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David Elliott, Ralf R. Meisenzahl, José-Luis Peydró, and Bryce C. Turner

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

David Elliott Ralf R. Meisenzahl José-Luis Peydró Bryce C. Turner

Abstract

We show that nonbanks (funds, shadow banks, fintech) affect the transmission of monetary policy to output, prices and the distribution of risk via credit supply. For identification, we exploit exhaustive US loan-level data since the 1990s, borrower-lender relationships and Gertler-Karadi monetary policy shocks. Higher policy rates shift credit supply from banks to nonbanks, thereby largely neutralizing associated consumption effects (via consumer loans), while just attenuating firm investment and house price spillovers (via corporate loans and mortgages). Moreover, different from the risk-taking channel, higher policy rates increase risk-taking, as less-regulated, fragile nonbanks —in all credit markets— expand supply to riskier borrowers.

JEL Classification: E51; E52; G21; G23; G28
Keywords: Nonbank Intermediaries; Banks; Monetary Policy Transmission; Household and Corporate Loans; Credit and Risk-Taking Channel.

*Elliott (David.Elliott@bankofengland.co.uk) is with the Bank of England, Meisenzahl (Ralf.Meisenzahl@chi.frb.org) is with the Federal Reserve Bank of Chicago, Peydró (jose.peydro@gmail.com) is with Imperial College London, ICREA-Universitat Pompeu Fabra-CREI-Barcelona GSE, and CEPR, and Turner (bturner@hbs.edu) is with the Harvard Business School. We thank Greg Buchak, Jordi Gali, Narayana Kocherlakota, Isabel Schnabel and seminar participants at the WIFI Vilanova, ECB, Goethe University Frankfurt, Frankfurt School of Finance and Management, IE Business School, CUNEF, CNMV, Bundesbank, Danish National Bank, Imperial College London, University of Bonn, University of Mannheim, UPF, Federal Reserve Bank of Kansas City, CREI, and participants of the AFA, NBER Summer Institute, Paris December Finance Meeting, and Barcelona GSE Summer Forum for helpful comments and suggestions. Project supported by a 2018 Leonardo Grant for Researchers and Cultural Creators, BBVA Foundation, by the PGC2018-102133-B-I00 (MCIU/AEI/FEDER, UE) grant and the Spanish Ministry of Economy and Competitiveness, through the Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2015-0563), and by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 648398).The views expressed here are those of the authors and do not necessarily reflect the views of the Bank of England, Board of Governors, Federal Reserve Bank of Chicago or staff of the Federal Reserve System.

1 Introduction

The structure of credit markets has changed dramatically over recent decades. Nonbank credit intermediaries now have a significant presence in many credit markets. In the US, nonbank lenders, including fintech firms, account for the majority of mortgage originations; finance companies capture around half of the consumer loan market; and investment funds and collateralized loan obligations (CLOs) have become key players in the corporate loan market. Globally, nonbank financial intermediaries now hold around 50% of financial assets (Financial Stability Board 2020). Moreover, the importance of monetary policy has been very salient since the 2008 crisis (e.g., El-Erian (2016)). However, despite the rise of nonbank lenders, there is scant evidence on how nonbanks affect the credit channel of monetary policy, which contrasts with the very large literature on the bank lending channel of monetary policy. (e.g., Bernanke and Blinder (1988; 1992); Jimenez et al. (2012); Drechsler, Savov, and Schnabl (2017)).

The effects of monetary policy on lending by nonbanks are conceptually multifaceted. First, policymakers have argued that monetary policy "gets in all the cracks" of the financial system by acting directly on market interest rates (Stein (2013), then governor of the Federal Reserve Board) – i.e., tighter monetary policy negatively affects the funding conditions of *all* financial intermediaries (banks and nonbanks) that borrow short-term. Second, specific frictions in funding markets may imply that monetary policy affects banks and nonbanks differently. On the one hand, tighter monetary policy reduces risk appetite (Brunnermeier and Sannikov 2012) and hence may affect nonbanks more negatively, since they tend to be more fragile and less regulated than banks (Pozsar et al. 2013). On the other hand, tighter monetary policy reduces bank credit supply via a reduction in bank reserves (Kashyap and Stein 1995; 2000; Stein 1998) and/or causes deposits to flow from banks to shadow banks due to banks' deposit marker power (Drechsler, Savov, and Schnabl 2017; Xiao 2020).

In this paper we analyze the nonbank credit channel of monetary policy. An important obstacle to studying the role of nonbank lenders in monetary transmission is the lack of comprehensive loan-level data that include both banks and nonbanks. In particular, to the best of our knowledge, virtually all central bank credit registers only include data on banks. To address this challenge, we exploit loan-level data from three US credit markets – corporate loans, consumer auto loans, and mortgages – in which we observe, for each loan, whether the lender is a deposit-taking institution (bank) or nonbank. We match each loan-level dataset to outcomes such as firm output, auto sales, and house prices. In each market, the data extend back to the 1990s, allowing us to exploit considerable time-series variation in monetary policy.

For identification, we use the Gertler and Karadi (2015) measure of monetary policy shocks, as well as pre-determined cross-sectional variation in borrower-lender relationships, which tend to be sticky (Chodorow-Reich 2014). We also control for realized and expected GDP growth, inflation, and VIX. For robustness, we also use the federal funds rate and Wu and Xia (2016) shadow rates, and instrument these policy rates with the Gertler-Karadi shocks. For each market, we first analyze the data at the loan level with high-dimensional fixed effects to control for borrower characteristics including credit demand. To analyze real effects, including some general equilibrium effects, we then aggregate the data to the firm, industry, or county level.

We start our empirical analysis with the corporate loan market, using the Thomson Reuters DealScan LPC database of syndicated loan originations. Syndicated loans are originated by multiple lenders, allowing us to use firm-quarter fixed effects to control for time-varying unobserved borrower characteristics, including credit demand (Khwaja and Mian 2008; Chodorow-Reich 2014), and hence identify the differential impact of monetary policy on credit *supply* by comparing how banks and nonbanks differentially lend in the same loan.

Using this within-loan variation, we find that nonbanks reduce corporate credit supply by less than banks after a monetary contraction, and hence attenuate the effect of the bank lending channel on total credit. On average, nonbank credit supply increases by 3.4% relative to bank credit supply after a 25 basis point monetary policy tightening surprise, with a larger effect for lending to ex ante riskier firms.

Consistent with informational frictions, we find that – following a monetary tightening – borrowers that lack relationships with nonbank lenders cannot substitute the reduction in bank credit with other sources of debt, and experience a larger reduction in total debt and investment. Moreover, to deal with general equilibrium effects such as substitution of credit and investment from one firm to another within the same industry (Nakamura and Steinsson 2018; Chodorow-Reich 2020), we conduct an industry-level analysis. We find that industries with a stronger ex ante dependence on nonbank credit experience a smaller reduction in debt, leverage, investment, and output following a monetary tightening. Further, the estimated industry (aggregate) effects are robust to removing time fixed effects and weighting each industry by its importance in aggregate output.

Next, we turn to nonbank lending to households. We focus first on consumer loans, using detailed household-level data from the New York Fed / Equifax Consumer Credit Panel. We focus on the auto loan market, because the data on auto loans identify whether the lender is a bank or nonbank. Auto loans represent over 30% of total consumer credit, and nonbank finance companies account for around half of the auto loan market.

Following Benmelech, Meisenzahl, and Ramcharan (2017), we exploit regional heterogeneity in the historical presence of nonbanks, as nonbanks are more likely to expand credit in locations where they are already present. Consistent with this idea, we find that households living in counties historically more dependent on nonbank credit relatively receive more credit from nonbanks after a monetary contraction compared to banks.

We also analyze substitution, risk-taking, real effects in this market. The nonbank and bank effects completely offset each other, implying perfect substitution from bank to nonbank credit after a monetary contraction. Moreover, the shift from bank to nonbank credit is larger for riskier borrowers, amplifying the redistribution of risk from banks to the unregulated nonbank sector. To get closer to aggregate effects, we aggregate the auto loan data to the county level (Chodorow-Reich 2020). Consistent with the household-level results, we find perfect substitution from bank to nonbank credit when monetary policy tightens, implying no significant impact of monetary policy via the credit supply channel on county-level auto credit or auto sales, an important component of durable goods consumption. Finally, to further get closer to general equilibrium effects we remove time fixed effects and weight observations by lagged county-level income, and find similar results.

We next study the largest lending market – mortgages – using data collected under the Home Mortgage Disclosure Act (HMDA). We use the confidential version of HMDA, which allows us to observe mortgage originations at quarterly frequency – unlike the public version, which only provides data at annual frequency. We first analyze nonbank lending at the loan level, controlling for borrower (demand) factors with county-quarter fixed effects and borrower observables (e.g. income, gender, and race). Consistent with the results for the other markets, we find that nonbanks cut lending by less than banks after a monetary contraction.

We then aggregate to the county level, and – in line with our approach for auto loans – exploit persistent geographical variation in the historical presence of nonbank lenders, which reflects local market knowledge. Focusing only on loans that remain on the lender's balance sheet (and which are therefore most affected by changes in funding conditions), we observe an increase in the nonbank share of mortgage lending following a monetary tightening. Effects are stronger for jumbo loans, which tend to be riskier as they cannot be sold to public agencies and often have higher loan-to-value (LTV) ratios. To get closer to general equilibrium effects, we consider *total* county-level mortgage lending – i.e. including both loans that remain on the lender's balance sheet and those that are sold. We find that total mortgage credit supply is less responsive to monetary policy in counties with higher historical dependence on nonbank lenders. Reflecting this differential credit supply effect, house prices fall by less in counties with a higher historical nonbank dependence after a monetary contraction. These results are robust to removing time fixed effects and weighting by lagged county-level income.

In summary, across all three markets, we find that nonbank lenders reduce the potency of monetary policy via credit supply. We identify this channel using granular loan-level data, and find that it also plays an important role at the industry or county level. The strength of the effect differs across markets depending on the strength of credit market frictions. Moreover, tighter money policy leads to a redistribution of risk from banks to the unregulated nonbank sector as nonbank lending increases relative to banks, particularly for riskier loans.

Contribution to the Literature Our main contribution to the literature on monetary policy and credit (Bernanke and Gertler 1995; Adrian and Shin 2010) is to show empirically that nonbanks affect the transmission of monetary policy to output (consumption and investment), house prices and the distribution of risk via a credit supply channel.

There is a large literature showing that banks cut credit supply when monetary policy tightens: the so-called bank lending channel (e.g., Bernanke and Blinder (1988; 1992); Jimenez et al. (2012); Drechsler, Savov, and Schnabl (2017)). However, as highlighted above, evidence on how nonbanks affect monetary policy transmission is scarce.

Our paper is most closely related to Drechsler, Savov, and Schnabl (2017; 2021) and Xiao (2020). Drechsler, Savov, and Schnabl (2017) show that tighter monetary policy leads to deposit outflows from banks, as banks use their market power to charge higher deposit spreads: the "deposits channel" of monetary policy. Xiao (2020) shows that these deposits flow to money market funds, which in turn provide funding to "downstream" nonbank lenders. We extend this literature in two main ways. First, we document the impact of monetary policy on nonbank lending in the retail and corporate credit markets, and therefore demonstrate the impact of nonbanks on the credit channel. Second, we estimate the real economic effects. Drechsler, Savov, and Schnabl (2021) compare bank and nonbank lenders in the mortgage market during the 2003-06 monetary tightening cycle. Buchak et al. (2018) use post-financial crisis data and a structural model to consider the impact of of different policies, including unconventional monetary policy, in the presence of nonbanks. In contrast, we study three major credit markets across several monetary policy cycles and analyze the associated real effects.

Our key contribution, therefore, is to provide a detailed assessment of the role of nonbanks in the credit channel of monetary policy. We show that nonbanks weaken the impact of monetary policy on credit supply, and that this in turn reduces the transmission to corporate investment, durable goods consumption, and house prices. However, the strength of these effects varies across markets and borrowers, depending on the strength of credit market frictions. The presence of nonbanks largely neutralizes the impact of monetary policy on auto loans and hence on car purchases. Meanwhile, in the corporate loan and mortgage markets – where informational frictions play a larger role – substitution from bank to nonbank credit is incomplete.

Our paper is also related to Chen, Ren, and Zha (2018), who analyze the impact of monetary policy on banks and shadow banks in China using lender-level data. Our paper differs on multiple dimensions. First, we compare three different credit markets. This reveals important differences across markets, as substitution from bank to nonbank credit is more complete for consumer loans than for corporate loans and mortgages. Second, we use loan-level data. This allows us to better identify the impact of monetary policy on credit supply by controlling for borrower fundamentals (including credit demand), and to analyze risk-taking. Third, since our loan-level data allow us to match firms and households to lenders, we can also analyze the real effects of monetary policy. Finally, China features a heavily regulated banking system, a large share of state-owned banks, and monetary policy based on targeting monetary aggregates, which potentially limits the external validity of the results.

We also contribute to the literature on the risk-taking channel of monetary policy (e.g., Adrian and Shin (2010), Brunnermeier and Sannikov (2012), Jimenez et al. (2014), dell'Ariccia, Laeven, and Suarez (2017)) which finds that banks reduce risk-taking when monetary policy tightens, suggesting that tighter monetary policy is associated with reduced financial sector risk. We contribute by analyzing the risk-taking channel for both banks and nonbanks. In all three credit markets, we find that when monetary policy tightens, nonbanks not only increase credit supply relative to banks, but also concentrate their credit supply more on ex-ante riskier borrowers. Given that nonbanks are typically less regulated than banks, often rely on fragile funding structures (Drechsler, Savov, and Schnabl 2021), and do not necessarily have access to central bank liquidity facilities, the shift in riskier credit supply from banks to nonbanks suggests that tighter monetary policy can actually *increase* risk in the financial system.

Finally, we contribute to the broader literature on nonbanks. The increased presence of nonbanks in lending markets can be attributed to technological advances, liquidity transformation, superior information, and bank regulation (Buchak et al. 2018; Ordoñez 2018; Moreira and Savov 2017; Irani et al. 2021). This increased presence of nonbanks may lead to better allocation of risk and lower borrowing costs for households (Fuster et al. 2019) and firms (Ivashina and Sun 2011; Shivdasani and Wang 2011; Nadauld and Weisbach 2012). But it might result in increased risk in crisis times (Irani et al. 2021). Relative to this literature, we show that monetary policy affects nonbank credit supply and the distribution of risk in the economy.

The paper proceeds as follows. Section 2 discusses the identification of monetary policy and summarizes our datasets. Section 3 examines the response of nonbank credit to monetary policy in the corporate loan market, while Section 4 examines household credit. In Section 5 we study bank and nonbank lending in the mortgage market. Section 6 provides further aggregate evidence. Section 7 concludes.

2 Monetary Policy Shocks and Data

Monetary policy is affected by economic conditions and hence is not exogenous. As our main measure of monetary policy, we therefore use 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 prices around FOMC policy announcements. While this series is measured in terms of *shocks*, we require a measure of the *level* of monetary policy, for two reasons. First, the deposits channel of monetary policy established by Drechsler, Savov, and Schnabl (2017) – which makes contrasting predictions for bank and nonbank credit supply (Xiao 2020) – operates via the level of the Fed Funds rate. Second, the dependent variable in our loan-level regressions is based on the *level* of new loan issuance, which cannot easily be converted into changes because individual firms and households take out loans infrequently. In line with recent literature, we therefore convert the shock series into a level series by taking the cumulative sum (Romer and Romer 2004; Coibion 2012; Ramey 2016; Cloyne and Hürtgen 2016; Nelson, Pinter, and Theodoridis 2017). In robustness tests, we also use the Gertler-Karadi cumulative shock series as an instrument for the Fed Funds target rate.

The Gertler-Karadi measure is available from 1990 – 2012. Since 2008, the Federal Reserve has employed a range of unconventional monetary policy tools, meaning that monetary policy is unlikely to be well captured by (surprises in) the Fed Funds rate. In robustness tests, we therefore extend our sample to 2017 and measure monetary policy using the shadow rate of Wu and Xia (2016), which reflects unconventional monetary policy tools when the Fed Funds rate is at the effective lower bound. We also instrument the Wu-Xia rate using the Gertler-Karadi cumulative shock series in robustness tests.

Following the monetary policy literature (Taylor 1993), we include a range of macroeconomic controls in all of our regressions: current and expected GDP growth, CPI inflation, and a measure of financial volatility (the VIX).

We obtain transaction-level information on syndicated loan originations to corporates from Thomson Reuters LPC DealScan. DealScan provides a lender classification, which allows us to identify most lenders as either banks (deposit-taking institutions) or nonbanks. Following Roberts (2015), we drop loans that we identify as likely to be amendments, because these do not necessarily involve new credit. We match the loan-level data from DealScan to borrower-level data from S&P Compustat using the updated link provided by Chava and Roberts (2008) to analyze risk-taking as well as real effects on firms. 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. We also use industry-level output data from the Bureau of Economic Analysis to study aggregate real effects.

We use data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (FRBNY/Equifax CCP).[1] This credit bureau dataset provides an anonymized, random sample of U.S. credit files from which we derive quarterly household-level auto loan balances by lender type (bank or nonbank) extending back to 1999. We draw a 10 percent random sample from the FRBNY/Equifax CCP, which yields a panel of about 1.6 million households. We use auto loans as the dataset identifies whether the lender is a bank or a nonbank. For details and summary statistics, see Appendix A. We also use county-level car sales data from Polk.

We use mortgage application data collected under the Home Mortgage Disclosure Act

[1]For details, see `https://www.newyorkfed.org/research/staff_reports/sr479`.

(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 confidential version of HMDA, which includes the origination date (the public version only includes the origination year). We use MSA-level GSE-limits to distinguish conforming and jumbo mortgages. Conforming mortgages have loan amounts up to the GSE limit, while jumbo loans exceed the GSE limit. Nonbank identification and summary statistics are described in Appendix A. We use county-level house price data from Corelogic.

3 Monetary Policy and Nonbank Lending to Firms

In this section we first use data on syndicated loan originations to explore the relationship between monetary policy and nonbank lending to firms at the borrower-lender-quarter level. We then study how monetary policy further affects the distribution of risk between bank and nonbank lenders. Finally, we analyze the real effects associated with nonbank lending at the firm and industry level.

The U.S. Syndicated Loan Market A syndicated loan is a loan extended by multiple lenders to a single borrower. The syndicated loan market is an important source of funding for US corporates, with issuance of around $2,600 billion 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.

Nonbank lenders in the syndicated loan market often rely on short-term funding to fund themselves. In the credit line segment, investment banks, which do not take deposits but fund themselves in the short-term market (e.g. repo), are key nonbank participants. In the term loan market a multitude of nonbank lenders are active, such as collateralized loan obligations (CLOs), which use short-term liquidity to finance warehousing before security issuances; finance companies, which often rely heavily on commercial paper; mutual funds, which respond to customer withdrawals; as well as pension funds and insurance companies, which have more stable funding sources.

The structure of the syndicated loan market allows for clean identification of the effects of monetary policy on credit supply for two reasons. First, syndicated loan facilities are extended by multiple lenders to one borrower at the time of loan origination. 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,[2] which are, except for rare cases, equivalent to loan package fixed effects and control for unobserved borrower-time characteristics (Chodorow-Reich 2014; Khwaja and Mian 2008). 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). Second, while borrowers choose the lead arranger, the other participants in the syndicate (banks and nonbanks) are selected in a book building process run by the lead arranger and are therefore beyond the borrower's control (Bruche, Malherbe, and Meisenzahl 2020).[3] Hence, the composition of the syndicate originating

[2]Throughout the paper we use "quarter" to refer to year-quarter.
[3]Most lead arrangers are banks.

the loans is typically not affected by the borrower's loan demand but by the credit supply provided by different financial intermediaries. We exploit the supply-driven composition of syndicates to isolate differential responses of bank and nonbank credit supply to a monetary policy shock.

Loan-Level Analysis For our analysis, we aggregate participations in new syndicated loans to a firm by a financial intermediary in a quarter. For simplicity, we refer to this aggregation as the loan level.[4] We first test whether nonbanks expand their syndicated lending relative to banks. We then test whether the effect is stronger for riskier firms. We estimate the following regression.

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

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. In separate regressions, we consider total lending, total term loans, and credit lines. Nonbank_l is a dummy variable indicating nonbank lenders. The main explanatory variable of interest is the interaction of the nonbank dummy with $\text{Monetary Policy}_{t-1}$, which is measured as the cumulative sum of Gertler-Karadi shocks (demeaned). Even though we exploit monetary policy surprises, given that monetary conditions vary with macro conditions (see, e.g., Taylor (1993)), we also include interactions of the nonbank dummy with four demeaned macroeconomic controls: VIX, GDP growth, one quarter ahead GDP forecast, and CPI inflation. We saturate the model

[4]Results are similar if we do not perform this aggregation, and instead run regressions at the level of lender participations in individual loan facilities (with facility fixed effects instead of borrower-quarter fixed effects).

with borrower-time fixed effects to account for unobservable borrower characteristics. We also include lender fixed effect to account for time-invariant lender characteristics (e.g. the business model).

Table 1
Impact of monetary policy on corporate lending

	Log(New credit amount)						
	All loans	All loans	Term loans	Credit lines	All loans	Term loans	Credit lines
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nonbank × GK	0.103**	0.134***	0.191***	0.050*	0.065	0.406***	0.007
	(0.041)	(0.031)	(0.049)	(0.025)	(0.040)	(0.125)	(0.041)
Nonbank × High yield × GK					0.205***	-0.125	0.172***
					(0.045)	(0.110)	(0.041)
Nonbank × High yield					0.078*	0.106	0.009
					(0.041)	(0.094)	(0.034)
Macro variable double interactions	YES	YES	YES	YES	YES	YES	YES
Macro variable triple interactions	NO	NO	NO	NO	YES	YES	YES
Borrower-quarter fixed effects	NO	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	NO	NO	NO	NO	NO	NO
Lender fixed effects	YES	YES	YES	YES	YES	YES	YES
Observations	98,755	92,876	14,913	76,323	48,824	5,260	42,520
Number of borrowers	10,137	6,584	1,920	5,206	1,868	425	1,613
Number of lenders	2,268	2,051	1,026	1,395	1,229	545	996
Number of quarters	90	90	90	90	90	89	90
R-squared	0.34	0.81	0.82	0.83	0.79	0.82	0.81

The table shows estimated regression coefficients for equation 1 including interactions with a high-yield borrower indicator. The dependent variable is the log of new lending quantity at the borrower-lender-quarter level 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. "Macro variable double interactions" refers to interactions of the macro controls with the nonbank indicator. "Macro variable triple interactions" refers to interactions of the macro controls with both the nonbank indicator and the high yield indicator. The sample consists of dollar-denominated loans to borrowers headquartered in the U.S. Standard errors in parentheses are clustered by borrower, lender and quarter. All variables are defined in Appendix A. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1 shows the results of estimating equation 1 for the sample of dollar-denominated loans newly extended to U.S. borrowers. In the first column, we exclude controls for credit demand and find that nonbanks reduce credit supply less than banks after a monetary contraction. In column 2, we control for credit demand and unobservable firm characteristics at the time of loan origination by including borrower-time fixed effects (Chodorow-Reich 2014). We find that a 25 basis point monetary tightening surprise increases lending by nonbanks by 3.4 percent relative to banks. Although the addition of the borrower-quarter fixed effects leads to a large increase in the R-squared (47 percentage points), the estimated effect is similar across columns 1 and 2.[5] Moreover, the relative expansion

[5]Adding borrower controls has a small effect on the estimated coefficient despite the fact that, as

of nonbank credit holds for term loans (column 3) and credit line extensions (column 4), with stronger quantitative effects for term loans.[6] In sum, the funding mix in corporate lending syndicates shifts from banks to nonbanks after a monetary contraction.

This result is consistent with the deposits channel of monetary policy documented by Drechsler, Savov, and Schnabl (2017). When monetary policy tightens, deposits flow out of banks and into money market funds (Xiao 2020). Given that many nonbank lenders in the syndicated loan market rely on short-term funding from investors such as money market funds, nonbanks can compete more with banks after a monetary contraction. Appendix B, Table B1 provides analysis of the effect of monetary policy on funding conditions for nonbanks.

We now assess whether the strength of this nonbank channel of monetary policy varies with the risk of the loan. To measure borrower risk, we use the DealScan-Compustat link provided by Michael Roberts to obtain the S&P long-term issuer credit rating.[7] Specifically, we interact an indicator variable for borrowers rated high-yield (below BBB-) with our nonbank indicator and macroeconomic variables.[8] The variable of interest is the triple interaction of the nonbank indicator with the monetary policy variable and the high-yield rating indicator.

shown in Table A4 in Appendix A, there are significant differences in observable characteristics for borrowers that obtain loans from nonbanks. This lack of importance of borrower controls is consistent with using monetary policy surprises as the main regressor.

[6] We find similar results when we use the monetary policy measure of Wu and Xia (2016) or the Federal Funds Rate, which also allows us to extend the end of the sample period from 2012 to 2017. The results are also robust to excluding the financial crisis and dropping the macroeconomic control variables. The relative increase in lending holds for both of the two main types of nonbank lender in the primary syndicated lending market – finance companies and investment banks – with the increase in term loans primarily driven by finance companies, and the increase in credit lines primarily driven by investment banks. We also find that the propensity of a nonbank to be a lead arranger in the loan increases when monetary policy tightens.

[7] The link data can be access here: `https://finance.wharton.upenn.edu/~mrrobert/styled-9/styled-12/index.html`. Since not all firms in DealScan are rated, the sample is somewhat smaller.

[8] We also include the lower-order interactions as controls.

Table 1, columns 5-7 show the results of adding the triple interaction to equation 1. We find that the nonbank credit supply effects are larger for high-yield borrowers (column 5). This effect is driven by credit lines (column 7); for term loans, the overall effect of monetary policy on nonbank credit is strong (column 3) but does not vary significantly with borrower risk (column 6).

Firm-Level Effects A natural question is whether the relative expansion of nonbank credit affects firm-level outcomes. Our empirical tests of whether the relative expansion of nonbank credit affects firm outcomes are guided by the theoretical literature on corporate finance decisions. In particular, the model of Bolton, Wang, and Yang (2019), in which firms face costly access to external financing, predicts the following outcomes in response to firms facing shocks to real and financial flexibility: (1) firms should reduce their reliance on external finance and their leverage should go down; (2) firms should reduce their investments; (3) firms should build up their liquid assets reserves for precautionary reasons.

Since a key friction in the syndicated loan market is that lending is based on soft information (Sufi 2007), and the lead arranger continuously monitors borrowers and shares the information with syndicate members (Gustafson, Ivanov, and Meisenzahl 2021), lenders in the syndicated loan market accumulate soft information about borrowers and industries over time. It then follows that, because of the informational advantage of lenders, and given our loan level results, borrowers with prior relationships with nonbanks are likely to experience a larger increase in credit supply from nonbanks after a monetary contraction.

To measure prior relationships with nonbanks, we construct an indicator variable that is equal to one for borrowers that took out loans with nonbanks in the syndicate at least two years prior to the current loan.[9] We then estimate regressions of the following form at the borrower-quarter level:

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

where b indexes borrowers, i indexes industries (two-digit SIC code), and t indexes quarters. $NonbankRelation_{b,t}$ is the indicator variable for borrowers that have borrowed from nonbanks in the past, and $MonetaryPolicy_{t-1}$ and macroeconomic controls are the same as in Table 1. $X_{b,t-1}$ is a vector of time-varying borrower-level controls: log of assets, and return on assets. We also include borrower fixed effects, and industry-quarter fixed effects to control for demand shocks.[10]

Table 2 shows the results of estimating equation 2 at quarterly frequency. We start by aggregating new syndicated loans to the borrower-quarter level in order to study how ex-ante nonbank relationships affect total credit availability to firms in this market. We find that firms with prior nonbank relationships borrow about 2.2 percent more in total (column 1) in response to a 25 basis point monetary tightening surprise, relative to firms without nonbank relationships. Moreover, the spreads that they pay on these loans are lower (column 2), which provides further evidence that the relative increase in syndicated

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

[10]In unreported results, we find that the results of table 1 are almost identical if we use borrower fixed effects and industry-quarter fixed effects (instead of borrower-quarter fixed effects), suggesting that these (borrower and industry-quarter) fixed effects are sufficient to control for credit demand and hence to isolate credit supply effects.

Table 2
Firm-level effects of monetary policy

	New Syndicated Credit		Firm Variables				
	Total borrowing	Spread	New Loan	Total debt	Leverage	Liquidity	Fixed Assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nonbank relation × GK	0.087**	-0.086***	0.012***	0.070**	0.032***	-0.009***	0.011***
	(0.040)	(0.026)	(0.003)	(0.029)	(0.007)	(0.003)	(0.003)
Macro variable interactions	YES	YES	YES	YES	YES	YES	YES
Borrower controls	YES	YES	YES	YES	YES	YES	YES
Borrower fixed effects	YES	YES	YES	YES	YES	YES	YES
Industry-quarter fixed effects	YES	YES	YES	YES	YES	YES	YES
Observations	23,448	18,286	389,182	316,909	355,957	382,979	368,897
Number of borrowers	5,041	4,391	9,374	8,978	9,158	9,248	9,047
Number of quarters	83	83	83	83	83	83	83
R-squared	0.80	0.79	0.08	0.89	0.61	0.70	0.90

This table shows estimated regression coefficients for equation 2. Total borrowing and Spread are based on new loan originations in DealScan. Both variables are in logs. New Loan is an indicator variable equal to 1 if the firm took out a new loan in the quarter. Total debt, Leverage, Liquidity, and Fixed Assets are based on balance sheet variables from Compustat. Total debt is in logs. Leverage, Liquidity and Fixed Assets are expressed as ratios to total assets. 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 that is equal to 1 if the firm took a loan with nonbanks in the syndicate at least 2 years previously. Borrower controls are lagged log(assets) and return on assets. "Macro variable interactions" refers to interactions of the lagged macro controls (GDP growth, GDP forecast, inflation, VIX) with the nonbank relation indicator. The regressions are at quarterly frequency. The sample period is 1992-2012. Standard errors in parentheses are clustered by borrower and quarter. All variables are defined in Appendix A. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

credit is supply-driven. These results suggest that informational asymmetries are a key friction limiting substitution across lenders in this market, and that establishing relationships with nonbank lenders allows borrowers to overcome this friction when monetary policy tightens.

We then study the impact on the probability of observing a new loan (extensive margin of credit) and balance sheet variables from Compustat.[11] We find that firms with prior nonbank relationships in the syndicated loan market are more likely to take out a new loan (column 3) when monetary policy tightens. These firms also take on 1.75 percent more total debt (column 4) and have higher leverage (0.8 percentage points, column 5) after a 25 basis point monetary tightening surprise. In addition to syndicated credit, these measures of debt include bonds and non-syndicated debt such as direct

[11] For these regressions, we use the complete Compustat sample period, rather than only including quarters in which the borrower takes out a syndicated loan. This explains why the sample size is much larger. However we only include in the sample firms that take out at least one syndicated loan during the sample period. This ensures that we are only comparing firms with or without nonbank relationships in the syndicated loan market, rather than firms with or without access to the market in general.

lending from private equity and business development companies (Chernenko, Erel, and Prilmeier 2019). The relative increase in these broader measures of debt suggests that firms without existing nonbank relationships are unable to perfectly substitute to other forms of debt when they lose access to syndicated credit during monetary contractions. We also find that firms with prior nonbank relationships relatively reduce liquid asset holdings when monetary policy tightens (0.2 percentage points less, column 6), suggesting reduced need for precautionary savings. Finally, column 7 shows that firms with prior nonbank relationships are also able to invest more in property, plants and equipment. For a firm with a past nonbank relationship, a 25 basis point monetary tightening surprise relatively increases holdings of fixed assets (property, plants and equipment) by around 0.3 percentage point.

Industry-Level Real Effects To assess the importance of nonbank credit on a more aggregated level, we now study industry-level outcomes. Based on the loan-level and firm-level results, we hypothesize that firms in industries that were historically more dependent on nonbank credit should experience a smaller reduction in credit supply after a monetary contraction, and should therefore expand relative to less nonbank-credit-dependent industries. To test these hypotheses, we compute quarterly variables at the two-digit SIC industry level using Compustat (total debt, leverage, liquidity, and fixed assets). For these regressions, we use all U.S. firms in Compustat, not just those active in the syndicated loan market. We also obtain annual industry-level output measures from 1997 onwards from the Bureau of Economic Analysis, which reflect all firms (listed and privately owned).[12] To test how historic dependence on nonbank credit impacts industry-

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

level outcomes, we estimate the following regression at quarterly or annual frequency:

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

Table 3
Industry-level real effects of monetary policy

	Quarterly Outcomes				*Annual Outcomes*	
	Total debt	Leverage	Liquidity	Fixed Assets	Real Gross Output	Real Value Added
	(1)	(2)	(3)	(4)	(5)	(6)
Past nonbank share × GK	1.054**	0.217**	-0.065	0.151**	1.363**	1.235**
	(0.446)	(0.096)	(0.040)	(0.059)	(0.516)	(0.496)
Macro Variable Interactions	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	4,115	4,115	4,115	4,115	863	863
R-squared	0.98	0.80	0.81	0.96	0.98	0.98

This table shows estimated regression coefficients for equation 3. Quarterly outcome variables are based on Compustat data aggregated to the two-digit SIC industry level. Total debt is in logs. Leverage, Liquidity and Fixed Assets are expressed as ratios to total assets. These regressions are at quarterly frequency for the sample period 1997-2012. Annual outcome variables are taken from the Bureau of Economic Analysis (BEA). Both variables are in logs. These regressions are at annual frequency for the sample period 1997-2012. In both panels, GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. "Past Nonbank share" is the ratio of nonbank syndicated borrowing to total syndicated borrowing for the industry over the period 1990-1996, estimated using DealScan. We use these dates because the annual outcome variables only become available in 1997. The nonbank share is computed using all borrowers headquartered in the USA. Industry controls are log(total assets), RoA, and the share of firms rated as high yield. "Macro variable interactions" refers to interactions of the macro controls (GDP growth, GDP forecast, inflation, VIX) with past nonbank share. Standard errors in parentheses are clustered by industry and quarter (quarterly variables) or industry and year (annual variables). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

where Past Nonbank Share$_i$ is the ratio of nonbank syndicated borrowing to total syndicated borrowing for industry i over the period 1990-1996, estimated using DealScan.[13] $X_{i,t-1}$ are industry-level controls computed from Compustat: log(total assets), RoA, and the share of firms rated as high yield.

Table 3 shows the results of estimating equation 3. Consistent with the firm-level results, we find that industries with stronger prior nonbank relationships have relatively

[13] We compute this ratio using U.S. borrowers only.

higher total debt (column 1) and leverage (column 2), lower liquid asset holdings (column 3), and higher holdings of fixed assets (column 4) after a monetary contraction.[14] The economic effects are comparable to the estimated firm-level effects: for an industry with the average level of past nonbank share (0.08), a 25 basis point monetary tightening surprise leads to an increase in fixed assets (property, plants and equipment) of around 0.3 percentage points.

To assess whether the positive effects of nonbank relationships on industry-level borrowing and investment also translate into higher output, we now estimate equation 3 for output measured at annual frequency. For these regressions, we use administrative data on total industry-level output from the Bureau of Economic Analysis, which includes not only the publicly-listed firms in Compustat, but also private firms. The point estimate reported in column 5 shows that after a monetary contraction, industries with large historical nonbank shares have higher real gross output relative to industries with low historical nonbank share. For the mean nonbank share industry (0.08), a 25 basis point tightening surprise is associated with a relative increase in gross output of approximately 2.7 percent. Column 6 shows that this result also holds for real value added with a comparable economic magnitude.

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. Hence, nonbank lenders attenuate the bank lending channel of monetary policy on total credit and the associated real effects on the economy. The key friction limiting substitution in this market is soft information. Consistent with this friction, firms and industries with stronger ex ante relationships with nonbank lenders obtain relatively

[14]The p-value on the estimate for liquid asset holdings is 0.109.

more credit after a monetary contraction. The partial substitution of bank credit with nonbank credit has real effects. Following a monetary contraction, firms or industries with high prior nonbank dependence reduce investment and production by less than firms or industries with low prior nonbank dependence. Moreover, our results suggest that nonbanks also significantly attenuate the risk-taking channel of monetary policy, as after a monetary tightening, credit supply—and especially credit supply to riskier firms—shifts from regulated banks to less regulated, more fragile nonbanks.

4 Monetary Policy and Nonbank Consumer Lending

In this section we explore the relationship between monetary policy and nonbank lending to consumers. We focus on auto loans, because for these loans we are able to use credit bureau data recording whether the lender is a bank or nonbank.

The U.S. Auto Loan Market Most new cars in the United States are bought on credit or leasing. At its peak in 2006, outstanding auto credit was $785 billion, accounting for 32% of consumer debt. Nonbank lenders — notably 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.

The key friction in this lending market is that lenders typically have long-term arrangements with auto dealers, limiting the choice of financing available to the consumer. This friction is distinct from the main friction in syndicated lending (studied in the section above). Auto lenders use standardized loan applications and 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. By studying the response of auto lending by banks and nonbanks to a monetary contraction, we therefore gain insights into whether substitution between bank and nonbank credit is affected by long-term arrangements between durable goods sellers and loan providers even if only hard information is used in lending decisions.

In the analysis we use household-level data from FRBNY/Equifax CCP. We identify whether a household took out a new auto loan, the loan amount, and the lender type (bank or nonbank).[15] The data also include balances on other loans (mortgage, credit card, consumer loans), the household head's age, the Equifax Risk Score and a bankruptcy indicator. These variables allow 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. We start by analyzing loan-level data before aggregating to the county level, where we analyze overall credit effects as well as real effects in terms of consumption (car purchases).

Household-Level Auto Loans To test the main hypothesis that nonbank lenders relatively increase credit supply in response to a contractionary monetary policy shock, we exploit the geographical variation in nonbank presence in our household panel data,

[15] 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).

by constructing a measure of the extent to which a county is considered a core market, based on historical presence. Benmelech, Meisenzahl, and Ramcharan (2017) argue that for historical reasons (e.g. arrangements with auto dealers) nonbank auto lenders have a large presence in some counties and a weak presence in other counties. In line with the bank lending channel, we hypothesize that banks retrench more from markets in which they have a weaker presence, and that nonbanks are more likely to expand in these markets.

We define county-level nonbank dependence as the share of outstanding auto loan balances extended by nonbank lenders as of 1999Q1 (the start of the sample). There is significant variation in the historical dependence on nonbank auto credit across U.S. counties (see Figure A3 in the Appendix).[16] To identify the effect of monetary policy on nonbank and bank auto credit, we interact the historical dependence variable with the monetary policy variable.

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

$$\begin{aligned}
\text{Loan Amount}_{ijt} \quad = \quad & \beta_1 \left(\text{Past Nonbank Share}_j \times \text{Monetary Policy}_{t-1}\right) \qquad (4) \\
& +\beta_2 \left(\text{Past Nonbank Share}_j \times \text{Macroeconomic Controls}_{t-1}\right) \\
& +\gamma X_{ijt-1} + \alpha_j + \theta_t + \epsilon_{ijt}
\end{aligned}$$

where *Loan Amount*$_{ijt}$ is the 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 defined as the share of outstanding auto loan balances extended by nonbanks in 1999Q1.

[16]The nonbank share on the national level also varies considerably over time. The correlation with the federal funds rate is 0.54 (Figure A4 in the Appendix).

Monetary Policy$_{t-1}$ is measured by the Gertler-Karadi cumulative shock time series.[17] Macroeconomic controls are GDP growth, GDP forecast, inflation and the VIX. X_{ijt-1} is a vector of controls including county-level income (to control for local economic conditions) and several household characteristics: birth year (fixed effects), outstanding credit card balance, outstanding mortgage balance, outstanding other consumer loan balance, and Equifax Risk Score.[18] We saturate the model with county-fixed effects (α_j) and with time fixed effects (θ_t).

The key variable is the interaction of historical nonbank dependence with the monetary policy variable, i.e. Past Nonbank Share$_j$ $\times$ Monetary Policy$_{t-1}$.

Table 4
Household-Level Effects on Auto Loans

	Log Amount			
	Nonbank	Nonbank	Bank	Total
	(1)	(2)	(3)	(4)
GK x Past Nonbank Share	0.029***	0.031***	-0.032***	-0.000
	(0.005)	(0.007)	(0.007)	(0.001)
Macro Variable Interactions	YES	YES	YES	YES
County Income	NO	YES	YES	YES
Household Characteristics	NO	YES	YES	YES
County FE	NO	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	54,243,705	54,243,317	54,243,317	54,243,317
R^2	0.01	0.01	0.01	0.01

This table shows the regression results of equation 4 on the household level. The dependent variable in columns 1 and 2 is the log of new auto loan amount extended by finance companies, in column 3 the log of new auto loan amount extended by banks, and in column 4 the log loan amount extended by both sources of financing. Nonbank share is defined as the county-level share of outstanding auto loans financed by nonbanks in 1999Q1. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 shows the results of estimating equation 4 for different left hand side variables. In column 1, where we do not include household characteristics or county fixed effects to control for demand, we find that nonbanks relatively increase lending in response to

[17]We obtain similar results when we use the Wu-Xia shadow rate or the Federal funds rate.

[18]Note that the data do not provide information on race or gender.

a monetary tightening, consistent with our main hypothesis. We then add demand side controls and again find that nonbanks relatively increase lending (column 2), while banks cut lending (column 3). On the loan level for the average value of Past Nonbank Share (0.57), the coefficients translate into a 0.44 percent increase in lending by nonbanks and a 0.46 percent decrease in lending by banks in response to a 25 basis point monetary tightening surprise. The expansion of nonbank credit exactly offsets the reduction in credit supply by banks, meaning that monetary policy has no effect on total credit (column 4).[19]

This close-to-perfect substitution between bank and nonbank credit is suggestive evidence for the mechanism driving the results. Banks experience deposit outflows when monetary policy tightens, resulting in a reduction in lending. However, these outflows lead to an expansion of funding available to nonbanks in the money markets (see Appendix B Table B1). Nonbanks take advantage of this funding expansion by increasing credit supply to households. In the case of auto loans, the substitution between nonbanks and banks is close to perfect. This perfect substitution is in contrast to the imperfect substitution in the corporate loan market documented above, suggesting important differences between the frictions in these two markets.

Risk-Taking in the Auto Loan Market A natural question is which types of borrower are most likely to be affected by changes in the credit supply from banks and nonbanks.

To test whether the credit supply effects depend on borrower risk, we include the triple

[19] We find similar results for the extensive margin, i.e. propensity of getting a new auto loan. 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.

Table 5
Household-Level Effects on Auto Loans: Risk

	Log Amount		
	Nonbank	Bank	Total
	(1)	(2)	(3)
GK x Past Nonbank Share x Equifax Risk Score	-0.091***	0.147***	0.052
	(0.031)	(0.023)	(0.039)
Macro Variable Triple Interactions	YES	YES	YES
Lower-Level Interactions	YES	YES	YES
Household Characteristics	YES	YES	YES
County-Time FE	YES	YES	YES
Observations	54,243,555	54,243,555	54,243,555
R^2	0.01	0.01	0.01

This table shows the regression results of equation 4 on the household level adding the triple interactions. 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. Past Nonbank share is defined as the county-level share of outstanding auto loans financed by nonbanks in 1999Q1. For ease of reading, the Equifax Risk Score is divided by 1000. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

interaction of the borrower's lagged Equifax Risk Score, the county's Past Nonbank Share, and monetary policy (as well as the triple interaction of the borrower's lagged Equifax Risk Score and the county's Past Nonbank Share with the other macroeconomic control variables).[20] This specification allows us to include county-time fixed effects to alleviate concerns that our results are driven by systematic variation between local demand and historical nonbank dependence over the cycle.

Table 5 shows the results from estimating the effect of monetary policy on auto loans by borrower risk. Column 1 shows that nonbanks increase their credit supply more to lower Equifax Risk 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 lower-risk borrowers (column 2). The substitution between banks and nonbanks is perfect across the Equifax Risk Score spectrum (column 3).[21]

[20] We also include the interaction of the macroeconomic variables with the Equifax Risk Score. The interactions of Past Nonbank Share with the macroeconomic variables are absorbed by the county-quarter fixed effects.

[21] We obtain similar results when we use an indicator for new loan as dependent variable. We do not

The results therefore suggest the presence of a risk-taking channel for nonbank lenders that offsets the risk-taking channel for banks.

County-level Auto Credit and Sales Next, we assess the real effects of this shift in auto loans from banks 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:

$$\begin{aligned} \text{Log(Auto Credit)}_{jt} &= \beta_1 \left(\text{Past Nonbank Share}_j \times \text{Monetary Policy}_{t-1}\right) \\ &\quad + \beta_2 \left(\text{Past Nonbank Share}_j \times \text{Macroeconomic Controls}_{t-1}\right) \\ &\quad + \gamma X_{jt-1} + \alpha_j + \theta_t + \epsilon_{jt} \end{aligned} \tag{5}$$

where $\text{Log(Auto Credit)}_{jt}$ is the log of new auto loan amounts in county j in quarter t. Macroeconomic controls are GDP growth, GDP forecast, inflation and the VIX. X_{jt-1} is a vector of controls that include county-level average credit score and county-level income to control for local economic conditions. We also include county-fixed effects (α_j) and time fixed effects (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 show that the relative expansion of auto credit by nonbanks in response to tighter monetary policy is larger in counties historically more dependent on nonbank credit, while banks' auto credit

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 nonbanks tend to charge higher interest rates on auto loans. The differences between bank and nonbank borrower characteristics are shown in the Appendix, Table A4.

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

	Auto Credit			Auto	Auto Credit	Auto
	Nonbank	Bank	Total	Sales	Total	Sales
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Past Nonbank Share	0.503***	-0.587***	0.109	0.034		
	(0.099)	(0.119)	(0.107)	(0.023)		
GK x Low Nonbank Share					-0.117*	-0.075***
					(0.068)	(0.023)
Macro Variable Interactions	YES	YES	YES	YES	YES	YES
Time-varying County Controls	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Observations	158,461	158,461	158,461	122,991	158,461	122,991
R^2	0.49	0.49	0.52	0.99	0.54	0.99

This table shows the regression results of equation 5. The dependent variable is the log amount of new auto loans extended by finance companies (column 1), the log amount of new auto loans extended by banks (column 2), or the log amount of all new auto loans (columns 3, 5). The dependent variable in columns 4 and 6 is the log of auto sales. Past Nonbank share is defined as the county-level share of outstanding auto loans financed by nonbanks in 1999Q1. Low Nonbank Share is a dummy equal to 1 if a county's dependency on nonbanks was in the lowest quartile in 1999Q1. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

contracts more in these counties. The point estimates in columns 1 and 2 suggest that, at the county level and controlling for county fixed effects and time-varying county controls, there is also close-to-perfect substitution between bank and nonbank credit.[22] For the average value of Past Nonbank Share (0.57), the coefficients translate into a 7.2 percent increase in lending by nonbanks and a 8.4 percent decrease in lending by banks in response to a 25 basis point monetary tightening surprise. Consistent with this, column 3 shows no significant net effect of higher monetary policy rates on auto credit at the county level.[23] These results are consistent with banks retrenching to focus on their core markets.

To 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 of equation 5 with log of auto sales as dependent variable. Consistent

[22]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.

[23]We obtain similar results when we use the Wu-Xia shadow rate or the federal funds rate. We also find similar patterns when we use the number of loans instead of the loan amount.

with perfect substitution between bank and nonbank credit, we find no effect of monetary policy on auto sales via the nonbank credit supply channel (column 4).[24]

We further test whether the key friction in this market — long-term arrangements between auto dealers and financial institutions — limits substitution between bank and nonbank credit, and hence generates real effects. Since nonbanks tend to expand credit in counties in which they have 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 was in the lowest quartile. In these counties substitution is expected to be limited and hence auto sales may fall in response to a retrenchment of bank credit. Indeed, consistent with imperfect substitution, we find that the effect of monetary policy on total auto credit is negative and significant in counties with low nonbank dependence (column 5), and that auto sales fall in these counties (column 6). That is, substitution to nonbank credit is limited in areas with small ex-ante nonbank presence.

Taken together, the results presented in this section suggest that contractionary monetary policy shocks shift auto credit supply from banks to nonbanks. In counties where the underlying friction in this market severely limits substitution between bank and nonbank credit, we find real effects of monetary policy via the credit channel. However, since nonbanks have a large presence in the auto loan market on average, the aggregate effects of this friction are limited, and hence the nonbank channel of monetary policy completely offsets the bank lending channel of monetary policy for both total credit and total auto sales.

[24]Weighting the observations by lagged county income or using different measures of monetary policy do not change the results.

5 Monetary Policy and Nonbank 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. (2018). Mortgage companies and fintech lenders, such as Quicken Loans, are included in the nonbank category. Fintech lenders are key financial intermediaries in this market.

The U.S. Mortgage Market With about \$10 trillion outstanding balances, the household mortgage market is 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 sell them in the secondary market. The main buyers of mortgages are the government-sponsored enterprises (GSEs): Fannie Mae and Freddie Mac. Before the 2008 financial crisis, private-label securitizers were also important.

Lenders must fund mortgages at origination, even if they sell the loan later. Nonbank lenders are exposed to liquidity pressure as many of them 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 private-label asset-backed securities (ABS), rely themselves heavily on short-term funding. Private-label ABS accounted for \$350 billion of mortgages in 2000, \$2.2 trillion in 2007, and \$1 trillion in 2012, further highlighting the importance of short-term funding market conditions for mortgage originations.

In general, two types of mortgages exist: conforming mortgages—mortgages that adhere to the guidelines set by the GSEs—and jumbo mortgages—mortgages that are 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 most regressions; however, when analyzing aggregate effects including house prices, we aggregate all new loans. Since we are also interested in outcomes beyond credit (i.e.in this market, house prices), we mostly focus on new purchase mortgages, because these are more directly related to house prices than refinance mortgages, although we do consider the latter in some regressions.

Mortgage lenders rely in part on hard information (such as income and the credit score) when deciding whether to extend a loan and when evaluating their ability to sell the loan to the GSEs. However, a key friction in the market for *new purchase* mortgages is that lenders also need knowledge of the local housing market, such as recent trends in neighborhoods and a range of possible assessments of the house value, as well as relationships with local mortgage brokers.[25] In other words, mortgage lenders need some local infrastructure.

Individual-Level Mortgage Lending As in the auto loan market, we begin with a loan-level analysis and, given our previous results on the other two credit markets, assess our main hypothesis that higher monetary policy rates increase nonbank credit availability in the mortgage market. We start by analyzing new purchase mortgages—that is, mortgages originated to buy a home (thereby excluding refinancing mortgages).

[25]Most refinancing deals require considerably less local knowledge.

The key advantage of loan-level data is that we can control for county-specific mortgage conditions, local housing market developments and other local economic conditions using county-quarter fixed effects. These fixed effects proxy for demand, and allow us to exploit variation between bank and nonbank lenders within the same county and quarter.

We estimate the following loan-level regression:[26]

$$\begin{aligned} \text{Log(Loan Amount)}_{i,l,j,t} \;=\;& \beta_1 \left(\text{Nonbank Dummy}_{l,t} \times \text{Monetary Policy}_{t-1}\right) \\ &+\beta_2 \left(\text{Nonbank Dummy}_{l,t} \times \text{Macroeconomic Controls}_{t-1}\right) \\ &\gamma X_{i,l,t-1} + \alpha_{j,t} + \theta_l + \epsilon_{i,l,j,t} \end{aligned} \tag{6}$$

where $\text{Log(Mortgage)}_{i,l,j,t}$ is the log of new mortgage amount of loan i originated by lender l in county j in quarter t. $NonbankDummy_{l,t}$ is an indicator variable equal to one for nonbank lenders. $\text{Monetary Policy}_{t-1}$ is measured by the Gertler-Karadi cumulative shock time series.[27] Macroeconomic controls are GDP growth, GDP forecast, inflation and VIX. $X_{i,l,t-1}$ is a vector of controls that include borrower characteristics (race, gender, income) and $Nonbank\ Dummy_{l,t}$ (accounting for charter switching).[28] We saturate the model with lender fixed effects (θ_l) to control for differences in time-invariant lender characteristics, and with county-time fixed effects ($\alpha_{j,t}$) to control for time-varying county-level characteristics such as economic conditions and house prices.

[26] The coverage of rural counties in HMDA is incomplete. To reduce potential noise stemming from incomplete coverage, 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. We start our sample period in 1995 because the nonbank share rose sharply in the early 1990s, perhaps because of the introduction of capital regulation prescribed in Basel I, which limited banks' ability to lend.

[27] We obtain similar results when we use the Wu-Xia shadow rate or federal funds rate.

[28] Some lenders in the mortgage market switch charters over our sample period. For details on the classification, see Appendix A.

Table 7
Loan-Level Regressions

	Loan Amount of New Purchase Loans				
	Conforming Held and Sold Amount	Conforming Held and Sold Amount	Jumbo Held and Sold Amount	Total Held and Sold Amount	Total Held only Amount
	(1)	(2)	(3)	(4)	(5)
GK x Nonbank Dummy	0.0468***	0.0177***	0.0151***	0.0162**	-0.0387***
	(0.007)	(0.00670)	(0.00247)	(0.00737)	(0.0105)
Macro Variable Interactions	YES	YES	YES	YES	YES
Borrower Controls	NO	YES	YES	YES	YES
Time FE	YES	NO	NO	NO	NO
County-Time FE	NO	YES	YES	YES	YES
Lender FE	YES	YES	YES	YES	YES
Observations	51,018,988	51,018,986	4,601,273	55,628,939	22,344,622
Adjusted R^2	0.22	0.38	0.65	0.50	0.53

Sample Period: 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. The dependent variable is measured in thousands and then logged. GK is the cumulative sum of monetary policy shocks from Gertler and Karadi (2015). Nonbank dummy is equal to 1 if lender is a nonbank. Macro variable interactions refers to interactions of lagged macro controls (GDP growth, GDP forecast, inflation, VIX) with the nonbank dummy. Applicant controls are race, gender, and income. Standard errors in parentheses are clustered at the date and county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7 shows the results of estimating equation 6. In the first column, we do not control for demand—that is, we include time fixed effects but not county-time fixed effects or borrower characteristics. Consistent with our main hypothesis, we find that, relative to banks, nonbank lenders reduce credit less than banks following higher monetary policy rates in the market for new home purchase conforming loans. This effect is smaller in size but remains statistically significant when we control for demand (column 2). A 25 basis point monetary tightening surprise relatively increases the size of a conforming loan by about 0.4 percent. In the jumbo mortgage market, we find that nonbanks also expand originations (column 3) and the effect is similar in magnitude. The effect is also positive and significant across total new purchase loans (column 4) — nonbanks relatively increase loan amounts by around 0.4 percent in response to a 25 basis point tightening surprise. Perhaps surprisingly, we find that loan amounts of loans that remain on the lender's balance sheet are differentially smaller for nonbanks (column 5), implying that the increase in credit is driven by sold loans; at least on the intensive margin of lending.

County-level Mortgage Lending As in the auto loan market, we also present county-level results to tighten the link between the loan-level mortgage results above and more aggregated effects, including the effect of nonbank mortgage lending on house prices that we show below. Importantly, lending quantities aggregated to the county level reflect the extensive margin (number of loans) as well as the intensive margin (loan size).

As discussed above, a key friction in the new purchase mortgage market is information about the local market, which is a crucial input in lending decisions, making it difficult for lenders to expand in non-core regions. We expect that substitution is more likely to take place in counties where nonbank lenders have accumulated information about the local market by having extended loans in the past. For identification, we therefore exploit geographical variation in historical nonbank lending. Specifically, we construct a county-level measure of historical nonbank dependence defined as the share of mortgages originated by nonbank lenders in the first quarter of our sample (1995Q1).[29] This approach also allows us to include time fixed effects, alleviating concerns that our results may be driven by the effects of the financial crisis of 2007-09 (though we also include interactions of our key variables with the VIX).

To test these hypotheses, we estimate the following model:

$$\begin{aligned} \text{Log(Loan Amount)}_{j,t} \;=\; & \beta_1 \left(\text{Past Nonbank Share}_j \times \text{Monetary Policy}_{t-1}\right) \\ & + \beta_2 \left(\text{Past Nonbank Share}_j \times \text{Macroeconomic Controls}_{t-1}\right) \\ & + \gamma X_{j,t-1} + \alpha_j + \theta_t + \epsilon_{j,t} \end{aligned} \tag{7}$$

where $\text{Log(Loan Amount)}_{j,t}$ is the log of new mortgage amounts in county j in quarter

[29] In the appendix, we show the national nonbank share in the mortgage market over time (Figure A7).

t, and *Past Nonbank Share*$_j$ is county j's dependence on nonbank credit measured as the share of mortgages extended by nonbanks in 1995Q1. Macroeconomic controls are GDP gowth, GDP forecast, inflation and the VIX. X_{jt-1} is a vector of controls that includes county-level average risk score and income. We saturate the model with county-fixed effects (α_j) and time fixed effects (θ_t).

Table 8
New Purchase Loans Held on Balance Sheet - County Level

	Panel A: Conforming Loans			
	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
	Panel B: Jumbo Loans			
	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

Sample period: 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 loans new purchase loans (excluding refinancing) that remain on the lender's balance sheet. GK is the cumulative sum of monetary policy shocks of Gertler and Karadi (2015). Past Nonbank Share is the county-level share of mortgages extended by nonbanks in 1995Q1. "Macro variable interactions" refers to interactions of lagged macro controls (GDP growth, GDP forecast, inflation, VIX) with Past Nonbank Share. Standard errors in parentheses are clustered at the county and quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 shows the results of estimating equation 7 for new purchase loans. We focus on loans held on balance sheet, because these are most affected by changes in relative funding conditions.[30] Panel A shows results for conforming mortgages and Panel B shows results for jumbo mortgages. Panel A, column 1 shows that there are no significant effects of monetary policy on bank lending for conforming mortgages. Column 2 shows that nonbank lending expands somewhat. However, on net, there is no significant change in lending at the county level for conforming mortgages (column 3). Consistent with our key channel, the nonbank share expands somewhat (column 4), although the effect is statistically insignificant. This weak result might reflect the fact that, while nonbanks may enjoy better funding conditions after a monetary contraction, conforming mortgages are relatively easy to sell at a later point to the GSEs, suggesting that advantages in financing conditions may be less important in the conforming loan market.

In contrast, Panel B shows significantly stronger evidence of substitution between bank and nonbank lending for jumbo mortgages. Banks appear to retrench after a contractionary monetary policy shock (column 1) even though the point estimate is insignificant. Meanwhile, nonbanks relatively expand significantly (column 2) both statistically and economically. While this finding appears to be at odds with the reduction in the *size* of loans originated by nonbanks and held on balance sheet (Table 7, column 5), we show in the appendix that the *number* of jumbo loans extended by nonbanks and held on balance sheet increases (Table C1, column 2). This increase in the extensive margin of credit reconciles the difference between the loan-level results in Table 7 and the county-level results in Table 8.

On net, we find no overall credit supply effect of monetary policy on county-level

[30]HMDA only records loan sales that occur in the calendar year in which the loan was originated. Mortgages originated in December are therefore generally shown as held on balance sheet, because the securitization process typically takes longer than one month. We therefore adjust the total loan amount held on balance sheet in December by multiplying the loan amount with the average held share over the first 9 months of the year.

origination of new jumbo mortgages subsequently held on balance sheet (column 3). But consistent with retrenchment by banks and expansion by nonbanks, the nonbank market share increases (column 4).[31] In sum, the results suggest substitution from banks to nonbanks in the potentially riskier jumbo mortgage market.

Total Mortgage Lending and House Prices The results above provide evidence of substitution from bank to nonbank mortgage credit after a monetary contraction, particularly for jumbo loans. To assess the real effects of this substitution, 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 on house price growth. We also consider loans that are not new but just refinanced. We estimate the following regression.

$$\begin{aligned} \text{Log(Outcome)}_{j,t} &= \beta_1 \left(\text{Past Nonbank Share}_j \times \text{Monetary Policy}_{t-1}\right) \\ &\quad + \beta_2 \left(\text{Past Nonbank Share}_j \times \text{Macroeconomic Controls}_{t-1}\right) \\ &\quad + \gamma X_{j,t-1} + \alpha_j + \theta_t + \epsilon_{j,t} \end{aligned} \tag{8}$$

where the outcome is either county-level total credit or the county-level house price index from Corelogic.

Table 9 shows the result of estimating equation 8. We find a relative expansion of total new purchase mortgage lending at the county level, though the effect is only significant at the 12 percent level (column 1). Note that we use conservative standard errors, by double-clustering at the county and time levels.[32] For the average level of Past Nonbank Share, a 25 basis point monetary tightening surprise increases mortgage lending by 5.3

[31] These results continue to hold when we exclude the financial crisis.
[32] See Abadie et al. (2017). We are not subsampling a part of the population.

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

	All New Mortgages- Amount	All Mortgages - Amount	House Prices
	(1)	(2)	(3)
Past Nonbank Share x GK	0.583†	0.509†	0.425**
	(0.370)	(0.318)	(0.191)
Macro Variable Interactions	YES	YES	YES
Time FE	YES	YES	YES
County Income	YES	YES	YES
County FE	YES	YES	YES
Observations	55,062	55,062	55,062
Adjusted R^2	0.98	0.97	0.85

Sample period: 1995q2 - 2012q3. Column 1 includes only new purchase mortgage, while column 2 also includes refinanced loans. The dependent variables are county-level mortgage credit and the county-level house price index. All counties issued at least 10 loans in every quarter prior to 2008. GK is the cumulative sum of monetary policy shocks from Gertler and Karadi (2015). Macro variable interactions refers to interactions of lagged macro controls (GDP growth, GDP forecast, inflation, VIX) with Past Nonbank Share. Standard errors in parentheses are clustered at the quarter and county level. † p<0.12, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

percent. This effect is similar when we also include refinancing loans (column 2).

This relative expansion of credit results in a positive, statistically significant effect of the nonbank share on house prices (column 3). For the average level of Past Nonbank Share, a 25 basis point tightening surprise relatively increases house prices by 3.9 percent. This finding suggests that the substitution from bank to nonbank lending after a monetary contraction supports house prices more in counties with a large nonbank lending share. Put differently, a monetary tightening surprise results in a lower reduction in house prices if there are more nonbank lenders ex-ante, consistent with a nonbank credit supply mechanism.

Taken together, the evidence in this section shows that the relative supply of credit by nonbanks increases after a contractionary monetary policy shock, especially in the (riskier) jumbo market. Evidence in this market is consistent with local information also being relevant. Moreover, house prices in markets with larger nonbank presence perform better relative to markets with few nonbank lenders after a monetary tightening—that is, house prices fall less after a monetary tightening surprise if there are more nonbank lenders ex-ante. These findings suggest that nonbank lending attenuates the real effects of monetary policy in the housing market via a credit supply channel.

6 Further Aggregate Effects of Nonbank Substitution

So far we have focused on loan-level data and—to provide evidence of macro effects—we have also focused on data aggregated at the industry level (corporate loans) and the county level (consumer loans and mortgages). Since our aim is to compare the lending behavior of banks and nonbanks, the identification strategy relies on time fixed effects, which control for overall unobserved macroeconomic shocks (and to tighten identification even further, we even use firm-time and county-time fixed effects in some regressions). In Table 10 we relax this tight identification and estimate the industry-level and county-level regressions for each market without time fixed effects. Moreover, in a WLS analysis we allow each observation to have a different weight depending on its lagged size (industry size for corporate lending and county size for household lending). The equations we estimate are very similar to those in Tables 3, 6 and 9, but instead of time fixed effects, we include the monetary policy measure (Gertler-Karadi cumulative shocks) and macro control variables (GDP growth, GDP forecast, inflation, VIX) in levels, as well as in interactions with Past Nonbank Share.

Table 10, columns 1 and 2 show the results of the industry-level regressions without time fixed effects. Column 1 shows that the estimated effect of past nonbank share interacted with lagged monetary policy on industry-level debt is positive and significant,

Table 10
Aggregate Lending and Outcomes

	Corporate Borrowing and Output		Auto Loans & Sales		Mortgages & House Prices	
	Total Debt	Annual Output	Total Loans	Auto Sales	New Mortgages	House Prices
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Past Nonbank Share	0.910**	1.261**	0.106	0.037	0.566†	0.448**
	(0.401)	(0.476)	(0.069)	(0.231)	(0.227)	(0.179)
GK	-0.047	-0.148***	-0.009	-0.321	-0.172	-0.373***
	(0.045)	(0.041)	(0.079)	(0.396)	(0.191)	(0.101)
Macro Cont.	Yes	Yes	Yes	Yes	Yes	Yes
Macro Cont. x Past Nonbank Share	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Industry Controls	Yes	Yes	No	No	No	No
County FE	No	No	Yes	Yes	Yes	Yes
County Controls	No	No	Yes	Yes	Yes	Yes
Crisis Interactions	No	No	Yes	Yes	No	No
Observations	4,115	863	158,461	122,991	55,062	55,062
Adjusted R^2	0.98	0.98	0.68	0.98	0.29	0.74

Columns 1 and 2 of this table are in parallel to table 3 with GK, GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effects. Each observation is weighted by the logarithm of debt lagged and logarithm of real output lagged, respectively. Standard errors are clustered by industry and time. Columns 3 and 4 of this table are in parallel to table 6 with GK, GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effects. Observations are weighted by lagged county income. Standard errors are clustered on the county and quarter level. Crisis interactions are the interactions of post-2008Q3 with macrovariables to account for the collapse of finance companies during the financial crisis. Columns 5 and 6 of this table are in parallel to table 9 with GK, GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effects. Observations are weighted by lagged county income. Standard errors are clustered on the county and quarter level. In all columns, GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. † p<0.12, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

suggesting partial substitution from banks to nonbanks at the industry level. Annual output falls after a monetary contraction but considerably less in industries with higher past nonbank share (column 2). The economic effects are comparable to the ones with time fixed effects reported in section 3. For an industry with the average level of past nonbank share, a25 basis point monetary tightening surprise leads to a relative increase in real gross output of 2.5 percent. In sum, nonbank lending in the corporate loan market significantly attenuates the effects of monetary policy on credit and output.

Table 10, columns 3 and 4 show the results of the county-level regressions without time fixed effects for the auto market. We find no effect of monetary policy via nonbanks on total lending in the auto loan market (column 3), indicating perfect substitution away from bank lending. Similarly, we find no evidence that the effect of monetary policy on auto sales depends on past nonbank share (column 4). The results suggest that nonbank lending in the auto loan market completely offsets any retrenchment by banks and nullifies any real effects associated with monetary policy via the nonbank credit channel.

Table 10, columns 5 and 6 show the results of the county-level mortgage and house price regressions without time fixed effects. Column 5 shows that a large past nonbank share reduces the effect of monetary policy on aggregate mortgage lending. For a county with the average level of past nonbank share, a 25 basis point monetary tightening surprise leads to a relative increase in new mortgage lending of 5.2 percent. While a monetary contraction generally slows house price growth, high past nonbank share significantly reduces the sensitivity of house prices to monetary policy (column 6) with an economic magnitude comparable to the regression with time fixed effects in Table 9 (about 4.1 percent). Therefore, substitution to nonbanks reduces the effectiveness of monetary policy in the mortgage market.

In our benchmark regressions we have measured monetary policy using the cumulative sum of Gerter-Karadi shocks. For easier interpretation of economic effect, our final set of regressions uses the Gertler-Karadi cumulative shocks as instruments for the federal funds rate and the interaction of Gertler-Karadi cumulative shocks with the past nonbank share as instrument for the interaction of the federal funds rate with the past nonbank share. The cumulative shocks and their interaction are strong instruments; the F-statistics are about or over 20 in all regressions.

Table 11 shows the results of the second stage of the IV estimation. In line with the reduced form results, we find that the linear term is negative throughout, consistent with a monetary contraction reducing overall economic activity. We also find evidence for substitution by nonbanks as the interaction of the federal funds rate with the past

Table 11
IV Estimation: Aggregate Lending and Outcomes

	Corporate Borrowing and Output		Auto Loans & Sales		Mortgages & House Prices	
	Total Debt	Annual Output	Total Loans	Auto Sales	New Mortgages	House Prices
	(1)	(2)	(3)	(4)	(5)	(6)
FFR x Past Nonbank Share	0.228**	0.278**	0.026	0.007	0.164†	0.139***
	(0.101)	(0.112)	(0.025)	(0.022)	(0.03)	(0.050)
FFR	-0.012	-0.032***	-0.110**	-0.032*	-0.057	-0.102***
	(0.011)	(0.012)	(0.050)	(0.018)	(0.053)	(0.028)
Macro Cont.	Yes	Yes	Yes	Yes	Yes	Yes
Macro Cont. x Past Nonbank Share	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Industry Controls	Yes	Yes	No	No	No	No
County FE	No	No	Yes	Yes	Yes	Yes
County Controls	No	No	Yes	Yes	Yes	Yes
Crisis Interactions	No	No	Yes	Yes	No	No
Kleinbergen-Paap first stage F-Stat	260.83	97.26	19.78	132.89	29.19	29.19
Observations	4,115	863	158,461	122,991	55,062	55,062

We instrument the federal funds rate (FFR) with Gertler-Karadi cumulative shocks and federal funds rate x past nonbank share with Gertler-Karadi cumulative shocks x past nonbank share. All columns only report the second stage. Columns 1 and 2 of this table are in parallel to table 3 with federal funds rate, GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effects. Each observation is weighted by the logarithm of debt lagged and logarithm of real output lagged, respectively. Standard errors are clustered by industry and time. Columns 3 and 4 of this table are in parallel to table 6 with the federal funds rate, GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effects. Observations are weighted by lagged county income. Standard errors are clustered on the county and quarter level (column 3) and only on the county level (column 4) as fewer quarters are available in the sales data. Crisis interactions are the interactions of post-2008Q3 with macrovariables to account for the collapse of finance companies during the financial crisis. Columns 5 and 6 of this table are in parallel to table 9 with federal funds rate, GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effects. Observations are weighted by lagged county income. Standard errors are clustered on the county and quarter level . † p<0.125, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

nonbank share is positive in all cases and statistically significant for the corporate and housing sectors, consistent with the results in Table 10.[33]

7 Conclusion

Our main contribution to the literature is to show empirically that nonbanks affect the transmission of monetary policy to output (consumption and investment), house prices and the distribution of risk via a credit supply channel. We find that higher policy rates shift credit supply from banks to nonbanks. This largely neutralizes the associated effects on consumption (via consumer loans), while significantly attenuating the effects on

[33]We find similar results when we instrument the shadow rate (Wu and Xia 2016) with the Gertler-Karadi cumulative shock series, see Appendix C.

firm investment and house prices (via corporate credit and mortgage supply). Moreover, in contrast to the so-called risk-taking channel, higher policy rates increase risk-taking, as less-regulated, more fragile nonbanks —in all three credit markets— expand credit supply, especially to riskier borrowers.

These changes in the mix of credit providers after a monetary contraction also raise questions about the interplay of monetary policy, the structure of credit markets, and financial stability. Looking forward, a more diversified financial system (fintech, funds, shadow banks) implies lower potency of monetary policy overall. Moreover, with respect to risk-taking, effects are less clear. On the one hand, 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. On the other hand, our results suggest that when monetary policy "leans against the wind," it might have unintended consequences for financial stability by causing risk to migrate from the banking system to the potentially more fragile nonbank system. More research is needed to understand these linkages and implications for monetary policy.

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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 sum of Gertler-Karadi monetary policy shocks	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	S&P500 Volatility Index	CBOE
Shadow Rate	Wu-Xia Shadow Rate	Wu and Xia (2016)
FFR	Federal Funds Target Rate	Federal Reserve Bank of St. Louis
Panel B: Syndicated Loans		
Nonbank	Indicator variable equal to one for nonbank lenders and zero for bank lenders	Thomson Reuters LPC DealScan
Past Nonbank Share	Industry-level ratio of nonbank syndicated borrowing to total syndicated borrowing over 1990-1996	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
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 by a lender to a borrower in a quarter	Thomson Reuters LPC DealScan
Credit Lines	Log of total credit line amount extended by a lender to a borrower in a quarter	Thomson Reuters LPC DealScan
Spread	Log of all-in Spread	Thomson Reuters LPC DealScan
New Loan	Indicator variable equal to one if the firm takes out a new loan in the quarter	Thomson Reuters LPC DealScan
Total Borrowing	Log of total credit extended to a borrower in a quarter (sum across lenders)	Thomson Reuters LPC DealScan
Total debt	Log of total debt (dlcq + dlttq)	S&P Compustat
Leverage	Book leverage ((dlcq + dlttq) / atq)	S&P Compustat
Liquidity	Ratio of cash and short-term investments to total assets (cheq / atq)	S&P Compustat
Fixed Assets	Ratio of property, plant and equipment to total assets (ppentq / atq)	S&P Compustat
Real Gross Output	Log of real industry-level gross output	Bureau of Economic Analyis
Real Value Added	Log of real industry-level value added	Bureau of Economic Analyis
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)	S&PCompustat
Panel C: Consumer Loans		
Past Nonbank Share	The share of 1999Q1 auto loan balances outstanding extended by nonbanks	FRBNY/Equifax CCP
Low Nonbank Share	Indicator equal to 1 if a county's past nonbank share was in the lowest quartile	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	
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
Auto Sales	Log number of autos sold	Polk
Panel D: Mortgages		
Past Nonbank Share	The share of 1995Q1 mortgages extended by nonbanks	HMDA
Nonbank Dummy	Indicator equal to 1 if lender is a nonbank	HMDA
Log Amount	Log of mortgage loan amount	HMDA
Log Amount Nonbank	Log of mortgage loan amount extended by a nonbank	HMDA
Log Amount Bank	Log of mortgage loan amount extended by a bank	HMDA
Race	Indicator equal to 1 if borrower is African American	HMDA
Gender	Indicator equal to 1 if borrower is female	HMDA
Income	Reported household income	HMDA
Log Income	Log of county-level quarterly total wages	Bureau of Labor Statistics
House Prices	Local House Price Index	Corelogic

Nonbank Classification in DealScan Based on the DealScan lender classification, we define banks and nonbanks 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 total lending in the U.S. syndicated loan market. Figure A2 shows the evolution of the nonbank share of total lending in this market. 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 nearly 20% of the total market.

Identifying Amendments in DealScan In line with the results in Roberts (2015), 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 credit lines in DealScan as being potential amendments to existing loans.

New Auto Loans and Lender types in Equifax The credit bureau data include auto loan balances by lender type. For each type of lender, we therefore identify new auto loans by a positive change in the balance of at least $500. We then compute the net new loan amount as the difference between the current quarter auto loan balance and the previous quarter auto loan balance.[34]

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 at the household and county level. The average nonbank share in 1999Q1 is 0.53 at 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. The nonbank share also varies considerably over time. The correlation with the federal funds rate is 0.54 (Figure A4).

Nonbank Classification in HMDA We identify nonbanks in the HMDA dataset using an algorithm based on that in Buchak et al. (2018). We begin by classifying all lenders as nonbanks, and then re-classify them as banks if they meet one of the four criteria below. A

[34] 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.

lender that does not meet any of these criteria remains classified as a nonbank. Table A5 shows the results of the classification algorithm.

First, all lenders regulated by the following agencies are classified as banks: OCC, FDIC, OTS, NCUA, CFPB.

Second, lenders regulated by the Federal Reserve System with the following strings in their name are classified as banks: "BANK", "BK", "BANCO", "BANC"", "B&T", "BNK". The strings are not case sensitive.

Third, lenders identified by HMDA's OTHER LENDER CODE as "Bank, Savings Association, or Credit Union" or "Mortgage Banking Subsidiary of a Community Bank" are classified as banks.

Fourth, following Buchak et al. (2018), we classify five lenders differently to the classification typically associated with their regulator. We classify Merrimack Mortgage Company (FDIC) and Suntrust Mortgage (CFPB) as nonbanks. And we classify the following HUD-regulated lenders as banks: Homeowners Mortgage Company, Liberty Mortgage Corporation, and Prosperity Mortgage Company.

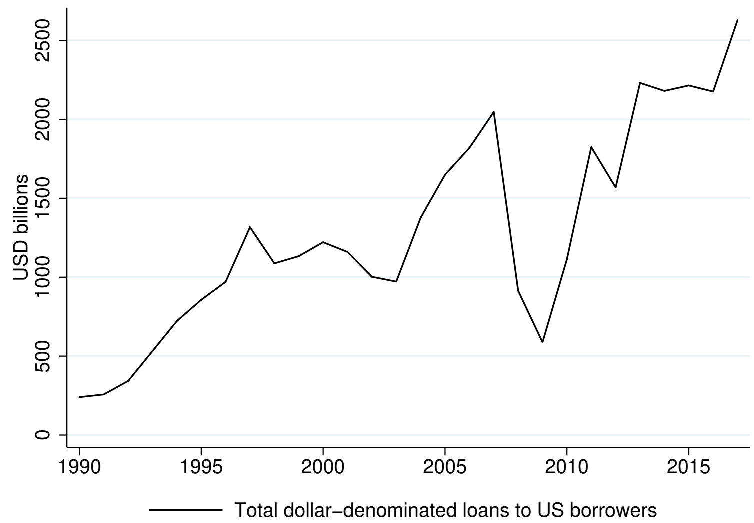
HMDA Sample and County-level Variation We require that a county have at least 10 mortgage originations in every quarter prior to 2007 to ensure that our results are not driven by small counties with entry and exit. Figure A5 shows that we nevertheless capture nearly 90 percent of the market.

Unlike the auto loan market, the mortgage market underwent some structural changes during the sample period. Specifically, in the early 1990s the introduction of Basel I bank capital requirements increased the nonbank share dramatically. We therefore start our sample in 1995Q1 in order to avoid the regulatory-driven variation in the early 1990s.

Figure A7 shows the time series of the average county-level nonbank share. The correlation with the federal funds rate is 0.73. Figure A6 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.

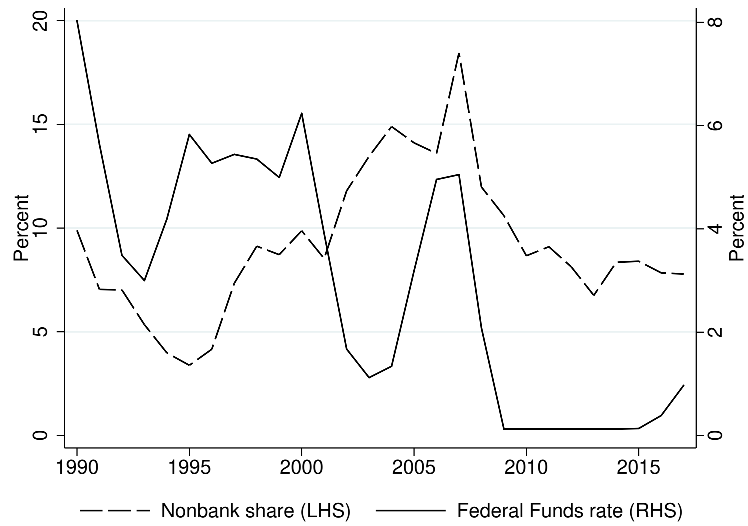
Borrower Characteristics Table A4 shows significant differences in borrower characteristics between bank and nonbank customers in all three markets. In particular, nonbanks tend to extend credit to riskier borrowers. As such, this table shows the importance of loan-level data and demand controls when analyzing the effects of monetary policy on lending by banks and nonbanks.

Figure A1: Total Syndicated Lending in the US



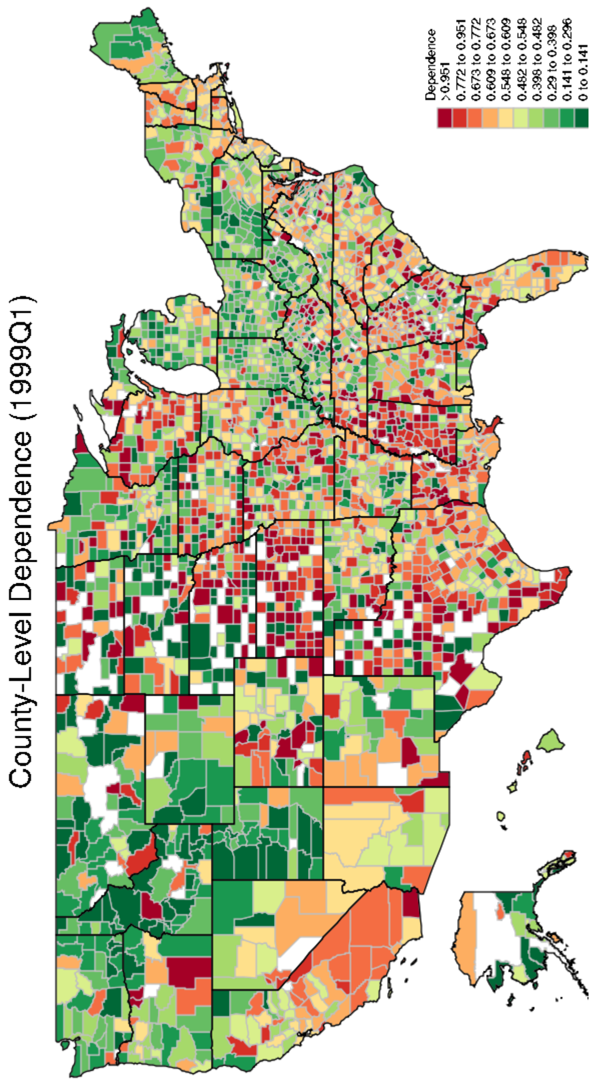
Notes: The chart shows annual syndicated lending quantities from DealScan. The sample consists of dollar-denominated loans to borrowers headquartered in the US.

Figure A2: Nonbank Share of Corporate Syndicated Lending



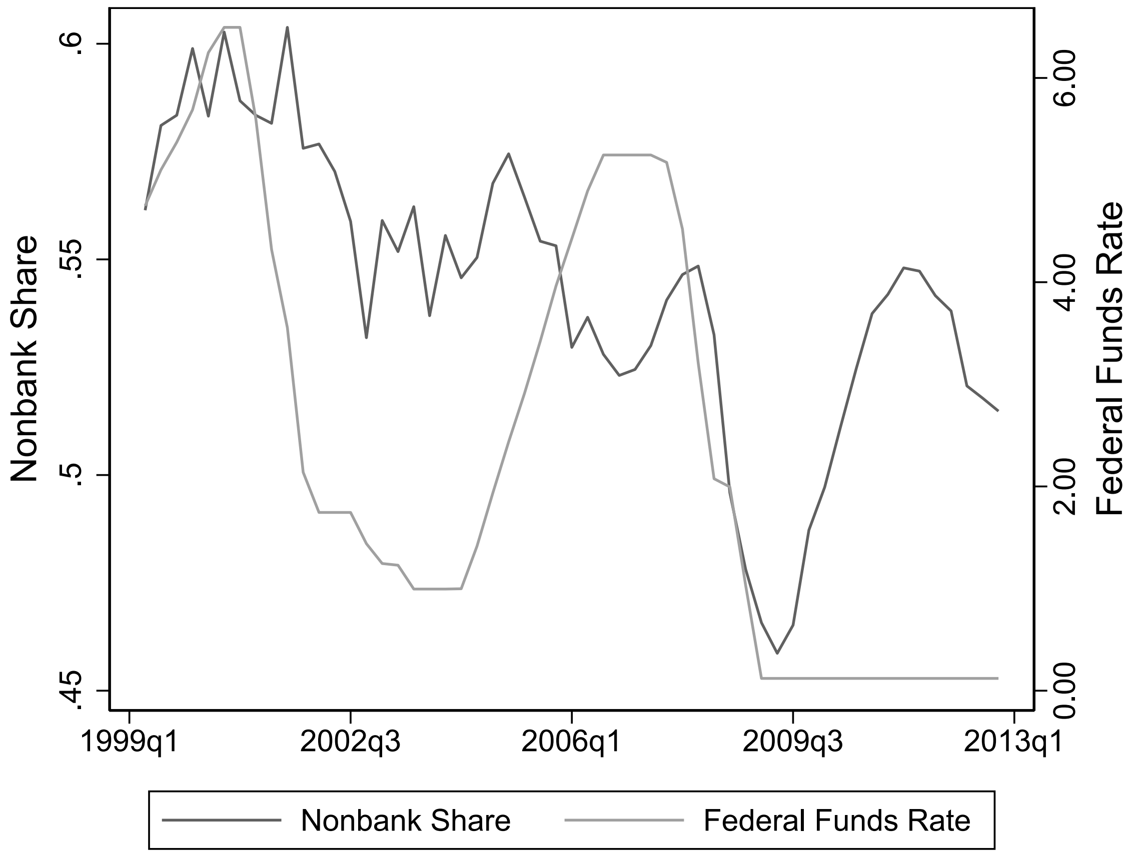
Notes: The solid line shows annual averages of the Federal Funds Target Rate. The dashed line shows nonbank lending as a proportion of total annual syndicated lending, based on DealScan. The sample consists of dollar-denominated loans to borrowers headquartered in the US. Only loans where lender shares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

Figure A3: Distribution of Household Dependence on Nonbank Auto Credit



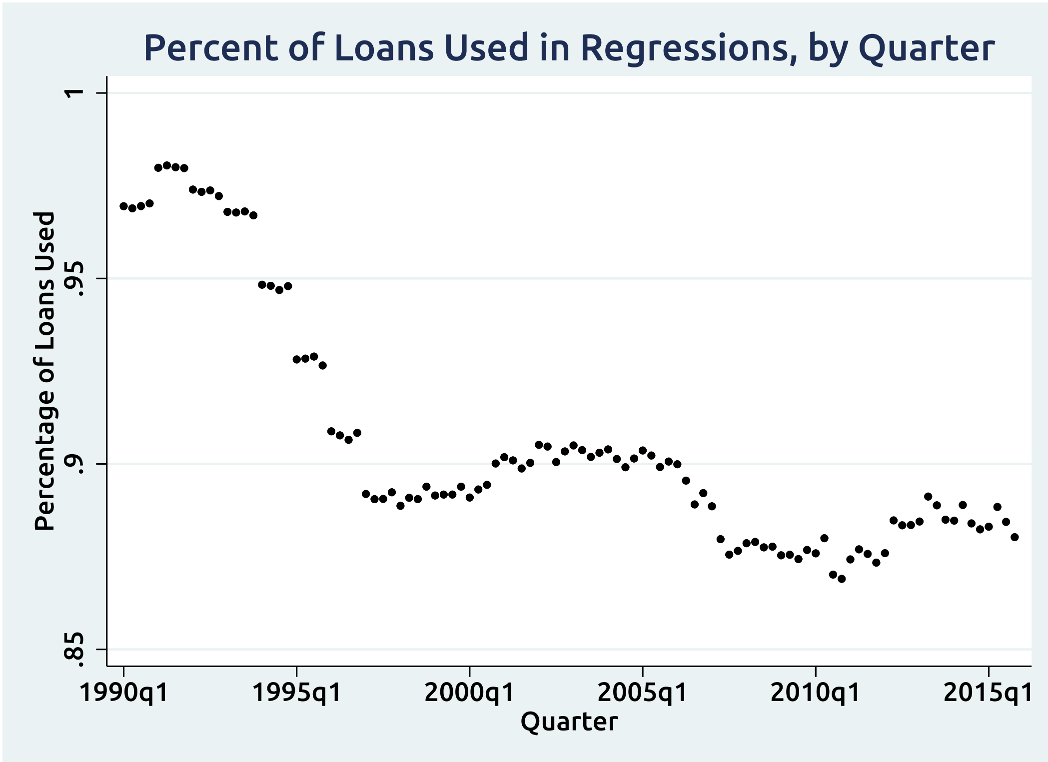
Source: FRBNY/Equifax CCP, authors' calculation

Figure A4: National Nonbank Share of Auto Lending



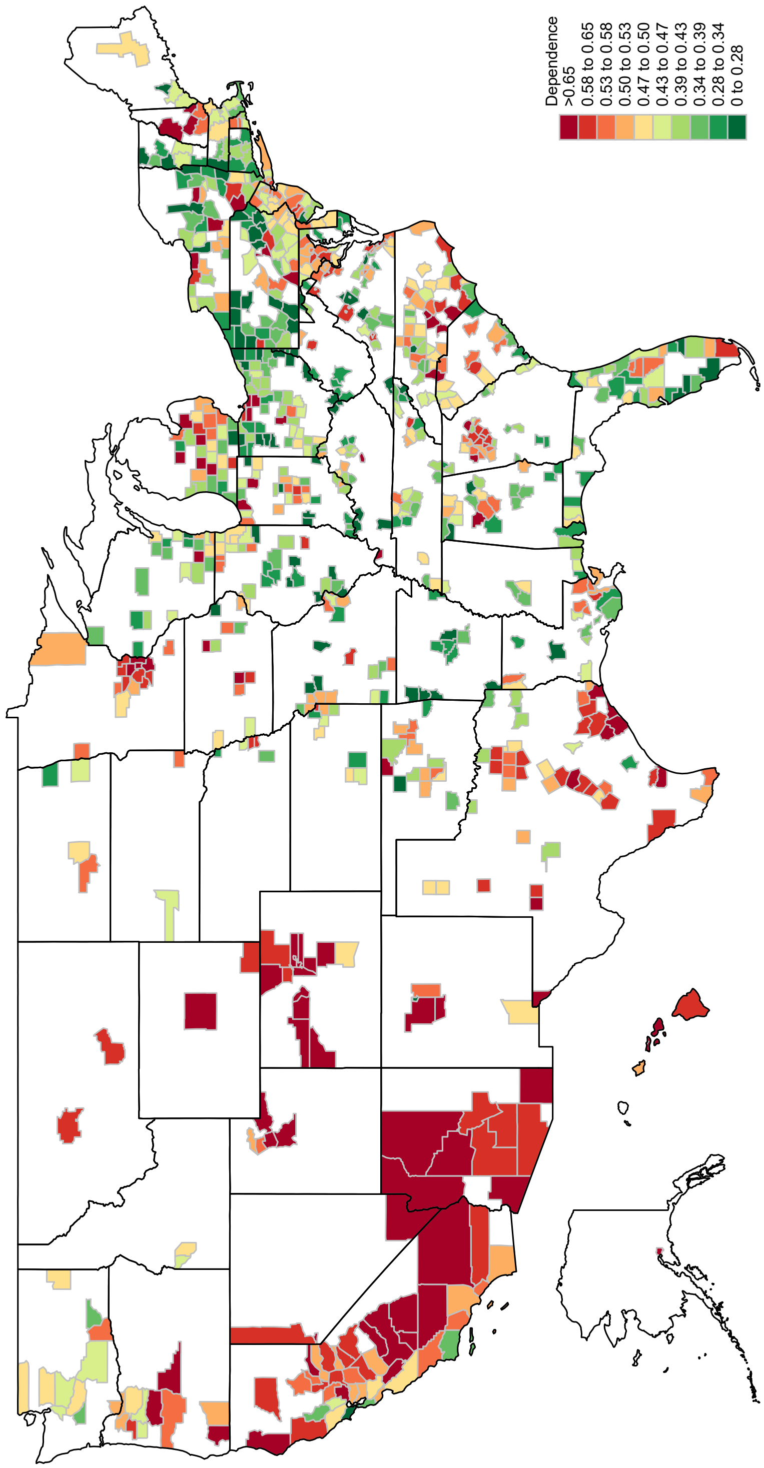
Source: FRBNY/Equifax CCP, authors' calculation

Figure A5: Percent of HMDA Loans Included in the Sample



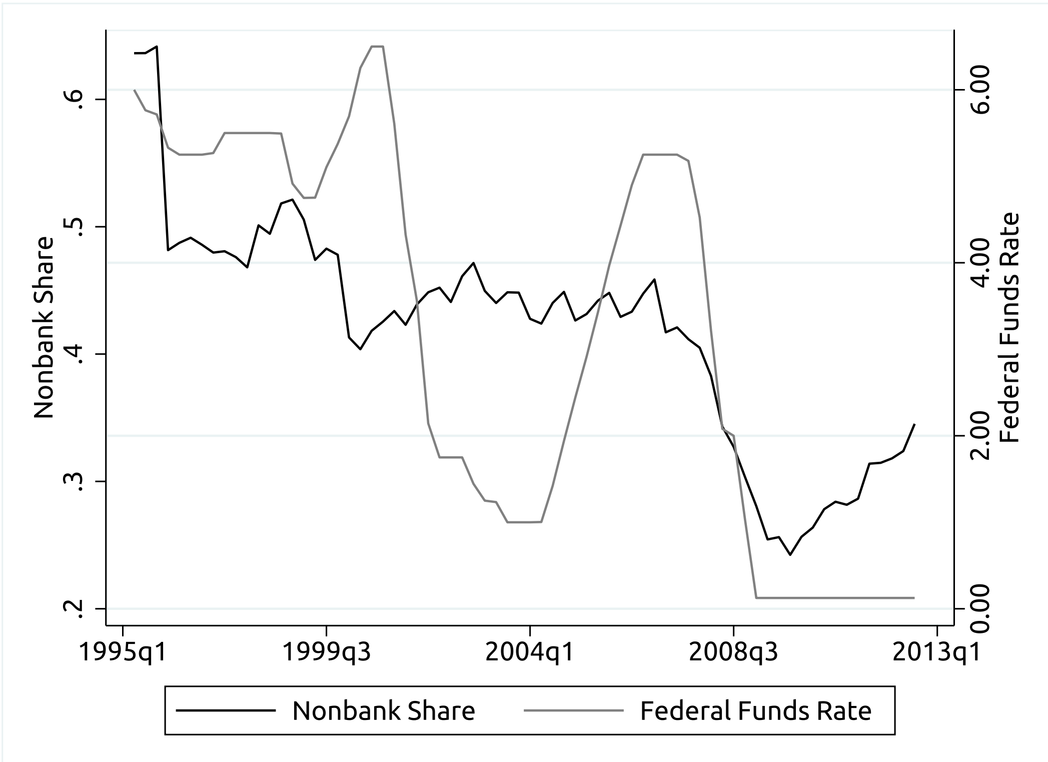
Source: HMDA, authors' calculation

Figure A6: Distribution of Household Dependence on Nonbank Mortgage Credit 1995Q1



Source: HMDA, authors' calculation

Figure A7: Nonbank Share of Mortgage Lending



Source: HMDA, authors' calculation

Table A1
Summary Statistics: DealScan and Compustat

Variable	N	mean	sd	p25	p50	p75
	Borrower-lender-quarter level					
Nonbank lender indicator (All loans)	102,499	0.11	0.31	0	0	0
Nonbank lender indicator (Term loans)	19,032	0.17	0.38	0	0	0
Nonbank lender indicator (Credit lines)	82,863	0.08	0.27	0	0	0
Log(All loans amount)	102,499	3.17	1.09	2.58	3.22	3.83
Log(Term loans amount)	18,422	2.45	1.22	1.70	2.42	3.18
Log(Credit lines amount)	82,464	3.20	1.05	2.64	3.22	3.86
	Borrower-quarter level					
Log(Total borrowing)	35,187	4.56	1.76	3.40	4.62	5.70
Log(Average loan spread)	28,626	5.03	0.88	4.47	5.23	5.70
New Loan indicator	458,442	0.08	0.27	0	0	0
Past nonbank relationship	458,442	0.27	0.45	0	0	1
Log(Total debt)	352,832	4.20	2.81	2.31	4.44	6.19
Leverage	393,420	0.29	0.27	0.07	0.25	0.42
Liquidity ratio	422,722	0.13	0.18	0.02	0.05	0.17
Investment ratio	408,069	0.29	0.25	0.08	0.21	0.44
Log(Total assets)	418,386	5.74	2.31	4.14	5.71	7.28
Return on assets	416,930	-0.01	0.07	-0.00	0.01	0.02
High yield indicator	123,802	0.46	0.50	0	0	1
	Industry-quarter level					
Past nonbank share	4476	0.08	0.07	0.03	0.07	0.12
Log(Total debt)	4476	9.68	2.38	8.60	9.84	11.08
Leverage	4476	0.30	0.14	0.21	0.29	0.38
Liquidity ratio	4476	0.09	0.06	0.04	0.07	0.11
Investment ratio	4476	0.33	0.21	0.15	0.28	0.51
	Industry-year level					
Log(Real gross output)	992	12.37	1.00	11.65	12.41	13.14
Log(Real value added)	992	11.61	1.12	10.84	11.64	12.44

This table shows summary statistics for the corporate loan regressions. For the borrower-lender-quarter level variables, the sample consists of dollar-denominated syndicated loans to borrowers headquartered in the US, and the variables are defined using loans where lender shares are observed in DealScan. The sample period is 1990-2012. For the borrower-quarter level variables, the sample consists of firms headquartered in the US that appear in both DealScan and Compustat. The sample period is 1990-2012. For the industry-level variables, the sample period is 1997-2012. All variables are defined in Appendix A.

Table A2
Summary Statistics FRBNY/Equifax CCP

Variable	N	mean	sd	p25	p50	p75
			Household Level			
Nonbank Share 1999Q1	54,258,810	0.57	0.16	0.49	0.59	0.67
Log Nonbank 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
Equifax Risk Score	54,258,810	687	107	608	708	780
Log County Income	54,258,810	21.05	1.92	19.68	21.28	22.49
			County-Level			
Log Nonbank 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 Equifax Risk Score	157,981	687.17	32.80	666.02	689.53	709.72
Log County Income	157,981	18.12	1.72	16.95	17.97	19.11

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

Table A3
Summary Statistics: HMDA

Variable	N	mean	sd	p25	p50	p75
		Loan-Level: Conforming Loans				
Logged Loan Value	115,049,375	4.747	0.745	4.344	4.844	5.268
Female Dummy	115,049,375	0.270	0.444	0.000	0.000	1.000
African American Dummy	115,049,375	0.065	0.247	0.000	0.000	0.000
Logged Applicant Income	115,049,375	4.234	0.617	3.850	4.220	4.605
Nonbank Dummy	115,049,375	0.386	0.487	0.000	0.000	1.000
		Loan-Level: Jumbo Loans				
Logged Loan Value	9,597,560	6.114	0.423	5.817	6.061	6.339
Female Dummy	9,597,560	0.176	0.381	0.000	0.000	0.000
African American Dummy	9,597,560	0.038	0.191	0.000	0.000	0.000
Logged Applicant Income	9,597,550	5.170	0.635	4.745	5.069	5.481
Nonbank Dummy	9,597,560	0.317	0.465	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
Past Nonbank Share	59,547	0.364	0.122	0.279	0.372	0.449
Log County Income	59,547	19.906	1.355	18.905	19.772	20.754

Table A4
Differences between Bank and Nonbank Borrowers

	Syndicated Loans - Nonbank Participation				
Variable	No Nonbank Participation	Nonbank Participation	Difference	t-stat	Normalized Difference
Log(Total borrowing)	4.188	5.172	0.984	53.227	0.412
Log(Total assets)	6.353	7.098	0.745	27.768	0.236
Log(Total debt)	4.803	5.819	1.016	30.111	0.271
Leverage	0.288	0.369	0.081	24.099	0.220
Liquidity ratio	0.097	0.081	-0.017	-10.687	-0.090
Investment ratio	0.317	0.327	0.010	3.305	0.029
Return on assets	0.002	-0.003	-0.005	-5.674	-0.049
High yield indicator	0.310	0.475	0.165	19.131	0.243
	Syndicated Loans - Nonbank Relation				
Variable	No Nonbank Relation	Nonbank Relation	Difference	t-stat	Normalized Difference
Log(Total borrowing)	4.235	5.385	1.150	62.362	0.502
Log(Total assets)	6.077	7.741	1.664	64.279	0.561
Log(Total debt)	4.497	6.462	1.965	59.272	0.551
Leverage	0.287	0.364	0.077	22.952	0.213
Liquidity ratio	0.102	0.074	-0.028	-18.309	-0.153
Investment ratio	0.313	0.326	0.013	3.853	0.035
Return on assets	-0.003	0.005	0.007	9.123	0.075
High yield indicator	0.312	0.436	0.124	14.113	0.182
	Auto Loans				
Variable	Bank (mean)	Nonbank (mean)	Difference	t-stat	Normalized Difference
Equifax Risk Score	704.8	658.2	46.7	250	0.49
Bankruptcy	0.0014	0.0045	-0.031	-29.4	-0.06
Log Credit Card Debt	2.676	2.003	0.672	96.6	0.19
Log Consumer Debt	0.733	0.852	-0.119	-25.7	-0.05
Log Mortgage Loans	5.464	4.262	1.202	110	0.21
Age	44.15	43.81	0.34	12.3	0.02
	Mortgages				
Variable	Bank (mean)	Nonbank (mean)	Difference	t-stat	Normalized Difference
All Loans					
Female Dummy	.270	.296	-.0259	-378.2	-0.06
African American Dummy	.074	.111	-.037	-850.9	-0.13
Log Income	4.27	4.14	.125	1197.4	0.18
Conforming Loans					
Female Dummy	0.276	0.300	-0.025	-327.1	-0.06
Black Dummy	0.070	0.108	-0.037	-799.3	-0.13
Log Income	4.22	4.12	0.095	881.9	0.15
Jumbo Loans					
Female Dummy	0.176	0.224	-0.048	-200.1	-0.12
Black Dummy	0.038	0.071	-0.033	-251.6	-0.15
Log Income	5.21	5.01	0.202	513.5	0.32

Table A5
Bank Share of Mortgage Lenders by Regulator

Regulator	Bank Share
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%

For each regulator, the table shows the share of mortgage lenders classified as banks by the classification algorithm.

B Monetary Policy and Nonbank Funding

We have documented that nonbanks lend relatively 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. If these deposits flow to products that provide funding for nonbanks, then this mechanism would enable nonbanks to expand lending.

To test this conjecture, we first investigate the products to which deposits flow in a monetary contraction. One alternative to bank deposits is money market mutual funds (MMF). 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 funds 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 2020). 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:

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

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).[35] 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.

We now test whether the inflows to MMFs result in improved funding conditions for nonbank lenders. 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.[36] Table B1, columns 3 and 4 show that money market funds also buy relatively more commercial paper and corporate bonds during a monetary contraction. This suggests that more funding becomes available to nonbank lenders. This finding is consistent with Xiao (2020) who, using disaggregated MMF data, shows that MMFs increase their holdings of commercial paper and ABCP when the federal funds rate is higher.

These MMF lending patterns suggest that nonbanks finance their expansion of credit to more risky borrowers after monetary contractions 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 both the asset and the liability side of nonbank financial institutions.

[35] We find similar results when we take the monetary policy measure by Wu and Xia (2016).

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

Table B1
Monetary Policy and MMF Flows

	Asset Growth		CP and 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

The table shows the results of estimating equation 9. Asset Growth is the quarterly growth rate of total MMF sector assets. CP and bond growth is the quarterly growth rate of holdings of open market paper and corporate bonds. All other variables are defined in Appendix A. The sample period is 1990-2012. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C: Robustness Tests

Extensive margin of mortgage credit

We first examine whether nonbanks extend a larger number of mortgages after a monetary contraction (extensive margin of credit). Table C1 shows that nonbanks extend more jumbo loans that they subsequently hold on their balance sheet after a monetary contraction.

Table C1
New Purchase Loans Held on Balance Sheet - Count

	Log(Number of Loans) - Conforming			
	Bank	Nonbank	Total	Nonbank Share
	(1)	(2)	(3)	(4)
Past Nonbank Share x GK	-0.272	0.020	-0.041	0.061
	(0.250)	(0.192)	(0.181)	(0.063)
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	0.81	0.83	0.81	0.74

	Log(Number of Loans) - Jumbo			
	Bank	Nonbank	Total	Nonbank Share
	(1)	(2)	(3)	(4)
Past Nonbank Share x GK	-0.114	1.472***	0.402	0.399***
	(0.457)	(0.266)	(0.426)	(0.041)
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	0.87	0.80	0.87	0.66

Sample period: 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. The sample includes new purchase loans (i.e. excluding refinancing loans) that remain on the lender's balance sheet. GK is the cumulative sum of monetary policy shocks of Gertler and Karadi (2015). "Macro variable interactions" refers to interactions of lagged macro controls (GDP growth, GDP forecast, inflation, VIX) with Past Nonbank Share. Standard errors in parentheses are double-clustered at the county and quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alternative measures of monetary policy

Next, to ensure that our results are not solely driven by the choice of the monetary policy variable, we present columns 1, 3 and 5 of Table 10 with two alternative measures of monetary policy: the Wu-Xia shadow rate and the federal funds rate.

Table C2 shows the results. We find effects similar to those using the Gertler-Karadi monetary policy measure.

Table C2
Aggregate Lending and Monetary Policy Measures

	Panel A: Industry-Level Debt	
	(1)	(2)
	Total debt	Total debt
Lagged FFR	-0.013	
	(0.010)	
Lagged FFR × Past Nonbank Share	0.169*	
	(0.087)	
Lagged shadow rate		-0.013
		(0.009)
Lagged shadow rate × Past Nonbank Share		0.141*
		(0.075)
Macro controls	YES	YES
Macro controls × Past Nonbank Share	YES	YES
Industry fixed effects	YES	YES
Industry controls	YES	YES
Observations	5,343	5,343
R-squared	0.98	0.98

	Panel B: Total Auto Loans	
	(1)	(2)
Lagged FFR	-0.037	
	(0.027)	
Lagged FFR x Past Nonbank Share	0.023	
	(0.021)	
Lagged Shadow Rate		-0.024
		(0.022)
Lagged Shadow Rate x Past Nonbank Share		0.018
		(0.018)
Macro Cont.	Yes	Yes
Macro Cont. x Past Nonbank Share	Yes	Yes
Crisis Interactions	No	Yes
County FE	Yes	Yes
County Controls	Yes	Yes
Observations	158,461	158,461
Adjusted R^2	0.49	0.48

	Panel C: New Held Mortgages	
	(1)	(2)
Lagged FFR	-0.119	
	(0.108)	
Lagged FFR x Past Nonbank Share	0.180***	
	(0.059)	
Lagged Shadow Rate		-0.089
		(0.092)
Lagged Shadow Rate x Past Nonbank Share		0.180***
		(0.058)
Macro Cont.	Yes	Yes
Macro Cont. x past Nonbank Share	Yes	Yes
County FE	Yes	Yes
County Cont.	Yes	Yes
Observations	55,062	55,062
Adjusted R^2	0.28	0.30

This table is in parallel to Table 10, columns 1, 3, and 5. In panel A, standard errors are clustered by industry and quarter, in panel B by county and quarter, and panel C by county and quarter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Last, we present the IV estimation results when instrumenting the shadow rate (Wu and Xia 2016) with Gertler-Karadi cumulative shocks instead of the federal funds rate (Table 11. Table C3 shows that our result does not change when using an interest rate measure that is

Table C3
Shadow Rate IV: Aggregate Lending and Outcomes

	Corporate Borrowing and Output		Auto Loans & Sales		Mortgages & House Prices	
	Total Debt	Annual Output	Total Loans	Auto Sales	New Mortgages	House Prices
	(1)	(2)	(3)	(4)	(5)	(6)
Shadow Rate x Past Nonbank Share	0.201**	0.240**	0.025	-0.002	0.145†	0.123***
	(0.090)	(0.094)	(0.022)	(0.017)	(0.092)	(0.045)
Shadow Rate	-0.011	-0.028***	-0.112**	-0.021	-0.050	-0.091***
	(0.010)	(0.008)	(0.051)	(0.015)	(0.048)	(0.025)
Macro Cont.	Yes	Yes	Yes	Yes	Yes	Yes
Macro Cont. x Past Nonbank Share	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Industry Controls	Yes	Yes	No	No	No	No
County FE	No	No	Yes	Yes	Yes	Yes
County Controls	No	No	Yes	Yes	Yes	Yes
Crisis Interactions	No	No	Yes	Yes	No	No
First Stage F-Stat	260.84	97.26	13.67	124.17	27.64	27.64
Observations	4,115	863	158,461	122,991	55,062	55,062

We instrument the shadow rate (Wu and Xia 2016) with Gertler-Karadi cumulative shocks and shadow rate x past nonbank share with Gertler-Karadi cumulative shocks x past nonbank share. All columns only report the second stage. Columns 1 and 2 of this table are in parallel to table 3 with federal funds rate, GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effects. Each observation is weighted by the logarithm of debt lagged and logarithm of real output lagged, respectively. Standard errors are clustered by industry and time. Columns 3 and 4 of this table are in parallel to table 6 with the federal funds rate, GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effects. Observations are weighted by lagged county income. Standard errors are clustered on the county and quarter level (column 3) and only on the county level (column 4) as fewer quarters are available in the sales data. Crisis interactions are the interactions of post-2008Q3 with macrovariables to account for the collapse of finance companies during the financial crisis. Columns 5 and 6 of this table are in parallel to table 9 with federal funds rate, GDP growth, GDP forecast, inflation, and VIX as additional controls but without time fixed effects. Observations are weighted by lagged county income. Standard errors are clustered on the county and quarter level. † p<0.125, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

not bounded at 0.