0.00891)			
ΔFF×MktSh×Nonbank				-0.0438			
				(0.115)			
Spec×Nonbank				-0.0567***			
				(0.0219)			
MktSh×Nonbank				-1.278***			
				(0.423)			
Observations	2,882,326	1,002,039	2,411,061	2,411,061	2,953,142	867,699	867,699
R-squared	0.258	0.457	0.413	0.413	0.441	0.373	0.376
Bank-Year FE	Y	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	N	Y	Y
County-Year-IB FE	N	N	N	N	Y	N	N
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to new mortgage lending growth using alternative mortgage market samples and an alternative lending market. The data are at the bank-county-year level from 1994 to 2019. New lending growth is the new mortgage lending growth in columns (1)-(5) and the new small business lending growth in columns (6)-(7) by a given bank in a given county and year. Columns (1) and (2) focus on all bank-county observations including markets where a given bank made less than 5 loans in the previous period and new mortgage lending originated to hold, respectively. Columns (3) and (4) focus on all institutions including depository and non-depository institutions. Column (5) differentiates between lending originated by a bank in a county and year into four different income buckets and includes county-year-income bucket fixed effects. Columns (6)-(7) focus on new small business lending. Nonbank is an indicator for non-depository institutions. All other variables are explained in Tables 2 and 3. The data are from the FFIEC and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *, *** indicate significance at the 0.1 and 0.01 levels, respectively.

Table A6: Lending, Specialization, and Monetary Policy: Alternative Samples Information Proxies

	New mortgage lending growth						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔFF$\times$Spec	-0.0189***	-0.0167***	-0.0222***	-0.0433***	-0.0190***	-0.0190***	-0.0222***
	(0.00415)	(0.00411)	(0.00500)	(0.0119)	(0.00415)	(0.00415)	(0.00500)
Spec	0.00588	0.00818	-0.0179*	-0.325***	0.00419	0.00419	-0.0176*
	(0.00854)	(0.00978)	(0.00972)	(0.0228)	(0.00834)	(0.00834)	(0.0100)
ΔFF$\times$MktSh	-0.0935***	-0.0804***	-0.0967***	-0.108***	-0.0937***	-0.0937***	-0.0964***
	(0.0312)	(0.0302)	(0.0320)	(0.0368)	(0.0312)	(0.0312)	(0.0320)
MktSh	-0.462***	-0.448***	-0.487***	-0.605***	-0.466***	-0.466***	-0.481***
	(0.0615)	(0.0683)	(0.0623)	(0.0701)	(0.0602)	(0.0602)	(0.0636)
Observations	1,529,159	1,333,918	1,362,781	1,266,627	1,557,766	1,557,766	1,337,718
R-squared	0.423	0.417	0.419	0.416	0.424	0.424	0.417
Bank-Year FE	Y	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to new mortgage lending growth for the different sub-samples used in Table 6. The data are at the bank-county-year level from 1994 to 2019 in columns (3) to (6). In columns (1) and (7) the sample spans from 1996 to 2019 and in column (2) from 2000 to 2019. New mortgage lending growth is the growth of new mortgage lending originated by a given bank in a given county and year. Columns (1) to (6) are estimated for the sub-sample of observations with information in $Newt-1$, $Newt-5$, $SameMkt$, $Dist$, $NBranches$, and $SpecD$, respectively. Column (7) is estimated for the sub-sample of observations with information in $Newt-1$, $SameMkt$, $NBranches$, and $SpecD$. All variables are explained in Tables 2, 3 and 5. The data are from the FFIEC, FDIC, and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *, *** indicate significance at the 0.1, and 0.01 levels, respectively.

Table A7: Lending, Specialization, and Monetary Policy: Bank Characteristics

	New mortgage lending growth		
	Size	NMarkets	BSpec
	(1)	(2)	(3)
ΔFF$\times$Spec	-0.0439***	-0.0743***	-0.0455***
	(0.00965)	(0.0134)	(0.00827)
Spec	-0.222***	-0.148***	-0.0290*
	(0.0204)	(0.0248)	(0.0153)
ΔFF$\times$Spec$\times$BankCharacteristic	-0.0127**	-0.0388***	0.0113***
	(0.00641)	(0.00895)	(0.00373)
Spec$\times$BankCharacteristic	-0.118***	-0.0785***	-0.0105
	(0.0131)	(0.0164)	(0.00698)
ΔFF$\times$MktSh$\times$BankCharacteristic	-0.0589**	-0.0642*	0.0642**
	(0.0274)	(0.0333)	(0.0285)
ΔFF$\times$MktSh	-0.0862***	-0.0794***	-0.0740***
	(0.0254)	(0.0237)	(0.0247)
MktSh$\times$BankCharacteristic	-0.529***	-0.516***	0.425***
	(0.0576)	(0.0702)	(0.0568)
MktSh	-0.368***	-0.387***	-0.370***
	(0.0409)	(0.0419)	(0.0402)
Observations	1,362,781	1,557,766	1,557,766
R-squared	0.420	0.425	0.425
Bank-Year FE	Y	Y	Y
County-Year FE	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County

Notes. This table estimates whether the effect of banks' local specialization on the transmission of monetary policy to new mortgage lending growth differs depending on different bank characteristics. The data are at the bank-county-year level from 1994 to 2019. New mortgage lending growth is the growth of new mortgage lending originated by a given bank in a given county and year. *BankCharacteristic* is the lagged natural logarithm of total assets, the lagged natural logarithm of the number of markets where the bank originates mortgages, and the lagged average bank specialization, in columns (1) to (3), respectively. All other variables are explained in Tables 2 and 3. The data are from the FFIEC, FDIC, and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *, **, and *** indicate significance at the 0.1, 0.5, and 0.01 levels, respectively.

Table A8: Mortgage Characteristics from Fannie Mae, Freddie Mac and HMDA

	N	mean	sd
Panel A: Population of mortgages from Fannie Mae and Freddie Mac			
MortgageSize (thousand $)	7,201,306	195.835	124.814
Rate (%)	7,201,306	5.19	1.284
NP	7,201,306	0.056	0.23
FICO	7,201,306	745.744	51.238
LTV	7,123,061	72.164	17.253
DTI	6,789,367	33.758	11.788
Panel B: Matched sample of mortgages from Fannie Mae and Freddie Mac with HMDA			
Mortgage size (thousand $)	2,144,232	196.982	123.103
Rate (%)	2,144,232	5.09	1.255
NP	2,144,232	0.053	0.224
FICO	2,144,232	746.123	52.153
LTV	2,120,595	71.939	18.582
DTI	2,003,270	32.923	11.671

Notes. This table provides summary statistics at the mortgage level for the population of mortgages from Fannie Mae and Freddie Mac, and for the matched sample with the HMDA data. Panel A and Panel B present mortgage level characteristics for the population of mortgages from Fannie Mae and Freddie Mac, and the matched sample with the HMDA data, respectively. The data are from the FFIEC, the FRED, the Fannie Mae loan performance data, and the Freddie Mac loan performance data. All variables are defined in Table 8. The underlying data are from the FFIEC, FDIC, and FRED for the years 2000 to 2017.

Table A9: Lending, Specialization, and Monetary Policy: Different Samples

	New mortgage lending growth			
	(1)	(2)	(3)	(4)
ΔFF×Spec	-0.0376***	-0.0649***	-0.0977***	-0.0998***
	(0.00418)	(0.00932)	(0.0329)	(0.0328)
Spec	-0.509***	-0.205***	-0.167**	-0.167**
	(0.0251)	(0.0440)	(0.0836)	(0.0837)
ΔFF×MktSh	-0.0609*	-0.0793	0.0474	0.0507
	(0.0344)	(0.0550)	(0.0408)	(0.0403)
MktSh	-2.488***	-2.068***	-2.280***	-2.279***
	(0.186)	(0.227)	(0.281)	(0.281)
ΔRate				-0.0810***
				(0.0121)
ΔFICO				0.0001
				(0.00008)
Observations	1,146,491	446,321	97,541	97,541
R-squared	0.441	0.578	0.468	0.469
Bank-Year FE	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County
Sample	HMDA	HMDA-SoldGSEs	HMDA-FF	HMDA-FF

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to new mortgage lending growth using different subsamples and sample periods for robustness. The data are at the bank-county level from 2000 to 2017. New mortgage lending growth is the growth of new mortgage lending originated by a given bank in a given county and year. Columns (1)-(3) report the results for the full sample of mortgages in HMDA, the subsample of mortgages originated to sell to GSEs in HMDA, and the matched sample from HMDA, Fannie Mae, and Freddie Mac, respectively. Column (4) reports the result for the matched HMDA, Fannie Mae, and Freddie Mac sample when we control for the difference in interest rates and FICO Score. All other variables are explained in Tables 2, 3, 8 and A10. The data are from the FFIEC, the FRED, the Fannie Mae loan performance data, and the Freddie Mac loan performance data. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. **, *** indicate significance at the 0.05 and 0.01 levels, respectively.

Table A10: Ex-Ante Riskiness, Ex-Post Performance, Specialization, and Monetary Policy: Bank-County Level

	ΔLTI	ΔLTI	ΔLTI	ΔFICO	ΔRate	ΔNP	ΔNP	ΔNP	ΔNP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔFF×Spec	-0.0884	0.0310**	0.00482	0.921	-0.0266*	-0.0297***	-0.0295***	-0.0281**	-0.0279**
	(0.179)	(0.0135)	(0.0413)	(1.889)	(0.0156)	(0.0113)	(0.0113)	(0.0111)	(0.0110)
Spec	-0.366	0.0102	-0.00625	0.00955	-0.00724	0.00152	0.00177	0.00198	0.00200
	(0.245)	(0.0140)	(0.0388)	(1.454)	(0.0153)	(0.00569)	(0.00575)	(0.00589)	(0.00587)
ΔFF×MktSh	1.392	0.0184	0.0424	1.210	0.0426**	0.0133*	0.0132*	0.0129*	0.0124
	(1.178)	(0.0193)	(0.0417)	(1.957)	(0.0192)	(0.00756)	(0.00755)	(0.00765)	(0.00759)
MktSh	-1.126*	0.0630*	0.224***	2.207	-0.0356**	-0.0117*	-0.00828	-0.00569	-0.00665
	(0.615)	(0.0380)	(0.0398)	(2.136)	(0.0177)	(0.00673)	(0.00716)	(0.00661)	(0.00659)
MortgageSizeGrowth	0.398***	0.122***	0.220***	0.830***	-0.0220***		0.00151	0.00272**	0.00122
	(0.0428)	(0.00694)	(0.00797)	(0.260)	(0.00295)		(0.00119)	(0.00118)	(0.00119)
ΔRate								0.0280***	0.0229***
								(0.00248)	(0.00252)
ΔFICO								-0.000725***	-0.000711***
								(0.00005)	(0.00005)
ΔLTV									0.000654***
									(0.00008)
ΔDTI									0.00002***
									(0.000005)
Observations	1,146,491	446,321	97,541	97,541	97,541	97,541	97,541	97,541	97,541
R-squared	0.233	0.124	0.238	0.294	0.800	0.284	0.284	0.311	0.312
Bank-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County
Sample	HMDA	HMDA-SoldGSEs	HMDA-FF	HMDA-FF	HMDA-FF	HMDA-FF	HMDA-FF	HMDA-FF	HMDA-FF

Notes. This table estimates the effect of banks' local specialization on the transmission of monetary policy to ex-ante measures of riskiness, the interest rate charged on the mortgage, and ex-post performance at the bank-county level for robustness. The data are at the bank-county level from 2000 to 2017. LTI, FICO, and Rate are weighted averages of the loan-to-income ratio, FICO score, and interest rate of the mortgages originated and sold to Fannie Mae or Freddie Mac by a given bank in a given county and year. NP is the weighted average of the delinquency status of the mortgages originated and sold to Fannie Mae or Freddie Mac by a given bank in a given county and year. Columns (1)-(3) report the results for the difference in the LTI for the full sample of mortgages in HMDA, the subsample of mortgages originated to sell to GSEs in HMDA, and the matched sample from HMDA, Fannie Mae, and Freddie Mac, respectively. Columns (4) and (5) report the results for the difference in the FICO score and interest rate charged on the mortgage for the matched HMDA, Fannie Mae, and Freddie Mac sample. Columns (6)-(9) report the results for the difference in the delinquency status of mortgages for the matched HMDA, Fannie Mae, and Freddie Mac sample including different controls. All other variables are explained in Tables 2, 3, and 8. The data are from the FFIEC, the FRED, the Fannie Mae loan performance data, and the Freddie Mac loan performance data. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank and county. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A11: Lending, Specialization, and Monetary Policy: Alternative Ex-Ante Riskiness Measures

	Borrower risk				Market risk	Bank risk		
	NML growth				NML growth	NML growth		
	IC1	IC2	IC3	IC4	CountyLTI	Liquidity	Capital	NPL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔFF×Spec	-0.00976	-0.0190***	-0.0377***	-0.0311***	-0.0190***	-0.0206***	-0.0224***	-0.0196***
	(0.00667)	(0.00517)	(0.00566)	(0.00655)	(0.00392)	(0.00526)	(0.00489)	(0.00561)
Spec	0.136***	0.147***	0.168***	0.171***	0.0057	-0.0176*	-0.0188**	-0.0216**
	(0.00926)	(0.0105)	(0.0135)	(0.0172)	(0.00833)	(0.00967)	(0.00960)	(0.00937)
ΔFF×Spec×Risk					-0.000073	0.00663	0.00500	0.00459
					(0.000287)	(0.00706)	(0.00533)	(0.00708)
Spec×Risk					-0.00047**	-0.00633	0.00747	-0.00141
					(0.000217)	(0.00733)	(0.00771)	(0.00702)
ΔFF×MktSh	-0.0858**	-0.116***	-0.118***	-0.123***	-0.103***	-0.106***	-0.0963***	-0.0860**
	(0.0355)	(0.0274)	(0.0374)	(0.0375)	(0.0289)	(0.0364)	(0.0333)	(0.0363)
MktSh	0.237***	0.295***	0.365***	0.284***	-0.460***	-0.486***	-0.480***	-0.481***
	(0.0443)	(0.0571)	(0.0800)	(0.102)	(0.0603)	(0.0617)	(0.0600)	(0.0560)
ΔFF×MktSh×Risk					0.00310***	-0.0437	0.00797	0.0534
					(0.000939)	(0.0630)	(0.0623)	(0.0603)
MktSh×Risk					-0.00190***	-0.0220	0.0722	-0.152***
					(0.000652)	(0.0629)	(0.0780)	(0.0393)
Observations	859,778	750,615	635,286	515,409	1,557,766	1,362,758	1,362,753	1,362,712
R-squared	0.453	0.484	0.500	0.480	0.425	0.419	0.419	0.419
Bank-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Cluster s.e.	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County	Bank&County

Notes. This table studies different proxies of risk-taking as an alternative mechanism for our main result. The data are at the bank-county-year level from 1994 to 2019. New mortgage lending growth is the growth of new mortgage lending originated by a given bank in a given county and year. Columns (1)-(4) examines the effect of specialization for the transmission of monetary policy to new mortgage lending growth for different subsamples depending on the income of borrowers, where IC1 are borrowers with the lowest income and IC4 borrowers with the highest income. Column (5) examines if the effect of specialization for the transmission of monetary policy is stronger in markets with a higher risk proxied by LTI at the county level. Columns (6)-(9) examine if the effect of specialization for the transmission of monetary policy is stronger for banks with heterogeneous risk proxied by liquidity ratio, capital ratio, non-performing loans (NPL) ratio, and return on equity (ROE), respectively. All other variables are explained in Tables 2 and 3. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A12: Bank-Level Ex-Post Performance, Specialization, and Monetary Policy

	Outstanding NP given year			New NP throughout history	
	ΔNP			ΔNP	
	(1)	(2)	(3)	(4)	(5)
ΔFF×BSpec	0.0370***	0.0414***	0.0920**	-0.00870***	-0.00954***
	(0.0133)	(0.0140)	(0.0394)	(0.00319)	(0.00338)
BSpec	0.00256	0.0128	-0.0749	-0.0131	-0.00232
	(0.0359)	(0.0508)	(0.155)	(0.0114)	(0.0112)
ΔFF×BMktsh	0.418***	0.448***	0.254*	-0.0136	-0.0180
	(0.0604)	(0.0654)	(0.140)	(0.0124)	(0.0128)
BMktsh	0.348**	0.511*	1.100**	0.000169	-0.0356
	(0.139)	(0.267)	(0.440)	(0.0250)	(0.0232)
MortgageGrowth	-0.000853	-0.0206**	0.0136	-0.00113	-0.00332
	(0.0450)	(0.0580)	(0.154)	(0.00229)	(0.00267)
ΔRate	-0.000853	-0.0206**	0.0136	0.00950*	0.0155**
	(0.00637)	(0.00845)	(0.0185)	(0.00547)	(0.00629)
ΔFICO				-0.000475***	-0.000480***
				(7.43e-05)	(8.61e-05)
ΔLTV				0.000279	0.000422**
				(0.000187)	(0.000205)
ΔDTI				0.000419*	0.000255
				(0.000245)	(0.000290)
Observations	104,590	75,300	11,510	15,081	11,516
R-squared	0.134	0.145	0.204	0.100	0.110
Bank FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	N	Y
Cluster s.e.	Bank	Bank	Bank	Bank	Bank
Sample	Call	Call	Call-HMDA-FF	HMDA-FF	HMDA-FF-Call
Period	1994-2019	2000-2017	2000-2017	2000-2017	2000-2017

Notes. This table estimates the effect of bank exposure to markets where they specialize for the transmission of monetary policy to mortgage ex-post performance. The data are at the bank-level from 1994 to 2019 in column (1) and from 2000 to 2017 in columns (2) to (5). NP is the percentage of outstanding non-performing mortgages from the U.S. Call Reports by a given bank and year in columns (1) to (3) and the percentage of mortgages originated and sold to Fannie Mae or Freddie Mac that are at least 90 days past due on their monthly payments, in foreclosure, or real estate owned through the history of the loan, by a given bank and year in columns (4) and (5). Columns (1) and (2) report the results for the full sample of banks in the U.S. Call Reports. Column (3) reports the results for the sample of banks with information in the U.S. Call Reports with information on HMDA, Fannie Mae, and Freddie Mac. Column (4) reports the results for the sample of banks with information in HMDA, Fannie Mae, and Freddie Mac. Column (5) reports the results for the sample of banks with information in HMDA, Fannie Mae, Freddie Mac, and the U.S. Call Reports. BSpec is the bank's average specialization for a given bank and year. BMktsh is the bank's average market share for a given bank and year. MortgageGrowth, FICO, LTV, and DTI are the weighted average of the FICO score, LTV ratio, and DTI ratio, respectively. Bank (not reported) controls are the lagged deposit ratio, lagged liquidity ratio, lagged leverage ratio, and lagged log of total assets. All other variables are explained in Table 2. The data are from the FFIEC, the FRED, the U.S. Call Reports, the Fannie Mae loan performance data, and the Freddie Mac loan performance data. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A13: Aggregate County Implications, Specialization, and Monetary Policy: Robustness

	New mortgage growth	HPI growth	Wage growth	Employment growth
	(1)	(2)	(3)	(4)
Panel A: JK monetary policy shocks				
MP×CSpec	-0.715***	-0.0192***	-0.0280***	-0.0229***
	(0.0617)	(0.00630)	(0.0107)	(0.00674)
CSpec	-1.229***	-0.00464	0.00301	-0.000911
	(0.0306)	(0.00312)	(0.00328)	(0.00219)
MP×CMktSh	-0.0558	0.0133	-0.00995	-0.0182*
	(0.0617)	(0.0127)	(0.0146)	(0.0100)
CMktSh	0.358***	0.0153***	-0.00101	-0.00247
	(0.0270)	(0.00286)	(0.00283)	(0.00193)
Observations	75,029	62,828	75,011	75,008
R-squared	0.501	0.402	0.230	0.217
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Fipszero FE	Y	Y	Y	Y
Additional Controls	Y	Y	Y	Y
Cluster s.e.	County	County	County	County
	New mortgage growth	HPI growth	Wage growth	Employment growth
	(1)	(2)	(3)	(4)
Panel B: Dependent variable logdifference				
ΔFF×CSpec	-0.151***	-0.0151***	-0.00912***	-0.00173*
	(0.0114)	(0.00159)	(0.00176)	(0.000940)
CSpec	-1.571***	-0.00557*	0.00324	0.000250
	(0.0426)	(0.00305)	(0.00322)	(0.00210)
ΔFF×CMktSh	-0.0319	0.000461	-0.00236	-0.00476***
	(0.0253)	(0.00248)	(0.00286)	(0.00142)
CMktSh	0.585***	0.0173***	0.000424	-0.00147
	(0.0397)	(0.00280)	(0.00276)	(0.00178)
Observations	75,029	62,828	75,011	75,008
R-squared	0.463	0.410	0.227	0.217
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Fipszero FE	Y	Y	Y	Y
Additional Controls	Y	Y	Y	Y
Cluster s.e.	County	County	County	County
	New mortgage growth	HPI growth	Wage growth	Employment growth
	(1)	(2)	(3)	(4)
Panel C: 1994 - 2013				
ΔFF×CSpec	-0.177***	-0.0159***	-0.00933***	-0.00114
	(0.0109)	(0.00166)	(0.00181)	(0.000987)
CSpec	-1.436***	-0.00384	-0.000374	-0.00262
	(0.0375)	(0.00411)	(0.00413)	(0.00269)
ΔFF×CMktSh	0.0228	0.00278	-0.00258	-0.00478***
	(0.0192)	(0.00257)	(0.00306)	(0.00158)
CMktSh	0.439***	0.0259***	0.00353	0.000377
	(0.0293)	(0.00318)	(0.00295)	(0.00212)
Observations	56,754	46,735	56,742	56,733
R-squared	0.545	0.499	0.279	0.238
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Fipszero FE	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Cluster s.e.	County	County	County	County

Notes. This table estimates the effect of county exposure to local specialized banks for the transmission of monetary policy to new mortgage lending, house price, wage, and employment growth using different specifications for robustness. The data are at the county-year level covering the years from 1994 to 2019 for Panel A and Panel B and from 1994 to 2013 for Panel C. Panel A uses monetary policy shocks following Jarociński and Karadi (2020). Panel B uses as dependent variables the log difference of new mortgage lending, HPI, total wages, and total employment. Panel C focuses on the period from 1994 to 2013. County (not reported) controls are the lagged log of the population, the lagged log of income per capita, the lagged proportion of securitized mortgages, C-HHI-Dep, C-HHI-Expo, and the interactions between these variables and the difference in the Fed funds rate. All other variables are explained in Tables 2 and 9. The data are from the FFIEC, the FRED, the FHFA, and the BLS. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by county. *, *** indicate significance at the 0.1, and 0.01 levels, respectively.

Table A14: Aggregate Bank Specialization and Monetary Policy: Robustness

	Bank's average specialization growth		
	JK Shocks	Logdifference	1994-2013
	(1)	(2)	(3)
ΔFF	-0.0446***	-0.00507***	-0.00483***
	(0.00530)	(0.000767)	(0.000703)
Observations	105,717	105,717	85,771
R-squared	0.048	0.051	0.059
Bank FE	Y	Y	Y
Bank Controls	Y	Y	Y
Cluster s.e.	Bank	Bank	Bank

Notes. This table estimates the effect of changes in the Fed funds rate on bank's average specialization growth using different specifications for robustness. The data are at the bank-year level covering the years from 1994 to 2019 for columns (1)-(2) and from 1994 to 2013 for column (3). Column (1) uses monetary policy shocks following Jarociński and Karadi (2020). Column (2) uses as dependent variables the log difference of bank's average specialization. Column (3) focuses on the period from 1994 to 2013. Bank (not reported) controls are the lagged deposit ratio, lagged liquidity ratio, lagged leverage ratio, and lagged log of total assets. All other variables are defined in Tables 2 and 10. The data are from the FFIEC and the FRED. Fixed effects are denoted at the bottom of the table. Standard errors are clustered by bank. *** indicates significance at the 0.01 level.