Nonbanks, Banks, and Monetary Policy: U.S. Loan-Level Evidence since the 1990s*

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Tuesday 25th February, 2020

Abstract

We show that nonbanks (funds, shadow banks, fintech) reduce the effectiveness of tighter monetary policy on credit supply and the resulting real effects, and increase risk-taking. For identification, we exploit exhaustive US loan-level data since 1990s and Gertler-Karadi monetary policy shocks. Higher policy rates shift credit supply from banks to less-regulated, more fragile nonbanks. The bank-to-nonbank shift largely neutralizes total credit and associated consumption effects for consumer loans and attenuates the response of total corporate credit (firm investment) and mortgages (house price spillovers). Moreover, different from the so-called risk-taking channel, higher policy rates imply more risk-taking by nonbanks.

JEL Classification: E51; E52; G21; G23; G28
Keywords: Nonbank Lending; Monetary Policy Transmission; Risk-Taking Channel.

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1 Introduction

The structure of credit markets has dramatically changed over the recent decades. Nonbank credit intermediaries, which are less regulated and supervised than banks, now have a significant presence in many credit markets . In US mortgage market fintech lenders account for more than 50% of mortgage originations. Similarly, finance companies capture about one half of the consumer lending market, and in corporate lending, collateralized loan obligations (CLOs) and investment funds are key players.[1] While a large literature shows that banks cut their credit supply and reduce risk-taking in response to a tightening of monetary policy, it is unclear whether, and how, nonbank lenders affect monetary policy transmission. Despite the academic and policy importance of how nonbanks affect the transmission of monetary policy, evidence is scant, mainly due to dearth of data on nonbanks.

Different views on the role of nonbanks in monetary policy transmission have emerged. On the one hand, the then-Governor of the Federal Reserve, Jeremy Stein, pointed out that monetary policy (relative to prudential policy) "gets in all the cracks" by acting directly on market rates and spreads (Stein 2013).[2] In other words, tighter monetary policy negatively affects the funding conditions of all financial intermediaries that borrow short-term, suggesting that bank and nonbank credit should respond similarly to monetary policy. On the other hand, tighter monetary policy reduces banks' credit supply via a reduction in bank reserves (Kashyap and Stein 1995; 2000; Stein 1998) and deposit outflows (Drechsler, Savov, and Schnabl 2017), which shift to nonbanks (Xiao

[1]Though our paper is about US and nonbanks in US are very important, nonbanks are also crucial in Europe (ECB, 2019) and in China (Chen, Ren, and Zha 2018).

[2]See also the Jackson Hole paper by Greenwood, Hanson, and Stein (2016). Caballero and Simsek (2019) provide a model linking asset prices to monetary policy.

forthcoming). Therefore, these views have conflicting predictions about whether the expansion of nonbank attenuates or strengthen the bank lending channel of monetary policy. For the risk-taking channel of monetary policy, prior studies show that low monetary policy rates increase banks' risk-taking substantially (Adrian and Shin 2010; Allen and Rogoff 2011; Borio and Zhu 2012; Diamond and Rajan 2012; Jimenez et al. 2014), while Rajan's (2005) Jackson Hole Paper and Di Maggio and Kacperczyk (2017) argue that nonbank intermediaries are also affected by low monetary policy rates. Therefore, similar to the bank lending channel, these views have conflicting predictions about how the risk-taking channel of monetary policy is affected by nonbanks.

Our main contribution to the literature is to show how nonbanks affect the effectiveness of monetary policy transmission to credit supply (and real effects) as well as the nonbank risk-taking of monetary policy by exploiting US loan-level data since 1990s for mortgages, corporate and consumer loans in conjunction with Gertler and Karadi (2015) monetary policy shocks. In brief, our robust results show that higher policy rates shift credit supply in all credit markets from regulated banks to less regulated, more fragile nonbanks. We first show that nonbanks reduce the effectiveness of the bank lending channel using loan-level data to isolate credit supply effects. However, when we then aggregate up to the industry-level for corporates or at the country-level for household loans, we find that the overall reduction in credit supply varies across lending markets, depending on the ex-ante size of nonbanks in the respective market. Total credit and real effects are largely neutralized in consumer loans (and the associated consumption), but not in corporate loans (and firm investment) or mortgages (and house prices). Finally, different from the so-called risk-taking channel of monetary policy, stating that lower policy rates result more risk-taking by banks, higher policy rates result in more risk-taking by nonbanks in all markets via higher credit supply, especially to ex-ante riskier borrowers. This finding implies that monetary policy redistributes risk across the financial system.

Preview of the paper In this paper we analyze the impact of monetary policy on lending (the supply of credit), and the associated real effects. We also analyze the distribution of risk. We analyze the key three credit markets: corporate loans, consumer credit and mortgages. For monetary policy, we use Gertler and Karadi (2015) shocks.[3] All our data starts in the 1990s, with considerable time-series policy rate variation and significant cross-sectional (firm/industry and household/county) variation on ex-ante dependence of nonbank lending. In all markets, our loan-level data allow us to identify whether the lender is a bank or a nonbank, in contrast to central banks' credit registers around the world, which do not have nonbanks but just banks, to the best of our knowledge.[4]

We start our empirical analysis of the nonbank lending channel of monetary policy on the loan-level in the corporate loan market. Using Thompson Reuters LPC DealScan (DealScan) database, we identify nonbank lenders and originations of new syndicated loans. The main advantage of studying syndicated loans is that they are originated by multiple lenders. This feature allows us to control for firm-level time-varying unobserved fundamentals (including firm-level demand) and therefore to identify the effects of monetary policy by comparing credit supply of bank and nonbank lenders to the same borrower in the same quarter controlling for a rich set of nonbank - macroeconomic variable (GDP, GDP forecast, inflation, and VIX) interactions.

Using this within-borrower variation in credit (i.e., firm-quarter fixed effects), we

[3]For robustness, we also use Fed Funds rates and shadow rates Wu and Xia (2016) and find similar results.

[4]The exception is the Shared National Credit Program in the U.S., which is recording the holders of syndicated loans but not originations (Irani et al. 2018).

find that nonbanks expand credit supply to US corporate borrowers after a monetary contraction relative to their bank peers. Nonbank credit supply increases by 12 percent relative to bank credit supply after a one standard deviation increase in the monetary policy measure, attenuating the bank lending channel. Moreover, the increase in credit supply is larger for ex-ante riskier firms, especially on credit line lending.

The substitution from bank to nonbank credit, however, is only partial. Substitution can be limited by the nature of the syndication process, which relies heavily on soft information and therefore involves high switching costs for borrowers and lenders. We therefore study whether borrowers that have established relationships with nonbank lenders in the past, which reduce borrower-lender frictions, are better able to access credit when monetary policy tightens. We find that borrowers that have previously borrowed from nonbanks experience a larger relative expansion in credit following monetary contractions, which is associated with a reduction in firm-level liquid asset holdings and an increase in total debt and investment. These findings suggest that nonbank lending relationships attenuate the bank lending channel and support real economic activity.

While the loan-level regressions with a rich set of fixed effects are useful to identify the presence of the nonbank channel, aggregating the results to general equilibrium effects is challenging (Nakamura and Steinsson 2018). Specifically our firm-level analysis would also be consistent substitution of investment within the same industry without an overall change in industry output. To get closer to the aggregate effect, we therefore conduct an industry-level analysis. We find that industries with ex-ante higher nonbank presence maintain higher debt, higher leverage, and higher investment and exhibit higher output after monetary contractions, suggesting that the mechanism with identify with loan-level data is also economically relevant in the aggregate.

Next, we turn to nonbank lending to U.S. households and focus first on consumer loans. We analyze auto loans, as in this market we have whether the lender is a bank or a nonbank. This market moreover represents over 30 percent of total consumer credit, and within the auto loans, finance companies account for about half of the lending market. We have detailed, household-level data from Equifax, a major credit bureau. Since customers often apply for auto credit at the auto dealer at the time of the auto purchase and those dealers have long-term arrangements with specific lenders, nonbank lenders are more likely to expand operations in locations in which they are already present. Exploiting this regional heterogeneity for the purpose of identifying the lending response of monetary policy, we show that households living in counties historically more dependent on nonbank credit experience a larger expansion of nonbank auto credit after a monetary contraction, while bank retrench more in counties in which they have a weaker presence. A one standard deviation contractionary monetary policy shock leads to a 10 percent increase in nonbank auto credit, completely offsetting the banks' cut in auto credit.

We then test whether the effects are larger for low credit score borrowers. By exploiting historic dependence on nonbank credit with monetary policy and the household risk score, we can also alleviate remaining concerns about time-varying unobservable county-level conditions—that is, we (can) include county-quarter fixed effects. We confirm perfect substitution between bank and nonbank credit and also find that nonbank credit is more sensitive to monetary policy for low credit score borrowers. This finding suggests that nonbanks take more risk in response to a monetary contraction.

To assess the real effects of substitution in consumer lending and to get closer to the general equilibrium effects in this market, we study whether county-level auto sales are affected by monetary policy.[5] Since most auto sales use some form of financing and our results on auto credit show perfect substitution between bank and nonbank credit, monetary policy is unlikely to affect auto sales via auto credit. Indeed, we find no significant average effects of monetary policy on auto sales on the county level. Only in counties in which substitution of bank and nonbank credit is limited—that is, in counties with a historically low nonbank dependence—do auto sales (and credit) fall in response to a monetary contraction.

Last, we study the largest lending market, mortgages, using Home Mortgage Disclosure Act (HMDA) data. We use the confidential version, which – unlike the publicly available version – includes the mortgage origination and action dates allowing us to study mortgage origination on the quarterly level.[6] To identify the response of nonbank lending to monetary policy, we control for demand with county-quarter fixed effects and find that on the loan level nonbanks expand lending relative to banks after a monetary contraction. This effect is more pronounced in the jumbo loan segment.

Aggregating to the county-level and focusing *only* on loans that remain on the lenders' balance sheets, we find that nonbanks expand lending somewhat in the conforming mortgage market and significantly in the jumbo loan market. As in the auto loan market, nonbanks relatively expand mortgage lending more in locations in which they have been more present in the past, while banks retrench more in counties in which they have a weaker ex-ante presence. There is more risk-taking by nonbanks after a monetary contraction in the mortgage market as jumbo loans can be considered as riskier in the sense that they cannot be sold later to government-sponsored enterprises (GSEs) and tend to

[5]This is comparable to industry-level results for corporate loans were we measure but dependence on the industry-level and rather than the county level.

[6]The non-confidential HMDA has data only at the yearly level, which is not ideal to study the effects of higher frequency phenomena such as monetary policy.

have higher loan volumes and potentially higher LTVs. Hence, our results on risk-taking are consistent across the three markets.

When we consider total mortgage lending, we find a positive effect of past nonbank dependence on total lending after a monetary contraction. This relative increase in total credit also results in relative higher house prices in counties with high past nonbank dependence when compared to counties with low past nonbank dependence. In sum, we find evidence for substitution in the mortgage market, a significant increase in the nonbank share in the potentially higher risk jumbo mortgage market, and house price spill-overs.

Our results show that the transmission of monetary policy varies across credit markets. Markets in which banks are more special (for corporate loans, soft information is more important) experience only a limited expansion of nonbank credit and therefore less attenuation of the potency of monetary policy. However, across all markets nonbanks significantly increase the risk-taking channel after a tightening of monetary policy and there is always a shift of credit supply from regulated banks to less regulated, more fragile nonbanks.

One remaining question is why nonbanks are able to expand their credit supply after a monetary contraction. To answer this question, we investigate the connection between monetary policy and nonbank funding conditions. MMFs provide funding to nonbanks by purchasing their bonds, notes, and (asset-backed) commercial paper. Using aggregate data for the money market fund (MMF) sector, we show that MMFs experience inflows in response to contractionary monetary policy. Moreover, we show that MMFs increase their holdings of bonds and (asset-backed) commercial paper, expanding funding available to nonbanks and thereby allowing nonbanks to expand their credit supply. One implication of this finding is that nonbanks finance their expansion of riskier assets—credit to more risky borrowers—after monetary contrary with fragile funding.

Contribution to the Literature Our main contribution is to the large literature on the transmission of monetary policy and credit by adding the response of nonbanks to monetary policy. In more detail, there is a large literature showing that banks cut the supply of credit due to tighter monetary policy conditions: the so-called bank lending channel of monetary policy (e.g., Bernanke and Blinder (1988; 1992), Kashyap and Stein (2000), Jimenez et al. (2012), Drechsler, Savov, and Schnabl (2017)), in turn affecting the credit channel of monetary policy (Bernanke and Gertler 1995). However, as highlighted above, theory and policymakers are not clear on whether nonbanks can mitigate the credit supply reduction. Therefore, a key contribution of our paper is to show that the presence of nonbanks attenuates the bank lending channel, so that total credit supply and real effects react less after a tightening of monetary policy when nonbanks are present and the degree of this attenuation depends in the ex-ante size of nonbank presence.

Moreover, we also contribute to the literature on the risk-taking channel of monetary policy (e.g., Adrian and Shin (2010), Jimenez et al. (2014), and dell'Ariccia, Laeven, and Suarez (2017)) by analyzing this channel for *both* banks and nonbanks. In particular, we find that nonbanks concentrate their credit supply more on ex-ante riskier borrowers when monetary policy conditions are tighter, which—in conjunction with the results on relatively higher credit supply from less regulated nonbanks than from banks—suggest a different interpretation on the risk-taking channel of monetary policy from the existing papers on the literature using only bank loans.[7] We find that the ex-ante size of nonbank

[7] Moreover, nonbanks receive a significant amount of funding from money market mutual funds, which are themselves more fragile, adding another layer of fragility to nonbank credit provision.

presence crucially affects the effectiveness of monetary policy and the distribution of risk across different lenders.

One recent paper, Chen, Ren, and Zha (2018), analyzes the impact of monetary policy on banks and shadow banks and concludes that nonbank lenders reduce the effectiveness of monetary policy in China.[8] Our paper differs on multiple dimensions. Our results show that the substitution is large (and complete) only in consumer loans and not corporate loans and mortgages; however, the risk-taking by nonbanks is similar across all three markets. Differently from the Chinese paper, we use loan-level data to trace the effectiveness of monetary policy, which allows us to control for credit demand and analyze risk-taking. Chen, Ren, and Zha (2018) use bank-level data and hence cannot identify credit demand versus supply driven effects or assess risk-taking. Importantly, as we can match firms and households to lenders, we also analyze the real effects associated with different types of credit supply and monetary policy, which are crucial for theory analysis and for central banking policy.

We also contribute to the literature on nonbanks. The increased presence of nonbanks in lending markets can be attributed to technological advances, liquidity transformation, and superior information (Buchak et al. 2018a; Ordoñez 2018; Moreira and Savov 2017). Bank regulation has also contributed to more nonbank participation in the syndicated loan market (Irani et al. 2018). This increased presence of nonbanks in many credit markets may lead to better allocation of risk and lower borrowing costs for households (Fuster et al. 2018) and firms (Ivashina and Sun 2011; Shivdasani and Wang 2011; Nadauld and Weisbach 2012), though it may result in worse real effects and asset-price effects in crisis

[8] Buchak et al. (2018b) assess the interplay of nonbank lenders and monetary policy in a structural model. Drechsler, Savov, and Schnabl (2019) study the expansion of nonbank lending between 2004 and 2006. In contrast, we assess the role of nonbank lending in the transmission of monetary policy in three important markets using large loan-level datasets.

times (Irani et al. 2018). Relative to this literature, we show that monetary policy affects nonbank presence, and that there is more risk-taking by nonbanks when monetary policy tightens, thereby changing the distribution of risk in the economy.

The paper proceeds as follows. Section 2 summarizes the data that we use in the paper. Section 3 presents the results and the empirical strategy for the response of nonbank credit extended to corporate borrowers to monetary policy shocks, while Section 4 examines household credit. In section 5 we study bank and nonbank lending in the mortgage market. Section 6 provides evidence on the effect of monetary policy on nonbank funding conditions. Section 7 concludes.

2 Data

Monetary policy measures Our main measure of monetary policy is the time series of monetary policy shocks constructed by Gertler and Karadi (2015). This measure is based on high-frequency changes in three-month-ahead Fed Funds futures around FOMC policy announcements (referred to as FF4 by Gertler and Karadi (2015)). Following Coibion (2012) and Nelson, Pinter, and Theodoridis (2017), we convert this measure of *shocks* to monetary policy into a *level* measure by taking the cumulative sum. This measure is available from 1990 to 2012.[9]

Syndicated loans We obtain transaction-level information on syndicated loan originations from DealScan. DealScan provides a lender classification, which allows us to identify most lenders as either banks (deposit-taking institutions) or nonbanks. Following Roberts

[9]For robustness, we use two additional measures of monetary policy in robustness tests: the Fed Funds target rate, and the shadow rate of Wu and Xia (2016). The shadow rate is essentially equal to the effective Fed Funds rate when this is above the zero lower bound. But unlike the Fed Funds rate, the shadow rate is not bounded below by zero.

(2015), we drop loans that we identify as likely to be amendments, because these do not necessarily involve 'new' money. We match the loan-level data in DealScan to borrower-level data in Compustat using the updated link provided by Chava and Roberts (2008). We collapse the dataset to the borrower-quarter level or the borrower-lender-quarter level. Lender classification, amendment identification, and summary statistics are provided in Appendix A.

Credit Bureau Data We use data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (FRBNY/Equifax CCP). These data are available quarterly and extend back to 1999. We draw a 10 percent random sample from Equifax, which yields a panel of about 1.6 million households. In this data, we observe auto loan balances by lender type (bank, nonbank) that allows us to construct new lending to consumers (for details and summery statistics, see Appendix A).

Mortgage Data We use the confidential mortgage application data that includes the origination date collected under the Home Mortgage Disclosure Act (HMDA). HMDA records the vast majority of approved home mortgages in the United States. The loan-level data include loan and borrower characteristics as well as the name of the lender. We use the respective GSE-limits to distinguish conforming and jumbo mortgages.[10] Conforming mortgages have loan amount up to the GSE-limit, while jumbo loans exceed the GSE-limit. Nonbank identification and summary statistics are described in Appendix A.

[10] We match the specific MSA-level limits to the HDMA data.

3 Monetary Policy and Nonbank Lending to Firms

In this section we explore the relationship between monetary policy and nonbank lending to firms using data on syndicated loan originations. We then study how monetary policy affects the distribution of risk between bank and nonbank lenders and the real effects associated with nonbank lending on the firm and industry level.

The U.S. Syndicated Loan Market

Annual gross issuance in the US syndicated loan market grew from $240 billion in 1990 to $2,047 billion in 2007, before falling sharply during the global financial crisis. The market recovered from 2010, and $2,628 billion was issued in 2017 (Figure A1). Typically, a borrower will take out a "package" that includes several individual loan "facilities." The two main types of facility are credit lines and term loans. Credit lines provide borrowers with a source of funds that can be drawn down and repaid flexibly over the lifetime of the facility. Term loans are instead drawn down as a lump sum and are then subject to a defined repayment schedule (which may be amortizing or non-amortizing). Over the period 1990-2017, credit lines accounted for 48 percent of total syndicated lending (by dollar value), term loans for 26 percent and other loans for 26 percent.

We exploit the structure of the syndicated loan market to tighten the identification of monetary policy effects for two reasons. First, syndicated loan facilities are extended by multiple lenders to one borrower. This feature allows us to analyze within-borrower variation at the time of loan origination alleviating concerns about unobservable borrower or loan characteristics. Specifically, we use borrower-quarter fixed effects, which are, except for rare cases, equivalent to loan package fixed effects and control for unobserved borrower characteristics at the time of loan origination in the spirit of Khwaja and Mian (2008) and Jimenez et al. (2012).[11] Second, while borrowers choose the lead arranger, the participating members of the syndicate are typically beyond the borrower's control as they are the result of a book building process (Bruche, Malherbe, and Meisenzahl forthcoming).[12] Hence, the composition of the syndicate originating the loans is typically not affected by the borrower's loan demand but by the overall credit supply provided by different types of financial institution. We exploit the supply-driven composition of syndicates to isolate differential responses of credit supply of different financial institutions to a monetary policy shock.

We assess whether nonbanks expand credit supply relative to their bank peers in response to a monetary policy shock. Nonbank lenders active in the syndicated loan market rely often rely short-term funding to fund themselves. In the credit line segment, investment banks, who do not take deposits but fund themselves on the short-term market (e.g. repo), are key nonbank participants. In the term loan market a multitude of nonbank lenders such as colleralized loan obligations (CLOs), which use short-term credit to finance warehousing before security issuances, mutual funds, which respond to in- and outflows, as well as pension funds and insurance companies, which have more stable funding sources. Given the short-term funding market reliance of numeours nonbank participants in the syndicated loan market, nonbanks should be able to compete more intensive with banks and increase their market share after a monetary contraction.

Firm-Level Credit

At the loan level, we first test whether nonbanks expand their syndicated lending

[11] When we split the sample by term loans and revolving credit lines, the borrower-quarter fixed effects are de facto loan facility-fixed effects (Irani and Meisenzahl 2017).

[12] Most lead arrangers are banks.

relative to banks. We then test our second hypothesis that the effect is stronger for riskier firms. We estimate the following regression.

$$\begin{aligned}\text{Log(Quantity)}_{b,l,t} \quad &= \quad \beta_1 \left(\text{Nonbank}_l \times \text{Monetary Policy}_{t-1}\right) \\ &+\beta_2 \left(\text{Nonbank}_l \times \text{Macroeconomic Controls}_{t-1}\right) + \alpha_{b,t} + \delta_l + \varepsilon_{b,l,t}\end{aligned} \tag{1}$$

wherhe b indexes borrowers, l indexes lenders, and t indexes quarters. The dependent variable, $\text{Log(Quantity)}_{b,l,t}$, is the log of the amount of credit extended by lender l to borrower b in quarter t.[13] In separate regressions, we consider total lending, total term loans, and total revolving credit facilities. Nonbank_l is a dummy variable indicating non-bank lenders. The main explanatory variable of interest is the interaction of the nonbank dummy with $\text{Monetary Policy}_{t-1}$, which is measured as cumulative sums of Gertler-Karadi shocks (demeaned). We also include interactions of the dummy variables with four demeaned macroeconomic controls: VIX, GDP growth, one quarter ahead GDP forecast, and CPI inflation. We saturate the model with borrower-quarter fixed effects to account for unobservable borrower and loan characteristics at the time of origination. We also include lender fixed effect to account for time-invariant lender characteristics (e.g. the business model).

Table 1, panel A shows the results of estimating equation 1 for the sample of dollar-denominated loans extended to U.S. borrowers. Since we include borrower-time fixed effects, we control for credit demand and unobservable firm characteristics at the time of loan origination (Khwaja and Mian 2008; Jimenez et al. 2012). We find that nonbanks expand credit supply to firms in response to a monetary policy shock when compared to

[13] In the Appendix B, we consider lending by lender type without controlling for demand-that is, with time fixed effects and also find a relative expansion of nonbank credit.

Table 1

Impact of US monetary policy on US corporate lending

The table shows estimated regression coefficients for equation 1 including interactions with a high-yield borrower indicator. The dependent variable is the log of lending quantity from DealScan. Only observations where lender shares are observed are included. GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. The regressions are at quarterly frequency. The sample period is 1990-2012. Macroeconomic controls are inflation, GDP growth, GDP growth forecast and VIX. Macroeconomic controls are lagged by one quarter. The sample consists of dollar-denominated loans where the borrower country is the USA. Standard errors in parentheses are clustered by borrower, lender and quarter. All variables are defined in Appendix A.

	Log(Total Credit Amount)					
	All Loans	Term Loans	Revolvers	All Loans	Term Loans	Revolvers
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Borrower-quarter fixed effects						
Nonbank x GK	0.135***	0.193***	0.0585**	0.0549	0.308**	-0.0135
	(0.0309)	(0.0488)	(0.0268)	(0.0387)	(0.128)	(0.0512)
Nonbank x High yield x GK				0.205***	-0.0261	0.194***
				(0.0456)	(0.103)	(0.0520)
Nonbank x High yield				0.0748*	0.190**	0.0255
				(0.0395)	(0.0861)	(0.0506)
Double Interactions	YES	YES	YES	YES	YES	YES
Triple Interactions	NO	NO	NO	YES	YES	YES
Borrower-quarter FEs	YES	YES	YES	YES	YES	YES
Lender FEs	YES	YES	YES	YES	YES	YES
Observations	92,971	14,956	54,312	46,900	4,887	25,107
Number of borrowers	6,589	1,921	4,804	1,744	393	1,336
Number of lenders	2,053	1,026	1,268	1,186	520	845
Number of quarters	90	90	90	90	88	90
R-squared	0.811	0.817	0.829	0.792	0.819	0.804
Panel B: No borrower fixed effects						
Nonbank x GK	0.105**	0.0839	-0.0116	0.147*	0.428**	-0.00855
	(0.0408)	(0.0916)	(0.0514)	(0.0883)	(0.165)	(0.0567)
Nonbank x High yield x GK				0.109	-0.236	0.135*
				(0.0718)	(0.148)	(0.0785)
Nonbank x High yield				-0.468***	-0.445***	-0.363***
				(0.0699)	(0.133)	(0.0622)
Double Interactions	YES	YES	YES	YES	YES	YES
Triple Interactions	NO	NO	NO	YES	YES	YES
Quarter FEs	YES	YES	YES	YES	YES	YES
Lender FEs	YES	YES	YES	YES	YES	YES
Observations	98,851	16,736	58,124	47,280	4,996	25,294
Number of borrowers	10,140	3,405	7,530	1,902	487	1,451
Number of lenders	2,270	1,161	1,414	1,204	527	855
Number of quarters	90	90	90	90	88	90
R-squared	0.335	0.393	0.289	0.291	0.536	0.314

their bank peers for the same borrower in the same quarter. This result holds for total lending (column 1), term loans (column 2), and credit line (revolver) extensions (column 3).[14] In other words, the funding mix in corporate lending syndicated shifts from banks

[14] We find similar results when we use the monetary policy measure of Wu and Xia (2016) or the

to nonbanks after a monetary contraction.

We now assess our second hypothesis that this substitution is stronger for riskier loans. We study which type of borrower is benefitting most from the substitution of bank credit with nonbank credit. For this purpose, we use the DealScan-Compustat merged sample provided by Michael Roberts and use the S&P long-term issuer credit rating as an indicator for borrower risk. Specifically, we interact a high-yield rating indicator with our nonbank and macroeconomic variables.[15] The variable of interest is the triple interaction of the nonbank indicator with the monetary policy variable and the high-yield rating indicator. Given that banks typically retrench from the riskiest borrowers first (Liberti and Sturgess 2018; de Jonge et al. 2018), we expect the substitution to be strongest for the marginal, more risky borrowers—that is, we expect the coefficient on the triple interaction to be positive and significant.

Table 1, panel A, columns 4-6 show the results of including the triple interaction in equation 1. We find that overall substitution is larger for high-yield borrowers (column 4). This effect is driven by credit lines (column 6): for term loans, we find no association between substitution and borrower risk (column 5).

Table 1, panel B, shows the results of estimating the regressions in panel A without borrower fixed effects. Comparing the results in panel A to those in panel B therefore allows us to assess the impact of firms' credit demand. The magnitude and the significance of the point estimates change significantly. We therefore conclude that accounting for demand factors is crucial for understanding how the bank-nonbank financing mix of corporate loans changes after a monetary contraction.

Federal Funds Rate.

[15] We also include the lower interactions as controls.

Firm Real Effects

A natural question is whether the relative expansion of nonbank credit affects firm-level outcomes. To answer this question, we test our third hypothesis: that having an existing relationship with nonbank lenders increases credit supply to a borrower after a monetary contraction, and that this expansion of credit supply has real effects on the firm level. A key friction in the syndicated loan market is that lending is based on soft information (Sufi 2007). Hence, borrowers with prior relationships with nonbanks should experience a larger increase in credit supply from nonbanks after a monetary contraction. To measure whether a borrower has prior nonbank relationships, we construct an indicator variable that is equal to one if the firm has borrowed from a nonbank in a previous syndicated loan. We only consider prior loans that were originated at least 2 years before the current quarter.[16] Our hypothesis is that borrowers with prior nonbank relations receive more credit and are therefore able to reduce precautionary cash holdings and increase investment. To test this hypothesis, we estimate the following regression:

$$\begin{aligned}\text{Outcome}_{b,i,t} \quad = \quad & \beta_1 \left(\text{Nonbank Relation}_b \times \text{Monetary Policy}_{t-1}\right) \\ & +\beta_2 \left(\text{Nonbank Relation}_b \times \text{Macroeconomic Controls}_{t-1}\right) + \alpha_b + \delta_{i,t} + \varepsilon_{b,i,t}\end{aligned} \tag{2}$$

where b indexes borrowers, i indexes borrower industry, and t indexes quarters. We consider several different dependent variables: the log of the amount of credit obtained through the syndicated loan market in quarter t, the log of the amount of credit obtained through the syndicated loan market in quarter t, the log of total debt on the balance sheet, leverage, the ratio of liquid assets to total assets, and the ratio of property, plant and

[16]We use this time window to avoid potential issues with refinancing. The results do not change if we instead include all previous loans.

equipment to total assets. As explained above, Nonbank Relation$_b$ is a dummy variable indicating nonbank participation in prior syndicated loans (excluding loans in the last two years). The main explanatory variable of interest is the interaction of the Nonbank Relation dummy with Monetary Policy$_{t-1}$. As before, we also include interactions of the nonbank relation dummy with four macroeconomic controls. We saturate the model with borrower fixed effects and industry-quarter fixed effects to account for unobservable borrower characteristics and industry-wide shocks.

Table 2

Real effects of US monetary policy in the U.S. corporate sector

This table shows estimated regression coefficients for equation 2. The dependent variable in column 1 is the log of total quantity of dollar-denominated syndicated loans, from DealScan. The dependent variables in columns 2 – 5 are balance sheet variables derived from Compustat (all in logs). GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. 'Nonbank relation' is an indicator variable equal to one for firms that have previously borrowed from a nonbank (excluding loans within the previous two years). The regressions are at quarterly frequency. Borrower controls are log of assets and past nonbank relations. The sample period is 1990-2012. The sample consists borrowers headquartered in the USA. Standard errors in parentheses are clustered by borrower and quarter. All variables are defined in Appendix A.

	Borrowing (1)	Total debt (2)	Leverage (3)	Liquidity (4)	Investment (5)
Past Nonbank relation x GK	0.0885**	0.0575***	0.0232***	-0.0048**	0.0065***
	(0.0418)	(0.0181)	(0.0232)	(0.0022)	(0.0024)
Macro Variable Interactions	YES	YES	YES	YES	YES
Borrower Controls	YES	YES	YES	YES	YES
Borrower FEs	YES	YES	YES	YES	YES
Industry-quarter FEs	YES	YES	YES	YES	YES
Observations	21,762	316,703	437,039	475,733	452,586
Number of borrowers	5,547	9,589	10,452	10,532	10,260
Number of quarters	83	83	83	83	83
R-squared	0.84	0.93	0.69	0.68	0.90

Table 2 shows the results from estimating equation 2. We find that borrowers with prior nonbank relationships receive more new credit in the syndicated loan market after a monetary contraction (column 1). Firms without prior nonbank relationships are not able to substitute syndicated loans with other types of credit, as firms with prior nonbank relationships also exhibit higher total debt (column 2) and higher leverage (column 3) after a monetary contraction. Having access to additional credit as a result of prior nonbank relationships reduces the need for precautionary savings in the form of liquid assets (column 4). Firms with prior nonbank relationships are also able to invest more in property, plants and equipment (column 5).

Industry-level Real Effects

We expand our analysis of real effects by analysis the importance of nonbank lending on the industry level. By aggregating to the industry level, we reduce the noise from infrequent firm-level borrowing. In the spirit of the firm-level analysis, we expect that firms in industry that were historically more dependent on nonbank credit should experience a smaller reduction in credit supply and therefore should expand relative to less nonbank-credit-dependent industries. We aggregate the quarterly firm-level outcomes (total debt, leverage, liquidity, and investment) to the 3-digit NAICS industry-level using Compustat. We obtain quarterly industry-level employment from BLS and annual industry-level output measures from 1997 on from the Bureau of Economic Analysis.[17] Using Dealscan, we calculate the past nonbank share as the average nonbank share 1990-96 for the sample of borrowers headquartered in the U.S. To test the industry-level hypothesis, we estimate the following regression at the annual frequency:

$$\begin{aligned} \text{Outcome}_{i,t} \;=\; & \beta_1 \left(\text{Past Nonbank Share}_i \times \text{Monetary Policy}_{t-1}\right) \\ & + \beta_2 \left(\text{Past Nonbank Share}_b \times \text{Macroeconomic Controls}_{t-1}\right) + \alpha_i + \delta_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where Past Nonbank Share$_i$ is the share of nonbank credit of total credit to industry i

[17]The quarterly industry-level output data are only available from 2005 on.

Table 3
Industry-level real effects of US monetary policy

Panel A of this table shows estimated regression coefficients for equation 3 on the 3-digit NAICS-industry level. Total debt, Leverage, Liquidity, and Investment are industry-level aggregate from Compustat. Employment is taken from the Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) dataset. Panel B of this table shows estimated regression coefficients for equation 3. Panel A regressions are at quarterly frequency. The dependent variables in columns 1 and 2 are industry level output and value added from the Bureau of Economic Analysis (BEA) GDP by industry dataset (all in logs). Panel B regressions are at annual frequency. In both panels, GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. 'Nonbank share' is the share of nonbanks in industry-level lending 1990-1996. The nonbank share is calculated on sample consisting of borrowers headquartered in the USA. The sample period is 1997-2013. Standard errors in parentheses are clustered by industry and year. All variables are defined in Appendix A.

Panel A: Quarterly Industry Level Outcomes

	Total debt	Leverage	Liquidity	Investment	Log(Employment)
	(1)	(2)	(3)	(4)	(5)
Past Nonbank share x GK	1.282	0.334***	-0.111*	0.222**	0.373
	(1.298)	(0.123)	(0.0639)	(0.0861)	(0.290)
Macrovar Interactions	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES
Observations	3934	4407	4407	4407	4917
Number of industries	71	72	72	72	78
Number of quarters	63	63	63	63	63
R-squared	0.923	0.766	0.754	0.943	0.990

Panel B: Annual Industry Level Outcomes

	Log(Real Gross Output)	Log(Real Value Added)
	(1)	(2)
Past Nonbank Share x GK	1.191**	0.999**
	(0.458)	(0.387)
Macrovar Interactions	YES	YES
Industry FE	YES	YES
Year FE	YES	YES
Observations	1,054	1,054
Number of Industries	62	62
R-squared	0.98	0.97

extended between 1990 and 1996. Quarterly outcomes are total debt, leverage, liquidity, investment, and employment. Annual outcomes are real gross income and real value added.

Table 3, Panel A shows the results of estimating equation 3 for outcomes measured on the quarterly frequency. Consistent with the firm-level results, we find that industries with more prior nonbank relationships have higher total debt (column 1), higher leverage (column 2) and lower liquidity (column 3) after a monetary contraction. Column 4 shows that industries with prior nonbank relationships are also able to invest more in property, plants and equipment. For employment, the point estimate is positive but statistically insignificant (column 5).

To assess whether the positive effects of nonbank relationships on industry-level borrowing and investment also translate in higher output, we now estimate equation 3 for output measured on the annual frequency. Table 3, Panel B shows the results. The point estimate reported in column 1 shows that after a monetary contraction industries with large historical nonbank shares have a higher real gross output relative to industries with low historical nonbank share. For the mean nonbank share industry (0.08), a one-standard-deviation increase in GK is associated with approximately 7% relative increase in output. Column 2 shows that this results also hold for real value added.

In sum, the results presented in this section show that nonbanks expand credit supply in the syndicated loan market relative to banks after a contractionary monetary policy shock. This suggests that the presence of nonbank lenders can significantly attenuate the bank lending channel of monetary policy. Moreover, the substitution from bank credit to nonbank credit is strongest for riskier borrowers, suggesting that nonbank lenders also attenuate the risk-taking channel of monetary policy. The partial substitution of bank credit with nonbank credit has real effects as firms with prior nonbank relationships (industries with high historical nonbank dependence) receive relatively more credit and invest (produce) more following a monetary contraction.

4 Monetary Policy and Nonbank Auto Lending

In this section we explore the relationship between monetary policy and nonbank lending to consumers using credit bureau data on auto loans.

The U.S. Auto Loan Market

Most new cars in the United States are bought on credit or leasing. At its peak in 2006, auto credit was $785 billion, accounting for 32% of consumer debt. Nonbank lenders, captive auto finance companies (e.g. Ford Motor Credit) and independent auto finance companies, have always been an important source of financing for auto purchases and particularly so for borrowers with lower credit scores (Barron, Chong, and Staten 2008). Most nonbank lenders in the auto loan market use short-term funding markets to finance the extension of new loans. These loans are then securitized. Benmelech, Meisenzahl, and Ramcharan (2017) provide a detailed account of the evolution of nonbank credit in the auto loan market and its financing.

A key difference between auto lending and syndicated lending (studied in the section above) is that the auto loan application process is standardized. Auto lenders rely on hard information such as the credit score and income when deciding whether to extend a loan, whereas lenders in the syndicated loan market also use soft information in their lending decisions. Moreover, lenders typically have long-term arrangements with auto dealers, limiting choices in financing available to the consumer. By studying the response of auto lending by banks and nonbanks to a monetary contraction, we gain insights into whether substitution between bank and nonbank credit is stronger when only hard information is used in lending decisions.

In the analysis we use household-level data from a major credit bureau. We identify whether a household took out a new auto loan, the loan amount, and the lender type (bank, nonbank).[18] The data also include balances on other loans (mortgage, credit card, consumer loans), the individuals age, and a bankruptcy indicator, which allows us to better control for potential demand and risk factors. Moreover, since this panel is representative of the U.S. population, the estimated effects can be interpreted as average economy-wide effects.

Individual-Level Auto Loans

To test the main hypothesis that nonbank lenders relatively increase credit supply while banks decrease credit supply in response to a contractionary monetary policy shock, we exploit the geographical variation in nonbank presence in our household panel data. We consider two potential determinants of expansion and retrenchment. The first is whether a county is considered a core market as lenders cut credit in non-core markets (Liberti and Sturgess 2018; de Jonge et al. 2018). Benmelech, Meisenzahl, and Ramcharan (2017) argue that for historical reasons nonbank auto lenders (e.g. arrangements with auto dealers) have a large presence in some counties and a weak presence in other counties. We measure historical dependence as the share of auto loan balances outstanding extended by nonbanks at the beginning of the sample (1999Q1). In line with the bank lending channel, we hypothesize that banks retrench more from markets in which they have a weaker presence. Second, in line with the risk-taking channel, we hypothesize that banks retrench more from lending to more risky borrowers (Liberti and Sturgess 2018; de Jonge et al. 2018).

We define lagged dependence as the share of outstanding auto loan balances reported

[18]While we are missing cash purchases, there is little evidence that consumers use other forms of credit such as home equity withdrawal to finance auto purchases (McCully, Pence, and Vine 2019).

in 1999Q1 that were owed to nonbank lenders. Figure A3 shows that there is significant variation in the historical dependence on nonbank auto credit across U.S. counties. To identify the effect of monetary policy on nonbank and bank auto credit, we interact the historical dependence with the monetary policy variable. By doing so, we can control for time-invariant county-level characteristics using county-fixed effects in addition to county-level income.

In the first model, we estimate the effects of monetary policy on nonbank and bank auto credit with the following regression:

$$\text{Loan Amount}_{ijt} = \beta_1 \text{Past Nonbank Share}_j \times MP_{t-1} + \gamma X_{ijt-1} + \alpha_j + \theta_t + \epsilon_{ijt} \quad (4)$$

where *Loan Amount* $_{ijt}$ is log of new auto loan amount for household i in county j in quarter t . *Past Nonbank Share*$_j$ is county's j dependency on nonbank credit measured as the share of auto loan balances outstanding extended by nonbanks in 1999Q1. MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[19] X_{ijt-1} is a vector of controls that includes the interaction of dependency with GDP, inflation and the VIX as well as the household's birth year (fixed effects), outstanding credit card balance, outstanding mortgage balance, outstanding other consumer loan balance, and risk score. We control for local economic conditions by including county-level income. We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics and with time fixed effect (θ_t).

The key variable is the interaction of the historical dependence of a county on nonbank credit interacted with the monetary policy variable Past Nonbank Share$_j$ $\times$ MP_{t-1}. We

[19] We obtain similar results when we use the Wu-Xia shadow rate.

expect the coefficient β_1 to be positive for auto loans *financed with nonbank credit.* The expansion of nonbank credit should substitute for bank credit—that is, we expect the coefficient β_1 to be negative for auto loans *financed with bank credit.*

Table 4
Household-Level Effects on Auto Loans

This table shows the regression results of equation 4 on the individual level. The dependent variable in column 1 is the log of new auto loan amount extended by finance companies, in column 2 the log of new auto loan amount extended by banks, and in column 3 the log loan amount extended by both sources of financing. The dependent variable is a dummy variable equal to 1 if new auto loans extended by finance companies (column 4), banks (column 5) or both sources of financing (column 6). Standard errors in parentheses are clustered by quarter and county. The sample period is from 1999 to 2012. All variables are defined in Appendix A.

	Log Amount			New Loan		
	Nonbank	Bank	Total	Nonbank	Bank	Any
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Past Nonbank Share	0.0312***	-0.0318***	-0.0004	0.0034***	-0.0038***	-0.0005
	(0.00715)	(0.00664)	(0.00113)	(0.000771)	(0.000733)	(0.0104)
Macro Variable Interactions	YES	YES	YES	YES	YES	YES
Household Characteristics	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Birth Year FE	YES	YES	YES	YES	YES	YES
Observations	54,243,317	54,243,317	54,243,317	54,243,317	54,243,317	54,243,317
R^2	0.005	0.007	0.010	0.005	0.007	0.010

Table 4 shows the results of estimating equation 4. Consistent with our main hypothesis, nonbank increase lending (column 1) while banks cut lending (column 2). For this measure of new credit, the expansion of nonbank credit also nearly exactly offsets the reduction in credit supply by banks (column 3).

Turning to the extensive margin, propensity of getting a new auto loan, we estimate equation 4 with a dummy variable for a new auto loan as dependent variable. We find that households is more likely to receive an auto loan from a nonbanks after a contractionary monetary policy shock (column 4). The propensity to receive an auto loan from a bank drops (column 5).[20] This point estimate implies that for a household living in a county

[20]Benmelech, Meisenzahl, and Ramcharan (2017) show that auto sales dropped more in counties more dependent on nonbank auto credit during the 2007-08 financial crisis. Our results hold when we constrain the sample to the pre-crisis period.

with average historical dependence (0.57), a household's probability of obtaining an auto loan from a nonbank increases by 0.05 percentage points in response to a 25 basis points increase in the policy rate. This represents a 5 percent increase in the probability to obtain an auto loan from a nonbank in a given quarter (mean 1 percent). Column 5 shows that this expansion of nonbank auto credit is matched by a similar decrease in the extension of auto credit by banks. On net, we find no effect for the propensity to obtain an auto loan from any source (column 6). In sum, the household-level results suggests that following a monetary contraction substitution between bank and nonbank lenders is perfect in the auto loan market.

This close-to-perfect substitution between bank and nonbank credit is suggestive evidence for the mechanism driving this result. Banks experience deposit experienced resulting in a reduction in lending. However, these outflow lead to an expansion of funding available to nonbanks in the money markets. Nonbanks take advantage of this funding expansion by increasing credit supply to households. In the case of auto loans, we find close-to-perfect substitution between nonbanks and banks.

Risk-Taking in the Auto Loan Market

A remaining concern with this specification is that we cannot control for time-varying county characteristics other than income as most consistent annual county-level data are only available from 2004 on. We address this concern by using county-time fixed effects when analysing the effects of monetary policy across the risk spectrum.

A natural question is which types of borrowers are mostly likely to be affected by changes in the credit supply from banks and nonbanks. Previous research, e.g. Liberti and Sturgess (2018) and de Jonge et al. (2018) suggests that banks are more likely to reduce the extension of credit to the least credit worthy borrowers.[21]

Table 5
Household-Level Effects on Auto Loans: Risk

This table shows the regression results of equation 4 on the individual level. The dependent variable in column 1 is the log of new auto loan amount extended by finance companies, in column 2 the log of new auto loan amount extended by banks, and in column 3 the log loan amount extended by both sources of financing. The dependent variable is the a dummy variable equal to 1 if new auto loans extended by finance companies (column 4), banks (column 5) or both (column 6). The sample period is from 1999 to 2012. Standard errors in parentheses are clustered by quarter and county. All variables are defined in Appendix A.

	Log Amount			New Loan		
	Nonbank	Bank	Total	Nonbank	Bank	Any
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Past Nonbank Share x Score	-0.0913***	0.147***	0.0521	-0.00972***	0.0162***	0.00601
	(0.0307)	(0.0229)	(0.0387)	(0.00335)	(0.00250)	(0.00416)
Macro Variable Triple Interactions	YES	YES	YES	YES	YES	YES
Lower-Level Interactions	YES	YES	YES	YES	YES	YES
Individual Characteristics	YES	YES	YES	YES	YES	YES
County-Time FE	YES	YES	YES	YES	YES	YES
Birth Year FE	YES	YES	YES	YES	YES	YES
Observations	54,243,555	54,243,555	54,243,555	54,243,555	54,243,555	54,243,555
R^2	0.009	0.012	0.014	0.009	0.012	0.014

Coefficient multiplied with 1000.

To test whether the substitution is dependent on borrower risk, we include a triple interaction of borrower's lagged credit score, the county's Past Nonbank Share, and monetary policy as well as the triple interaction of borrower's lagged credit score and the county's Past Nonbank Share with of with all other macroeconomic variables.[22] We hypothesis that banks retrench more from borrowers with lower credit scores while nonbanks expand in this segment. In other words, the higher the borrower's credit score, the less likely is a reduction of credit supply from banks and an increase of credit supply from nonbanks. Hence, we expect the coefficient on the triple to be negative and significant for the loan amount financed by nonbanks and positive for the loan amount financed

[21] In unreported results, we find that counties with a concentrated banking sector, measured as concentration in deposit taking, exhibit an increase in auto credit provided by banks). This finding is consistent with banks focusing on their core markets or markets in which they have price setting power. However, we find that the include bank deposit taking concentration does not affect our main result.

[22] We also include the interaction of the macroeconomic variables with the risk score. The interaction of the Past Nonbank Share is absorbed by the county-quarter fixed effects.

by banks. This specification allows us to include county-time fixed effects to alleviate concerns that our results are driven by local demand varying systematically with the historical dependence on nonbank auto credit over the cycle.

Table 5 shows the results of estimating the effect of monetary policy on auto loans by borrower risk. Column 1 shows that nonbank increase their credit supply to lower credit score borrowers in response to higher monetary policy rates. This expansion of nonbank credit occurs when banks retreat from this segment of the market and shift credit supply to relatively better borrowers (column 2). The substitution between banks and nonbank is perfect across the credit risk spectrum (column 3). We obtain similar results when we use the log new loan amount as dependent variable (columns 4-6).[23]

County-level Auto Credit and Sales

Next, we assess the real effects of this shift in auto loans from bank to nonbanks after a monetary contraction. Since auto sales data are only available at the county-level, we first aggregate our data to the county-level and then replicate our household-level results for auto credit. We estimate the following model:

$$\text{Log(Auto Credit)}_{jt} = \beta_1 \text{Past Nonbank Share}_j \times MP_{t-1} + \gamma X_{it-1} + \alpha_j + \theta_t + \epsilon_{jt} \quad (5)$$

where $\text{Log(Auto Credit)}_{jt}$ is the log of new auto loan amounts in county j in quarter t. *Past Nonbank Share*$_j$ is county's j dependency on nonbank credit measured as the share of auto loan balances outstanding extended by nonbanks as of 1999Q1. MP_{t-1} is

[23] Unfortunately, we do not observe the interest rates charged on an auto loan. However, the literature suggests that this substitution means that, while low credit score borrowers may still have access to auto loans, the terms of these loans are likely to be less favorable. Specifically, Charles, Hurst, and Stephens (2008) show that auto loan interest rate vary by source of financing and that nonbanks tend to charge higher rates.

Table 6
County-Level Effects on Auto Loans and Auto Sales

This table shows the regression results of equation 5. The dependent variable is the log amount of new auto loans extended by finance companies (columns 1, 5), the log amount of new auto loans extended by banks (columns 2,6), or the log amount of all new auto loans (columns 3, 7). The dependent variable in columns 4 and 8 is the log of auto sales. Low Nonbank Share is a dummy equal to 1 if a county's dependency on nonbank was in the lowest quartile in 1999. The sample period is from 1999 to 2012 for auto loans and 2002 to 2012 for auto sales. Standard errors in parentheses are clustered by quarter and county. All variables are defined in Appendix A.

	Auto Credit			Auto	Auto Credit			Auto
	Nonbank	Bank	Total	Sales	Nonbank	Bank	Total	Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GK x Past Nonbank Share	0.503***	-0.587***	0.109	0.034				
	(0.0986)	(0.119)	(0.107)	(0.023)				
GK x Low Nonbank Share					-0.295***	0.271***	-0.0686	-0.035**
					(0.0986)	(0.0532)	(0.0790)	(0.015)
Macro Variable Interactions	YES	YES	YES	YES	YES	YES	YES	YES
Time-varying County Controls	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	158,461	158,461	158,461	122,991	158,461	158,461	158,461	122,991
R^2	0.489	0.490	0.502	0.991	0.489	0.489	0.502	0.463

the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[24] X_{jt-1} is a vector of controls that includes the interaction of dependency with GDP, inflation and the VIX. We control for local economic conditions by including average risk score and county-level income. We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics and with time fixed effect (θ_t).

Table 6 shows the results of estimating equation 5 at the county level. Consistent with the household-level results (Table 4), columns 1 and 2 show that nonbanks expand auto credit more in response to higher monetary policy rates in counties historically more dependent on nonbank credit, while banks' auto credit contracts more in these counties. The point estimates in columns 1 and 2 suggest that, on the county-level and controlling for aggregate demand, there is also close-to-perfect substitution between bank and nonbank credit.[25] Indeed, column 3 shows no significant net effect of contraction monetary policy on auto credit at the county level.[26] These results are consistent with banks retrenching to focus on their core markets.

To better understand whether the substitution between bank and nonbank auto credit has real effects, we study county-level auto sales using data from Polk. We repeat our county-level estimation shown in equation 5 with auto sales as dependent variable. We find no effect of monetary policy on auto sales (column 4).[27]

[24]We obtain similar results when we use the Wu-Xia shadow rate.

[25]In theory, these results could be consistent with and expansion of bank credit and contraction of nonbank credit (but these effects weaker in counties with higher nonbank share). However, the aggregate results shown in Appendix B, table C3. Ludvigson (1998) documents an increase in the market share of nonbanks in the auto loan market after a monetary contraction for the period 1965-1994 using aggregate time series. Given an average *Lagged Nonbank Share*$_j$ of 0.53, the coefficients are comparable in magnitude to the ones reported in table C3.

[26]In unreported results, we also find similar patterns when we use the number of loans instead of the loan amount.

[27]Weighting the observation with lagged county income or using different measures of monetary policy does not change the results.

We then test whether montary policy has real effects in terms of auto sales in counties in which the substitution between bank and nonbank credit is limited. Since nonbanks tend to expand credit in counties in which they had a historically large market share, we use an indicator variable that is equal to 1 if a county's historical dependence on nonbank credit is in the lowest 25th percentile. In these counties substitutions is expected to be limited and hence auto sales should fall in response to a retrenchment of bank credit. For auto credit, we find a negative and statistically significant effect on the interaction of low historical dependence and monetary policy for auto credit extended by nonbanks, meaning relative to the comparison group consisting of higher nonbank dependence nonbank auto credit expands less in these counties (column 5). Banks however retrench less (column 6). On net, the effect in auto credit in low dependence counties is negative but statistically not significant (column 7).[28] Consistent with limited substitution, auto sales in low nonbank dependency counties fall after a monetary contraction (column 8).

Taken together, the results presented in this section show that contractionary monetary policy shocks shift the auto credit supply from banks to nonbanks. Where substitution between bank and nonbank credit is limited, we find real effects of monetary policy. More generally, our results indicate that in lending markets in which lending decisions are based on hard information substitution between bank and nonbank lender can be perfect.

[28]In unreported results, we find that the effect is concentrated in the lowest quantile. The effect in counties of the second lowest dependency quantile is half the size.

5 Monetary Policy and Mortgage Lending

In this section we explore the relationship between monetary policy and nonbank mortgage lending using the confidential HMDA data, which include the mortgage issuance date allowing us to construct quarterly panel data. We classify bank and nonbank lenders using the methodology of Buchak et al. (2018a). Mortgage companies and Fintech lenders, such as QuickLoans, are included in the nonbank category.

The U.S. Mortgage Market

With about \$10 trillion outstanding balances, mortgages to households are the largest lending market in the United States. Mortgages are originated by bank and nonbank lenders. These lenders choose to either hold the mortgages on their balance sheets, securitize them, or to sell them in the secondary market. The main buyers of mortgages are government-sponsored enterprises (GSEs); Fannie Mae and Freddie Mac and, before the 2008 financial crisis, private-label securitizers.

Lenders originate mortgages using their own funds, even if they sell the loan later. To finance the origination of new loans, nonbank lender use warehouse financing—-short-term credit extended to the nonbank lender until the mortgage is sold into the secondary market. Nonbank lenders are exposed to liquidity pressure as many of them they finance mortgage originations with warehouse lines of credit—a form of short-term credit extended mostly by commercial and investment banks (Kim et al. 2018). The lines are paid off with the proceeds of mortgage sales and securitization. At the same time, some buyers in the secondary market, especially issuers of asset-backed securities (ABS) that engaged in private-label securitization, rely themselves heavily on short-term funding. ABS accounted for \$350 billion of mortgages in 2000, \$2.2 trillion in 2007, and \$1 trillion in 2012, highlighting the importance short-term funding market conditions for mortgage originations.

In general, two types of mortgages exit: conforming mortgages—mortgages that are not insured or guaranteed by the federal government and adhere to the guidelines set by the GSEs—and jumbo mortgages—mortgages that exceed the guidelines set by the GSEs and are therefore not eligible to be purchased, guaranteed or securitized by the GSEs. As the conforming mortgage market and the jumbo mortgage market differ regarding the lender's post-origination options, we consider mortgage originations in these markets separately.

For lenders, knowledge of the local housing market, such as recent trends in neighborhoods and range of possible assessments for the house value, is crucial for the lending process suggesting the need for appropriate local level control variables. However, since the application process for mortgages is standardized with mortgage lenders relying on hard information such as the credit score and income when deciding whether to extend a loan and the lender's ability to sell the mortgage to the GSEs, bank and nonbank lenders can use similar lending technologies and compete in the same markets.

Individual-Level Mortgage Lending

As in the auto loan market, we begin with a loan level analysis and assess our main hypothesis whether contractionary monetary policy increases nonbank lending in the mortgage market. We start by analyzing new purchase mortgages—that is, mortgages originated to buy a home thereby excluding refis. The key advantage of loan level data is that we can control for county-specific mortgage demand and other time trends such as local housing market developments. Specifically, to alleviate these concerns about time-varying, local economic conditions, we exploit variation between bank and nonbank lenders in response to monetary policy shock within a county-quarter.

The coverage of rural counties in HMDA is incomplete. To reduce potential noise stemming from this coverage issue, we restrict our sample to counties with at least 10 mortgage originations in each quarter. This restriction reduces the sample to 860 counties covering about 90 percent of all mortgages reported in HMDA. As our loan level identification strategy relies on within county-quarter difference, Figure A7, showing the distribution of county-level nonbank dependence in the mortgage market as of 1995Q1, illustrates that, while there is significant variation of nonbank share across the United States, most counties had a significant nonbank presence already in the early 1990s.[29]

This variation allows us to identify the effects of monetary policy in the mortgage market by estimating the following regression:

$$\begin{aligned} \text{Log(Loan Amount)}_{i.k,j,t} = &\beta_1 \text{Nonbank Dummy}_{k,t} \times MP_{t-1} + \\ &\beta_2 \text{Nonbank Dummy}_{i,k,j,t} + \gamma X_{t-1} + \alpha_{j,t} + \theta_k + \epsilon_{i,k,j,t} \end{aligned} \tag{6}$$

where $\text{Log(Mortgage)}_{i,j,t}$ is the log of new mortgage amount of loan i in county j in quarter t. *Nonbank Dummy*$_{i,t}$ is equal to 1 if the lender in loan i was a nonbank in quarter t.[30] MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[31] X_{jt-1} is a vector of controls that includes the

[29]We start in 1995 as the nonbank share rose sharply in the early 1990s, perhaps because of the introduction of capital regulation prescribed in Basel I, limiting banks' ability to lend.

[30]Some lenders in the mortgage market switch charters over our sample period. The point estimate β_2 is identified by these switchers. For details on the classification, see Appendix.

[31]We obtain similar results when we use the Wu-Xia shadow rate.

interaction of *Nonbank Dummy*$_{i,t}$ with GDP, inflation and the VIX. We saturate the model with lender fixed effects (θ_k) and with county-time fixed effects (α_{jt}) to account for differences in time-varying county-level characteristics such as economic conditions and house prices.

Table 7
Loan-Level Regressions on Loan Amounts, by Loan Type

Date Range: 1995q2 - 2012q3. All counties issued at least 10 loans in every quarter of date range. Conforming loans are defined as loans beneath the conforming loan limit. Jumbo loans are defined as loans above the conforming loan limit. The dependent variable is measured in thousands and then logged. GK is the cumulative sum of Monetary Policy Shocks from Gertler and Karadi (2015). All macro variables are on a one quarter lag. All macro variables are logged. Applicant controls are race, gender, and income. Standard errors inparentheses are clustered at the lender-county level

	New Loans Only		
	Conforming	Jumbo	All - Held
	(1)	(2)	(3)
GK x Nonbank Dummy	0.0303	0.0329**	-0.012
	(0.0189)	(0.0086)	(0.0225)
Macro Interact	YES	YES	YESS
Applicant Char	YES	YES	YES
County-Time FE	YES	YES	YES
Lender FE	YES	YES	YES
Observations	62,063,250	5,461,377	34,246,735
Adjusted R^2	0.36	0.48	0.42

Table 7 shows the results of estimating equation 6. Consistent with our main hypothesis, we find that on the loan-level nonbank lender extend more credit after a monetary contraction in the market for new conforming loans (column 1), however this effect is not statistically significant. In the jumbo mortgage market, we find that nonbanks also expand originations (column 2) and, while in magnitude about the same as in the confirming loan market, this expansion is statistically significant. A one standard deviation increase in the monetary policy variable increases the size of a jumbo loan by about 1.5 percent. Since jumbo loan cannot be sold as easily as conforming loans, they are riskier to originate. This finding is therefore also consistent with nonbank attenuating the risk-taking channel of monetary policy. However, we do not find evidence that loan amounts of loans that remain on the lender's balance sheets are differentially larger for nonbanks (column 3).

County-level Mortgage Lending

As in the auto loan market, we also present county-level results that to tighten the link between the loan-level mortgage results and the effect of nonbank mortgage lending on house prices that we show below. In the county-level analysis, we exploit the geographical variation in nonbank lending for identification purposes. Since information about the local market is a crucial input in lending decisions and lenders cannot easily scale operations in non-core regions, the ease of substitution between bank and nonbank lenders may depend on the historic presence of nonbanks in a county. We expect that substitution is more likely to take place when nonbank lenders have accumulated information about the local market by having extended loans in a county in the past. We therefore construct the county-level historic dependence of nonbank market credit as the share of mortgage originated by nonbank lenders in 1995Q1.[32] This approach allows us to include time fixed effects, alleviating concerns that our results are driven by the effects of the financial crisis of 2007-09.

We hypothesize that banks reduce mortgage lending more in counties with a large nonbank presence in response to a monetary contraction while nonbanks expand. We focus on loans that are held on the balance sheets as they are most affected by changes in the relative funding conditions.[33] Moreover, we expect stronger effects for jumbo loans

[32]In the appendix, we show the nonbank share in the mortgage for new mortgage loans (Figure A6).

[33]Since HMDA is a year-end data set, mortgages originated in December are generally shown as held

that are differentially larger and generally less liquid.

To test these hypotheses, we estimate the following model:

$$\text{Log(Loan Amount)}_{j,t} = \beta_1 \text{Past Nonbank Share}_j \times MP_{t-1} + \gamma X_{j,t-1} + \alpha_j + \theta_t + \epsilon_{j,t} \quad (7)$$

where $\text{Log(Mortgage)}_{j,t}$ is the log of new mortgage amounts in county j in quarter t . *Past Nonbank Share*$_j$ is county's j dependency on nonbank credit measured as the share of mortgages extended by nonbanks in 1995Q1. MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[34] X_{jt-1} is a vector of controls that includes the interaction of dependency with GDP, inflation and the VIX. We control for local economic conditions by including average risk score and county-level income.[35] We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics and with time fixed effects (θ_t).

Table 8 shows the results of estimating equation 7 for conforming and jumbo mortgage origination for new house purchases. The top panel, column 1 shows that there are no significant effects of monetary policy on bank and lending.[36] Column 2 shows that nonbank lending expands somewhat but, on net, there is no increase in lending on the county level for new mortgages (column 3). The nonbank share expand somewhat (column 4). This is consistent wit the key channel we are focusing on. While nonbanks may enjoy better funding conditions after a monetary contraction, financing for conforming mortgage origination can also be obtained from the GSEs. Moreover, conforming mort-

on the balance sheet because the securitization process takes somewhat longer. We therefore adjust the total loan amounts held on the balance sheets in December by multiplying the loan amount with the average share over the first 9 months of the year.

[34]We obtain similar results when we use the Wu-Xia shadow rate.

[35]Consistent time series for local house prices going back to 1990 are not available.

[36]In rhe appendix, we drop the time fixed effect and find that overall lending activity contracts with a contractionary monetary policy.

Table 8
New Loans Held on Balance Sheet - County Level

Date Range: 1995q2 - 2012q3. All counties issued at least 10 loans in every quarter prior to 2008. Conforming loans are defined as loans beneath the conforming loan limit. Jumbo loans are defined as loans above the conforming loan limit. This sample includes only new loans excluding refinancing that remain on the lender's balance sheet. GK, the MP Shock, is the cumulative sum of monetary policy shocks of Gertler and Karadi (2015). Macro variables are lagged GDP, lagged GDP forecast, lagged inflation, and lagged VIX. All lagged variables are on a one quarter lag. Observations weighted with lagged county-level income. Standard errors in parentheses are double-clustered at the county and quarter level.

	New Conforming Loans - Held			
	Bank	Nonbank	Total	Nonbank Share
	(1)	(2)	(3)	(4)
Past Nonbank Share x GK	0.045	0.367*	0.309	0.049
	(0.425)	(0.214)	(0.319)	(0.069)
Macro Variable Interactions	YES	YES	YES	YES
Time-varying Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Observations	59,547	59,547	59,547	59,547
Adjusted R^2	0.78	0.80	0.78	0.75

	New Jumbo Loans - Held			
	Bank	Nonbank	Total	Nonbank Share
	(1)	(2)	(3)	(4)
Past Nonbank Share x GK	-0.691	3.192***	-0.064	0.390***
	(0.913)	(0.886)	(0.856)	(0.040)
Macro Variable Interactions	YES	YES	YES	YES
Time-varying Controls	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Observations	59,547	59,547	59,547	59,547
Adjusted R^2	0.79	0.73	0.78	0.62

gages are are relatively easy to sell at a later point to the GSEs, advantages in financing conditions may be less important in the conforming loan market.

In the jumbo mortgage market shown in the bottom panel, we find lending patterns consistent with substitution between bank and nonbank lending in the mortgage market. Banks appear to retrench after a contractionary monetary policy shock (column 1) even though the point estimate is not significant. Nonbanks expand significantly (column 2).

However, controlling for aggregate demand, in this market we find no credit supply effect of monetary policy on new jumbo mortgage origination subsequently held on the balance sheet (column 3) at the county level. Consistent with the banks' retrenchment and the nonbanks' expansion, the nonbank market share increases (column 4).[37] In sum, the results suggest substitution from banks to nonbanks in the potentially more risky jumbo mortgage markets.

Total Mortgage Lending and House Prices

To assess the real effects of nonbank credit, we estimate the effect on total mortgage lending (mortgages that are sold and those that are held on the balance sheet including FHA and VA loans) and whether nonbank lending is associated with house price growth. We estimate the following regression.

$$\text{Log(Outcome)}_{j,t} = \beta_1 \text{Past Nonbank Share}_{j,t} \times MP_{t-1} + \quad \gamma X_{j,t-1} + \alpha_j + \theta_t + \epsilon_{j,t} \quad (8)$$

where the outcomes is either total credit or the house price index.

Table 9 shows result of estimating equation 8. We detect an relative expansion of total new mortgage lending at the county level, though the effect is only significant at the 11.2 percent level (column 1). A one standard deviation increase in the monetary policy measure increase mortgage lending by 5 percent. This effect becomes slightly larger and weak statistically significant when we also include refinancing loans (column 2). This relative expansion of credit results in a positive, weakly statistically significant effect of the nonbank share on house prices (column 3). This finding suggest that the substitution from bank to nonbank lending after a monetary contraction supports house prices more

[37] These results are not driven by the financial crisis.

Table 9
Nonbank Presence, Mortgage Credit, and County-level House Prices

Date Range: 1995q2 - 2012q3. All counties issued at least 10 loans in every quarter of date range. The dependent variable is the county-level mortgage credit and the respective county-level house price index. GK is the cumulative sum of Monetary Policy Shocks from Gertler and Karadi (2015). All macro variables are on a one quarter lag. All macro variables are logged. Standard errors in parentheses are clustered at the quarter-county level.

	All New Mortgages (1)	All Mortgages (2)	House Prices (3)
Past Nonbank Share x GK	0.494†	0.508*	0.397*
	(0.307)	(0.279)	(0.200)
Macro Variable Interactions	YES	YES	YES
County Income	YES	YES	YES
County FE	YES	YES	YES
Observations	55,860	55,860	55,860
Adjusted R^2	0.98	0.98	0.84

in counties with a large nonbank lending share.

Taken together, the evidence in this section shows that there is substitution between bank and nonbank mortgage lenders after a contractionary monetary policy shock especially in the jumbo market market. House prices in markets with larger nonbank presence perform better relative to markets with few nonbank lenders. These findings suggest that nonbank lending attenuates the real effects of monetary policy in the housing market.

6 Nonbank Substitution and Aggregate Effects

So far we have focused on the identification of the nonbank substitution in lending market and the attenuation of the bank balance sheet and risk-taking channels of monetary policy. The identification strategies rely on time fixed-effects, which precludes statements about general equilibrium effects. To gauge the aggregate effects of nonbank substitution, we now relax the tight identification assumptions and estimate the sector-level or county-level regressions in each market without time fixed effect but with our preferred measure of monetary policy (Gertler-Karadi cumulative shocks) and macro-level controls (GDP growth, GDP forecast, inflation, VIX).

Table 10
Aggregate Lending and Outcomes

Panel A of this table is in parallel to table 3 with GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effect. Standard errors are clustered by industry and time. Panel B of this table is in parallel to table 6 with GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effect. Standard errors are clustered on the county and quarter level. Panel C of this table is in parallel to table 9 with GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effect. Standard errors are clustered on the county and quarter level. In all panels, GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US.

	Panel A: Corporate Borrowing and Real Outcomes					
	Industry-Level Borrowing		Industry-Level Investment		Annual Industry Output	
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged GK	0.105	-0188	-0.029***	0.006	-0.114***	-0.215***
	(0.135)	(0.128)	(0.033)	(0.012)	(0.035)	(0.051)
Lagged GK x past Nonbank Share		2.146		0.223**		1.191**
		(1.864)		(0.086)		(0.461)
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls x past Nonbank Share	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,560	4,560	4,407	4,407	1,054	1,054
Adjusted R^2	0.61	0.62	0.94	0.94	0.97	0.97

	Panel B: Auto Loan & Sales					
	Nonbank Loans		Total Loans		Auto Sales	
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged GK	0.207***	-0.074	-0.010	-0.080	0.418***	0.398***
	(0.047)	(0.079)	(0.033)	(0.072)	(0.018)	(0.025)
Lagged GK x past Nonbank Share		0.506***		0.113		0.038
		(0.116)		(0.115)		(0.035)
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls x past Nonbank Share	No	Yes	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	158,461	158,461	158,461	158,461	122,991	122,991
Adjusted R^2	0.50	0.47	0.53	0.49	0.98	0.98

	Panel C: Mortgages & House Prices					
	New Held Mortgages		All Mortgages		House Prices	
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged GK	-0.167***	-0.514**	-0.314***	-0.540**	-0.161***	-0.373***
	(0.064)	(0.216)	(0.033)	(0.160)	(0.026)	(0.100)
Lagged GK x past Nonbank Share		0.733*		0.475		0.488**
		(0.443)		(0.308)		(0.179)
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls x past Nonbank Share	No	Yes	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55,062	55,062	55,062	55,062	55,062	55,062
Adjusted R^2	0.29	0.28	0.90	0.89	0.73	0.69

Table 10, Panel A shows the results of the industry-level regressions without time fixed effects for corporates. Column 1 shows that one quarter lagged monetary policy does not affect industry-level corporate borrowing. Nonbank substitution may account for that as the interaction term between monetary policy and past nonbank share is positive but imprecisely estimated (column 2). For investment, we find that no overall effect of one quarter lagged monetary policy on investment (column 3), in part because industries with higher past nonbank share maintain investment expenditures (column 4). Annual output falls after a monetary contraction (column 5) but considerably less in industries with higher past nonbank share (column 6). In sum, nonbank lending in the corporate loan market significantly attenuates the effects of monetary policy on investment and output.

Table 10, Panel B shows the results of the county-level regressions without time fixed effects for the auto market. Column 1 shows that one quarter lagged monetary policy increases borrowing from nonbank lenders the auto loan market. This increase is driven by counties with higher past nonbank share (column 2). Total lending in the auto loan market is however unaffected (column 3) even in counties with higher past nonbank share (column 4), indicating substitution away from bank lending. While auto sales appear to increase after a monetary contraction (column 5), perhaps because we cannot perfectly control for demand in the aggregate regression, they do not rise differently more in counties with higher past nonbank share (column 6). Nonbank lending in the auto loan market completely offset any retrenchment of banks in the auto loan market.

Table 10, Panel C shows the results of the county-level regressions without time fixed effects for the mortgage market. Column 1 shows that one quarter lagged monetary policy reduce mortgages held on the balance sheet but that reduction is mitigated by in counties with higher past nonbank share (column 2). We find a similar pattern for all mortgages (columns 3 and 4). While a monetary contraction generally slows house price growth (column 5), high past nonbank share significantly reduces the sensitivity of house prices to monetary policy (column 6). Substitution by non lender in the mortgage market reduces the effectiveness of monetary policy in the mortgage market.

Taken together, the regressions results on the aggregate level show that the nonbank substitution identified above affects aggregate outcomes in all three markets.[38] By substitution for bank lending, nonbank lending offsets the bank credit supply effects of monetary policy and hence attenuates the effectiveness of monetary policy economy-wide.

7 Conclusion

The significantly larger presence of nonbank lenders in many credit markets critically affects the effectiveness of monetary policy. Deposits leaving the banking sector after a monetary contraction flow to the shadow banking system that provides financing to nonbank lenders. Nonbank lenders are therefore able to increase lending after a monetary contraction, offsetting the reduction in lending by banks and reducing the effectiveness of monetary policy.

This attenuation of the bank lending channel is particular pronounced in the consumer credit market that relies on hard information. Nonbank lenders expand credit provision in the auto loan market by about 10 percent after a one standard deviation increase in the policy rate. This increase matches the retrenchment by banks. On net, we do not

[38]In the Appendix, we provide suggestive evidence that nonbank substitution is weakened during times of uncertainty.

find a statistically significant effect of monetary policy on total auto credit. We also find evidence for substitution in the mortgage market and in the syndicated corporate loan market. Nonbanks expand lending relative to their bank peers after a monetary contraction. On aggregate, syndicated corporate lending and total mortgage falls due to reduced demand but credit provision shifts to nonbank funding.

The changes in the mix of credit providers after a monetary contraction that we document also raises questions about the interplay of monetary policy, the structure of credit markets, and financial stability. If nonbank providers become more important sources of credit for the real economy in the wake of a monetary contraction then risk in the financial system becomes more diversified. At the same time, a large presence of nonbank credit providers is likely to limit central banks' ability to counteract subsequent credit market disruptions. More research is needed to understand these linkages.

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Appendices – For Online Publication

A Data Summary

Variable definitions

This appendix presents the definitions for the variables used throughout the paper.

Variable	Definition	Source
Panel A: Macro Variables		
GK	Cumulative Gertler-Karadi Monetary Policy Rate	Gertler and Karadi (2015)
Inflation	Inflation Rate	Federal Reserve Bank of St. Louis
GDP	Gross Domestic Product Growth Rate	Federal Reserve Bank of St. Louis
GDP Forecast	One-quarter-ahead forecast of Gross Domestic Product Growth	Federal Reserve Bank of Philadelphia
VIX	Volatility Index	CBOE
WX	Wu-Xia Shadow Rate	Wu and Xia (2016)
Fed Funds	Federal Funds Target Rate	Federal Reserve Bank of St. Louis
Panel B: Consumer Loans		
Lagged Nonbank Share	The share of 1999Q1 auto loan balances outstanding extended by nonbank	FRBNY/Equifax CCP
Low Nonbank Share	Indicator equal to 1 if a county's dependency on nonbank was in the lowest quartile	FRBNY/Equifax CCP
New Loan Nonbank	Indicator equal to 1 if a household received a new auto loan from a nonbank	FRBNY/Equifax CCP
New Loan Bank	Indicator equal to 1 if a household received a new auto loan from a bank	FRBNY/Equifax CCP
Log Amount Nonbank	Log of new auto loan amount extended by a nonbank	FRBNY/Equifax CCP
Log Amount Bank	Log of new auto loan amount extended by a bank	
Market Share	The nonbank share of new auto loan balances outstanding	FRBNY/Equifax CCP
Credit Card Balance	Log of credit card debt outstanding	FRBNY/Equifax CCP
Mortgage Balance	Log of first mortgage debt outstanding	FRBNY/Equifax CCP
Consumer Balance	Log of consumer credit (other than auto loans) outstanding	FRBNY/Equifax CCP
Bankruptcy	Indicator equal to 1 if household had declared either Chapter 7 or 13 bankruptcy	FRBNY/Equifax CCP
Risk Score	Equifax Risk Score	FRBNY/Equifax CCP
Log Income	Log of county-level quarterly total wages	BLS
Panel C: Syndicated Loans		
Nonbank	Indicator variable equal to one for nonbank lenders and zero for bank lenders	Thomson Reuters LPC DealScan
Past Nonbank relation	Indicator variable equal to one for borrowers who have previously borrowed from a nonbank (excluding loans in the previous two years)	Thomson Reuters LPC DealScan
Nonbank amount	Log of total credit extended to a borrower in a quarter from nonbanks	Thomson Reuters LPC DealScan
Bank amount	Log of total credit extended to a borrower in a quarter from banks	Thomson Reuters LPC DealScan
Nonbank share	Log of the ratio of total credit extended from nonbanks to total credit extended from all lenders	Thomson Reuters LPC DealScan
All loans	Log of total credit extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Term loans	Log of total term loan amount extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Revolvers	Log of total credit line amount extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Borrowing	Log of total credit extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Total debt	Log of total debt net of cash (dlcq + dlttq - cheq)	Compustat
Leverage	Book leverage net of cash ((dlcq + dlttq - cheq) / atq)	Compustat
Liquidity	Ratio of cash and short term investments to total assets (cheq / atq)	Compustat
Investment	Ratio of property, plant and equipment to total assets (ppentq / atq)	Compustat
High yield	Indicator variable equal to one if the borrower has a high yield credit rating, and equal to zero if it has an investment grade credit rating (splticrm)	Compustat
Log(borrower assets)	Log of lagged total assets (at)	Compustat

Nonbank Classification in DealScan Based on the DealScan lender classification, we define the two groups as follows:

- **Banks:** US bank, Western European bank, foreign bank, mortgage bank, Middle Eastern bank, Eastern European/Russian bank, Asia-Pacific bank, thrift / S&L, African bank (plus unclassified firms that have 'bank' in the name).
- **Non-banks:** insurance company, corporation, finance company, investment bank, mutual fund, trust company, leasing company, pension fund, distressed (vulture) fund, prime fund, collateralized loan obligation (CLO), hedge fund, other institutional investor.

Figure A1 shows the evolution of the total syndicated loan market. Figure A2 shows the evolution of bank and nonbank syndicated lending in the US.[39] Over the full sample period (1990-2017), nonbank lending has accounted for around 9% of total syndicated lending, by dollar volume. However there has been substantial heterogeneity over time: between 1995 and 2007, nonbank lending increased from less than 5% to more than 20% of the total market.

Identifying Amendments in DealScan We drop a loan if it satisfies one of the following three criteria: First, the loan has the word "amends" in the comment. Second, at the time that the new loan is originated, there is already an outstanding loan of the same type to the same borrower with maturity date within one year of the maturity date of the new loan. Third, at the time that the new loan is originated, there is already an outstanding loan of the same type to the same borrower with dollar amount within 25% of the amount of the new loan. This approach identifies around 30% of all term loans and revolvers in DealScan as being potential amendments.

New Auto Loans and Lender types in Equifax While the credit bureau data include auto loan balances by lender type, they do not provide an indicator variable for new auto loans. For each type of lender, we therefore identify new auto loans by a positive change in the balance of at least $500. We are interested in the net extension of credit. We compute the net new loan amount as the difference between the current quarter auto loan balance and the previous quarter auto loan balance.[40]

Nonbanks lenders account for about 40 percent of auto loans in the U.S. The extension of auto loans by these nonbanks is not uniform across the country: some counties depend more on nonbank credit than others. Following Benmelech, Meisenzahl, and Ramcharan (2017), we construct a measure of a county's historical dependence on nonbank auto credit using the ratio of county-level auto loan balances outstanding to nonbanks divided by county-level total auto loan balances outstanding at the beginning of the sample (1999Q1).

Table A2 shows summary statistics for the Equifax sample on the household and county level. The average nonbank share in 1999Q1 is 0.53 on the county level but there is considerable variation in this measure of dependence on nonbank credit. For instance, the inter-quartile range is 0.37. Figure A3 visualizes the local variation in county-level nonbank dependence. This distribution is relatively stable over time (Figure A4).

Nonbank Identification in HDMA The identification of nonbanks in the HMDA data adapts the identification method used in Buchak et al. (2018a). There are four steps in the

[39] This chart only use loans where lender shares are observed.

[40] We only observe credit-financed auto purchases in the FRBNY/Equifax CCP data and no cash purchases. Our measure therefore focuses on the intensive margin of financing composition—that is, the substitution between bank and nonbank credit.

process, which begins by assuming that all lenders are nonbanks and then re-classifying them into banks where appropriate. A lender is classified as a bank if it meets at least one of the following criteria below. A lender that fails to meet any of the criteria remains classified as a nonbank. The order in which these steps are presented are the same as they appear in the algorithm.

The first step utilizes the lender's regulator. All lenders regulated by the following agencies are classified as banks; OCC, FDIC, OTS, NCUA, and CFPB. This methodology includes the lenders who filed to the state. In Buchak et al. (2018a) there are just 5 individual lenders that violate this classification, which are addressed in the fourth step.

Second, classifying lenders regulated by the Federal Reserve System is done using text analysis of the lender's name. Lenders regulated by the Federal Reserve with the following strings in their name are classified as banks; "BANK", "BK", "BANCO", "BANC", "B&T", "BNK". These strings are not case sensitive. Lenders regulated by the Federal Reserve without these strings remain classified as nonbanks.

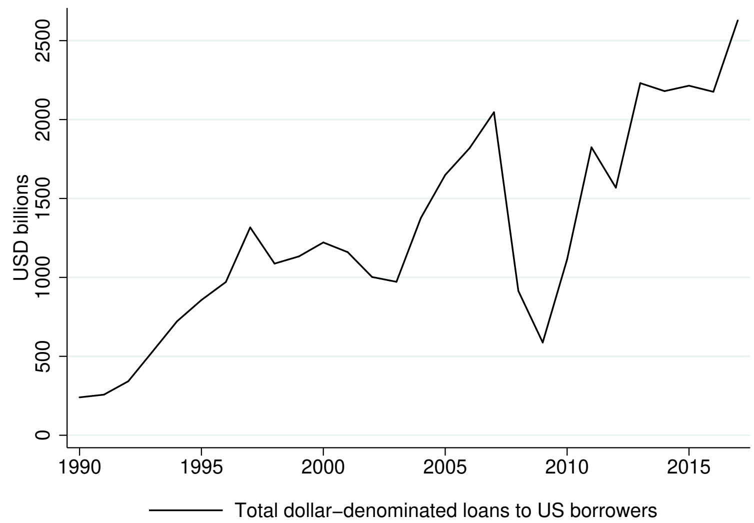
Third, any bank identified as a "Bank, Savings Association, or Credit Union" or a "Mortgage Banking Subsidiary of a Community Bank" are classified as a bank. This is done using HMDA's OTHER_LENDER_CODE variable.

Finally, the method identifies the five one-off lenders consistent with the one-offs in Buchak et al. (2018a). The following are classified as nonbanks despite their regulator; Merrimack Mortgage Company (FDIC) and Suntrust Mortgage (CFPB). The following are classified as banks despite being regulated by HUD; Homeowners Mortgage Company, Liberty Mortgage Corporation, and Prosperity Mortgage Company. Table A4 shows the results of the classification algorithm.

HMDA Sample and County-level Variation We require that a county have at least 10 mortgage originations in every quarter prior to 2007 to ensure that our results are not driven by small counties with entry and exit. Figure A5 shows that we nevertheless capture more than 80 percent of the market.

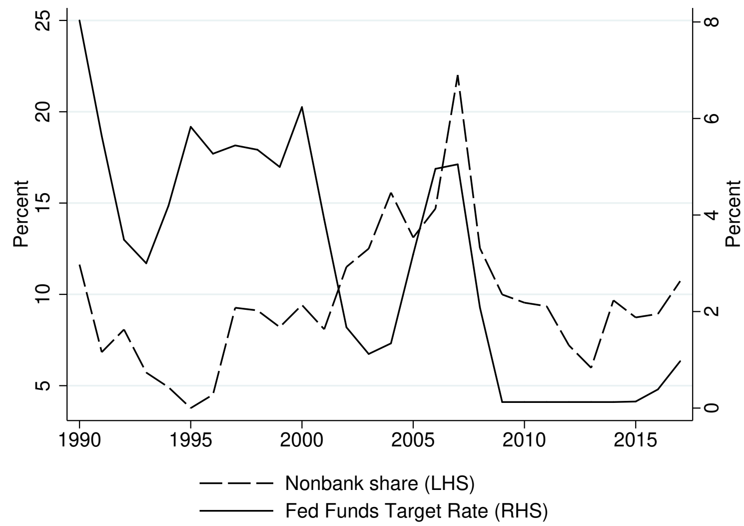
Different from the auto loan market, the mortgage market underwent some structure changes during the sample period. Specifically, in the early 1990s the introduction of Basel I capital requirements for banks increased the nonbank share dramatically. Figure A6 shows the time series of the distribution of county-level nonbank shares. We use 1995Q1 as starting point of our analysis as the figure indicates that around that quarter a new equilibrium between banks and nonbank mortgage lenders had been reached. Figure A7 shows the local variation in the nonbank share that we use for identification in the main mortgage market analysis. Table A3 provides the summary statistics for the HMDA sample.

Figure A1: Total Syndicated Lending in the US



Notes: The chart shows syndicated lending quantities from DealScan. The sample consists of dollar-denominated loans to borrowers headquartered in the US.

Figure A2: Syndicated lending in the US: Nonbank lending as proportion of total



Notes: The chart shows annual syndicated lending quantities from DealScan, and annual averages of the Federal Funds Target Rate. The figure shows nonbank lending as a proportion of total lending. The sample consists of dollar-denominated loans to borrowers headquartered in the US. Only loans where lender shares are observed in DealScan are included.

Figure A3: Distribution of Household Dependence on Nonbank Auto Credit

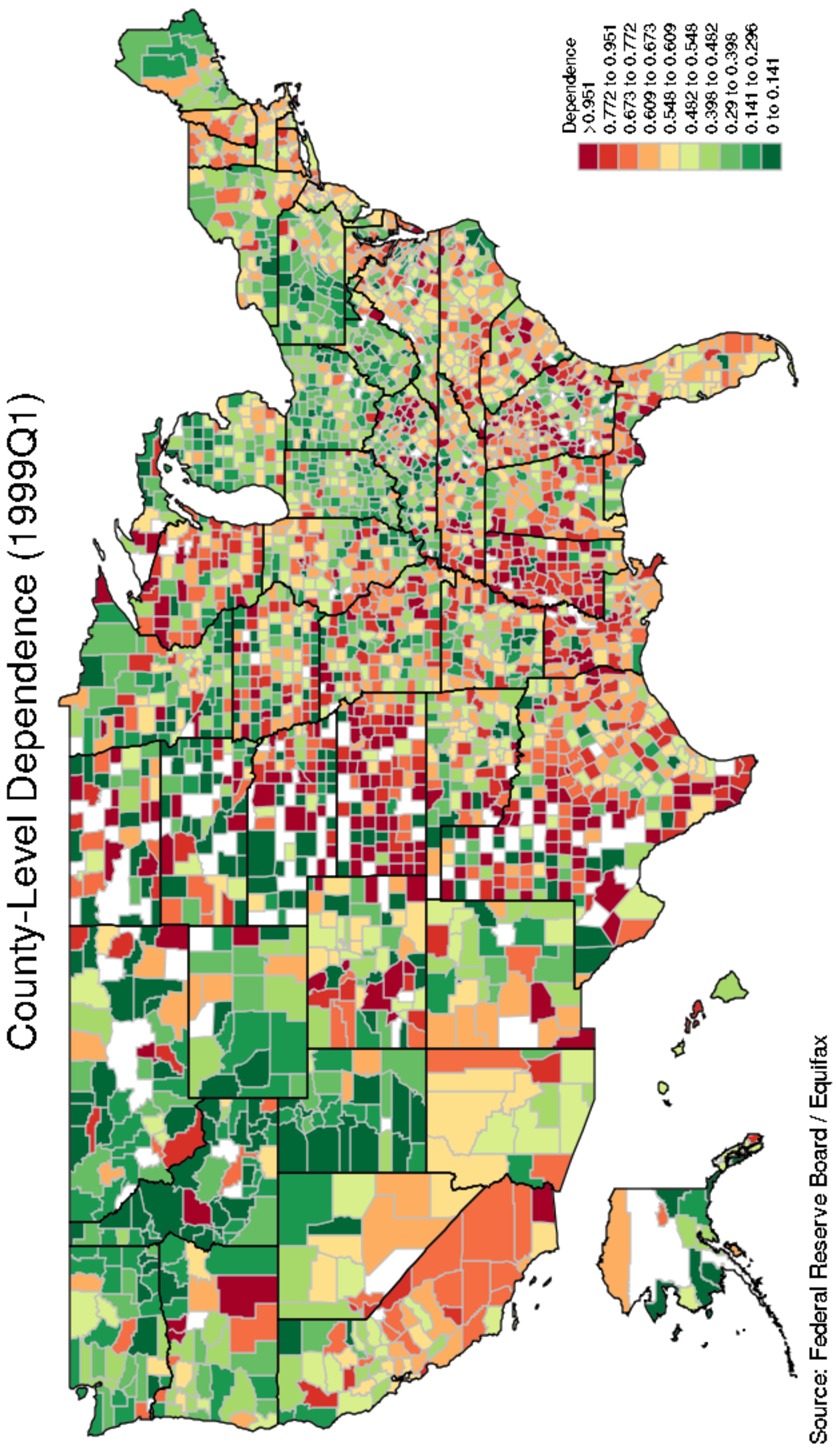


Figure A4: Nonbank Share in the Auto Loan Market over Time

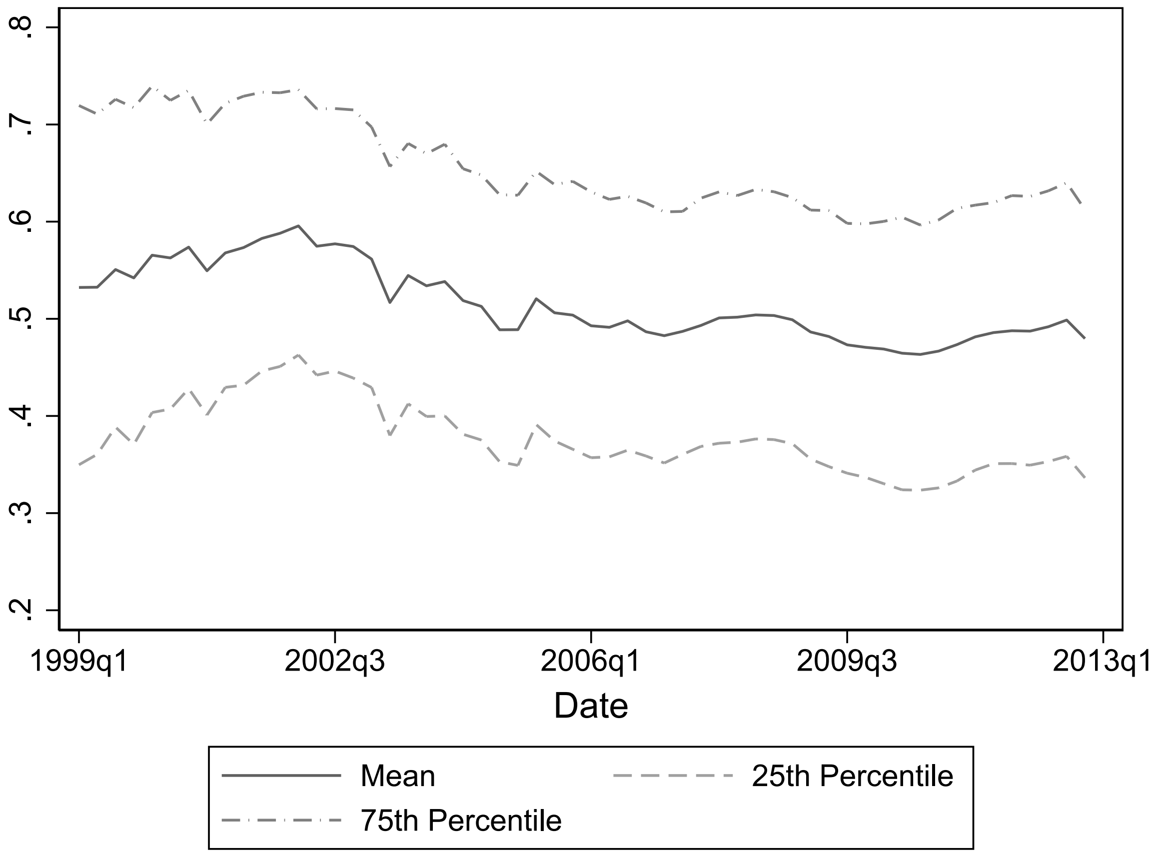


Figure A5: Percent of HMDA Loans Included in the Sample

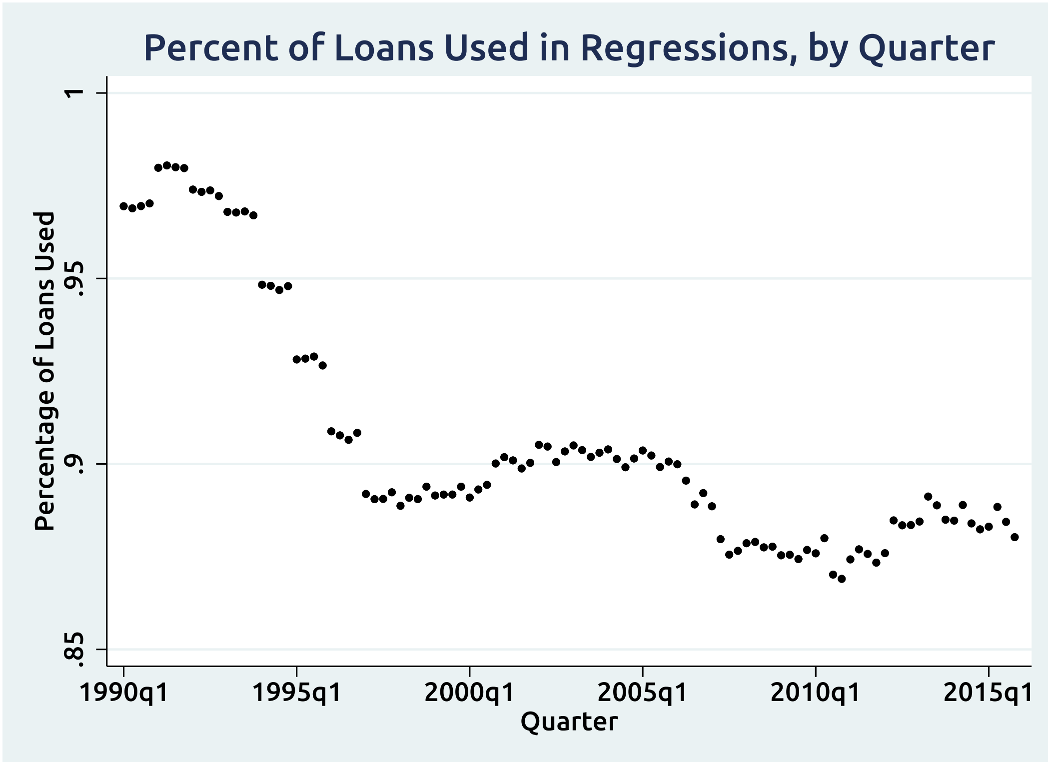


Figure A6: Nonbank Share in the Mortgage Market over Time

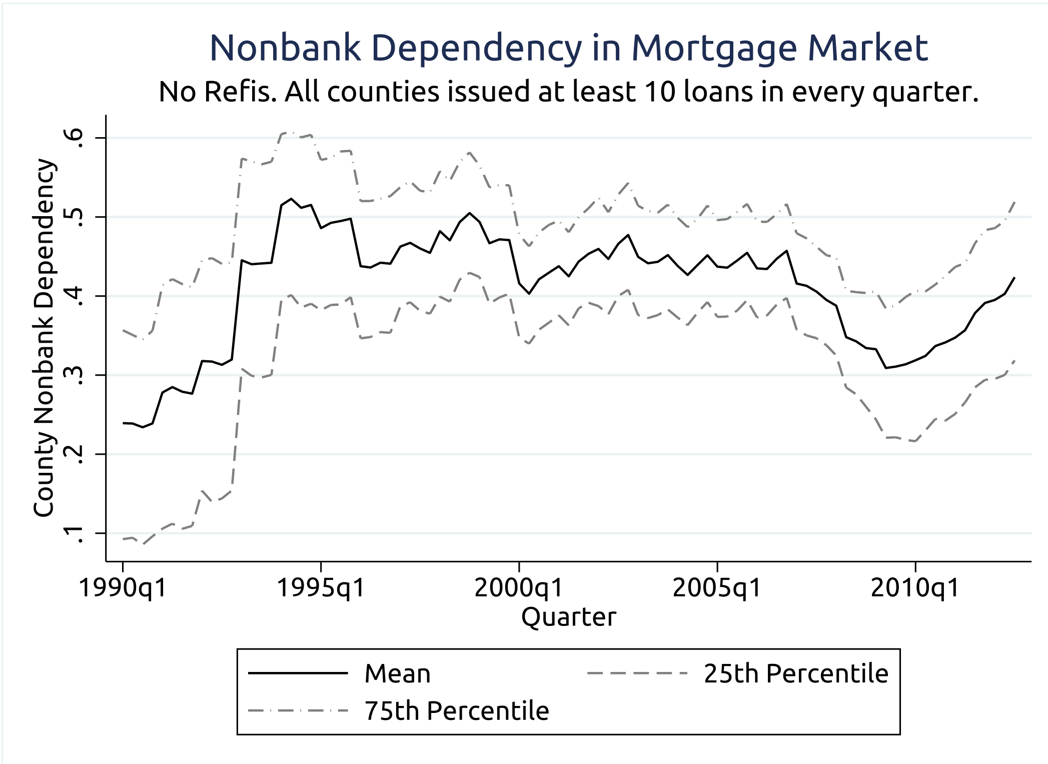


Figure A7: Distribution of Household Dependence on Nonbank Mortgage Credit 1995Q1

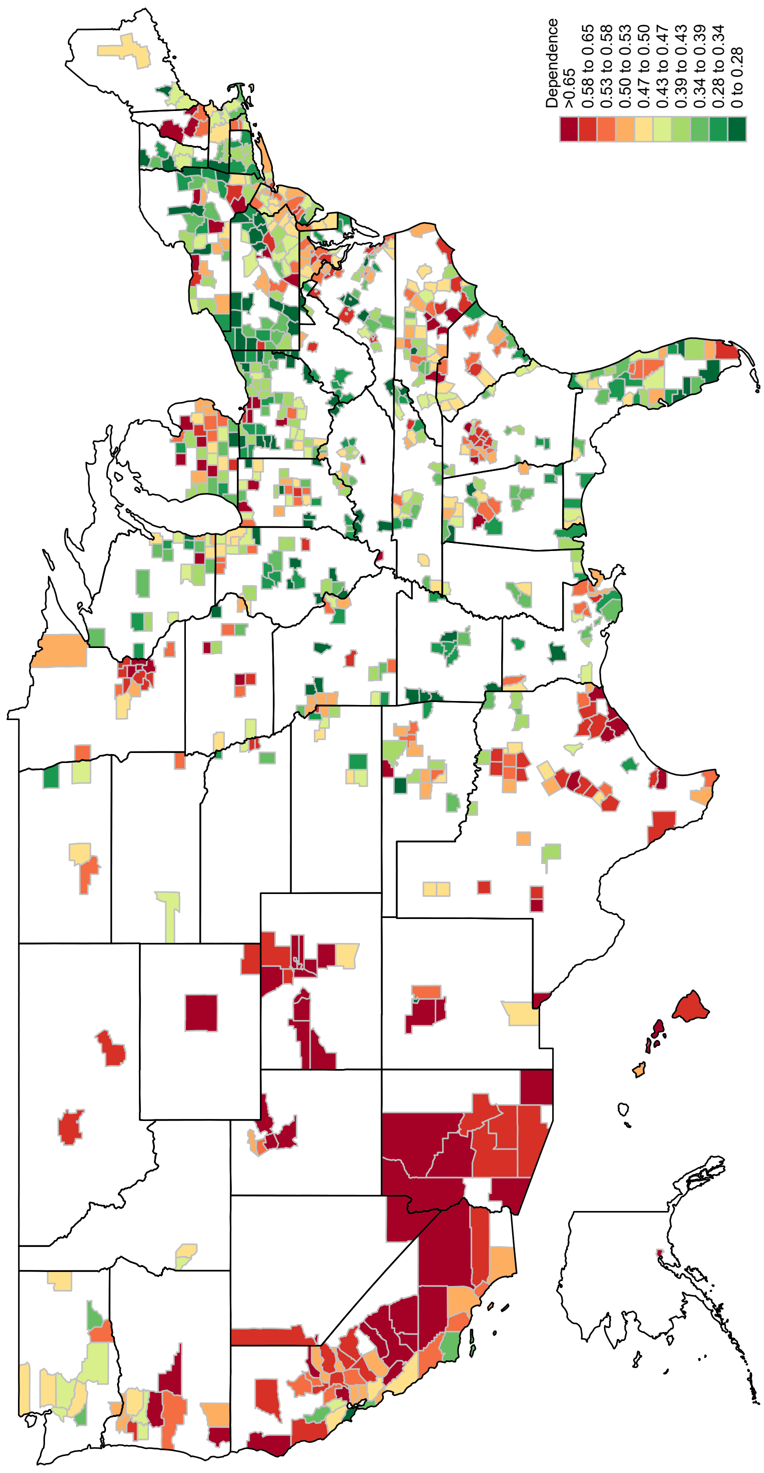


Table A1
Summary Statistics: DealScan and Compustat

This table shows summary statistics for the merged DealScan-Compustat dataset. The sample consists of dollar-denominated loans to borrowers headquartered in the US. The sample period is 1990-2012. All variables are defined in Appendix A. The variables 'log total borrowing' and 'nonbank relation' are defined using all loans, even where lender shares are unobserved. The other variables derived from DealScan are defined using only loans where lender shares are observed.

Variable	N	mean	sd	p25	p50	p75
		Borrower-quarter level				
Log total borrowing	62,558	18.28	1.554	17.40	18.32	19.27
Log nonbank amount	5,471	17.26	1.355	16.45	17.22	18.10
Log bank amount	15,545	17.84	1.878	16.52	17.91	19.16
Nonbank relation	623,359	0.226	0.418	0	0	0
Total debt	371,420	5.061	2.684	3.240	5.138	6.801
Leverage	371,305	-1.406	1.026	-1.798	-1.199	-0.802
Liquidity	546,829	-3.118	1.681	-4.152	-2.974	-1.868
Investment	519,073	-1.760	1.306	-2.433	-1.495	-0.749
Log total assets	578,098	6.166	2.598	4.375	6.059	7.764
High yield	194,721	0.427	0.495	0	0	1
		Borrower-lender-quarter level				
Nonbank lender	103,337	0.109	0.312	0	0	0
Log all loans amount	103,337	16.98	1.100	16.38	17.03	17.63
Log term loan amount	18,763	16.25	1.222	15.49	16.22	16.99
Log revolver amount	60,303	16.85	1.003	16.30	16.91	17.49

Table A2
Summary Statistics Equifax

This table shows the summary statistics for the Equifax sample. All variables are defined in Appendix A.

Variable	N	mean	sd	p25	p50	p75
		Individual Level				
Nonbank Share 1999Q1	54,258,810	0.57	0.16	0.49	0.59	0.67
New Loan Finance	54,258,810	0.01	0.10	0	0	0
New Loan Bank	54,258,810	0.01	0.09	0	0	0
Log Finance Amount	54,258,810	0.09	0.95	0	0	0
Log Bank Amount	54,258,810	0.08	0.89	0	0	0
Bankruptcy	54,258,810	0.00	0.05	0	0	0
Log Credit Card Balance	54,258,810	1.40	2.96	0	0	0
Log Consumer Credit Balance	54,258,810	0.33	1.55	0	0	0
Log Mortgage Balance	54,258,810	2.65	4.90	0	0	0
Riskscore	54,258,810	687	107	608	708	780
Log Income	54,258,810	21.05	1.92	19.68	21.28	22.49
		County-Level				
Nonbank Share 1999Q1	2,936	0.53	0.28	0.35	0.55	0.72
Market Share (Amt)	157,981	0.35	0.37	0	0.33	0.63
Market Share (Loans)	157,981	0.36	0.38	0	0.27	0.67
Log New Loans Finance	157,981	0.80	0.90	0	0.69	1.10
Log New Loans Bank	157,981	0.80	0.88	0	0.69	1.39
Log Finance Amount	157,981	6.14	5.26	0	9.29	10.69
Log Bank Amount	157,981	5.95	5.34	0	9.25	10.68
Mean Riskscore	157,981	687.17	32.80	666.02	689.53	709.72
Log Income	157,981	18.12	1.72	16.95	17.97	19.11

Table A3
HMDA Summary Statistics

Variable	N	mean	sd	p25	p50	p75
		Loan-Level: Conforming Loans				
Logged Loan Value	190,922,127	4.656	0.773	4.220	4.754	5.193
Female Dummy	190,922,127	0.282	0.450	0.000	0.000	1.000
African American Dummy	190,922,127	0.088	0.283	0.000	0.000	0.000
Logged Applicant Income	190,922,127	4.115	0.647	3.714	4.094	4.511
Nonbank Dummy	190,922,127	0.409	0.492	0.000	0.000	1.000
		Loan-Level: Jumbo Loans				
Logged Loan Value	12,510,881	6.138	0.431	5.841	6.087	6.366
Female Dummy	12,510,881	0.191	0.393	0.000	0.000	0.000
African American Dummy	12,510,881	0.049	0.215	0.000	0.000	0.000
Logged Applicant Income	12,510,881	5.151	0.658	4.727	5.050	5.481
Nonbank Dummy	12,510,881	0.330	0.470	0.000	0.000	1.000
		County Level: Without Refinances				
Log Bank Conforming Amount	59,547	11.208	1.356	10.236	11.140	12.116
Log Nonbank Conforming Amount	59,547	10.637	1.534	9.558	10.574	11.683
Log Total Conforming Amount	59,547	11.694	1.386	10.689	11.619	12.629
Nonbank Market Share Conforming Loans	59,547	0.330	0.115	0.247	0.334	0.411
Log Bank Jumbo Amount	59,547	8.465	3.090	7.353	8.825	10.316
Log Nonbank Jumbo Amount	59,547	5.927	4.203	0.000	7.088	9.002
Log Total Jumbo Amount	59,547	8.780	3.028	7.602	9.059	10.597
Nonbank Market Share Jumbo Loans	59,547	0.026	0.041	0.000	0.011	0.033
Reliance on Nonbanks	59,547	0.364	0.122	0.279	0.372	0.449
Log of Lagged Income	59,547	19.906	1.355	18.905	19.772	20.754

Table A4
Nonbanks by regulator

This tables shows the result of the classification algorithm.

HDMA Regulator Code	Share Bank
1 - OCC	100%
2 - FRS	53.7%
3 - FDIC	99.98%
4 - OTS	100%
5 - NCUA	100%
7 - HUD	0.06%
8 - PMIC	0%
9 - CFPB	97.17%

B Monetary Policy and Nonbank Funding

So far, we have documented that nonbanks lend more when monetary policy tightens. We now examine one mechanism that enables nonbanks to expand lending after a monetary contraction.

Stein (2013) claims that an advantage of monetary policy is that it "gets in all the cracks" of the financial system and therefore affects all financial intermediaries in a similar manner. At the same time, Drechsler, Savov, and Schnabl (2017) show that banks experience deposit outflows in a monetary tightening cycle, which in turn reduces banks' ability to lend. This observation raises two interrelated questions about other parts of the financial system: 1) To which financial products do the deposits flow? and 2) Do financial products that experiences inflows provide funding for nonbanks?

With respect to the first question, we observe that one alternative to bank deposits is money market funds (MMFs). The returns of these funds tend to track the federal funds rate closely. If banks do not raise their deposit rates to match increases in the federal fund rate (as shown by Drechsler, Savov, and Schnabl (2017)) then depositors will find switching from holding deposits to holding money market fund shares attractive (Xiao forthcoming). To test whether this occurs, we estimate how MMF assets respond to monetary policy. Using data from the Financial Accounts of the United States, we estimate the following equation:

$$\begin{aligned} \text{MMF Asset Growth}_t \;&=\; \beta_1 \text{Monetary Policy}_{t-1} + \\ &\quad\; \beta_2 \text{Macroeconomic Controls}_{t-1} + \text{Trend}_t + \text{Trend}_t^2 + \alpha + \epsilon_t \end{aligned} \tag{9}$$

A monetary contraction should lead to bank deposit outflows and, as a result, money market funds should experience inflows. Hence, we expect the coefficient on Monetary Policy$_{t-1}$, β_1, to be positive and significant.

Table B1 shows the results of estimating equation 9. We measure monetary policy using the cumulative sums of Gertler-Karadi shocks. Money market funds grow more during a monetary contraction (column 1). This relationship holds when excluding the 2007/08 financial crisis (column 2). This finding shows that after a monetary contraction deposits migrate from the banking sector to money market funds.

In response to the second question, whether financial products that experiences inflows provide funding for nonbanks, we note that, among other short-term investments, money markets funds invest in short-term paper of firms and asset-backed commercial paper (ABCP). Many nonbanks rely on this type of funding from money market funds.[41] Table B1, columns 3 and 4 show that money market funds also buy relatively more open market paper and corporate bonds during a monetary contraction. This suggests that more funding becomes available to nonbank lenders.[42] This finding is consistent with Xiao (forthcoming) who, using disaggregated MMF data, shows that MMFs increase their holdings of commercial paper and ABCP when the federal funds rate is higher.

The key implication of the MMF lending patterns is that nonbanks finance their expansion of credit to more risky borrowers after monetary contrary with short-term funding. In other words, nonbank lenders fund the expansion of risky assets with fragile funding. Hence, a monetary contraction leads to more risk on the asset and the liability side of nonbank financial institutions.

[41] For instance, Benmelech, Meisenzahl, and Ramcharan (2017) document that auto finance companies funded the vast major for their credit supply with ABCP. For a more general overview of funding flows, see Pozsar et al. (2013).

[42] We find similar results when we take the monetary policy measure byWu and Xia (2016).

Table B1
Monetary Policy and MMF Flows

The table shows the results of estimating equation 9. Asset Growth is the quarterly growth rate of total MMF sector assets. CP/Bond growth is the quarterly growth rate of holdings of open market paper and corporate bonds. All variables are defined in Appendix A. The sample period is 1990-2012.

	Asset Growth		CP/Bond Growth	
	All	Pre-2008	All	Pre-2008
	(1)	(2)	(3)	(4)
GK Lagged	0.0826***	0.105***	0.103***	0.103***
	(0.0249)	(0.0204)	(0.0296)	(0.0240)
GDP Lagged	0.000538	0.000941	0.00377	0.00434
	(0.00170)	(0.00221)	(0.00273)	(0.00331)
GDP Forecast Lagged	0.000882	0.00422	-0.00207	-0.00571
	(0.00728)	(0.00757)	(0.00997)	(0.00923)
VIX Lagged	-0.000280	-0.000832	-0.000973	-0.00254
	(0.000868)	(0.00114)	(0.00112)	(0.00167)
Inflation lagged	0.00597	-0.0143	-0.00580	-0.00876
	(0.00615)	(0.00856)	(0.0102)	(0.0107)
Trends	YES	YES	YES	YES
Observations	86	67	86	67
R^2	0.332	0.297	0.347	0.299

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C: Robustness Tests

We start with a regression analyses of loan amounts extended by nonbanks and banks in each market. For corporate loans, we estimate the following equation at the borrower-quarter level without controlling for firm-specific demand or time fixed effects:

$$\text{Log(Quantity)}_{b,t} = \beta_1 \text{Monetary Policy}_{t-1} + \beta_2 \text{Macroeconomic Controls}_{t-1} + \alpha + \varepsilon_{b,t} \quad (10)$$

Table C1 shows the results from estimating equation 10. Nonbank lending declines in response to a contractionary monetary policy shock (column 1). However, this reduction in lending is smaller than the reduction by banks (column 2). Consequently, the nonbank share increases after a monetary contraction (column 3). We find similar effects when including industry fixed effects (column 4-6). Table C2, we show that these results are robust to including firm controls and trends as well as weighting observations by loan size and using other measures of monetary policy. The fact that both bank and nonbank lending decline after a monetary contraction suggests that demand for credit in the syndicated loan market is sensitive to monetary policy. A second factor possibly limiting substitution between bank and nonbank lenders is that this market relies on soft information and therefore has high switching cost.

We now turn to auto loans, where we estimate the following regression:

$$\text{Log(Auto Credit)}_{j,t} \quad = \quad \beta_1 \text{MP}_{t-1} + \beta_2 \text{Macroeconomic Controls}_{t-1} + \beta_3 X_{j,t-1} + \alpha_j + \varepsilon_{j,t} \quad (11)$$

where *Auto Credit*$_{jt}$ the log of new auto loan amounts in county j in quarter t . MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[43] Macroeconomic Controls_{t-1} is a vector of macroeconomic controls that includes GDP, GDP forecast, inflation and the VIX. $X_{j,t-1}$ is a vector of time-varying county-level controls (the average credit-bureau reported risk score and income). We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics.

Following Drechsler, Savov, and Schnabl (2017), we expect banks experiencing deposit outflows after a monetary contraction to cut auto lending—that is, we expect β_1 to be negative and significant for *new auto loans extended by banks.* To be clear, a negative coefficient could also be interpreted as a drop in credit demand. One indication that the reduction in bank lending is attributable to tighter bank funding constraints rather than a drop in demand would be an increase in lending by nonbanks —that is, we expect β_1 to be positive and significant for *new auto loans extended by nonbanks.*

Table C3 shows the results of estimating equation 11. Consistent with relative relaxation of nonbanks' funding constraints after a monetary contraction, we find that nonbanks increase auto lending (column 1). Banks reduce auto lending in response to a monetary contraction (column 2). A 25 bps surprise increase in the policy rate leads to reduction in new auto loans extended by banks by over 5 percent. The increased nonbank lending activity suggests that the fall in bank lending is driven by credit supply rather than credit demand. In the aggregate, we find that the substitution between bank and nonbank lending is perfect. The estimated effect of changes in monetary policy on total auto credit in a county is close to zero and statistically insignificant (column 3).

Last, we consider the mortgage market and estimate the following regression:

$$\begin{aligned}\text{Log(Mortgage Amount)}_{j,t} = &\alpha_j + \beta_1 \text{MP}_{t-1} + \beta_2 \text{Macroeconomic Controls}_{t-1} + \\ &\beta_3 X_{j,t-1} + \varepsilon_{j,t}\end{aligned} \quad (12)$$

[43] We obtain similar results when we use the Wu-Xia shadow rate.

Table C1

Aggregate Syndicated Loans: Substitution across Banks and Nonbanks

The table shows estimated regression coefficients for equation 10. The dependent variable is the log of lending quantity from DealScan (columns 1, 2, 4, 5) or the log share of nonbanks in syndicates (columns 3, 6). Only observations where lender shares are observed are included. GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. The regressions are at quarterly frequency. The sample period is 1990-2012. The sample consists of dollar-denominated loans where the borrower country is the USA. Standard errors clustered by borrower and quarter. All variables are defined in Appendix A.

	Nonbank Amount (1)	Bank Amount (2)	Nonbank Share (3)	Nonbank Amount (4)	Bank Amount (5)	Nonbank Share (6)
GK	-0.522***	-0.885***	0.633***	-0.503***	-0.807***	0.562***
	(0.0407)	(0.0410)	(0.0280)	(0.0392)	(0.0367)	(0.0272)
VIX	0.0124	0.0340***	-0.0203***	0.00953	0.0260***	-0.0173***
	(0.00792)	(0.0101)	(0.00635)	(0.00705)	(0.00806)	(0.00569)
Inflation	0.202***	0.195***	-0.105***	0.190***	0.173***	-0.0734***
	(0.0373)	(0.0443)	(0.0300)	(0.0317)	(0.0357)	(0.0270)
GDP growth	-0.00848	-0.0198	0.00736	-0.00807	-0.00884	0.00190
	(0.0162)	(0.0256)	(0.0169)	(0.0132)	(0.0214)	(0.0151)
GDP growth forecast	0.0765	0.223***	-0.0494	0.0509	0.131**	-0.0138
	(0.0543)	(0.0728)	(0.0482)	(0.0467)	(0.0579)	(0.0469)
Industry FEs	No	No	No	YES	YES	YES
Observations	5,349	15,195	5,349	5,041	14,598	5,041
Number of borrowers	3,876	9,508	3,876	3,572	8,923	3,572
Number of quarters	90	90	90	90	90	90
R-squared	0.0942	0.154	0.216	0.278	0.364	0.369

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

where $Mortgage\ Amount_{jt}$ is the log of new mortgage loan amounts in county j in quarter t . MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[44] Macroeconomic Controls_{t-1} is a vector of macroeconomic controls that includes GDP, GDP forecast, inflation and the VIX. $X_{j,t-1}$ includes time-varying county-level controls (log income). We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics.

Table C4 shows the results of estimating equation 12. We start by analyzing the response of conforming mortgage originations, shown in columns 1-4. In response to a contractionary monetary policy shock, originations of conforming mortgages by banks fall (column 1). Similarly, originations of conforming mortgages by nonbanks fall (column 2), leading to an overall reduction in the origination of conforming mortgages (column 3) and a somewhat lower nonbank market share (column 4).

In the jumbo loan market, we find a small positive effect of monetary policy on bank originations of jumbo mortgages (column 5). The effect is larger for nonbanks (column 6). The estimated effect on total jumbo loan originations shown in column 7, is positive and significant with the nonbank market share increasing slightly , though this increase is not statistically significant (column 8).

[44] We obtain similar results when we use the Wu-Xia shadow rate.

Table C2
Aggregate Syndicated Loans: Substitution - Robustness

The table shows estimated regression coefficients for equation 10. The dependent variable is the log share of nonbanks in syndicates. Only observations where lender shares are observed are included. GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. The regressions are at quarterly frequency. In columns 1-3, the sample period is 1990-2012. The sample consists of dollar-denominated loans where the borrower country is the USA. Column 1 includes time-varying borrower-level controls. Column 2 includes borrower fixed effects. Column 3 estimates the equation using weighted least squares (WLS), with the weights provided by the log of borrower total assets. Columns 4 and 5 replace GK with the Fed Funds target rate or Wu-Xia shadow rate, respectively. For these columns, the sample period is 1990-2017. Column 6 restricts the sample period to 1990-2006. Standard errors clustered by borrower and quarter. All variables are defined in Appendix A.

	Nonbank Share					
	(1)	(2)	(3)	(4)	(5)	(6)
	Firm controls	Firm FE	WLS	Fed Funds	Wu-Xia	Pre-crisis
GK	0.131**	0.265***	0.545***			0.568***
	(0.0649)	(0.0553)	(0.0380)			(0.0389)
Fed Funds				0.143***		
				(0.0154)		
Wu-Xia					0.129***	
					(0.0123)	
VIX	0.00428	-0.00421	-0.0153**	-0.00752	-0.0109*	-0.0201**
	(0.00647)	(0.00482)	(0.00727)	(0.00643)	(0.00625)	(0.00765)
Inflation	0.0492	0.0132	-0.0470	0.0267	0.0284	-0.0987***
	(0.0408)	(0.0301)	(0.0320)	(0.0356)	(0.0345)	(0.0360)
GDP growth	-0.00898	-0.0301*	-0.0100	0.00642	0.00646	0.0126
	(0.0183)	(0.0156)	(0.0178)	(0.0202)	(0.0196)	(0.0177)
GDP growth forecast	0.0598	0.0757*	0.0170	0.0616	0.0395	0.0319
	(0.0485)	(0.0450)	(0.0522)	(0.0667)	(0.0621)	(0.0488)
High yield borrower	0.513***					
	(0.0862)					
Log(Borrower assets)	-0.141***					
	(0.0273)					
Industry FEs	YES	No	YES	YES	YES	YES
Borrower FEs	No	YES	No	No	No	No
Observations	1800	2355	3699	5824	5824	4031
Number of borrowers	1029	882	2463	4068	4068	2978
Number of quarters	90	90	90	112	112	67
R-squared	0.384	0.722	0.355	0.314	0.320	0.367

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C3
Aggregate Auto Loans: Substitution across Banks and Nonbanks

This table shows the regression results of equation 11. The dependent variable is the log amount of new auto credit extended by finance companies (column 1), by banks (column 2) and by both sources (3). The sample period is from 1999 to 2012. Standard errors clustered by county and state x quarter. All variables are defined in Appendix A.

	Log New Loan Amount		
	Nonbank	Bank	Total
	(1)	(2)	(3)
Lagged GK	0.207***	-0.269***	-0.00996
	(0.0474)	(0.0467)	(0.0420)
Lagged GDP Forecast	0.0755***	0.165***	0.113***
	(0.0285)	(0.0221)	(0.0228)
Lagged Inflation	0.0323**	-0.0237	0.00153
	(0.0157)	(0.0149)	(0.0142)
Lagged VIX	-0.0132***	-0.00930***	-0.0120***
	(0.00340)	(0.00278)	(0.00266)
Lagged GDP	0.0449***	-0.0570***	-0.00358
	(0.00806)	(0.00745)	(0.00658)
Time-varying County Controls	YES	YES	YES
County FE	YES	YES	YES
Observations	169,216	169,216	169,216
R^2	0.499	0.509	0.530

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C4
Conforming and Jumbo Loan Issuance by Lender-Loan Type

Date Range: 1995q2 - 2012q3. All dependent variables are logged. All counties issued at least 10 loans in every quarter of date range. MP Shock is cumulative sum of monetary policy shocks of Gertler and Karadi (2015). Jumbo loans are loans above the conforming loan limit. Sample includes refinances

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Conventional				Jumbo			
	Banks	Nonbanks	Total	Nonbank Share	Banks	Nonbanks	Total	Nonbank Share
Lagged GK	0.0275	-0.375***	-0.0538***	-0.0614***	0.251***	-0.231***	0.140***	-0.0148**
	(0.0306)	(0.0257)	(0.0151)	(0.00562)	(0.0427)	(0.0585)	(0.0304)	(0.00663)
Lagged GDP Forecast	0.0423***	0.0938***	0.0545***	0.0112***	0.0722***	0.158***	0.110***	0.00347**
	(0.00918)	(0.0107)	(0.00852)	(0.00182)	(0.0176)	(0.0283)	(0.0151)	(0.00149)
Lagged Inflation	-0.0934***	-0.332***	-0.196***	-0.0361***	-0.220***	-0.107***	-0.154***	0.0138***
	(0.0102)	(0.0159)	(0.00805)	(0.00246)	(0.0196)	(0.0395)	(0.0202)	(0.00201)
Lagged VIX	0.00875***	0.0169***	0.00533***	0.00242***	0.00911*	-0.0222***	-0.00219	-0.00229***
	(0.00295)	(0.00265)	(0.00156)	(0.000515)	(0.00536)	(0.00825)	(0.00485)	(0.000409)
Lagged GDP	-0.00311**	-0.0422***	-0.0154***	-0.00580***	0.00774*	-0.0493***	-0.00782**	-0.00200***
	(0.00156)	(0.00248)	(0.00169)	(0.000308)	(0.00434)	(0.00725)	(0.00364)	(0.000422)
Log of Lagged Income	1.239***	3.806***	2.304***	0.383***	2.132***	4.290***	2.763***	0.0340**
	(0.0821)	(0.239)	(0.110)	(0.0308)	(0.128)	(0.274)	(0.140)	(0.0166)
Observations	45,768	45,768	45,768	45,768	45,768	45,768	45,768	45,768
R^2	0.932	0.907	0.967	0.678	0.931	0.897	0.934	0.701
Adjusted R^2	0.927	0.901	0.965	0.658	0.926	0.891	0.931	0.683
rmse	0.681	0.797	0.395	0.118	1.028	1.378	1.013	0.0446
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C5
Aggregate Lending and Outcomes - Risk

Panel A of this table is in parallel to table 3 with GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effect. Standard errors are clustered by industry and time. Panel B of this table is in parallel to table 6 with GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effect. Standard errors are clustered on the county and quarter level. Panel C of this table is in parallel to table 9 with GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effect. Standard errors are clustered on the county and quarter level. In all panels, GK refers to lagged cumulative sums of the monetary policy shocks of Gertler-Karadi for the US.

	Corporate Borrowing (1)	Total Auto Loan (2)	Jumbo Mortgage (3)
Lagged GK x Nonbank	0.143***		0.016***
	(0.030)		(0.002)
Lagged GK x Lagged VIX x Nonbank	-0.011***		-0.0004
	(0.004)		(0.0003)
Lagged GK x past Nonbank Share		0.039	
		(0.038)	
Lagged GK x Lagged VIX x past Nonbank Share		-0.002	
		(0.002)	
Macro Controls	Yes	Yes	Yes
Macro Controls x past Nonbank Share	Yes	Yes	Yes
Borrower-Quarter FE	Yes	No	No
Lender FE	Yes	No	Yes
County FF	No	Yes	No
Birth Year FE	No	Yes	No
Quarter FE	No	Yes	No
County-Quarter FE	No	No	Yes
Observations	929741	54243317	5461367
Adjusted R^2	0.81	0.01	0.49