Nonbanks, Banks, and Monetary Policy: U.S. Loan-Level Evidence*

David Elliott   Ralf R. Meisenzahl   José-Luis Peydró

January 7, 2019

Abstract

We analyze the effects of monetary policy on banks and nonbank credit intermediaries, including shadow banks. For identification, we exploit U.S. monetary policy shocks and loan-level data for both firms and households since the 1990s. Contractionary monetary policy shifts both real-economy credit supply and funding liquidity from banks to nonbanks. Nonbank credit supply expands relative to banks, demand factors matter, and effects are stronger for ex-ante riskier loans. In the corporate loan market, nonbanks relatively increase credit supply by 12 percent in response to a one standard deviation increase in our measure of monetary policy shocks, but overall substitution is limited due to demand factors. In the consumer credit market, the corresponding overall increase in nonbank credit supply is just 10 percent, but completely offsetting the retrenchment by banks. Despite the fact that monetary policy affects all intermediaries by impacting market rates, our results show that nonbank lenders significantly attenuate the credit and risk-taking channels of monetary policy. However, there are limits to nonbank expansion, in particular in loans to firms as compared to households (including the associated real effects on investment and consumption), thereby suggesting that banks are special in credit markets which rely more on soft information.

JEL Classification: E51; E52; G21; G23; G28
Keywords: Nonbank Lending; Monetary Policy; Syndicated Loans; Consumer Loans.

*Elliott (David.Elliott@bankofengland.co.uk) is with Imperial College London and the Bank of England, Meisenzahl (ralf.r.meisenzahl@frb.gov) is with the Board of Governors of the Federal Reserve System, and Peydró (jose.peydro@upf.edu) is with ICREA-Universitat Pompeu Fabra, CREI, Barcelona GSE, Imperial College London and CEPR. We thank Jordi Gali, Narayana Kocherlakota, and Isabel Schnabel for helpful comments and suggestions. Peydró acknowledges financial support from both the Spanish Ministry of Economics and Competitiveness Feder EU (project ECO2015-68136-P) and the European Research Council Grant (project 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 or staff of the Federal Reserve.

1 Introduction

The structure of financial markets in general, and credit markets in particular, has dramatically changed over the last decades. Nonbank credit intermediaries (e.g. hedge and investment funds, private equity, and broker dealers) now have a significantly larger presence. A crucial question that arises is whether, and how, the transmission of monetary policy has changed due to this new market structure. A large literature shows that banks cut their supply of credit in response to a tightening of monetary policy. Therefore, a key question is whether nonbank credit intermediaries attenuate or increase the potency of the credit channel of monetary policy.

Several theories suggest that banks are central in the credit supply reduction after a monetary policy tightening. For instance, Kashyap and Stein (1995, 2000) and Stein (1998) argue that tighter monetary policy reduces credit supply via a reduction in bank reserves. Complementary, Drechsler, Savov, and Schnabl (2017) show that banks experience deposit outflows after a monetary contraction, which, in turn, forces them to cut lending. However, the deposits leaving the banking sector may be shifted to nonbanks (Xiao 2017). Nonbanks could then use this additional funding available to them after a monetary contraction to expand their lending activities. Under these theoretical channels, the reduction in bank lending following a contractionary monetary policy shock might be offset by an expansion of credit provision by nonbanks. Such a substitution between bank and nonbank lending could considerably attenuate the bank lending channel of monetary policy.

An alternative view is that a tightening of monetary policy negatively affects the funding conditions of *all* financial intermediaries that borrow short-term, potentially limiting nonbanks' ability to substitute for bank credit.[1] As formulated by a then Governor of the Federal Reserve (Stein 2013), an advantage of monetary policy (relative to prudential policy) is that

[1]Bernanke (2007), following Bernanke, Gertler, and Gilchrist (1999), applies the financial accelerator theory to financial intermediaries.

it "gets in all the cracks," as it acts directly on market rates and spreads that affect all actors in the financial system, irrespective of the regulatory regime under which they operate.[2] It is therefore an empirical question whether and to what extent monetary policy differently affects banks' and nonbanks' lending behaviour and therefore whether and to what extent such differences result in an attenuation or strengthening of the credit channel of monetary policy.

Our main contribution to the literature is to document how nonbank credit supply to firms and households responds to changes in monetary policy. For identification, in addition to monetary policy shocks, we exploit U.S. loan-level data for both firms and households since the 1990s, where we know whether the lender is a bank or a nonbank. We find that contractionary monetary policy shifts both real-economy credit supply and funding liquidity from banks to nonbanks. Nonbank credit supply relatively expands, demand factors matter, and effects are stronger for ex-ante riskier loans. Despite the fact that monetary policy affects all intermediaries by impacting market rates, our results show that nonbank lenders significantly attenuate the credit and risk-taking channels of monetary policy. However, there are limits to nonbank expansion, in particular in loans to firms as compared to households (including the associated real effects on investment and consumption), thereby suggesting that banks are special in credit which is more based on soft information.

We first investigate the connection between monetary policy and funding conditions of nonbanks. Using aggregate data for the money market fund (MMF) sector, we show that MMFs experience inflows in response to a contractionary monetary policy shock. Consistent with Xiao (2017), we show that MMFs increase their holdings of bonds and (asset-backed) commercial paper. In other words, MMFs provide more funding to nonbank lenders after a monetary contraction.

Having established that nonbanks' access to funding liquidity increases after a contrac-

[2]See also the Jackson Hole paper by Greenwood, Hanson, and Stein (2016).

tionary monetary policy shock, we analyze the response of nonbank credit supply and the associated real effects. We start with the syndicated corporate loan market. Using data from Thomson Reuters LPC DealScan (DealScan), we identify nonbank lenders and originations of new syndicated loans. The main advantage of studying syndicated loans is that they are originated by multiple lenders. This feature allows us to identify the effects of monetary policy by comparing credit provided by bank and nonbank lenders to the same borrower in the same month or quarter. This allows us to control for firm-level credit demand and therefore isolates the role of credit supply.

Using this within borrower variation in credit supply, we find that nonbanks expand lending to US corporate borrowers after a monetary contraction relative to their bank peers. Nonbank credit supply increases by 12 percent relative to bank credit supply after a one standard deviation increase in the monetary policy measure. The increases are larger for ex-ante riskier (non-investment grade) firms.

When we aggregate to the borrower-quarter level, we find that nonbanks attenuate the reduction in bank lending following monetary contractions, but the substitution from bank to nonbank credit is partial. In these regressions, when not controlling for firm-level demand and risk using firm-time fixed effects, we find that nonbank lending decreases after a monetary policy tightening, but it does so at a lower rate than bank lending. As a consequence, the proportion of credit provided by nonbank lenders increases after a monetary policy tightening. Our results suggest that one key factor explaining of the limited substitution is that the overall reduction in credit volume is partly driven by demand factors rather than by a reduction in credit supply. Moreover, substitution could also be limited by the nature of the syndication process, which relies heavily on soft information and therefore involves high switching costs for borrowers and lenders.

We therefore study whether borrowers that have established relationships with nonbank lenders in the past are better able to access credit when monetary policy tightens. We find that borrowers that have borrowed from nonbanks in the past experience a larger expansion in credit following monetary contractions, and that this is associated with a reduction in liquid asset holdings and an increase in fixed assets (investment). These findings suggest that nonbank lending relationships can attenuate the bank lending channel and support real economic activity.

Next, we turn to nonbank lending to U.S. households and focus on auto loans, which account for over 30 percent of total consumer credit. For this market, we have detailed, household-level data from Equifax, a major credit bureau, which allow us to study the response of auto credit extended by bank and nonbank lenders to a contractionary monetary policy shock, at the county level and at the household level. We document that banks retrench in response to such a shock. This reduction in bank lending could be driven by a reduction in funding or by weaker credit demand. Consistent with our evidence on corporate borrowers, we find that nonbank lenders expand auto credit supply to households while banks retrench, suggesting that the response of bank auto credit is in fact driven by banks' supply (funding) conditions. A one standard deviation increase in the policy rate leads to a 10 percent increase in nonbank auto lending. Banks cut credit at the same rate. In the aggregate, we do not find any effect of monetary policy on auto credit supply at the county or at the household level. This finding suggests that nonbank lending by providing a substitute for bank lending limits the response of household consumption to monetary policy and thereby significantly attenuates the credit channel of monetary policy.

To better understand whether there is regional heterogeneity in the auto loan market and for identification purposes, we follow Benmelech, Meisenzahl, and Ramcharan (2017) and study whether households living in counties historically more dependent on nonbank credit experience a larger expansion of nonbank auto credit and a larger reduction of bank auto credit after a monetary contraction. We use this county-level dependency on nonbank credit measure because lenders are more likely to expand operations in locations in which they are already present. Conversely, banks should retrench more in counties in which they have a weaker presence. By interacting the historic county-level dependence on nonbank credit with monetary policy, we can control for quarter-specific factors with time fixed effects and for unobserved, time-invariant county characterstics with county fixed effects, improving the identification of the effects of monetary policy. We find that banks reduce credit more in counties in which they historically extended less credit. Nonbanks completely offset this retrenchment.

We then test whether the effects are larger for low credit score borrowers. By interacting historic dependence on nonbank credit with monetary policy and the household risk score, we can also alleviate remaining concerns about time-varying unobservable county-level conditions—that is, we include county-time fixed effects. We find that nonbank credit is more sensitive to monetary policy for low credit score borrowers. This finding is consistent with the literature on bank portfolio allocation (the so-called risk-taking channel of monetary policy) but also suggests that nonbanks take more risk in response to a monetary contraction.

Last, we study whether auto sales are affected by monetary policy. Since most auto sales use some form of financing and our results on auto credit show complete substitution between bank and nonbank credit, monetary policy is unlikely to affect auto sales. Indeed, we find no significant effect of monetary policy on auto sales on the county level. Only in counties in which substitution of bank and nonbank credit is limited—that is, in counties with a historically low nonbank dependence—do auto sales fall in response to a monetary contraction.

Together our results suggest that nonbank lenders can expand more easily in credit markets in which lending relies on hard information such as credit scores and income rather than the soft information that is often transmitted in the negotiations of syndicated loans.[3]

[3]Sufi (2007) documents the presence of asymmetric information in the syndicated loan market. The

Put differently, the transmission of monetary policy varies across credit markets. Markets in which banks are more special experience only a limited expansion of nonbank credit and therefore less attenuation of the effectiveness of monetary policy.

Our paper contributes to the monetary policy literature. There is a large literature showing that banks cut the supply of credit due to tighter monetary policy conditions: the so-called bank lending channel of monetary policy (e.g., Bernanke and Blinder (1988, 1992), Kashyap and Stein (2000), Jimenez et al. (2012), Drechsler, Savov, and Schnabl (2017)), in turn affecting the credit channel of monetary policy (Bernanke and Gertler 1995). However, as highlighted above, theory is not clear on whether nonbanks can mitigate the credit supply reduction. Therefore, a key contribution of our paper is to show that the presence of nonbanks attenuates the credit channel, so that total credit reacts less after a tightening of monetary policy when nonbanks are present. Moreover, we also contribute to the literature on the risk-taking channel of monetary policy (e.g., Adrian and Shin (2010), Jimenez et al. (2014), and dell'Ariccia, Laeven, and Suarez (2017)) by analyzing this channel for *both* banks and nonbanks. In particular, we find that nonbanks concentrate their lending more on riskier borrowers when monetary policy conditions are tighter, thereby weakening the risk-taking channel of monetary policy.

One recent paper, Chen, Ren, and Zha (2018), analyzes the impact of monetary policy on banks and shadow banks and concludes that nonbank lenders reduce the effectiveness of monetary policy in China.[4] Our paper differs on multiple dimensions. Our results show that the substitution is larger (and complete) in consumer loans rather than corporate loans. Differently from the Chinese paper, we use firm-level and household-level loan data to trace the effectiveness of monetary policy, which allows us to test whether or not credit demand factors matter. Chen, Ren, and Zha (2018) use bank-level data and hence cannot identify the

syndication process in which soft information is transmitted is descripted in detail in Bruche, Malherbe, and Meisenzahl (2017).

[4]Buchak et al. (2018) assess the interplay of nonbank lenders and monetary policy in a structural model.

credit demand versus supply driven effects. We find that in corporate loans, demand effects are crucial for the results. Unlike the Chinese paper, we also analyze the risk-taking channel of monetary policy associated to nonbanks. Moreover, our setting focuses on differences in funding rather than heavy bank regulation in bank quantities (both in lending and liquidity) for Chinese banks when monetary policy changes. In addition, Chinese monetary policy targets M2 (quantities) whereas US monetary policy is primarily based on prices (e.g. short-term rates). Finally, we use monetary policy shocks (based on policy surprises) to better identify the role of monetary policy. Importantly, we also analyze the real effects associated with credit supply and monetary policy.

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

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

2 Data

2.1 Monetary policy measures

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

We use two additional measures of monetary policy in robustness tests: the Fed Funds target rate, and the shadow rate of Wu and Xia (2016). The shadow rate is essentially equal to the effective Fed Funds rate when this is above the zero lower bound. But unlike the Fed Funds rate, the shadow rate is not bounded below by zero. Using these alternative measures of monetary policy also allows us to extend our analysis to 2017. Figure 1 shows the time series of these three monetary policy measures.

2.2 Syndicated loans

Our analysis of the syndicated loan market is based on the DealScan dataset. This provides transaction-level information on syndicated loan originations, including the identities of the borrowers and lenders.

Importantly, DealScan provides a lender classification, which allows us to identify most lenders as either banks or nonbanks. We define the two groups as follows:

- **Banks:** US bank, Western European bank, foreign bank, mortgage bank, Middle Eastern bank, Eastern European/Russian bank, Asia-Pacific bank, thrift / S&L, African bank (plus unclassified firms that have 'bank' in the name).

- **Non-banks:** insurance company, corporation, finance company, investment bank, mutual fund, trust company, leasing company, pension fund, distressed (vulture) fund, prime fund, CDO, hedge fund, other institutional investor.

As shown by Roberts (2015), many observations in DealScan are likely to be amendments to existing loans rather than new originations, and it is often difficult to distinguish between amendments and originations. We drop loans that we identify as likely to be amendments, because these do not necessarily involve 'new' money.[5]

We match the loan-level data in DealScan to borrower-level data in Compustat using the link provided by Chava and Roberts (2008). We collapse the dataset to the borrower-quarter level or the borrower-lender-quarter level. This typically involves summing over multiple loan facilities within a loan package (for example, a loan package will often consist of both a term loan and a revolving credit facility). However this aggregation only rarely involves summing over multiple packages, because borrowers rarely take out multiple packages within the same quarter. In some regressions, we also separately consider term loans and revolving credit facilities (these loan types make up around three-quarters of all loan facilities). Summary statistics for the merged DealScan-Compustat dataset are provided in Table 1.

Figure 2 shows the evolution of bank and nonbank syndicated lending in the US.[6] Over the full sample period (1990-2017), nonbank lending has accounted for around 9% of total syndicated lending, by dollar volume. However there has been substantial heterogeneity over time: between 1995 and 2007, nonbank lending increased from less than 5% to more than 20% of the total market.

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

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

2.3 Credit Bureau Data

We use data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (FRBNY/Equifax CCP). Equifax is one of the three major credit bureaus in the United States. The FRBNY/Equifax CCP provides individuals' outstanding loan balances, broken down by category of loan (auto loan, credit card, mortgage, etc.). For auto loans the data set provides loan balances by lender type (bank and nonbank) but the identities of individual lenders are not provided. These data are available quarterly and extend back to 1999. We draw a 10 percent random sample from Equifax, which yields a panel of about 1.6 million households.

While the credit bureau data include auto loan balances by lender type, they do not provide an indicator variable for new auto loans. For each type of lender, we therefore identify new auto loans by a positive change in the balance of at least $500. We are interested in the net extension of credit. We compute the net new loan amount as the difference between the current quarter auto loan balance and the previous quarter auto loan balance.[7]

The key nonbank lenders in the auto loan market are finance companies. These nonbanks 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 2 show summary statistic for the Equifax sample on the household and county level. The average nonbank share in 1999Q1 is 0.53 on the county level but there is considerable variation in this measure of dependence on nonbank credit. For instance, the inter-quartile

[7]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.

range is 0.37. Figure 3 visualizes the local variation in county-level nonbank dependece. This local variation allows us to isolate the effects of monetary policy.

3 Mechanism and Hypothesis Development

Stein (2013) claims that an advantage of monetary policy is that it "gets in all the cracks" of the financial system. At the same time, Drechsler, Savov, and Schnabl (2017) show that banks experience deposit outflows in a monetary tightening cycle, which in turn reduces banks' ability to lend. This observation raises three interrelated questions about other parts of the financial system: 1) To which financial products do the deposits flow?, 2) Do financial products that experiences inflows provide funding for nonbanks?, and 3) Does nonbank credit expand when bank credit contracts in response to a monetary tightening?

These three questions guide our research. With respect to the first question, we observe that one alternative to bank deposits is money market funds. The return of these funds tend to track the federal funds rate closely. If banks do not raise their deposit rates to match increases in the federal fund rate as shown by Drechsler, Savov, and Schnabl (2017) then depositors will find switching from holding deposits to holding money market fund shares attractive (Xiao 2017). We provide suggestive evidence that funding to nonbanks becomes more available in response to a monetary contraction, as described above. Specifically, we show that money market fund assets grow in response to a monetary contraction complementing the bank deposit outflow documented by Drechsler, Savov, and Schnabl (2017). Using data from the Financial Accounts of the United States, we estimate the following equation:

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

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

Table 3 shows the results of estimating equation 1. We measure monetary policy using the cumulative sums of Gertler-Karadi shocks. Money market funds grow relatively more during a monetary contraction (column 1). This relationship holds when excluding the 2007/08 financial crisis (column 2). This finding shows that after a monetarty contraction deposits migrate from the banking sector to money market funds.

In response to the second question, whether financial products that experiences inflows provide funding for nonbanks, we note that, among other short-term investments, money markets funds invest in short-term paper of firms and asset-backed commercial paper (ABCP) paper backed by collateral pools. Many nonbanks rely on this type of funding from money market funds.[8] Table 3, columns 3 and 4 show that money market funds also buy relatively more open market paper and corporate bonds during a monetary contraction. This suggests that more funding becomes available to nonbank lenders.[9] This finding is consistent with Xiao (2017) who, using disaggregated MMF data, shows that MMF increase their holdings of commercial paper and ABCP when the federal fund rate is higher.

The results above show that funding available from money market funds to nonbanks expands in response to a monetary contraction. We now turn to the third question:Does nonbank credit expand when bank credit contracts in response to a monetary tightening? To answer this question, we derive several hypothesis for two specific lending markets, the syndicated loan market and the auto loan market, that we will test in sections 4 and 5. In the syndicated loan market, our main hypothesis is that within loan syndicate formation,

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

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

nonbanks should participate more—that is, take larger shares of a loan—in response to a contractionary monetary policy shock.[10] Our second hypothesis is that this effect should be stronger for riskier firms as banks typically retrench from the riskiest borrowers first (de Jonge et al. 2018; Liberti and Sturgess 2018). Our third hypothesis for the syndicated loan market is that since this market is based on soft information, borrowers with past relationships with nonbanks should experience a larger increase in credit supply from nonbanks after a monetary contraction and that this expansion of credit supply could have real effects at the firm level.

We also study the auto loan market for consumers. Here, our main hypothesis is that bank lending in the auto loan market should go down, and nonbanks dependent on wholesale funding markets should expand credit provision, in response to a monetary contraction—that is, there should be sustitution from bank credit to nonbank credit. Our second hypothesis is that after a funding shock stemming from monetary policy, banks reduce auto lending more to marginal borrowers—that is, either risky borrowers or borrowers outside their core markets (de Jonge et al. 2018; Liberti and Sturgess 2018).

4 Monetary Policy and Nonbank Lending to Firms

In this section we explore the relationship between monetary policy and nonbank lending to firms using data on syndicated loan originations.

We assess whether nonbanks expand credit supply relative to their bank peers in response to a monetary policy shock. Nonbank lenders active in the syndicated loan market such as investment banks rely heavily on short-term funding (e.g. repo transaction) to fund themselves. Hence after a monetary contraction nonbanks should be able to compete more

[10] Ludvigson (1998), using aggregate time series and VARs, shows that contractionary monetary policy produces a statistically significant effect on the composition of automobile credit with nonbanks gaining market share. Nelson, Pinter, and Theodoridis (2017), using aggregate data, show that the shadow banking system expands in response to a contractionary monetary policy shock.

intensive with banks and increase their market share in the syndicated loan market.

Our main hypothesis is that after a monetary contraction, banks experience deposit outflows and therefore reduce credit supply, and that nonbanks fill this void. We start with a regression analysis of loan amounts extended by nonbanks and banks. We estimate the following equation at the borrower-quarter level without controlling for firm-specific demand:

$$\text{Log(Quantity)}_{b,t} = \alpha_b + \beta_1 \text{Monetary Policy}_{t-1} + \beta_2 \text{Macroeconomic Controls}_{t-1} + \varepsilon_{b,t} \quad (2)$$

where α_b is an industry-fixed effect.

Table 4 shows the results from estimating equation 2. Nonbank lending declines in response to a contractionary monetary policy shock (column 1). However, this reduction in lending is smaller than the reduction by banks (column 2). Consequently, the nonbank share increases after a monetary contraction (column 3). We find similar effects when including industry fixed effects (column 4-6).[11] The fact that both, bank and nonbank lending, decline after a monetary contraction, suggests tha demands for credit in the syndicated loan market is sensitive to monetary policy. A second factor possibly limiting substitution between bank and nonbank lenders is that this market relies on soft information and therefore has high switching cost.

Having documented that the market share of nonbanks increases after a monetary contraction, we now tighten identification by exploiting the structure of the syndicated loan market. This structure allows us to identify the effects of monetary policy on nonbank lending for two reasons. First, syndicated laon facilities are extended by multiple lenders to one borrower. This feature allows us to analyze with-borrower variation at the time of loan origination. Using within-borrower variation at loan origination alleviates concern about unobservable borrower or loan characteristics. Specifically, we use borrower-quarter

[11] In the appendix, table B2, we show that these results are robust to including firm controls and trends as well as weighting observations by loan size and other measures of monetary policy.

fixed effects, which are, except for rare cases, equivalent to loan package fixed effects and control for unobserved borrower characteristics at the time of loan origination in the spirit of Khwaja and Mian (2008) and Jimenez et al. (2012).[12] Second, while borrowers choose the lead arranger, the participating members of the syndicate are typically beyond the borrower's control as they are the result of a book building process (Bruche, Malherbe, and Meisenzahl 2017).[13] Hence, the composition of the syndicate originating the loans is typically not affected by the borrower's loan demand but by the overall credit supply provided by different types of financial institution. We exploit the credit supply driven composition of syndicates to isolate differential responses of credit supply of different financial institutions to a monetary policy shock.

At the loan level, we first test whether nonbanks expand their syndicated loan lending relative to banks. We then test our second hypothesis that the effect is stronger for more risky firms. We estimate the following regression.

$$\begin{aligned} \text{Log(Quantity)}_{b,l,t} &= \alpha_{b,t} + \delta_l + \beta_1 \left(\text{Nonbank}_l \times \text{Monetary Policy}_{t-1}\right) \\ &\quad + \beta_2 \left(\text{Nonbank}_l \times \text{Macroeconomic Controls}_{t-1}\right) + \varepsilon_{b,l,t} \end{aligned} \tag{3}$$

wherhe b indexes borrowers, l indexes lenders, and t indexes quarters. The dependent variable, $\text{Log(Quantity)}_{b,l,t}$, is the log of the amount of credit extended by lender l to borrower b in quarter t. In seperate regressions, we consider total lending, total term loans, and total revolving credit facilities. Nonbank_l is a dummy variable indicating non-bank lenders. The main explanatory variable of interest is the interaction of the nonbank dummy with $\text{Monetary Policy}_{t-1}$, which is measured as cumulative sums of Gertler-Karadi shocks. We also include interactions of the dummy variables with four demeaned macroeconomic con-

[12]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).

[13]Most lead arrangers are banks.

trols: VIX, GDP growth, one quarter ahead GDP forecast, and CPI inflation. We saturate the model with borrower-quarter fixed effects to account for unobservable borrower and loan characteristics at the time of origination. We also include lender fixed effect to account for time-invariant lender characteristics (e.g. the business model).

Table 5, panel A shows the results of estimating equation 3 for the sample of dollar-denominated loans extended to U.S. borrowers. Since we include borrower-time fixed effects, we control for credit demand and unobservable firm characteristics at the time of loan origination (Jimenez et al. 2012; Khwaja and Mian 2008). We find that nonbanks expand credit supply to firms in response to a monetary policy shock when compared to their bank peers for the same borrower in the same quarter. This result holds for total lending (column 1), term loans (column 2), and credit line (revolver) extensions (column 3).[14] In other words, the funding mix in corporate lending syndicated shifts from banks and nonbanks after a monetary contraction.

We now assess our second hypothesis that this relative substitution is stronger for more risky loans. We study which type of borrower is benefitting most from the substitution of bank credit with nonbank credit. For this purpose, we use the DealScan-Compustat merged sample provided by Michael Roberts and use the S&P long-term credit rating as an indicator for borrower risk. Specifically, we interact a high-yield rating indictor with our nonbank and macroeconomic variables.[15] The interaction of interest is the triple interaction of the nonbank indicator with the monetary policy variable and the high-yield rating indicator. We expect the substitution effects to be strongest for the marginal, more risky borrowers—that is, we expect the coefficient on the triple interaction to be positive and significant.

Table 5, panel A, columns 4-6 show the results of including the triple interaction in equation 3. We find that the effect of nonbank lending is larger for high-yield borrowers(column

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

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

4). When considering different types of credit, we find no statistically significant effect in the extension of term loans (column 5). However, we find a statistically significant effect on the extension of credit lines (column 6).[16]

Table 5, panel A shows the results of estimating equation 3 for the sample of dollar-denominated loans extended to U.S. borrowers. Since we include borrower-time fixed effects, we control for credit demand and unobservable firm characteristics at the time of loan origination (Jimenez et al. 2012; Khwaja and Mian 2008). We find that nonbanksexpand credit supply to firms in response to a monetary policy shock when compared to their bank peers for the same borrower in the same quarter. This result holds for total lending (column 1), term loans (column 2), and credit line (revolver) extensions (column 3).[17] In other words, the funding mix in corporate lending syndicates shifts from banks to nonbank lenders after a monetary contraction.

We now assess our second hypothesis that this substitution is stronger for more risky loans. For this purpose, we use the DealScan-Compustat link provided by Chava and Roberts (2008) and use the S&P long-term issuer credit rating as a measure of borrower risk. Specifically, we define an indicator variable for firms with a high-yield credit rating, then create triple interactions between the high yield indicator, the nonbank indicator and our macroeconomic variables. [18] The interaction of interest is the triple interaction of the nonbank indicator with the monetary policy variable and the high-yield rating indicator. We expect the substitution effects to be strongest for the marginal, more risky borrowers—that is, we expect the coefficient on the triple interaction to be positive and significant.

Table 5, panel A, columns 4-6 show the results when we include the triple interaction

[16] In the appendix, we assess potential international spillovers from U.S. monetary policy to nonbank lending. We consider the sample of loans where the borrower country is not the USA. This approach is similar to Bräuning and Ivashina (2017) who study whether U.S. monetary policy affects the loan supply to international borrowers generally. We find significant spillovers of monetary policy.

[17] We find similar results when we use the monetary policy measure of Wu and Xia (2016) or the Federal Funds Rate.

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

in equation 3. When the dependent variable is total lending, the coefficient on the triple interaction is positive and significant, implying that substitution from banks to nonbanks is stronger for high-yield borrowers (column 4). We find no statistically significant effect in the extension of term loans (column 5). However, we find a statistically significant effect on the extension of credit lines (column 6).[19]

Table 5, panel B, shows the results of estimating the regressions in panel A without borrower fixed effects. Comparing the results in panel A to those in panel B therefore allows us to assess the impact of firms' credit demand. The magnitude and the significance of the point estimates change significantly, especially for term loans (column 2) and high-yield firms (columns 4-6). We therefore conclude that accounting for demand factors is crucial for understanding how the bank-nonbank financing mix of corporate loans changes after a monetary contraction.

A natural question is whether the relative expansion of nonbank credit affects firm-level outcomes. To answer this question, we test our third hypothesis: that having an existing relationship with nonbanks increases credit supply to a borrower after a monetary contraction, and that this expansion of credit supply has real effects on the firm level. A key friction in the syndicated loan market is that lending is based on soft information (Sufi 2007). Hence, borrowers with prior relationships with nonbanks should experience a larger increase in credit supply from nonbanks after a monetary contraction. To measure whether a borrower has prior nonbank relationships, we construct an indicator variable that is equal to one if the firm has borrowed from a nonbank in a previous syndicated loan. We only consider prior loans that were originated at least 2 years before the current quarter.[20] Having nonbanks

[19] In the appendix, we assess potential international spillovers from U.S. monetary policy to nonbank lending. We consider the sample of dollar-denominated loans to borrowers headquartered outside of the USA. This approach is similar to Bräuning and Ivashina (2017) who study whether U.S. monetary policy affects loan supply to international borrowers generally. We find significant spillovers of monetary policy.

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

in prior origination syndicates establishes information flows to nonbanks and may serve as borrower certification for other nonbanks. Hence, our hypothesis is that borrowers with prior nonbank relations receive more credit and are therefore able to reduce precautionary cash holdings and increase investment. To test this hypothesis, we estimate the following regression:

$$\begin{aligned} \text{Outcome}_{b,t} &= \alpha_b + \delta_{i,t} + \beta_1 \left(\text{Nonbank Relation}_b \times \text{Monetary Policy}_{t-1}\right) \\ &\quad + \beta_2 \left(\text{Nonbank Relation}_l \times \text{Macroeconomic Controls}_{t-1}\right) + \varepsilon_{b,t} \end{aligned} \tag{4}$$

where b indexes borrowers, i indexes borrower industry, and t indexes quarters. We consider several different dependent variables: the log of the amount of credit obtained through the syndicated loan market in quarter t, the log of total debt on the balance sh eet, the log of leverage, the log of the ratio of liquid assets to total assets, and the log of the ratio of property, plant and equipment to total assets. As explained above, Nonbank Relation$_b$ is a dummy variable indicating nonbank participation in prior syndicated loans (excluding loans in the last two years). The main explanatory variable of interest is the interaction of the Nonbank Relation dummy with Monetary Policy$_{t-1}$. As before, we also include the interactions of the nonbank relation dummy with four macroeconomic controls. We saturate the model with borrower and industry-quarter fixed effects to account for unobservable borrower characteristics and industry-wide shocks.

Table 6 shows the results from estimating equation 4. We find that borrowers with prior nonbank relationships receive more new credit in the syndicated loan market after a monetary contraction (column 1). Firms without prior nonbank relationships are not able to substitute syndicated loans with other types of credit, as firms with prior nonbank relationships also exhibit higher total debt (column 2) and higher leverage (column 3) after a monetary contraction. Having access to additional credit as a result of prior nonbank relationships reduces the need for precautionary savings in the form of liquid assets (column 4). Firms with prior nonbank relationships are also able to invest more in property, plants and equipment (column 5).

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

5 Monetary Policy and Nonbank Lending to Households

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

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

A key difference between auto lending and syndicated lending studied in the section above is that the auto loan application process is standardized. Auto lenders rely on hard information such as the credit score and income when deciding to whether to extend a loan whereas lenders in the syndicated loan market also use soft information in their lending decisions. By studying changes of auto lending by banks and nonbanks in response to a monetary contraction, we gain insights whether substitution between bank and nonbank credit is stronger when only hard information is used in lending decisions.

To test your main hypothesis that nonbank lenders increase credit supply while banks decrease credit supply in response to a contractionary monetary policy shock, we use county-level data from a credit bureau on newly extended auto loans by lender type. We estimate the following regression:

$$\text{Log(Auto Credit)}_{j,t} = \alpha_j + \beta_1 \text{MP}_{t-1} + \beta_2 \text{Macroeconomic Controls}_{t-1} + \beta_3 X_{j,t-1} + \varepsilon_{j,t} \quad (5)$$

where *Auto Credit*$_{jt}$ the log of new auto loan amounts in county j in quarter t . MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[21] Macroeconomic Controls_{t-1} is a vector of macroeconomic controls that includes GDP, GDP forecast, inflation and the VIX. $X_{j,t-1}$ is a vector of time-varying county-level controls (the average credit-bureau reported risk score and income). We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics.

Following Drechsler, Savov, and Schnabl (2017), we expect that banks experiencing deposit outflows after a monetary contraction to cut auto lending—that is, we expect β_1 to be negative and significant for *new auto loans extended by banks.* To be clear, a negative coefficient could also be interpreted as a drop in credit demand. One indication that the re-

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

duction in bank lending is attributable to tighter bank funding constraints is that nonbanks whose funding constraints loosened expand lending activity—that is, we expect β_1 to be positive and significant for *new auto loans extended by nonbanks*. To what extent substitution between bank and nonbank lending exists in the auto loan market is an empirical question that we will answer below.

Table 7 shows the results of estimating equation 5. Consistent with relative relaxation of nonbanks' funding constraints after a monetary contraction, we find that nonbanks increase auto lending (column 1). Banks reduce auto lending in response to a monetary contraction (column 2). A 25 bps surprise increase in the policy rate leads to reduction in new auto loans extended by banks by almost 5 percent. This increased nonbank lending activity mitigates concerns that the results for banks are driven by credit demand rather than credit supply. In the aggregate, we find that the substitution between bank and nonbank lending is perfect. The estimated effect of changes in monetary policy on total auto credit in a county is close to zero and statistically insignificant (column 3).

To better understand the substitution between bank and nonbank auto credit, we now study whether substitution occur uniformly or whether banks (nonbanks) make strategic choices from which markets they retrench (in which markets they expand). One determinant of retrenchment could be whether a county is considered a core market. Benmelech, Meisenzahl, and Ramcharan (2017) argue that for historic reasons nonbank auto lenders have a large presence in some counties and a weak presence in other counties. We measure historic dependence as the share of auto loan balances outstanding extended by nonbanks at the beginning of the sample (1999Q1). We hypothesize that banks retrench more from markets in which they have a weaker presence—those with a high dependence on nonbank credit—and from lending to more risky borrowers (de Jonge et al. 2018; Liberti and Sturgess 2018). Figure 3 shows that there is significant variation in the historical dependence on nonbank credit across U.S. counties.

To test these hypotheses, we estimate the following model:

$$\text{Log(Auto Credit)}_{j,t} = \beta_1 \text{Nonbank Share } 1999Q1_j \times MP_{t-1} + \gamma X_{it-1} + \alpha_j + \theta_t + \epsilon_{jt} \quad (6)$$

where $\text{Log(Auto Credit)}_{j,t}$ is the log of new auto loan amounts in county j in quarter t . *Nonbank Share 1999Q1*$_j$ is county's j dependency on nonbank credit measured as the share of auto loan balances outstanding extended by nonbanks. MP_{t-1} is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[22] X_{jt-1} is a vector of controls that includes the interaction of dependency with GDP, inflation and the VIX. We control for local economic conditions by including average risk score and county-level income. We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics and with time fixed effect (θ_t).

Table 8 shows the results of estimating equation 6 and the county-level. Columns 1 and 2 show that nonbanks expand auto credit in response to higher monetary policy rates in counties historically more dependent on nonbank credit while banks' auto credit contracts more in these counties. Given an average *Nonbank Share 1999Q1*$_j$ of 0.53, the coefficients are comparable in magnitude to the ones reported in table 7. The point estimates in columns 1 and 2 suggest that, on the county-level, there is also close-to-perfect substitution between bank and nonbank credit irrespective of the prior dependency of nonbank credit. Indeed, column 3 shows no significant net effect of contraction monetary policy on auto credit.[23] These results are consistent with banks retrenching to focus on their core markets.

We now examine whether banks retrench differently more from market with low risk score—on average, more risky borrowers. Columns 4-6 show the results for lending in counties with below median average credit score and columns 7-9 show the results for lending in

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

[23] We find similar patterns when we use the number of loans instead of the loan amount, see Table B3 in the appendix.

counties with above median average credit score. We find that in both samples nonbank lenders expand after a contractionary monetary policy shock while banks retrench. The overall effect, shown in column 6 and 9, shows that the substitution between bank and nonbank lenders is perfect in both samples.[24]

Two concerns remain. First, using data on the county-level potentially mask important heterogeneity among borrowers within a county. Second, while we control for county-level income and county-fixed effect, time-varying demand factor could still affect our results.

To address both concerns, we use household-level credit bureau data. We identify whether a household took out a new auto loan, the loan amount of a new auto loan, and the lender type (bank, nonbank). The data also include balances on other loans (mortgage, credit card, consumer loans), the individuals age, and a bankruptcy indicator, which allows us to better control for potential demand and risk factors.

We first replicate the county-level findings using the household-level data by estimating the following model via ordinary least squares (OLS):

$$\text{Auto Loan}_{ijt} = \beta_1 \text{Nonbank Share 1999}Q1_j \times MP_{t-1} + \gamma X_{ijt-1} + \alpha_j + \theta_t + \epsilon_{ijt} \qquad (7)$$

where *Auto Loan*$_{ijt}$ is either an indicator equal to 1 if for household i in county j a new auto loan appears in quarter t or the log of new auto loan amount. *Nonbank Share 1999Q1*$_j$ is county's j dependency on nonbank credit measured as the share of auto loan balances outstanding extended by nonbanks. MP$_{t-1}$ is the stance of monetary policy in $t-1$ measured by the Gertler-Karadi cumulative shock time series.[25] X_{ijt-1} is a vector of controls that

[24] The increase in nonbank lending results in considerable increased in the new lending market share of nonbanks. In the appendix, table B5 shows that the new lending market share of nonbank increases by about 7 percent in response to a 100 basis points increase in the policy rate. 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. In table B4 we confirm that the effect is not concentrated in the low credit score counties.

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

includes the interaction of dependency with GDP, inflation and the VIX as well as the household's birth year (fixed effects), outstanding credit card balance, outstanding mortgage balance, outstanding other consumer loan balance, and risk score. We control for local economic conditions by including county-level income. We saturate the model with county-fixed effects (α_j) to account for differences in time-invariant county-level characteristics and with time fixed effect (θ_t).

Due to fixed cost in lending technology, nonbanks are more likely to increase lending in counties in which they already have a strong presence. Hence, the key variable is the interaction of the historical dependence of a county on nonbank credit interacted with the monetary policy variable Nonbank Share1999$Q1_j \times MP_{t-1}$. We expect the coefficient β_1 to be positive for auto loans *financed with nonbank credit.* The expansion of nonbank credit should occur when banks retreat from the same markets. In the presence of substitution, we expect β_1 to be negative for *auto loans financed with bank credit.* As on the county-level, the extent of substitutions is given by estimating β_1 with any auto loan as dependent variable.

Table 9 shows the results of estimating equation 7. Nonbank increase lending by 3.1 percent (column 4) while banks cut lending by 3.2 percent (column 5). For this measure of new credit, the expansion of nonbank credit also nearly exactly offsets the reduction in credit supply by banks (column 6). This perfect substitution between bank and nonbank credit suggests that the deposit outflows experienced by banks are matched by an expansion of funding available to nonbanks in the money markets. Nonbanks take advantage of this funding expansion by increasing credit supply to households.

Nonbanks are more likely to extend additional auto loans to households in counties historically dependent on nonbank auto loans after an increase in the policy rate (column 4).[26] This point estimate implies that for a household living in a county with average historical

[26] 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.

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

A remaining concern with this specification is that we cannot control for time-varying county characteristics other than income as most consistent annual county-level data are only available from 2004 on. We address this concern by using county-time fixed effects below.

A natural question is which types of borrowers are mostly likely to be affected by changes in the credit supply from banks and nonbanks. Previous research, e.g. Liberti and Sturgess (2018) and de Jonge et al. (2018) suggests that banks are more likely to reduce the extension of credit to the least credit worthy borrowers.[27]

To test whether the substitution is dependent on borrower risk, we include a triple interaction of borrower's lagged credit score, the county's Nonbank Share1999Q1, and monetary policy as well as the triple interaction of borrower's lagged credit score and the county's Nonbank Share1999Q1 with of with all other macroeconomic variables.[28] We hypothesis that banks retrench more from borrowers with lower credit scores while nonbanks expand in this segment. In other words, the higher the borrower's credit score, the less likely is a re-

[27]In the appendix, we show that counties with a concentrated banking sector, measured as concentration in deposit taking, exhibit an increase in auto credit provided by banks (Table B7). This finding is consistent with banks focusing on their core markets or markets in which they have price setting power. However, we find that the include bank deposit taking concentration does not affect our main result.

[28]We also include the interaction of the macroeconomic variables with the risk score. The interaction of the Nonbank Share1999Q1 is absorbed by the county-quarter fixed effects.

duction of credit supply from banks and an increase of credit supply from nonbanks. Hence, we expect the coefficient on the triple to be negative and significant for the loan amount financed by nonbanks and positive for the loan amount financed by banks. This specification allows us to include county-time fixed effects to alleviate concerns that our results are driven by local demand varying systematically with the historical dependence on nonbank auto credit over the cycle.

Table 10 shows the results of estimation the effect of monetary policy on auto loans by borrower risk. Column 1 shows that nonbank increase their credit supply to lower credit score borrowers in response to higher monetary policy rates. This expansion of nonbank credit occurs when banks retreat from this segment of the market and shift credit supply to relatively better borrowers (column 2). The substitution between banks and nonbank is perfect across the credit risk spectrum (column 3). We obtain similar results when we use the log new loan amount as dependent variable (columns 4-6).[29]

To better understand whether the substitution between bank and nonbank auto credit has any real effects, we study county-level auto sales using data from Polk. We replicate the county-level findings using the auto sales data by estimating the following model via ordinary least squares (OLS):

$$\text{Auto Sales}_{jt} = \beta_1 \text{Nonbank Share } 1999Q1_j \times MP_{t-1} + \gamma X_{jt-1} + \alpha_j + \theta_t + \epsilon_{jt} \tag{8}$$

where $\textit{Auto Sales}_{jt}$ is the logarithm of total new auto sales inn quarter t in county j.

Table 11 shows the results from estimating equation 8. We find no effect of monetary policy on auto sales when we use the Gertler-Karadi cumulative shock time series as our

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

measure of monetary policy (column 1). When we use Wu-Xia shadow rate (column 2) or the federal funds rate (column 3) we find a small, but statistically positive effect of monetary policy on auto sales. However, this effect is not robust to weighting the observation with past county-level income (columns 4-6).

We then test whether montary policy has real effects in terms of auto sales in counties in which the substitution between bank and nonbank credit is limited. Since nonbanks tend to expand credit in counties in which they had a historically large market share, we use an indicator variable that is equal to 1 if a county's historical dependence on nonbank credit is in the lowest 25th percentile. In these counties substitutions is expected to be limited and hence auto sales should fall in response to a retrenchment of bank credit. Columns 7-9 show that this is the case. We find a negative and statistically significant effect of monetary policy on auto sales in low nonbank dependency counties regardless of the monetary policy measure used.[30]

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

6 Conclusion

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

[30]These results are robust to weighting the observations with past county-level income.

offsetting the reduction in lending by banks and reducing the effectiveness of monetary policy.

This attenuation of the bank lending channel is particular pronounced in the consumer credit market that relies on hard information. Nonbank lenders expand credit provision in the auto loan market by about 10 percent after a one standard deviation increase in the policy rate. This increase matches the retrenchment by banks. On net, we do find a statistically significant effect of monetary policy on total auto credit. We also find evidence for substitution in the syndicated corporate loan market. Within loans, nonbanks expand lending relative to their bank peers after a monetary contraction. On aggregate, syndicated corporate lending falls due to reduced demand but credit provision shifts to nonbank funding.

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

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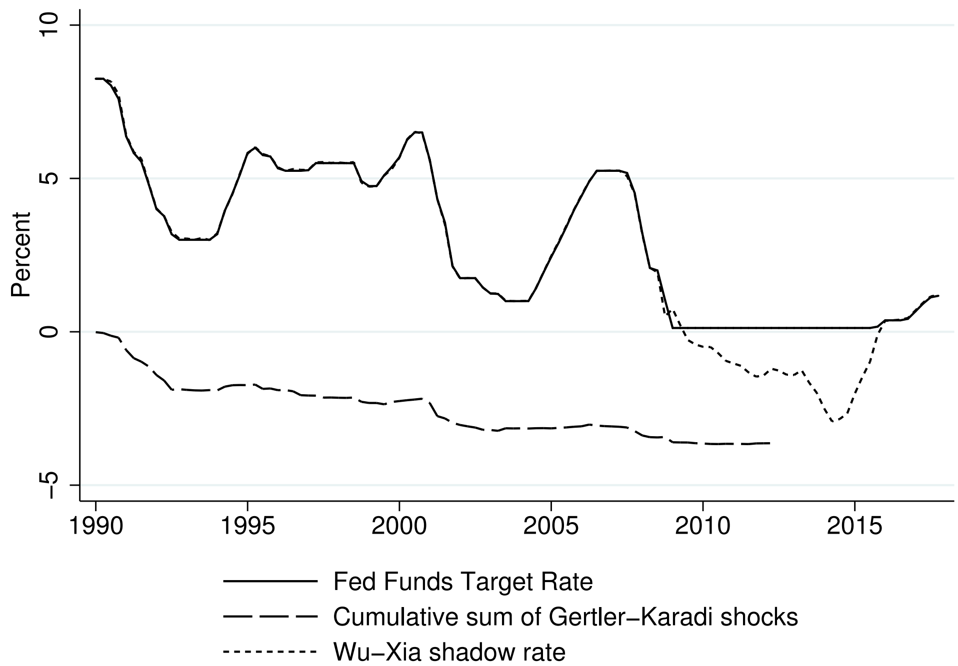
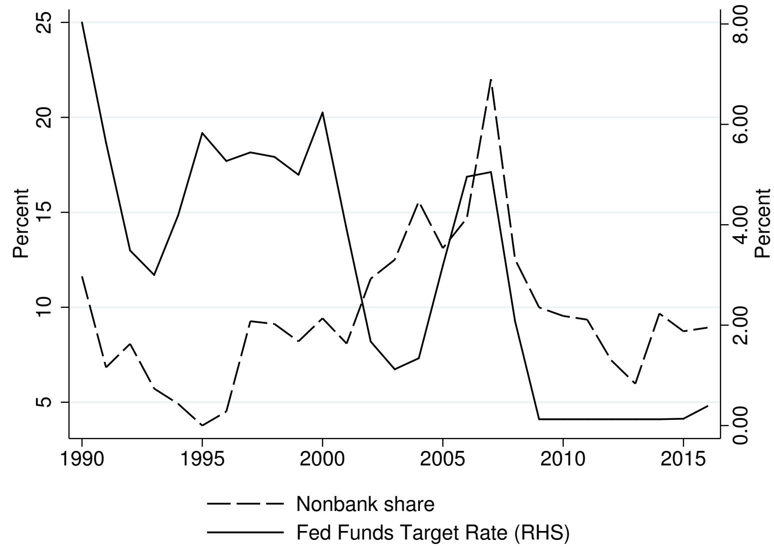
Figure 1: Monetary policy measures



Notes: The chart shows the Federal Funds Target Rate, shadow rates of Wu and Xia (2016), and cumulative sums of the monetary policy shocks of Gertler and Karadi (2015). Quarterly averages.

Figure 2: Syndicated lending in the US: Nonbank lending as proportion of total



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

Figure 3: Distribution of Household Dependence on Nonbank Auto Credit

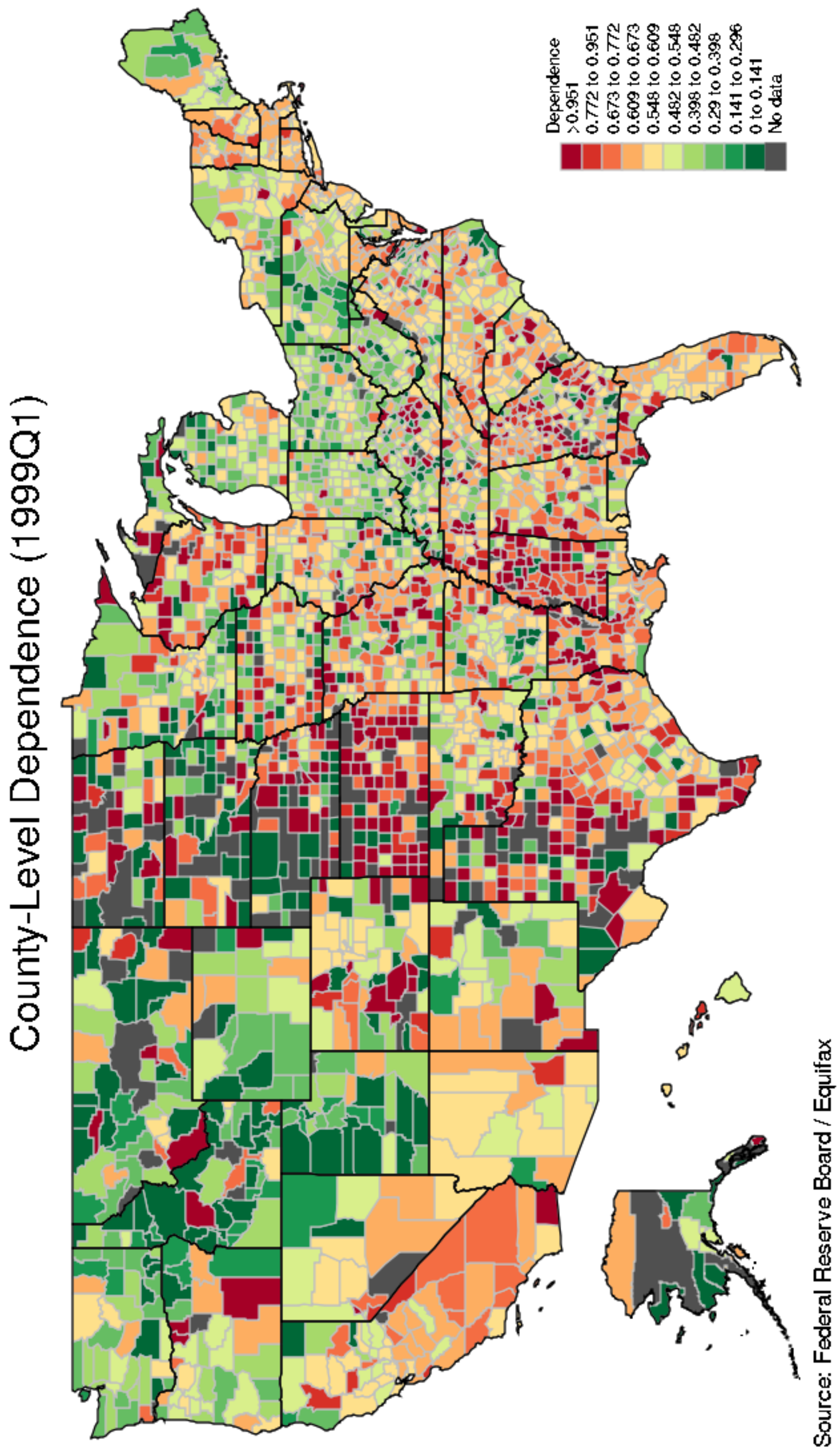


Table 1
Summary Statistics: DealScan and Compustat

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

Variable	N	mean	sd	p25	p50	p75
		Borrower-quarter level				
Log total borrowing	62,558	18.28	1.554	17.40	18.32	19.27
Log nonbank amount	5,471	17.26	1.355	16.45	17.22	18.10
Log bank amount	15,545	17.84	1.878	16.52	17.91	19.16
Log nonbank share	5,471	-1.311	1.165	-2.244	-1.312	0
Nonbank relation	623,359	0.226	0.418	0	0	0
Log total debt	371,420	5.061	2.684	3.240	5.138	6.801
Log leverage	371,305	-1.406	1.026	-1.798	-1.199	-0.802
Log liquid asset ratio	546,829	-3.118	1.681	-4.152	-2.974	-1.868
Log PPE / assets	519,073	-1.760	1.306	-2.433	-1.495	-0.749
Log total assets	578,098	6.166	2.598	4.375	6.059	7.764
High yield	194,721	0.427	0.495	0	0	1
		Borrower-lender-quarter level				
Nonbank lender	103,337	0.109	0.312	0	0	0
Log all loans amount	103,337	16.98	1.100	16.38	17.03	17.63
Log term loan amount	18,763	16.25	1.222	15.49	16.22	16.99
Log revolver amount	60,303	16.85	1.003	16.30	16.91	17.49

Table 2
Summary Statistics Equifax

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

Variable	N	mean	sd	p25	p50	p75
				Individual Level		
Nonbank Share 1999	54,258,810	0.57	0.16	0.49	0.59	0.67
New Loan Finance	54,258,810	0.01	0.10	0	0	0
New Loan Bank	54,258,810	0.01	0.09	0	0	0
Log Finance Amount	54,258,810	0.09	0.95	0	0	0
Log Bank Amount	54,258,810	0.08	0.89	0	0	0
Bankruptcy	54,258,810	0.00	0.05	0	0	0
Log Credit Card Balance	54,258,810	1.40	2.96	0	0	0
Log Consumer Credit Balance	54,258,810	0.33	1.55	0	0	0
Log Mortgage Balance	54,258,810	2.65	4.90	0	0	0
HHI	54,258,810	0.17	0.11	0.11	0.15	0.21
Riskscore	54,258,810	687	107	608	708	780
Log Income	54,258,810	21.05	1.92	19.68	21.28	22.49
				County-Level		
Nonbank Share 1999	2,936	0.53	0.28	0.35	0.55	0.72
Market Share (Amt)	157,981	0.35	0.37	0	0.33	0.63
Market Share (Loans)	157,981	0.36	0.38	0	0.27	0.67
Log New Loans Finance	157,981	0.80	0.90	0	0.69	1.10
Log New Loans Bank	157,981	0.80	0.88	0	0.69	1.39
Log Finance Amount	157,981	6.14	5.26	0	9.29	10.69
Log Bank Amount	157,981	5.95	5.34	0	9.25	10.68
HHI	157,981	0.32	0.21	0.18	0.26	0.39
Mean Riskscore	157,981	687.17	32.80	666.02	689.53	709.72
Log Income	157,981	18.12	1.72	16.95	17.97	19.11

Table 3
Monetary Policy and MMF Flows

The table shows the results of estimating equation 1. Asset Growth is the quarterly growth rate of total MMF sector assets. CP/Bond growth is the quarterly growth rate of holdings of open market paper and corporate bonds. All variables are defined in Appendix A. The sample period is 1990-2012.

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

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

Table 4
Aggregate Syndicated Loans: Substitution across Banks and Nonbanks

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

	Nonbank Amount (1)	Bank Amount (2)	Nonbank Share (3)	Nonbank Amount (4)	Bank Amount (5)	Nonbank Share (6)
GK	-0.522***	-0.885***	0.633***	-0.503***	-0.807***	0.562***
	(0.0407)	(0.0410)	(0.0280)	(0.0392)	(0.0367)	(0.0272)
VIX	0.0124	0.0340***	-0.0203***	0.00953	0.0260***	-0.0173***
	(0.00792)	(0.0101)	(0.00635)	(0.00705)	(0.00806)	(0.00569)
Inflation	0.202***	0.195***	-0.105***	0.190***	0.173***	-0.0734***
	(0.0373)	(0.0443)	(0.0300)	(0.0317)	(0.0357)	(0.0270)
GDP growth	-0.00848	-0.0198	0.00736	-0.00807	-0.00884	0.00190
	(0.0162)	(0.0256)	(0.0169)	(0.0132)	(0.0214)	(0.0151)
GDP growth forecast	0.0765	0.223***	-0.0494	0.0509	0.131**	-0.0138
	(0.0543)	(0.0728)	(0.0482)	(0.0467)	(0.0579)	(0.0469)
Industry FEs	No	No	No	Yes	Yes	Yes
Observations	5349	15195	5349	5041	14598	5041
Number of borrowers	3876	9508	3876	3572	8923	3572
Number of quarters	90	90	90	90	90	90
R-squared	0.0942	0.154	0.216	0.278	0.364	0.369

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

Table 5
Impact of US monetary policy on US corporate lending

The table shows estimated regression coefficients for equation 3 including interactions with a high-yield borrower indicator. The dependent variable is the log of lending quantity from DealScan. Only observations where lender shares are observed are included. GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. The regressions are at quarterly frequency. The sample period is 1990-2012. Macroeconomic controls are inflation, GDP growth, GDP growth forecast and VIX. Macroeconomic controls are lagged by one quarter. The sample consists of dollar-denominated loans where the borrower country is the USA. Standard errors clustered by borrower, lender and quarter. All variables are defined in Appendix A.

	Log(Total Credit Amount)					
	All Loans	Term Loans	Revolvers	All Loans	Term Loans	Revolvers
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Borrower-quarter fixed effects						
Nonbank x GK	0.135***	0.193***	0.0585**	0.0549	0.308**	-0.0135
	(0.0309)	(0.0488)	(0.0268)	(0.0387)	(0.128)	(0.0512)
Nonbank x High yield x GK				0.205***	-0.0261	0.194***
				(0.0456)	(0.103)	(0.0520)
Nonbank x High yield				0.0748*	0.190**	0.0255
				(0.0395)	(0.0861)	(0.0506)
Double Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Triple Interactions	No	No	No	Yes	Yes	Yes
Borrower-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Lender FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92971	14956	54312	46900	4887	25107
Number of borrowers	6589	1921	4804	1744	393	1336
Number of lenders	2053	1026	1268	1186	520	845
Number of quarters	90	90	90	90	88	90
R-squared	0.811	0.817	0.829	0.792	0.819	0.804
Panel B: No borrower fixed effects						
Nonbank x GK	0.105**	0.0839	-0.0116	0.147*	0.428**	-0.00855
	(0.0408)	(0.0916)	(0.0514)	(0.0883)	(0.165)	(0.0567)
Nonbank x High yield x GK				0.109	-0.236	0.135*
				(0.0718)	(0.148)	(0.0785)
Nonbank x High yield				-0.468***	-0.445***	-0.363***
				(0.0699)	(0.133)	(0.0622)
Double Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Triple Interactions	No	No	No	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Lender FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98851	16736	58124	47280	4996	25294
Number of borrowers	10140	3405	7530	1902	487	1451
Number of lenders	2270	1161	1414	1204	527	855
Number of quarters	90	90	90	90	88	90
R-squared	0.335	0.393	0.289	0.291	0.536	0.314

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

Table 6
Real effects of US monetary policy in the U.S. corporate sector

This table shows estimated regression coefficients for equation 4. The dependent variable in column 1 is the log of total quantity of dollar-denominated syndicated loans, from DealScan. The dependent variables in columns 2 5 are balance sheet variables derived from Compustat (all in logs). GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. 'Nonbank relation is an indicator variable equal to one for firms that have previously borrowed from a nonbank (excluding loans within the previous two years). The regressions are at quarterly frequency. The sample period is 1990-2012. The sample consists borrowers headquartered in the USA. Standard errors clustered by borrower and quarter. All variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)
	Borrowing	Total debt	Leverage	Liquid asset ratio	PPE / Assets
Nonbank relation x GK	0.156***	0.0420**	0.0371**	-0.0654**	0.0326**
	(0.0384)	(0.0182)	(0.0180)	(0.0240)	(0.0137)
Nonbank relation x VIX	0.000944	0.000953	0.00172*	0.00196	-0.000793
	(0.00413)	(0.00114)	(0.00102)	(0.00129)	(0.000598)
Nonbank relation x Inflation	0.0178	-0.00752	-0.0124*	0.00429	-0.000985
	(0.0325)	(0.00567)	(0.00652)	(0.00783)	(0.00304)
Nonbank relation x GDP	0.00616	0.000285	0.000477	-0.00248	-0.000204
	(0.00885)	(0.00202)	(0.00184)	(0.00269)	(0.00113)
Nonbank relation x GDP forecast	-0.0193	0.00947	0.0212***	-0.000485	-0.000983
	(0.0317)	(0.00695)	(0.00730)	(0.00957)	(0.00389)
Log(Borrower assets)	0.373***	0.841***	0.0218*	-0.208***	0.0333***
	(0.0212)	(0.0149)	(0.0110)	(0.00914)	(0.00777)
Borrower FEs	Yes	Yes	Yes	Yes	Yes
Industry-quarter FEs	Yes	Yes	Yes	Yes	Yes
Observations	23027	340613	340560	502396	476752
Number of borrowers	5776	9748	9747	10633	10225
Number of quarters	90	90	90	90	90
R-squared	0.844	0.925	0.549	0.630	0.872

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

Table 7
Aggregate Auto Loans: Substitution across Banks and Nonbanks

This table shows the regression results of equation 5. The dependent variable is the log amount of new auto credit extended by finance companies (column 1), by banks (column 2) and by both sources (3). The sample period is from 1999 to 2012. Standard errors clustered by county and state x quarter. All variables are defined in Appendix A.

	Log New Loan Amount		
	Nonbank	Bank	Total
	(1)	(2)	(3)
Lagged GK	0.207***	-0.269***	-0.00996
	(0.0474)	(0.0467)	(0.0420)
Lagged GDP Forecast	0.0755***	0.165***	0.113***
	(0.0285)	(0.0221)	(0.0228)
Lagged Inflation	0.0323**	-0.0237	0.00153
	(0.0157)	(0.0149)	(0.0142)
Lagged VIX	-0.0132***	-0.00930***	-0.0120***
	(0.00340)	(0.00278)	(0.00266)
Lagged GDP	0.0449***	-0.0570***	-0.00358
	(0.00806)	(0.00745)	(0.00658)
Time-varying County Controls	YES	YES	YES
County FE	YES	YES	YES
Observations	169216	169216	169216
R^2	0.499	0.509	0.530

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

Table 8
County-Level Effects on Auto Loans

This table shows the regression results of equation 7. The dependent variable is the log amount of new auto loans extended by finance companies (columns 1, 4, 7), the log amount of new auto loans extended by banks (columns 2, 5, 8), or the log amount of all new auto loans (columns 3, 6, 9). Columns 4-6 show results for counties with an average credit score below the median across all counties. Columns 7-9 show results for counties with an average credit score above the median across all counties. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log New Credit Amount								
	All Counties			Below Median Risk Score Counties			Above Median Risk Score Counties		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Nonbank	Bank	Total	Nonbank	Bank	Total	Nonbank	Bank	Total
GK x Nonbank Share 1999	0.503***	-0.587***	0.109	0.415***	-0.671***	-0.0268	0.559***	-0.736***	0.114
	(0.0986)	(0.119)	(0.107)	(0.129)	(0.189)	(0.145)	(0.154)	(0.146)	(0.164)
GDP x Nonbank Share 1999	0.0186	-0.0127	0.0257	0.0153	-0.0123	0.0236	0.0249	-0.0148	0.0259
	(0.0182)	(0.0219)	(0.0178)	(0.0217)	(0.0288)	(0.0252)	(0.0284)	(0.0245)	(0.0257)
Inflation x Nonbank Share 1999	-0.0258	0.0572**	0.0182	-0.0383	0.0603	0.0325	-0.0219	0.0113	-0.0311
	(0.0343)	(0.0244)	(0.0318)	(0.0388)	(0.0397)	(0.0537)	(0.0550)	(0.0421)	(0.0383)
VIX x Nonbank Share 1999	0.0215***	-0.0197*	0.00125	0.0322***	-0.0274**	-0.00509	0.00776	-0.0134	0.00392
	(0.00588)	(0.0106)	(0.00891)	(0.00716)	(0.0132)	(0.00933)	(0.0118)	(0.0137)	(0.0141)
GDP Forecast x Nonbank Share 1999	0.0804	-0.0879	-0.0108	0.118*	-0.118	-0.0571	0.0275	-0.0531	0.0275
	(0.0484)	(0.0702)	(0.0557)	(0.0606)	(0.100)	(0.0682)	(0.0764)	(0.0796)	(0.0779)
Time-varying County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	158461	158461	158461	72059	72059	72059	86270	86270	86270
R^2	0.489	0.490	0.502	0.535	0.529	0.547	0.456	0.463	0.472

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

Table 9
Household-Level Effects on Auto Loans

This table shows the regression results of equation 7 on the individual level. The dependent variable in column 1 is the log of new auto loan amount extended by finance companies, in column 2 the log of new auto loan amount extended by banks, and in column 3 the log loan amount extended by both sources of financing. The dependent variable is a dummy variable equal to 1 if new auto loans extended by finance companies (column 4), banks (column 5) or both sources of financing (column 6). Standard errors are clustered by quarter and county. The sample period is from 1999 to 2012. All variables are defined in Appendix A.

	Log Amount			New Loan		
	Nonbank	Bank	Total	Nonbank	Bank	Any
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.0312***	-0.0318***	-0.000376	0.00339***	-0.00377***	-0.000542
	(0.00715)	(0.00664)	(0.00113)	(0.000771)	(0.000733)	(0.0104)
GDP x Nonbank Share 1999	0.00121	-0.000614	0.0000482	0.000119	-0.0000705	0.000595
	(0.00109)	(0.00157)	(0.000169)	(0.000115)	(0.000174)	(0.00153)
Inflation x Nonbank Share 1999	-0.000705	0.00301	0.000241	-0.0000785	0.000327	0.00225
	(0.000868)	(0.00297)	(0.000311)	(0.0000944)	(0.000323)	(0.00283)
VIX x Nonbank Share 1999	0.00122***	-0.000230	0.000104	0.000130***	-0.0000250	0.000990
	(0.000394)	(0.000640)	(0.0000708)	(0.0000427)	(0.0000705)	(0.000650)
GDP Forecast x Nonbank Share 1999	0.00404	-0.00312	0.000115	0.000422	-0.000311	0.000956
	(0.00361)	(0.00412)	(0.000536)	(0.000384)	(0.000451)	(0.00498)
Lagged Risk Score	-0.000200***	0.000155***	-0.00000742***	-0.0000228***	0.0000154***	-0.0000446**
	(0.0000142)	(0.00000947)	(0.00000173)	(0.00000149)	(0.000000982)	(0.0000168)
Lagged Mortgage Balance	0.00590***	0.00757***	0.00138***	0.000606***	0.000792***	0.0133***
	(0.000317)	(0.000267)	(0.0000494)	(0.0000330)	(0.0000281)	(0.000474)
Lagged Consumer Loan Balance	0.0154***	0.00955***	0.00262***	0.00164***	0.00101***	0.0247***
	(0.00112)	(0.000375)	(0.000123)	(0.000122)	(0.0000392)	(0.00114)
Lagged Credit Card Balance	0.00441***	0.00769***	0.00125***	0.000450***	0.000813***	0.0120***
	(0.000385)	(0.000307)	(0.0000587)	(0.0000404)	(0.0000324)	(0.000560)
Lagged Bankruptcy Indicator	0.0621***	-0.00341	0.00650***	0.00686***	-0.000355	0.0587***
	(0.00614)	(0.00299)	(0.000751)	(0.000663)	(0.000336)	(0.00698)
County-Level Income	0.000413	-0.00355***	-0.000369**	0.0000349	-0.000405***	-0.00314*
	(0.00128)	(0.000698)	(0.000177)	(0.000133)	(0.0000733)	(0.00170)
County FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Birth Year FE	YES	YES	YES	YES	YES	YES
Observations	54243317	54243317	54243317	54243317	54243317	54243317
R^2	0.005	0.007	0.010	0.005	0.007	0.010

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

Table 10
Household-Level Effects on Auto Loans: Risk

This table shows the regression results of equation 7 on the individual level. The dependent variable in column 1 is the log of new auto loan amount extended by finance companies, in column 2 the log of new auto loan amount extended by banks, and in column 3 the log loan amount extended by both sources of financing. The dependent variable is the a dummy variable equal to 1 if new auto loans extended by finance companies (column 4), banks (column 5) or both (column 6). The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log Amount			New Loan		
	Nonbank	Bank	Total	Nonbank	Bank	Any
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999 x Score	-0.0913***	0.147***	0.0521	-0.00972***	0.0162***	0.00601
	(0.0000307)	(0.0229)	(0.0387)	(0.00335)	(0.00250)	(0.00416)
VIX x Nonbank Share 1999 x Score	-0.00217	-0.00327**	-0.000551**	-0.000226	-0.000332**	-0.000566**
	(0.00000149)	(0.00132)	(0.00224)	(00000161)	(0.000140)	(0.000233)
Inflation x Nonbank Share 1999 x Score	0.00647*	0.00776	0.0141	0.000797**	0.00881	0.000167
	(0.00000326)	(0.00949)	(0.0101)	(0.000331)	(0.000964)	(0.00103)
GDP x Nonbank Share 1999 x Score	0.00558*	0.00393	0.00938*	0.000602*	0.0000439	0.00103*
	(0.00311)	(0.00366)	(0.00512)	(0.000355)	(0.000379)	(0.000543)
GDP Forecast x Nonbank Share 1999 x Score	-0.0153	-0.0288***	-0.0440**	-0.00170	-0.00312***	-0.00482**
	(0.0119)	(0.00993)	(0.0183)	(0.00126)	(0.00107)	(0.00192)
Lower-Level Interactions	YES	YES	YES	YES	YES	YES
Individual Characteristics	YES	YES	YES	YES	YES	YES
County-Time FE	YES	YES	YES	YES	YES	YES
Birth Year FE	YES	YES	YES	YES	YES	YES
Observations	54243555	54243555	54243555	54243555	54243555	54243555
R^2	0.009	0.012	0.014	0.009	0.012	0.014

Standard errors are in parentheses. Coefficient multiplied with 1000.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11
Auto Sales and Monetary Policy

This table shows the regression results for the real effects of monetary policy on auto sales. The dependent variable is the log of auto sales. Low Nonbank Share 1999 is a dummy equal to 1 if a county's dependency on nonbank was in the lowest quartile in 1999. Columns 4-6 are weighted with past county-level income. The sample period is from 2002 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log Auto Sales								
	All Counties - Unweighted			All Counties - Weighted			Lowest 25th Nonbank Dependence		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nonbank Share 1999 x GK	0.0344			0.157					
	(0.0230)			(0.138)					
Nonbank Share 1999 x WX		0.00415*			0.0142				
		(0.00223)			(0.0122)				
Nonbank Share 1999 x FFR			0.00529**			0.0165			
			(0.00261)			(0.0141)			
Low Nonbank Share 1999 x GK							-0.0352**		
							(0.0146)		
Low Nonbank Share 1999 x WX								-0.00396**	
								(0.00148)	
Low Nonbank Share 1999 x FFR									-0.00450**
									(0.00185)
Nonbank Share 1999 x GDP	0.00255*	0.00302**	0.00314**	0.0138**	0.0130**	0.0129**			
	(0.00130)	(0.00117)	(0.00119)	(0.00535)	(0.00597)	(0.00623)			
Nonbank Share 1999 x GDP Forecast	0.000666	0.00439	0.00454	-0.0174	-0.00307	-0.00226			
	(0.00306)	(0.00400)	(0.00423)	(0.0170)	(0.0290)	(0.0299)			
Nonbank Share 1999 x Inflation	0.00340	0.00217	0.00162	0.00664	0.00125	-0.0000632			
	(0.00222)	(0.00208)	(0.00200)	(0.0108)	(0.00977)	(0.0101)			
Nonbank Share 1999 x VIX	-0.000341	0.000127	0.000219	0.000605	0.00133	0.00147			
	(0.000456)	(0.000450)	(0.000447)	(0.00238)	(0.00314)	(0.00314)			
Low Nonbank Share 1999 x GDP							-0.000687	-0.00123	-0.00119
							(0.000814)	(0.000767)	(0.000854)
Low Nonbank Share 1999 x GDP Forecast							-0.00105	-0.00560**	-0.00590**
							(0.00207)	(0.00264)	(0.00291)
Low Nonbank Share 1999 x Inflation							-0.000247	0.000720	0.00106
							(0.00117)	(0.00110)	(0.00113)
Low Nonbank Share 1999 x VIX							0.000384	-0.000215	-0.000256
							(0.000273)	(0.000299)	(0.000324)
County-Level Income	0.407***	0.418***	0.418***	0.518***	0.518***	0.519***	0.395***	0.407***	0.407***
	(0.0276)	(0.0288)	(0.0288)	(0.0561)	(0.0575)	(0.0578)	(0.0272)	(0.0287)	(0.0287)
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	122991	125920	125920	122991	125920	125920	131468	134598	134598
R^2	0.989	0.988	0.988	0.991	0.991	0.991	0.988	0.988	0.988

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

Appendix A

Variable definitions

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

Variable	Definition	Source
Panel A: Macro Variables		
GK	Cumulative Gertler-Karadi Monetary Policy Rate	Gertler and Karadi (2015)
Inflation	Inflation Rate	Federal Reserve Bank of St. Louis
GDP	Gross Domestic Product Growth Rate	Federal Reserve Bank of St. Louis
GDP Forecast	One-quarter-ahead forecast of Gross Domestic Product Growth	Federal Reserve Bank of Philadelphia
VIX	Volatility Index	CBOE
WX	Wu-Xia Shadow Rate	Wu and Xia (2016)
Fed Funds	Federal Funds Target Rate	Federal Reserve Bank of St. Louis
Panel A: Consumer Loans		
Nonbank Share 1999	The share of auto loan balances outstanding extended by nonbank	FRBNY/Equifax CCP
Low Nonbank Share 1999	Ddummy equal to 1 if a county's dependency on nonbank was in the lowest quartile	FRBNY/Equifax CCP
HHI	Sum of squared deposit market shares (Drechsler, Savov, and Schnabl 2017)	FDIC
New Loan Nonbank	Indicator equal to 1 if a household received a new auto loan from a nonbank	FRBNY/Equifax CCP
New Loan Bank	Indicator equal to 1 if a household received a new auto loan from a bank	FRBNY/Equifax CCP
Log Amount Nonbank	Log of new auto loan amount extended by a nonbank	FRBNY/Equifax CCP
Log Amount Bank	Log of new auto loan amount extended by a bank	
Market Share	The nonbank share of new auto loan balances outstanding	FRBNY/Equifax CCP
Credit Card Balance	Log of credit card debt outstanding	FRBNY/Equifax CCP
Mortgage Balance	Log of first mortgage debt outstanding	FRBNY/Equifax CCP
Consumer Balance	Log of consumer credit (other than auto loans) outstanding	FRBNY/Equifax CCP
Bankruptcy	Indicator equal to 1 if household had declared either Chapter 7 or 13 bankruptcy	FRBNY/Equifax CCP
Risk Score	Equifax Risk Score	FRBNY/Equifax CCP
Subprime Dummy	Indicator equal to 1 if household's risk score is less than 620	FRBNY/Equifax CCP
Log Income	Log of county-level quarterly total wages	BLS
Panel B: Syndicated Loans		
Nonbank	Indicator variable equal to one for nonbank lenders and zero for bank lenders	Thomson Reuters LPC DealScan
Nonbank relation	Indicator variable equal to one for borrowers who have previously borrowed from a nonbank (excluding loans in the previous two years)	Thomson Reuters LPC DealScan
Nonbank amount	Log of total credit extended to a borrower in a quarter from nonbanks	Thomson Reuters LPC DealScan
Bank amount	Log of total credit extended to a borrower in a quarter from banks	Thomson Reuters LPC DealScan
Nonbank share	Log of the ratio of total credit extended from nonbanks to total credit extended from all lenders	Thomson Reuters LPC DealScan
All loans	Log of total credit extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Term loans	Log of total term loan amount extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Revolvers	Log of total credit line amount extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Borrowing	Log of total credit extended to a borrower in a quarter	Thomson Reuters LPC DealScan
Total debt	Log of total debt net of cash (dlcq + dlttq - cheq)	Compustat
Leverage	Log of book leverage net of cash ((dlcq + dlttq - cheq) / atq)	Compustat
Liquid asset ratio	Log of ratio of cash and short term investments to total assets (cheq / atq)	Compustat
PPE / Assets	Log of ratio of property, plant and equipment to total assets (ppentq / atq)	Compustat
High yield	Indicator variable equal to one if the borrower has a high yield credit rating, and equal to zero if it has an investment grade credit rating (splticrm)	Compustat
Log(borrower assets)	Log of lagged total assets (at)	Compustat

Appendix B: Robustness Tests

In Table B1 show results of estimating equation 3 for non-U.S. borrowers. In these specifications we also employ borrower-month fixed effects that implicitly control for the borrower's home country monetary policy and macroeconomic conditions. In this sample, we also find that nonbanks expand credit supply to non-U.S. borrowers in response to a monetary policy shock when compared to their bank peers for the same borrower. The estimated effect are in magnitude comparable to n the effects on U.S. borrowers. However, we do not find any additional effect for nonbanks with fragile funding.

Table B1
Impact of US monetary policy on non-US corporate lending

The table shows estimated regression coefficients for equation 3. The dependent variable is the log of lending quantity from DealScan. Only observations where lender shares are observed are included. GK refers to lagged cumulative sums of the monetary policy shocks of Gertler and Karadi (2015) for the US. The regressions are at quarterly frequency. The sample period is 1990-2012. The sample consists of dollar-denominated loans where the borrower country is not the USA. Standard errors clustered by borrower, lender and month. All variables are defined in Appendix A.

	Total Lending (1)	Term Loans (2)	Revolvers (3)	Total Lending (4)	Term Loans (5)	Revolvers (6)
Nonbank x GK	0.269***	0.221***	0.0823	-0.0229	0.257**	0.0704
	(0.0536)	(0.0773)	(0.0544)	(0.108)	(0.112)	(0.135)
Nonbank x VIX	-0.00363	-0.00142	-0.00380	0.00608	-0.00833	0.00666
	(0.00340)	(0.00457)	(0.00690)	(0.00772)	(0.00755)	(0.0136)
Nonbank x Inflation	0.00520	0.0458**	-0.0185	0.00459	-0.0234	-0.132
	(0.0205)	(0.0205)	(0.0367)	(0.0490)	(0.0309)	(0.0853)
Nonbank x GDP	0.00611	0.00657	0.00993	0.000554	0.00280	0.0268
	(0.00677)	(0.00756)	(0.0164)	(0.0131)	(0.0164)	(0.0220)
Nonbank x GDP forecast	-0.0496	-0.0312	-0.0365	-0.00268	-0.0349	0.000485
	(0.0301)	(0.0343)	(0.0440)	(0.0420)	(0.0499)	(0.0839)
Quarter FEs	-	-	-	Yes	Yes	Yes
Borrower-quarter FEs	Yes	Yes	Yes	No	No	No
Lender FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62561	31408	10907	63425	31964	11050
Number of borrowers	4789	3230	955	5364	3658	1074
Number of lenders	2841	2120	996	2870	2139	1002
Number of quarters	90	89	87	90	89	88
R-squared	0.867	0.866	0.921	0.475	0.494	0.505

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

Table B2
Aggregate Syndicated Loans: Substitution - Robustness

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

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

Standard errors in parentheses

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

Table B3
County-Level Effects - Number of Loans

This table shows the regression results of equation 7. The dependent variable is the log of the number of new loans extended by finance companies (columns 1, 4, 7), the log of the number of new loans extended by banks (columns 2, 5, 8), or the log of the number of all new loans (column 3, 6, 9). Columns 4-6 show results for counties with an average credit score above the median across all counties. Columns 7-9 show results for counties with an average credit score above the median across all counties. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log New Loans								
	All Counties			Below Median Risk Score Counties			Above Median Risk Score Counties		
	Nonbank	Bank	Total	Nonbank	Bank	Total	Nonbank	Bank	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GK x Nonbank Share 1999	0.0673***	-0.0799***	-0.00596	0.0704***	-0.0983***	-0.0137	0.0513***	-0.0782***	-0.0201
	(0.0128)	(0.0173)	(0.0171)	(0.0187)	(0.0183)	(0.0238)	(0.0151)	(0.0233)	(0.0196)
GDP x Nonbank Share 1999	0.00341*	-0.000989	0.00348	0.00348	-0.000754	0.00330	0.00411	-0.00192	0.00318
	(0.00200)	(0.00330)	(0.00245)	(0.00277)	(0.00352)	(0.00324)	(0.00248)	(0.00373)	(0.00307)
Inflation x Nonbank Share 1999	-0.00141	0.00701	0.00465	-0.00211	0.00548	0.00181	-0.00249	0.00326	0.00222
	(0.00316)	(0.00483)	(0.00304)	(0.00473)	(0.00637)	(0.00497)	(0.00440)	(0.00415)	(0.00494)
VIX x Nonbank Share 1999	0.00260***	-0.00140	0.000720	0.000702	-0.00183	-0.000575	0.00407***	-0.000825	0.00172
	(0.000803)	(0.00149)	(0.00137)	(0.00140)	(0.00178)	(0.00204)	(0.001000)	(0.00136)	(0.00109)
GDP Forecast x Nonbank Share 1999	0.00810	-0.00541	0.00145	0.000000244	-0.00853	-0.00387	0.0137**	0.00265	0.00803
	(0.00584)	(0.00944)	(0.00913)	(0.00925)	(0.00940)	(0.0117)	(0.00675)	(0.0112)	(0.00823)
Time-varying County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	158461	158461	158461	86270	86270	86270	72059	72059	72059
R^2	0.787	0.749	0.826	0.769	0.729	0.810	0.812	0.771	0.846

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

Table B4
County-Level Effects on Auto Loans

This table shows the regression results of equation 7. The dependent variable is the log of new auto loans extended by finance companies (columns 1, 4), the log of new auto loans extended by banks (columns 2, 5), or the log of all new auto loans (column 3, 6). Columns 1-3 show results for counties with an average credit score below the 25th percentile across all counties. Columns 4-6 show results for counties with an average credit score above lowest quartile across all counties. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log New Loan Amounts					
	Riskiest Loans			Less Risky Loans		
	Nonbank	Bank	Total	Nonbank	Bank	Total
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.109	-0.394**	-0.0329	0.581***	-0.743***	0.0574
	(0.261)	(0.196)	(0.237)	(0.0853)	(0.161)	(0.113)
GDP x Nonbank Share 1999	0.0506	-0.00709	0.0500	0.0234	-0.0134	0.0248
	(0.0513)	(0.0351)	(0.0493)	(0.0167)	(0.0246)	(0.0206)
Inflation x Nonbank Share 1999	0.0384	-0.0498	0.00154	-0.0449	0.0721***	0.0195
	(0.0654)	(0.0567)	(0.0574)	(0.0291)	(0.0262)	(0.0379)
VIX x Nonbank Share 1999	0.0316*	-0.0151	0.0258	0.0211***	-0.0185*	-0.00359
	(0.0168)	(0.0145)	(0.0161)	(0.00454)	(0.0106)	(0.00827)
GDP Forecast x Nonbank Share 1999	0.161	-0.110	0.0682	0.0535	-0.0591	-0.0392
	(0.106)	(0.0865)	(0.111)	(0.0361)	(0.0826)	(0.0588)
Lagged Risk Score	-0.00332	0.00344	-0.000465	-0.00389***	-0.00136	-0.00418***
	(0.00238)	(0.00243)	(0.00258)	(0.00132)	(0.00139)	(0.00135)
County-Level Income	0.769***	0.852***	1.033***	0.645***	0.528***	0.660***
	(0.214)	(0.192)	(0.206)	(0.103)	(0.0902)	(0.110)
Time FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Observations	39500	39500	39500	118858	118858	118858
R^2	0.431	0.428	0.444	0.513	0.503	0.526

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

Table B5
County-Level Effects on Auto Loan Market Share

This table shows the regression results of equation 7. The dependent variable is the finance companies' county-level market share measured as share of new loan amounts (columns 1-3) or the finance companies' county-level market share measured as share of new loans (columns 4-6). Columns 2 and 5 show results for counties with an average credit score above the median across all counties. Columns 3 and 6 show results for counties with an average credit score above the median across all counties. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	All Counties	Above Median Score	Below Median Score	All Counties	Above Median Score	Below Median Score
		Market Share Amount			Market Share Loans	
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.0654***	0.0741***	0.0597***	0.0699***	0.0612***	0.0799***
	(0.00984)	(0.0140)	(0.0132)	(0.00985)	(0.0136)	(0.0142)
GDP x Nonbank Share 1999	0.00328*	0.00377	0.00299	0.00283	0.00342	0.00266
	(0.00172)	(0.00252)	(0.00227)	(0.00174)	(0.00235)	(0.00254)
Inflation x Nonbank Share 1999	-0.00349	-0.00471	-0.00200	-0.00346	-0.00190	-0.00468
	(0.00393)	(0.00555)	(0.00380)	(0.00401)	(0.00364)	(0.00572)
VIX x Nonbank Share 1999	0.00228***	0.00141	0.00284***	0.00219***	0.00249***	0.00146
	(0.000494)	(0.000891)	(0.000731)	(0.000585)	(0.000797)	(0.000982)
GDP Forecast x Nonbank Share 1999	0.00873**	0.00587	0.00956	0.00843*	0.00602	0.00795
	(0.00401)	(0.00653)	(0.00611)	(0.00450)	(0.00708)	(0.00726)
Lagged Risk Score	-0.000351***	-0.000250	-0.000359**	-0.000397***	-0.000395***	-0.000294*
	(0.000102)	(0.000159)	(0.000139)	(0.000104)	(0.000138)	(0.000155)
County-Level Income	0.0276***	0.00768	0.0455***	0.0291***	0.0448***	0.0117
	(0.00885)	(0.0132)	(0.0103)	(0.00846)	(0.0102)	(0.0130)
County FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	158461	86270	72059	158461	72059	86270
R^2	0.205	0.188	0.225	0.215	0.234	0.197

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

Table B6
County-Level Effects - Weighted Regressions

This table shows the regression results of equation 7. The dependent variable is the log of new auto loans extended by finance companies (columns 1, 4), the log of new auto loans extended by banks (columns 2, 5), or the log of all new auto loans (column 3, 6). Columns 1-3 show results for counties with an average credit score above the median across all counties. Columns 4-6 show results for counties with an average credit score in the median across all counties. Observations are weighted with lagged total auto loan balances. The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log New Loan Amount					
	Below Median Risk Score Counties			Above Median Risk Score Counties		
	Nonbank	Bank	Total	Nonbank	Bank	Total
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.184	-0.332*	0.0696	0.333*	-0.445**	0.178
	(0.195)	(0.166)	(0.0984)	(0.193)	(0.167)	(0.107)
GDP x Nonbank Share 1999	0.00462	0.00464	0.0171	0.0230	0.00995	0.0200
	(0.0420)	(0.0224)	(0.0148)	(0.0355)	(0.0292)	(0.0167)
Inflation x Nonbank Share 1999	-0.0134	0.0141	-0.0148	-0.0499	0.0588	-0.00711
	(0.0884)	(0.0246)	(0.0250)	(0.0488)	(0.0451)	(0.0243)
VIX x Nonbank Share 1999	0.0431***	0.00259	0.0195***	0.00238	-0.00216	0.000934
	(0.0140)	(0.00844)	(0.00493)	(0.0130)	(0.0131)	(0.00774)
GDP Forecast x Nonbank Share 1999	-0.0309	0.0122	0.0519	-0.124	-0.128	-0.0875
	(0.158)	(0.0702)	(0.0501)	(0.106)	(0.0835)	(0.0594)
Lagged Risk Score	-0.00360	-0.00110	-0.00239	-0.00482*	0.00160	-0.00176
	(0.00262)	(0.00250)	(0.00191)	(0.00266)	(0.00266)	(0.00196)
County-Level Income	0.806***	0.414***	0.477***	0.757***	0.866***	0.719***
	(0.142)	(0.123)	(0.0854)	(0.130)	(0.156)	(0.0936)
Time FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Observations	70786	70786	70786	85428	85428	85428
R^2	0.637	0.602	0.668	0.628	0.615	0.658

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

Table B7
County-Level Effects Dependency vs HHI

This table shows the regression results of equation 7. The dependent variable is the log amount of new auto loans extended by nonbanks (column 1) or by banks (column 2), log number of new auto loans extended by nonbanks (column 3)or by banks (column 4), or market share of nonbanks (columns 5 and 6). The sample period is from 1999 to 2012. Standard errors are clustered by quarter and county. All variables are defined in Appendix A.

	Log Loan Amount		Log Loans		Market Share	
	Nonbank	Bank	Nonbank	Bank	(Amount)	(Loans)
	(1)	(2)	(3)	(4)	(5)	(6)
GK x Nonbank Share 1999	0.501***	-0.595***	0.0654***	-0.0816***	0.0697***	0.0649***
	(0.102)	(0.117)	(0.0127)	(0.0172)	(0.00992)	(0.00989)
HHI x GK	-0.00671	0.390***	-0.123*	-0.0350	-0.0108	-0.0373**
	(0.180)	(0.142)	(0.0651)	(0.0423)	(0.0169)	(0.0173)
GDP x Nonbank Share 1999	0.0161	-0.0125	0.00289	-0.000804	0.00250	0.00297*
	(0.0187)	(0.0219)	(0.00199)	(0.00332)	(0.00174)	(0.00172)
Inflation x Nonbank Share 1999	-0.0264	0.0570**	-0.00146	0.00729	-0.00360	-0.00363
	(0.0341)	(0.0245)	(0.00304)	(0.00500)	(0.00401)	(0.00392)
VIX x Nonbank Share 1999	0.0218***	-0.0196*	0.00259***	-0.00141	0.00220***	0.00230***
	(0.00615)	(0.0106)	(0.000809)	(0.00152)	(0.000587)	(0.000496)
GDP Forecast x Nonbank Share 1999	0.0843	-0.0881	0.00776	-0.00627	0.00903**	0.00934**
	(0.0505)	(0.0706)	(0.00599)	(0.00960)	(0.00448)	(0.00401)
HHI x VIX	0.00546	-0.0250***	-0.000419	-0.00219	0.0000324	0.000685
	(0.0105)	(0.00838)	(0.00445)	(0.00361)	(0.00116)	(0.00121)
HHI x Inflation	-0.0163	0.0496	-0.0000336	0.0260	-0.00686	-0.00761
	(0.0538)	(0.0609)	(0.0221)	(0.0219)	(0.00627)	(0.00648)
HHI x GDP	-0.110***	0.00758	-0.0284**	0.0138*	-0.0163***	-0.0156***
	(0.0277)	(0.0221)	(0.0124)	(0.00804)	(0.00250)	(0.00287)
HHI x GDP Forecast	0.0887	-0.237***	-0.0293	-0.0766**	0.0267***	0.0292***
	(0.0831)	(0.0649)	(0.0432)	(0.0316)	(0.00799)	(0.00883)
Lagged Risk Score	-0.00409***	-0.000400	-0.000343***	0.0000718	-0.000411***	-0.000376***
	(0.00100)	(0.00124)	(0.000113)	(0.000156)	(0.000103)	(0.000102)
County-Level Income	0.687***	0.660***	0.0611***	0.0889***	0.0287***	0.0268***
	(0.0874)	(0.0846)	(0.0125)	(0.0127)	(0.00838)	(0.00879)
Lagged HHI	-0.0690	0.734*	-0.0725	-0.0846	0.0243	-0.00332
	(0.435)	(0.387)	(0.135)	(0.112)	(0.0484)	(0.0511)
County FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	157981	157981	157981	157981	157981	157981
R^2	0.488	0.489	0.787	0.749	0.214	0.204

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