Fintech, Market Power and Monetary Transmission*

Vincent Yao†

December 28, 2022

Abstract

Using automobile credit data, we study individual lenders' responses to monetary policy shocks and how they are affected by local market power. We find that all lenders, except new fintech firms, respond to an increase in the policy rate by significantly increasing their rates on auto loans, and their loan originations contract as a result. However, the magnitude varies across lenders, borrowers, and markets. Our results suggest that the rising market power of shadow banks significantly increases banks' responses to the rate hike. The results are robust using cross-sectional variation and an event study approach that exploits the rise of fintech as a quasi-exogenous shock.

Keywords: Fintech; Banks; Shadow Banking; Monetary Policy Transmission; Market Power; Automobile

JEL Classification: E51, E52, G51, G21, G23, G28

*I thank Rodney Ramcharan for providing useful feedback and discussions.
†J. Mack Robinson College of Business, Georgia State University. Email: wyao2@gsu.edu.

1. Introduction

In the aftermath of the Great Financial Crisis (GFC), the Federal Reserve has undertaken various accommodative monetary policies to combat the crisis. It not only quickly lowered its conventional policy tool—the federal funds rate (FFR)—to the zero lower bound (ZLB), but also implemented two main types of unconventional monetary policies, namely forward guidance (FG) and large-scale asset purchases (LSAP), through rounds of quantitative easing (QE). In recent years, QE's effectiveness, the channels through which it affects the real economy, and its distributional impact have been at the center of a vigorous policy and academic debate.[1] During the same period, consumer credit markets have witnessed a disruptive force: the rise of online intermediaries and, more generally, fintech companies: firms that apply technology to improve financial activities. Their provision of financial services is different in many ways not only from banks but also from traditional shadow banks. The rise of fintech brings about renewed promise of improving efficiency in the financial services (Philippon, 2016; Berg et al., 2021), as well as fresh concern over shifting systemic risk to less-regulated, more-fragile financial intermediaries (Peydró et al., 2020; Di Maggio and Yao, 2021). This paper investigates important questions about the role of new fintech companies in the transmission of monetary policy, including how do they respond to monetary policy shocks and, more importantly, how does their rising market power affect the responses of other lenders, especially banks, to monetary policy.

We explore these questions using data from the U.S. automobile markets in the post-GFC era. There are several advantages to this choice of data source. First, while the automobile loan market is smaller than the mortgage market, it has been more responsive and robust in the post-GFC recovery. Second, compared to the mortgage market that mainly affects homeowners, auto loans are accessible to more Americans who may not have mortgages but do rely on cars for work and life, thus providing a much broader scope in assessing monetary policy effect. Third and most importantly, the auto market has experienced dramatic

[1] See, for example, Gilchrist and Zakrajšek (2013); Rodnyansky and Darmouni (2017); Chakraborty et al. (2020); Di Maggio et al. (2020); Luck and Zimmermann (2020).

organizational changes in recent years with the rise of fintech lenders (autofi) that leverage advanced technologies to offer people new ways to purchase and finance cars. This offers a unique opportunity to explore how these new lenders differ from existing ones in providing credit to car buyers, as well as how the increased competition affects other lenders' monetary response (e.g., Foohey, 2021).

We exploit several variations in the auto market that may entail different exposure to monetary policy shocks: (1) lenders that rely on different sources of funds, (2) prime and nonprime borrowers who face different availability of funds due to government regulation, and (3) markets with high or low market power of shadow banks. We classify lenders into four categories: banks, captives (e.g., Ford Credit), autofi, and other noncaptives. Our primary outcome variables are changes in interest rates and balances for prime and nonprime auto loans aggregated at the lender quarter or lender county quarter level. We use a panel Local Projection Instrumental Variable (LP-IV) set up, following Jordà et al. (2020), to study the heterogeneous response of individual segments to the rise of the one-year interest rate instrumented with the exogenous monetary policy shocks as identified by the macroeconomics literature.

Our paper is organized in three parts. In the first, we explore the heterogeneous responses across lenders and borrowers to a rise in the interest rate. Using the LP-IV method, we find that most lenders respond to an increase in the policy rate by significantly increasing the rates they charge on auto loans, and their loan originations contract as a result. However, the magnitude of the responses varies across lenders and borrowers. Banks and captives are the most responsive to the rate hike among all lenders. Following a 100 bps increase in the policy rate, banks increase rates on both prime and nonprime loans by 18 and 21.9 bps, respectively, while captives increase their rates on prime and nonprime loans by 26.4 and 22.9 bps, respectively. As a result of the rate increase, banks and captives experience a 5–7% decline in their lending volume. In contrast, traditional noncaptives only increase their rates marginally and in a much smaller magnitude, and the new autofi firms cut their rates instead following a rate hike.

The second part of our analysis explores the effect of market power of shadow banks—noncaptives in our setting—on individual lenders' responses to a rise in interest rate. We interact the instrumented interest rate with county-level market share of noncaptives and compare the monetary responses between counties with the highest and lowest noncaptives' share. We find that all lenders increase their rates by significantly more in markets with the highest noncaptives' share. Following a 100 bps increase in policy rate, banks increase their rates on prime and nonprime loans in markets with the highest noncaptives' share by significantly more at 2.7 and 6.7 bps, respectively, compared to markets with the lowest noncaptives' share. For captives, the differential rate on prime loans between the high- and low-power markets is 10.5 bps and significant at the 1% level, but it is not significant for nonprime loans. Noncaptives increase their rates on prime loans in markets with the highest noncaptives power by significantly more at 40.5 bps, compared to a rate increase that is not statistically different in markets with the lowest noncaptives' power. These results suggest that variation in the market power of noncaptives significantly affects most lenders' responses to the rise in interest rate. Noncaptives were able to pass the rate hike to borrowers to the most extent with their high market power, and their market power also bolsters banks' ability to respond to the increase in policy rate.

We also test the difference in lenders' responses to the monetary policy shocks between counties with high and low market power of autofi. Following an increase in policy rate, banks increase their rates on prime and nonprime loans by 2.5 and 6.0 bps more, respectively, in markets with the highest autofi share than in markets with the lowest autofi share. For captives, the differential rate between regions with the highest and lowest autofi power is 10.8 bps for prime loans but is not significant for nonprime loans. Nonautofi noncaptives also increase their rates on prime and nonprime loans by 2.6 and 6.0 bps more, respectively, in markets with the highest autofi share.

In the third part, we estimate the role of shadow banks' market power in monetary transmission by exploiting the entry of autofi as a quasi-exogenous shock to local market power and using an event study approach. To address the selection concern that the entry of autofi may be a highly endogenous decision, we match the low- to high-share counties using a propensity score matching (PSM) procedure based on county-level variables measuring local auto-market conditions and demographic characteristics prior to the entry, and we use the resulting matched sample in the event study and difference-in-difference (DID) regressions.

We find that following a 100 bps rate rise, banks increase rates on prime and nonprime loans in the treated counties by significantly less before the entry of autofi, relative to those in the control counties and the entry year. Immediately after the entry, they increase rates on prime and nonprime loans in the treated counties by significantly more, resulting in a swing of 37.7 to 41.7 bps from year 1 to year +1, relative to the entry year, in their response to the rate hike. The difference between the treated and control counties continues to increase, reaching by nearly 65 bps more in year 6. Captives adjust their rate on nonprime loans similar to banks, and so do nonautofi noncaptives on prime loans. That is, following a rate hike, they increase the rates on prime loans in the treated counties by significantly more after the entry, resulting in a large swing from years 1 to +1. Put together, the entry of autofi is associated with significant decrease in other lenders' lending businesses, especially in the nonprime segment. Meanwhile, we.

We offer two plausible mechanisms through which the entry of autofi may affect other lenders' responses to the increase in interest rate. First, the entry and rapid expansion of autofi increases the competition against other lenders in the nonprime segment, resulting in significant revenue losses to them. Under the pressure, other lenders are more synced with the interest rate set by the Fed. Second, existing lenders may learn how autofi lenders price their loans. For example, banks have also been learning to adopt the use of big data and machine learning techniques in their underwriting and pricing decisions, as well as to provide new forms of credit to underserved markets.

Related Literature The main contribution of this paper is to shed light on the heterogeneous responses, across lenders, borrowers, and markets, to the monetary policy shocks as well as on the effect of the rising market power of nonbanks, especially the new fintech lenders, on existing lenders' monetary responses. Thus, this paper is related to the extensive literature that examines effects of monetary policies on aggregate outcomes.[2] Recent works have found that the unprecedented quantitative easing strategy significantly increased household consumption through mortgage refinancing and new credit card issuance, and that the effect is attenuated by various market frictions.[3] This paper provides fresh evidence of the effect of monetary policy on the automobile market.

Second, related literature in monetary economics explores how different financial institutions pass through credit. Drechsler et al. (2017) propose the deposits channel, in which following the Fed's monetary tightening, depository institutions increase their deposit spreads by significantly more in areas where they have higher market power, resulting in significant deposit outflows and significant contraction in their lending activities.[4] There is also evidence that nonbanks attenuate the effect of the contractionary monetary policy by attracting more deposits from banks when the Fed raises rates through the so-called "shadow banking channel" (Xiao, 2020).[5] Both channels show that local market concentration is an important source of friction in the monetary transmission.[6] We study the direct role of market power of shadow banks, especially the new fintech lenders, in financial institutions' responses to the monetary policy.

A third group of related literature has to do with the risk-taking channel of monetary policy in which banks reduce their risk-taking in response to a tightening of monetary policy (and other regulations implemented simultaneously) while nonbanks—who do not face as much hard constraint—may choose to increase their credit supply, especially to riskier borrowers, thus

[2]For early literature, see, for example, Romer and Romer (2004); Gürkayanak et al. (2005); Krishnamurthy and Vissing-Jorgensen (2011); Wright (2012).

[3]See, for example, Keys et al. (2016); Di Maggio et al. (2017); Agarwal et al. (2018); Beraja et al. (2019); Eichenbaum et al. (2022); Andersen et al. (2020); Berger et al. (2021); Cloyne et al. (2020); Cravino et al. (2020); Di Maggio et al. (2020); Agarwal et al. (2022).

[4]There are also differences between insured and uninsured depositors, which intertwine with banks' financial distress in passing through the credit (Egan et al., 2017).

[5]Jiang (2020) also shows that shadow banks respond to monetary policy by indirectly accessing banks' deposits through warehouse loans or the wholesale channel, ending up offsetting banks' response to the monetary policies.

[6]There is also evidence that market concentration can influence the effect of monetary policies through other channels (e.g., Brissimis et al., 2014; Scharfstein and Sunderam, 2016; Wang et al., 2020; Enkhbold, 2021).

neutralizing the expected decline of bank loans and hampering the effectiveness of monetary policy. Two recent papers by Chen et al. (2018) and Peydró et al. (2020) provide evidence on this risk-taking channel using data from China and the U.S., respectively. Our paper is particularly related to Peydró et al. (2020), who examine the effect of monetary policy on nonbanks' lending activities using data from three key credit markets: corporate loans, auto loans, and mortgages. Their finding that higher policy rates shift credit supply from banks to nonbanks highlights the unintended consequences of rate hikes for financial stability.

Our paper differs from Peydró et al. (2020) on a number of dimensions. First, while we also study the differential effect of monetary transmission between banks and nonbanks, our primary scope is to study the effect of local market power—induced by the rise of new fintech lenders—on individual lenders' monetary transmission. Second, the two papers adopt different identification strategies for the impact of monetary policy. Their paper exploits the historical regional dependence on nonbanks in 1999Q1, first adopted by Benmelech et al. (2017), with the idea that nonbanks are more likely to expand in markets where banks historically have a weak presence. Ours exploits the post-GFC-era entry of new autofi lenders into counties, which has significantly increased the local market power of nonbanks in these markets relative to elsewhere. Third, we employ different empirical specifications. They estimate the loan amount on the interaction of monetary policy shocks from Gertler and Karadi (2015) and the historical nonbank share using loan-level data, while we estimate the effect of the policy rate instructed by monetary policy shocks from Swanson (2021) by controlling for individual lender or lender by county fixed effects using the LP-IV method. We can look at nonbanks closely by separating them into captives that respond more like banks, traditional noncaptives, and the new autofi. We find that each nonbank differs in responding to the monetary policy shocks in their own way.

Lastly, our paper also connects to the burgeoning literature on fintech. Many papers in this field explore the design and functioning of a specific fintech area.[7] Some papers examine

[7] Chen et al. (2021) survey economic research on blockchains, for example, Cong and He (2019), Chiu and Koeppl (2019), Cong et al. (2021), and Liu and Tsyvinski (2021), and provide an economic perspective on what blockchains are envisioned to be and why they would be useful.

the fintech entry in various lending markets, including marketplace lending in the unsecured personal loan market[8] and fintech lenders in the mortgage and small business lending markets (e.g., Buchak et al., 2018; Fuster et al., 2019; Gopal and Schnabl, 2022). Unlike any of these papers, we focus on the macro perspective of fintech lending—how the rise of fintech affects the monetary transmission of financial intermediaries.

The remainder of the article is organized as follows. Section 2 describes the data and the sample construction and provides summary statistics. Section 3 presents results on the heterogeneous response across lenders, borrowers, and markets to the monetary policy shocks. In Section 4, we assess the effect of nonbanks' market power in different lenders' monetary policy responses. Section 5 provides the analysis of the role of nonbanks' market power using the event study approach and based on a matched sample. The last section concludes.

2. Data

2.1. Data Sources

The data on auto lending are from one of the nation's largest credit bureaus, which provides information on households' balance sheets as well as the underlying loans, including auto loans, mortgages, student loans, and credit cards. The information includes the main features of these individual loans, such as date opened, loan balance, monthly scheduled payment, and lender. This paper focuses exclusively on auto loans with data readily available from 2010 onward. We calculate the effective rate for most of the loans. We also link these loans to their primary borrowers to obtain their location and credit score at the month of origination.

We use the one-year Treasury rate, $GS1$, as the primary measure of monetary policy, collected from Federal Reserve Economic Data (FRED). Panel A of Figure 1 plots the time series of $GS1$ as well as average note rates on auto loans, separately for prime and nonprime

[8]For example, Iyer et al. (2016), Balyuk (2016), Cornaggia et al. (2017), Balyuk and Davydenko (2018), Danisewicz and Elard (2018), De Roure et al. (2018), Hertzberg et al. (2018), Vallée and Zeng (2019), Balyuk (2019), Havrylchyk et al. (2019), Tang (2019), Berg et al. (2020), and Di Maggio and Yao (2021).

borrowers, from 2010 to 2020. It shows that the note rates on auto loans move up and down following the changes in policy rate, but with some considerable lags. In addition, we collect data on county characteristics from the 2010 U.S. Census and use the county-level median income, population, unemployment rate, percent of people holding bachelor's degrees, and percent of people in poverty while matching counties exposed to the autofi entry and those not.

2.2. Identifying Monetary Policy Shocks

Identifying the dynamic causal effects of monetary policy on consumption requires tackling the potential reverse causality: interest rates respond to the macroeconomic conditions, but also affect them. This is a standard challenge in the empirical macro literature (Nakamura and Steinsson, 2018a) but presents more issues in micro data analysis because monetary policy responses to aggregate economic conditions may be correlated with specific conditions in certain sectors or regions. Thus, we need to identify a component of monetary policy that is plausibly exogenous to future output and can thus be used to directly estimate the effects of policy on auto lending in our setting.

During our sample period, the Fed primarily implemented two unconventional monetary policy tools—FG and LSAP—largely as a result of the ZLB. My identification strategy uses discontinuity-based methods that identify the immediate causal effect of FOMC announcements on financial markets using the high-frequency (30-minute) financial data used by Nakamura and Steinsson (2018b) and Swanson (2021). The plausible identifying assumption is that nothing else occurs within this time window which could drive both private sector behavior and monetary policy decisions. Nakamura and Steinsson (2018b) use the method to investigate a "Fed information effect" of FG, while Swanson (2021) focuses on comparing the FG and LSAP effects during the ZLB period. Because we believe that LSAP has a direct impact on auto lending during our sample period by directly providing liquidity to lenders who originate auto loans, we use the monetary policy shocks from Swanson (2021) that estimate separate factors for FFR, FG, and LSAP instruments.

[Insert Figure 1 Here.]

As is common in the macro literature, we sum our monetary policy shocks to quarterly frequency. Panel B of Figure 1 plots the three monetary policy shock series updated through June 2019, with the LSAP factor being multiplied by -1 to have the same sign as the other two series. It shows that during the ZLB period from December 2008 through December 2015, the LSAP factor was the dominant monetary policy tool with large swings when the Fed implemented rounds of LSAP. Beginning in December 2014, as markets expected the FOMC to signal a hike in the FFR but were surprised when additional caution was signaled instead, FG was more frequently used. This continued through the end of our sample period. Using these factors, Swanson (2021) finds that FG was more effective than LSAPs at moving short-term Treasury yields, while LSAPs were more effective than forward guidance and the federal funds rate at moving longer-term Treasury and corporate bond yields. Since auto lenders may fund their loan originations using both short-term and long-term funding sources, we expect all three factors to affect the auto-lending market.

2.3. Sources of Variation

To identify different responses to the monetary policy shocks, we exploit three sources of variations in the automobile market.

Different Lenders The first source of variation is in lenders that have different sensitivity to changes in interest rates due to their funding structures and portfolio compositions. The Fed's conventional and unconventional monetary policy tools affect depository institutions' lending activities through the deposits and other channels. In addition, monetary policy also affects the shadow banking system when monetary tightening drives deposits from the banking sector to money market funds (MMF), resulting in an expansionary effect on the assets and lending of downstream shadow banks funded by MMF. In the automobile market, depository institutions include both commercial banks and credit unions; downstream shadow banks include both captives (e.g., Ford Credit) that are a subsidiary of the manufacturer parent and noncaptives (e.g., State Farm) that are not integrated with the car manufacturer.

Following the financial crisis, a new form of noncaptives—autofi—emerged and have become an increasingly important supplier of auto credit, especially to many that have been shut out of the credit market by traditional lenders. While auto lenders have traditionally adopted technologies in delivering their financial services, and fintech refers to many technological innovations (e.g., peer to peer, clouding, AI, machine learning, etc.), autofi lenders display at least two distinct features enabled by the advanced technologies. First, they are online marketplaces that trade mostly used cars, allowing users to buy or sell cars online or via mobile apps. Second, they offer direct lending as opposed to the indirect lending model of traditional dealerships. For example, both Carvana and CarMax offer a vertically integrated dealer-lender model by using their own proprietary technologies (e.g., Deal Score Band) aimed to provide better customer experience and stronger loan economics.

[Insert Figure 2 Here.]

Figure 2 plots the number of auto loans originated by four lender types over time based on the credit report data. Unlike the mortgage market, the U.S. automobile credit market quickly recovered from the downturn during the financial crisis. The figure exhibits two important changes in the automobile credit market. First, while a few autofi lenders such as CarMax were in service even before the financial crisis, their share was negligible until around 2014 when many fintech companies emerged in different credit markets. The rise of autofi was driven by the entry of new autofi lenders such as Carvana, as well as expansion of some existing lenders into more markets and more borrowers. Second, from 2016 onward, the total number of loans originated by banks stagnated or even declined through the end of our sample. This could be driven by the increased competition from new lenders and the end of ZLB around the same time.

Borrower Segments The second source of variation is across borrowers who face different availability of funds due to changes in government regulation. For example, higher capital-ratio or ability-to-pay requirements in the Dodd-Frank Act or the Basel Accord resulted in tighter underwriting standards and higher costs of financial services, especially among banks. Many borrowers have been shut out of the credit market due to lower or no credit score. We define nonprime borrowers as those with a credit score below 660, a threshold used by many lenders in eligibility decisions, and prime borrowers as those with a credit score at or above 660. Johnson et al. (2022) finds that fintech pricing is primarily segmented by whether the borrower's credit score is above or below 660 and that other risk factors explain very little variation in the interest rates. Nevertheless, we use nonprime and prime borrowers to separate borrower segments in that we believe that they may respond to the change in the policy interest rates differently due to their access to the credit market.

Local Markets The third source of variation is across regions that have different market concentration and structure. The literature of monetary transmission has documented that the effect of monetary policy depends on market concentration. For example, Drechsler et al. (2017) show that bank branches located in more concentrated markets raise their deposit spread by more and experience greater outflows, and their lending contracts more. Similarly, an increase in banking concentration can increase the effect of monetary policy in the shadow banking channel (Xiao, 2020). We focus on the effect of dynamic change in the market competition of a local market—induced by the entry of autofi—on the existing lenders' response to monetary policy. While the timing and location choice of the autofi entry may be highly endogenous, we carefully match the treated and control counties based on the conditions in the automobile market as well as local social-economic characteristics prior to the entry, and we compare the evolution of their respective auto-lending outcomes before and after the entry year in response to the monetary policy shocks.

2.4. Descriptive Statistics

Table 1 presents summary statistics for the three samples used in the analysis.[9] Panel A summarizes all the variables in the lender quarter sample, split by lender type. We observe several patterns in the loan rates. First, there is a great variation in the note rate of loans across lenders, with the rates charged by banks and captives being much lower than those charged by noncaptives. The average rate on banks loans is 4.96%, compared to 4.13% for those by captives, 12.33% for those by nonautofi and 19.75% for those by autofi, respectively. Second, banks and captives both charge higher rates on nonprime loans than their prime loans, by 2.58% on average. In contrast, the interest rate spread between prime and nonprime loans is much smaller among loans originated by noncaptives, at 1.24% for those originated by nonautofi and 0.58% for those by autofi. Third, loans originated by autofi not only are the most costly among all lender-by-borrower segments, but they also have narrow dispersion, measured by standard deviation as a ratio of the mean, suggesting that these loans are universally expensive.

[Insert Table 1 Here.]

During our sample period, auto-loan rates decline for most loans, primarily due to the expansionary monetary policies the Fed has taken. The average $\Delta Rate$ is -0.076% for bank loans, -0.041% for captive loans, and -0.014% for nonautofi noncaptive loans. The only exception is autofi loans, whose rates increase by 0.052% on average. Between nonprime and prime loans, the decline is greater for nonprime loans for originations by banks, while smaller for loans originated by captives and nonautofi. The average one-year policy rate in our sample is around 0.6% for most loans, but slightly higher for autofi loans, reflecting relatively recent presence of the lenders, especially after the end of ZLB policy. Otherwise, policy rates are similar across lender and borrower segments.

[9] While the automobile loan variables, calculated from loan-level data, are available through 2021, the monetary policy shock series are updated only through June 2019. Thus, samples used in the regression analysis contain loans originated in 2010 through June 2019. We plot all the time series figures through 2020.

Looking at the total origination balance at the lender-by-time level, captives have the largest size among all—primarily due to their number of loans originated being the largest as well—followed by banks and then noncaptives. The prime and nonprime loans split is 2.7/1 for banks, 2.4/1 for captives, 1.4/1 for nonautofi, and 0.45/1 for autofi, respectively. This highlights different loan composition across lenders—that is, the new autofi lenders specialize in lending to nonprime, especially deep subprime, borrowers, while both banks and captives mostly service prime borrowers, and nonautofi noncaptives lie somewhere in the middle.

Figure A.1 in the Appendix plots the year-over-year growth rates of the aggregated number of auto loans from our sample against a similar national statistic—personal consumption expenditure (PCE) on motor vehicles and parts from the National Income and Product Accounts (NIPA). In essence, auto loans are used to finance car purchases, while the PCE number includes spending on both buying and maintaining cars. Nevertheless, the two series track each other very closely, bolstering our confidence in the micro loan data.

3. Heterogeneous Responses of Auto Lending to an Increase in Policy Rate

This section presents our baseline analysis of responses in the different auto-loan market segments to an increase in policy rate.

3.1. Specification for Aggregate Responses

Before starting the micro data analysis, we first check whether monetary policy has an effect on durable consumption measured by PCE on motor vehicles and parts from NIPA. We uncover the impulse response functions (IRFs) for aggregate outcomes in the automobile markets (e.g., spending or loans originations) as well as in the large economy (e.g., employment, production, and consumption) using the following sequence of local projections for any horizon h:

$$\Delta y_{t+h} = \alpha^h + \beta^h \widehat{R_t} + \sum_{l=1}^{L} \zeta_l \Delta y_{t-l} + v_{t+h}, \tag{1}$$

wherein $\Delta y_{t+h} = y_{t+h} - y_{t-1}$ is the change in aggregate outcomes (e.g., PCE) from $t-1$ to $t+h$, and R_t is the end-of-quarter one-year policy rate. The nominal rate R_t is instrumented using our extracted series of monetary policy shocks. We control for four lags. The coefficient β^h refers to the IRF at period h. Standard errors are adjusted using the Newey-West method.

Figure A.2 in the Appendix shows that an initial 25 bps rise in the policy rate leads to a fall in PCE on motor vehicles and parts of around 0.5–0.7% after one year. The response is very persistent at least through 4 years after the initial shock. We also report the results for employment, industrial production, and total PCE to show that our results are qualitatively and quantitatively consistent with those in the literature (e.g., Gertler and Karadi, 2015; Cloyne et al., 2018). Compared to the total PCE, PCE on motor vehicles and parts is more responsive to the rate hike.

3.2. Panel Regression Specification

Panel data allows us to control for individual fixed effects and capture the heterogeneous effects of monetary policy on different individuals. To estimate the dynamic causal effects from the micro panel data, we use a panel Local Projection Instrumental Variable (LP-IV) set up, following Jordà et al. (2020). In our baseline empirical specification, we estimate IRFs for individual groups using the following LP-IV approach:

$$\Delta Y_{i,t+h} = \alpha_i^h + \sum_{c=1}^{C} \beta_c^h \left(\mathbb{1}\{i \in c\} \times \widehat{R_t}\right) + \sum_{c=1}^{C} \gamma_c^h \, \mathbb{1}\{i \in c\} + \sum_{l=1}^{L} \zeta_l \left(\Delta Y_{i,t-l}\right) + \epsilon_{i,t+h}, \tag{2}$$

wherein $\Delta Y_{i,t+h} = Y_{i,t+h} - Y_{t-1}$ is the change in auto-lending outcomes (average rates and total originations) by lender i from $t-1$ to $t+h$, and the indicator $\mathbb{1}\{i \in c\}$ takes a value of 1 if lender i falls in a particular group c (e.g., banks, captives, and noncaptives). We can further define i and c as finer groups, for example, lender different borrower segments (e.g., prime vs. nonprime) or lender different regions (e.g., high vs. low share of noncaptives). In essence, this provides a flexible semiparametric way of estimating the heterogeneous effects, β_c^h, of monetary policy by different lenders, regions, or households. We do not include other time or group-time fixed effects, as we want to interpret these coefficients as group-specific impulse response functions, including any general equilibrium effects. However, we also include individual fixed effects α_i^h and $\mathbf{1}\{i \in c\}$ to absorb any cross-sectional difference and exploit within-lender or within-cohort variation, as well as quarterly dummies to control for seasonal factors. The end-of-quarter one-year policy rate R_t is instrumented by the three monetary policy shocks. Standard errors are clustered by cohort and time to deal with possible serial correlation in the forecast errors $\epsilon_{i,t+h}$, a standard feature of the local projects technique. We set the number of lags to 4 and estimate IRFs over a forecast horizon of 10 quarters.

3.3. The Average Response

We first compare the IRFs for all individuals in our sample with the dynamics of IRFs based on aggregate national accounts data and to provide a benchmark for the heterogeneous responses of individual groups. To estimate the average effect, we drop the group dummies from Equation (2) and replace the group-specific coefficients on the interest rate β_c^h with a single parameter β^h for the full sample and for each horizon h. We interpret β^h as the average effect of change in interest rates on auto-lending outcomes at horizon h.

Column (1) of Table 2 reports the effect of monetary policy shocks on $\Delta Rate_{i,t}$—the change in interest rates on auto loans at horizon 1. The average rates on auto loans increase significantly by 17.1 (4.3) bps following a 100 (25) bps rise in the policy rate. Column (6) of Table 2 reports the effect of monetary policy shocks on $\Delta Volume_{i,t}$—the logarithm change in the number of auto loans at horizon 1. Total auto-loan volume decreases significantly by 4.096% (1.024%) following a 100 (25) bps rise in the policy rate.

[Insert Table 2 Here.]

3.4. Heterogeneous Responses Across Lenders and Borrowers

In this section, we present the analysis of heterogeneous responses across lenders and borrowers.

Table 2 also reports the results based on subsamples delineated by lender types, in which the first five columns use $\Delta Rate_{i;t}$ as the dependent variable and the next five columns use $\Delta Volume_{i;t}$ as the dependent variable. Columns (2)–(5) show that following a 100 bps rate increase, banks and captives respond the most in the first period by increasing their auto-loan rates by 20.2 and 25.6 bps, respectively.[10] Noncaptives are much less responsive, with nonautofi noncaptives increasing their rates by only 9.9 bps and autofi lenders decreasing their rates by 21.8 bps (significant at the 10% level). The opposite sign for autofi is expected, since these new lenders often race to expand their market share once they open their business.

Columns (7)–(10) show that the negative response of auto-loan volume in Column (6) is primarily driven by banks that see their originations decrease significantly (at the 1% level) by 5.189% following a 100 bps rate hike. Captives also experience a similar magnitude decrease in their originations, but only significant at the 10% level. In contrast, the auto originations by both types of noncaptives do not change significantly.

Lenders may respond to the increase in interest rate differently depending on the borrowers' risk levels. On the one hand, prime borrowers are more creditworthy than nonprimes, and adjustments in lending to primes may result in less concern over possible future losses. On the other hand, nonprime borrowers tend to be more liquidity constrained with fewer options and thus are less sensitive to changes in rate and financial terms than are primes. We test this conjecture by regressing the average rates and number of originations for prime and nonprime borrowers separately on the policy rate instrumented with the monetary policy shocks. Results are reported in Table 3.

[Insert Table 3 Here.]

[10] The magnitude of the estimate for banks is smaller than the estimates of banks' response in deposit spread following a 100 bps increase in the FFR in Drechsler et al. (2017), which range from 63 to 75 bps depending on the market concentration.

Panel A presents the analysis of $\Delta Rate_{i;t}$. It shows that banks increase the rates charged on both prime and nonprime loans by 18 and 21.9 bps, respectively, following a 100 bps increase in the policy rate, suggesting the rate hike is passed on slightly more to nonprime borrowers than to prime ones. Captives also respond to the rate hike positively by increasing their rates on prime and nonprime loans by 26.4 and 22.9 bps, respectively. In contrast, nonautofi noncaptives only change their rates on prime loans marginally by 11.6 bps; their rates on nonprime loans do not change significantly. Autofi lenders do not change their rates on prime loans significantly but decrease rates on nonprime loans instead.

Panel B presents the analysis of $\Delta Volume_{i;t}$. Consistent with the rate results above, it shows that banks and captives see their originations of both prime and nonprime loans decline significantly following a 100 bps rate increase. Contraction in prime loan volume is similar for both banks and captives, by nearly 6%; contraction in nonprime loan volume is more for captives than for banks, by 7.1% and 5.6%, respectively (significant at the 10% level or lower).

[Insert Figure 3 Here.]

Figure 3 plots IRFs of $\Delta Rate_{i;t}$ (in Panel A) and $\Delta Volume_{i;t}$ (in Panel B) by lender and borrower types following a 25 bps rate hike. Panel A shows that the increase in interest rates on auto loans is more persistent for banks than for captives, and among all loans originated by banks, is more for nonprimes than for primes. Panel B shows that the decrease in auto-loan originations is only persistent for prime loans originated by banks; the decrease in nonprime originations originated by banks recovers after two years; the decreases in both prime and nonprime originations originated by captives last only two quarters before they recover to the pre-shock level.

3.5. Summary

Taking stock of the above results, we find that most lenders respond to an increase in policy rate by increasing the rates they charge on auto loans, and their loan originations drop as a result. However, banks and captives are the most responsive to the rate hike among all lenders and experience more decline in their lending volume. In contrast, traditional noncaptives only increase their rates marginally and with a much smaller magnitude; the new autofi lenders cut their rates instead following a rate hike. Furthermore, banks increase rates more on nonprime loans than on prime loans, while captives pass through the rate hike more on prime loans.[11]

4. Role of Nonbanks' Local Market Power

In this section, we consider the interaction of different lenders—mainly between nonbanks and banks—in individual lenders' responses to the change in monetary policy shocks. In a recent paper, Peydró et al. (2020) find that higher monetary policy rates shift credit supply from banks to less-regulated, more-fragile nonbanks, largely neutralizing the associated consumption effects via consumer loans. We focus on if and how the increased market power of nonbanks—noncaptives in our setting—affect (other) lenders' responses to monetary policy shocks. This question is also related to the market power mechanism documented in the literature. In our setting, the market competition is identified in lending opportunities (asset side) that allow lenders—including both banks and nonbanks—to grow revenue and extract profits, instead of in funding side (e.g., deposits). This is a little complicated since, for example, Jiang (2020) finds that shadow banks may compete with banks in the downstream mortgage origination market while accessing banks' deposits through the wholesale channel. Thus, we measure the market power and concentration using the county-level market share of noncaptives instead of the Herfindahl-Hirschman Index (HHI).

[11] To explore if there is any asymmetry between the effects of increasing (contractionary) or decreasing (expansionary) monetary policies on auto loans, we repeat the regressions in Table 3 based on split subsamples: 2010-2015 and 2016-2019. Results, reported in Table A.1 in the Appendix, suggest that all lenders but autofi (and prime loans originated by captives) are more responsive to the monetary policy shocks in the decreasing rate environment than in the increasing rate environment. Moreover, while lenders adjust the rates charged on prime loans in both increasing and decreasing rate environments, they only adjust the rates charged on nonprime loans during the increasing rate environment.

4.1. Market Power of Noncaptives

To test the role of noncaptives' market power in affecting lenders' responses to a rise in interest rate, we expand the lender quarter sample to the lender county quarter level, and interact the lender-type indicators $\mathbb{1}\{i \in c\}$ in Equation (2) with quartile dummies of the noncaptives' share as follows:

$$\Delta Y_{i,t+h} = \alpha_i^h + \sum_{c=1,q=1}^{C,4} \beta_{c,q}^h \, \mathbb{1}\{i \in c\} \, \mathbb{1}\{Noncapt_q\} \, \widehat{R_t} + \sum_{c=1}^{C} \gamma_c^h \, \mathbb{1}\{i \in c\} + \sum_{l=1}^{L} \zeta_l \, \Delta Y_{i,t-l} + \epsilon_{i,t+h}, \tag{3}$$

where i denotes a pair of lender and county. $\mathbb{1}\{Noncapt_q\}$ $(q = 1, 2, 3, 4)$ are four dummy variables defined based on the market share of noncaptives in a county averaged over the sample period: $\mathbb{1}\{Noncapt_4\}$ refers to the counties wherein noncaptives account for the highest market share and thus have high market power, compared to $\mathbb{1}\{Noncapt_1\}$, which refers to the counties in which noncaptives have low market power. The difference between $\beta_{c,4}^h$ and $\beta_{c,1}^h$ captures the effect of the market power of noncaptives on other lenders' responses to the monetary policy shocks.

Table 4 presents the analysis. Panel A reports the results using $\Delta Rate_{i,t}$ as the dependent variable. Column (1) shows that banks increase their rates on prime loans by significantly more in markets where noncaptives have high market power. Following a 100 bps increase in policy rate, banks increase their rates on prime loans by 19.3 bps in markets with the highest noncaptives' share, compared to 16.6 bps in markets with the lowest noncaptives' share, a difference of 2.7 bps (significant at the 1% level). Column (2) shows that captives increase their rates on prime loans significantly by 46.9 bps in markets with the highest noncaptives' share, up from 36.4 bps in markets with the lowest noncaptives' share, a difference of 10.5 bps, significant at the 1% level. Column (3) shows that nonautofi noncaptives increase their rates on prime loans significantly (at the 1% level) by 35.5 bps in markets with the highest noncaptives' share, compared to a rate increase that is only marginally significant in markets with the lowest noncaptives' share. Similarly, Column (4) shows that autofis increase their rates on prime loans significantly (at the 1% level) by 48.9 bps in markets with the highest noncaptives' share, compared to a rate increase that is not significant in markets with the lowest noncaptives' share. These results suggest that all lenders respond more to the rate hike by increasing their rates on primes loans the most in markets with the highest noncaptives' share.

[Insert Table 4 Here.]

Columns (5)–(8) show that banks and autofis increase their rates on nonprime loans by significantly more in markets with the highest noncaptives' share compared to those with the lowest noncaptives' share. Following a 100 bps increase in policy rate, banks increase their rates on nonprime loans significantly by 25.5 bps in markets with the highest noncaptives' share, compared to 18.8 bps in markets with the lowest noncaptives' share, a difference of 6.7 bps (significant at the 1% level). Meanwhile, autofis increase their rates on nonprime loans significantly by 32.6 bps in markets with the highest noncaptives' share, compared to no significant change in their rates on nonprime loans in markets with the lowest noncaptives' share. In contrast, captives and other noncaptives do not increase their rates on nonprime loans differently across markets with high and low noncaptives' share.

Panel B reports the results of $\Delta Volume_{i;t}$. Columns (1) and (5) show that banks see their prime and nonprime loan originations decline significantly across all markets, regardless of the market share of noncaptives. Column (5) further shows that banks lose more nonprime business in places where noncaptives have higher market share. Following a 100 bps increase in policy rate, banks' nonprime originations decrease significantly by 6.6% in markets with the highest noncaptives' share, compared to only 2.6% in markets with the lowest noncaptives' share. The difference is almost threefold at 4.0 pp and significant at the 1% level, suggesting that a higher market share of noncaptives significantly erodes banks' nonprime auto business in these markets. Columns (2) and (6) show that captives experience significant decline in their lending volume to either prime or nonprime borrowers in markets that the noncaptives' share is high, compared to no significant change in markets with the lowest noncaptives' share.

Columns (3) and (7) show that nonautofi noncaptives see significant contraction in prime loan originations across all markets, with the most contraction in markets with lower noncaptives' share; they only experience significant decrease of their nonprime originations in markets with higher noncaptives' share while seeing no significant change in markets with the lowest noncaptives' share. The different patterns are likely due to noncaptives mainly competing against captives in the prime loan market and against new autofi lenders in the nonprime market. Columns (4) and (8) show that autofi's originations have a significant decrease in prime loan originations in most of the markets, but not nonprime loans.

The above patterns in the changes in loan rates suggest that variation in the market power of noncaptives affects several lenders' responses to the rise in interest rate. Among all lenders and borrower segments, following a rate hike, autofis are affected the most by increasing their rates on prime and nonprime loans by the largest spread in markets with the highest noncaptives' share, followed by prime loans originated by other noncaptives, prime loans originated by captives, then nonprime loans by banks, and lastly, prime loans by banks. Noncaptives were able to pass the rate hike to borrowers to the most extent with their high market power. Meanwhile, noncaptives' market power also bolsters banks' ability to respond to the increase in policy rate.

Results on the change in volume highlight the competition and substitution between bank and nonbank loans. Banks suffer the steepest decline in their nonprime auto-loan businesses in markets where noncaptives have the highest market share. Captives and noncaptives are also affected, seeing significant decline in their lending volume to both prime and nonprime borrowers only in places where the noncaptives' market share is above the median.

4.2. Market Power of Autofi

In this subsection, we focus on the market power of autofi—the automobile industry's fintech model and the most high-profile type of shadow bank. We run similar regressions as in Equation (3), but replacing indicator variables $\mathbf{1}\{Noncapt_q\}$ with three dummies variables $\mathbf{1}\{Autofi_q\}$ (q = Low, Med, High) defined based on the market share of autofi. This provides a benchmark on the effect of cross-sectional differences in autofi penetration on the auto-lending responses before we switch to exploiting within-market changes.

Table 5 presents the analysis. We exclude autofi loans from the analysis in order to focus on the effect of autofi's market power on other lenders. Panel A reports the results of $\Delta Rate_{i,t}$. Consistent with Table 4, we find that banks increase their rates on prime loans by more in response to a rate hike where autofi accounts for a much higher market share. Following a 100 bps increase in policy rate, banks increase the rates on prime loans in markets with a high share of autofi by 2.5 bps more (= 18.3   15.8, significant at the 1% level) than in markets with a low autofi share. Captives and nonautofi noncaptives have similar responses. Following a 100 bps increase in policy rate, captives increase the rates on prime loans in markets with a high share of autofi by 10.8 bps more (= 51.6   40.8, significant at the 1% level) than in markets with a low autofi share; nonautofi noncaptives increase the rates on prime loans in markets with a high share of autofi by 2.9 bps more (= 29.7   26.8, significant at the 1% level) than in markets with a low autofi share. Thus, autofi's market power affects all other lenders' responses in prime lending rates to the rise of interest rate.

[Insert Table 5 Here.]

Columns (4)–(6) show similar relationship between the sensitivity of the interest rates on nonprime loans and market share of autofi. Following an increase in policy rate, banks increase their rates on nonprime loans in markets with a high autofi share by 6.0 bps more (= 25.4   19.4, significant at the 1% level) than in markets with a low autofi share; nonautofi noncaptives increase their rates on nonprime loans in markets with a high autofi share by 6.0

bps more (= 26.2 20.2, significant at the 1% level) than in markets with a low autofi share; in contrast, there is no significant difference in captives' rates on nonprime loans between markets with high and low autofi shares.

Panel B reports the results of $\Delta Volume_{i;t}$. Column (1) shows no significant difference in the changes in prime loan originations by banks between markets with a high or low autofi share. In contrast, Column (4) shows that banks see their nonprime loan volume in markets with a high share of autofi drop by 3 pp more (= 7.1 4.1, significant at the 1% level). Similarly, captives experience decline in their prime originations in markets with a high autofi share by 2.4 pp more (= 2.4 0.01, significant at the 1% level) than in markets with a low autofi share. Nonautofi noncaptives captives experience more decline in their nonprime originations by 1.9 pp (= 7.426 5.488, significant at the 1% level) in markets with a high autofi share than in markets with a low autofi share. However, Column (3) shows that nonautofi noncaptives experience 1.9 pp more decline in their prime originations in markets with a high autofi share (= 6.335 4.358, significant at the 1% level) than in markets with a low autofi share.

4.3. Discussion

Introducing the interaction between lenders in a local market, we find that the local market power of noncaptives, and to a lesser degree that of autofis, significantly affects lenders' responses to a rise in interest rate. In markets where noncaptives have the highest market power, noncaptives as a whole are also most responsive to the rate hike by increasing the rates they charge on auto loans significantly more compared to other lenders as well as to their own loans in other markets. This finding is different from what Drechsler et al. (2017) find in the bank deposits channel of monetary policy: banks widen the deposit spreads by more in more concentrated markets. One key difference is that market power is based on the supply of deposits across bank branches in their setting, but on market share of nonbanks' lending in ours.

Furthermore, we find that higher market power of noncaptives significantly increases banks' response to the rate hike and results in even more losses of their lending businesses due to competition from noncaptives. This competition channel helps bolster the effect of monetary policy.

5. Event Study Analysis of Autofi Entry

This section continues to explore the role of shadow banks' market power in monetary transmission by exploiting a quasi-exogenous shock to local market power—the entry of autofi—and adopting the event study approach.

5.1. Matched Sample

One of the challenges in adopting the event study or DID approach is that the entry of autofi into a particular local market is a highly endogenous decision, largely determined by the existing market competition, availability of targeted borrowers, and local regulations (Foohey, 2021). Panel A of Figure 4 demonstrates the issue by plotting the market share of autofi lenders in three markets: high, medium, and low autofi-share markets as used in Section 4.2. It shows that while the high-share market experienced the fastest entry and expansion of autofi lending following 2014, their initial share is also higher than the other markets.

To address the selection concern, we match the low- to high-share counties while leaving the medium-share counties out, using a propensity score matching (PSM) procedure. The matching score is estimated following a logit regression in which the dependent variable is an indicator variable that equals 1 for the high-share counties and 0 for the low-share counties, and independent variables include measurements of local auto-market conditions—e.g., HHI, the logarithm of average quarterly number of auto loans, market shares of noncaptives and autofi in 2010—as well as local demographic characteristics including the logarithms of median income and population, unemployment rate, percent of people with a bachelor's degree, and percent of people in poverty from the 2010 Decennial Census. The logit regression results are reported in Table A.2 in the Appendix, where Column (3) with the full specification is used to produce the final matched sample.

[Insert Figure 4 Here.]

Panel B of Figure 4 plots the autofi share based on only the matched counties. It shows that the two sets of counties appear to have very similar autofi market share, both below 1%, before 2014, but they increasingly diverge over time. By 2019, the average autofi market share for the high-share (treated) counties rose rapidly to 10% with some counties having a share as high as 15%, while that for the low-share (control) counties was 3%, 7 pp apart between the two groups. Following Figure 4, we adopt 2014 as the entry year of autofi.

5.2. Specification

Consider a lender l that lends in multiple markets denoted as c in time t, including treated and control counties. Our DID analysis examines how the existing lenders' lending rates and volumes evolve over time in the treated counties relative to control counties within the same lender. The estimating equation is thus

$$\Delta Y_{l,c,t} = \sum_{\tau=-2}^{+6} \beta_{\tau} \mathbf{1}\{c \in Treated\} \mathbf{1}\{t \in \tau\} \widehat{R_t} + \mu_l + \mu_c + \mu_t + \epsilon_{l,c,t}, \tag{4}$$

wherein $\mathbf{1}\{c \in Treated\}$ is an indicator variable that equals 1 if the auto loans were originated in the treated counties that experienced autofi entry, and 0 for loans in the control counties; μ_l, μ_c, and μ_t represent lender, county, and time fixed effects, respectively; $\widehat{R_t}$ is defined the same as in Equation (2). The sequence of coefficients, β_{τ}, measures the relative difference in lending outcomes over time for auto loans originated in the treated counties compared to those in control counties within the same lender.

5.3. Responses Following Autofi Entry

In Table 6, we present our event study analysis following Equation (4). Panel A reports the $\Delta Rate$ results. Columns (1) and (4) show a consistent pattern for bank loans: following a 100 bps rate rise, compared to the control counties and relative to the entry year, banks increase the rates on prime and nonprime loans originated in the treated countries by 21.6–47.3 bps less (significant at the 1% level) before the entry year; immediately after the entry, they increase the rates in the treated counties by significantly more with a swing of 37.7 (= 12.9   24.8) to 41.7 (= 20.0   21.7) bps from year   1 to year +1; banks' rate responses for loans in the treated counties continue to increase relative to those in the control counties and reach the peak in year 5 by nearly 65 bps more. The estimates suggest that banks become more responsive to the rate increase in the treated counties following the autofi entry.

[Insert Table 6 Here.]

Columns (2) and (5) show a similar but less clean pattern for captives. Following the rate hike, captives increase the rates on prime and nonprime loans in the treated counties by marginally more in years before the autofi entry relative to those in the control counties; the difference in rate increases between the treated and control counties becomes more significant and positive, and grows in magnitude over time after the entry. The estimates suggest that captives' responses to the rate hike for loans in the treated counties increase by significantly more at 16.4–65.3 bps per 100 bps rate increase following the autofi entry, relative to those in the control counties.

Columns (3) and (6) show that nonautofi noncaptives adjust their rate on prime loans similar to banks. That is, following a rate hike, they increase the rate on prime loans in the treated counties by significantly less relative to those in the control counties before the entry; the difference in rate increases between the treated and control counties become significantly positive after the entry and grows in magnitude over time. Estimates in Column (3) suggest that there is an immediate and large swing in the differential rate increase between the treated and control counties of 122.6 (= 39.5   83.1) bps from years 1 to +1; the difference in rate increases ranges from 35.6 to 59.7 bps per 100 bps rate increase following the autofi entry. Column (6) shows that the differences in rate increases on nonprime loans between the treated and control counties are of a much smaller magnitude, but significant and positive.

Panel B reports the volume results. It shows that all three lenders experience significantly more decrease in their lending volume in the treated counties following the entry of autofi, compared to that in the control counties. The within-lender-county differences between the treated and control counties are much more pronounced for nonprime loans. Banks see an immediate relative decrease in the treated counties after the entry, while others see the relative decline in year +3, and the decline stays elevated afterwards. In year +3, nonprime loan originations decline by 12.4%–18.6% more in the treated counties relative to those in the control counties. Relative differences in the changes of prime originations are not very consistent following the autofi entry.

Put together, the entry of autofi is associated with significant decrease in other lenders' lending businesses, especially in the nonprime segment. Meanwhile, all three nonautofi lenders have become more responsive to the change in policy rate.

5.4. Plausible Mechanisms

In this section, we explore several plausible mechanisms through which the entry of autofi may affect the responses of existing lenders to the increase in interest rate. The first is about what loans autofi lenders concentrate on providing. Panel A of Figure 5 plots the share of autofi among prime and nonprime loans, respectively, in the treated counties. It shows that both shares were below 1.0% before the entry year 2014, but diverged afterwards. The autofi share of nonprime loans grew to above 20% by 2019, in stark contrast to the stagnated autofi share of prime loans over time. This suggests that autofi lenders primarily focus on the nonprime market. Panel B plots the county-level average number of auto loans originated by all other lenders including banks, captives, and nonautofi noncaptives. Consistent with patterns in

Panel A, it shows that nonautofi lenders—including banks, captives, and other noncaptives—experience decline not only in their market share of nonprime loans, but also in absolute terms. In contrast, their prime originations grew steadily throughout the sample period. Combining the two panels, we find that the entry and rapid expansion of autofi increases the competition against other lenders in the nonprime segment, resulting in revenue losses to them.

[Insert Figure 5 Here.]

The second mechanism is learning that has to do with how autofi lenders price their loans, which may be different from traditional lenders. Panel C plots the average rates on auto loans originated by autofi and other lenders, respectively. It shows that the average rates charged by autofi were much higher than those by other lenders, even before autofi's rapid entry and expansion in 2014. Their average rates are at 13% for nonprime loans and 10% for prime loans before 2014, compared to 7% and 4% for prime and nonprime loans by other lenders. After 2014, the average rates charged by autofi increased to nearly 20% for nonprime loans and 15% for prime loans, while those charged by other lenders were stable over time. The increase in interest rates by autofi is enabled by a number of unique features in autofi offering. First, fintech lenders are generally known for the use of big data and machine learning techniques, which allow lenders to estimate applicants' credit risk even based on sparse information;[12] Second, many autofi lenders (e.g., Credit Acceptance Corporation) significantly expanded the applicant pool by offering credit access to deep subprime borrowers that would be turned down by other lenders. Their loans are underwritten and closed online, and as a result, they are able to attract more impatient buyers who do not fully understand the details of the financing terms (Foohey, 2021). There is evidence that banks have also been learning to adopt the use of big data and machine learning techniques in their underwriting and pricing decisions, as well as to provide new forms of credit to underserved markets (e.g., Di Maggio and Yao, 2021; Di Maggio et al., 2022).

[12] Such tools are especially useful for assessing borrowers with thin or no credit history. (Chatterjee et al., 2007; Di Maggio et al., 2022; Athreya et al., 2012, among others).

6. Conclusions

This paper studies the role of new fintech companies in the transmission of monetary policy based on automobile loan data. Using the LP-IV method, we find that following an increase in policy rate, most lenders respond by significantly increasing the rates on auto loans, and their loan originations contract as a result. However, the magnitude of the responses varies across lenders and borrowers, with banks and captives being the most responsive among all lenders. In contrast, traditional noncaptives only increase their rates marginally and with a much smaller magnitude, and the new autofi lenders cut their rates instead as they look to expand their market share in the post-GFC era.

We also find that individual lender's responses to the monetary policy shocks are affected by the market power of shadow banks in the local market. Our results show that all lenders increase their rates by significantly more in markets with the highest noncaptives' share, compared to markets with the lowest noncaptives' share. The estimated responses monotonically increase with the market power. Noncaptives' high market power not only allows them to pass the rate hike to borrowers to the greatest extent, but it also bolsters banks' ability to respond to the monetary policy shocks. Results are similar when we focus on the market power of autofi as the latest form of shadow bank, suggesting that banks, captives, and other noncaptives all increase their rates on prime and nonprime loans by significantly more in markets with the highest autofi share, compared to markets with the lowest autofi share.

We also estimate the role of autofi's rising market power in monetary transmission using an event study approach and based on a matched sample. We find that relative to loans in the control counties and year of autofi entry, all lenders increase their rates in the treated counties by significantly more following the entry. The differential rate increases between the treated and control counties grow in magnitude over time. These results suggest that nonautofi lenders have become significantly more responsive to the change in policy rate following the autofi entry.

References

Agarwal, Sumit, Gene Amromin, Souphala Chomsisengphet, Tim Landvoigt, Tomasz Piskorski, Amit Seru, and Vincent Yao, 2022, Mortgage refinancing, consumer spending, and competition: Evidence from the home affordable refinancing program, *The Review of Economics Studies* Forthcoming.

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel, 2018, Do banks pass through credit expansions to consumers who want to borrow?, *The Quarterly Journal of Economics* 133, 129–190.

Andersen, Steffen, John Y. Campbell, Kasper Nielsen, and Tarun Ramadorai, 2020, Sources of inaction in household finance: Evidence from the Danish mortgage market, *American Economic Review* 110, 3184–3230.

Athreya, Kartik, Xuan S. Tam, and Eric R. Young, 2012, A quantitative theory of information and unsecured credit, *American Economic Journal: Macroeconomics* 4, 153–183.

Balyuk, Tetyana, 2016, An empirical study of related-party lending, SSRN Working Paper 2803750.

Balyuk, Tetyana, 2019, Financial innovation and borrowers: Evidence from peer-to-peer lending, SSRN Working Paper 2802220.

Balyuk, Tetyana, and Sergei A. Davydenko, 2018, Reintermediation in fintech: Evidence from online lending, SSRN Working Paper 3189236.

Benmelech, Efraim, Ralf R Meisenzahl, and Rodney Ramcharan, 2017, The real effects of liquidity during the financial crisis: Evidence from automobiles, *The Quarterly Journal of Economics* 132, 317–365.

Beraja, Martin, Andreas Fuster, Erik Hurst, and Joseph Vavra, 2019, Regional heterogeneity and the refinancing channel of monetary policy, *The Quarterly Journal of Economics* 134, 109–183.

Berg, Tobias, Valentin Burg, Ana Gombović, and Manju Puri, 2020, On the rise of fintechs: Credit scoring using digital footprints, *The Review of Financial Studies* 33, 2845–2897.

Berg, Tobias, Andreas Fuster, and Manju Puri, 2021, Fintech lending, Working Paper 29421, NBER.

Berger, David, Konstantin Milbradt, Fabrice Tourre, and Joseph Vavra, 2021, Mortgage prepayment and path-dependent effects of monetary policy, *American Economic Review* 111, 2829–2878.

Brissimis, Sophocles N, Maria Iosifidi, and Manthos D Delis, 2014, Bank market power and monetary policy transmission, SSRN Working Paper 2858468.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru, 2018, Fintech, regulatory arbitrage, and the rise of shadow banks, *Journal of Financial Economics* 130, 453–483.

Chakraborty, Indraneel, Itay Goldstein, and Andrew MacKinlay, 2020, Monetary stimulus and bank lending, *Journal of Financial Economics* 136, 189–218.

Chatterjee, Satyajit, Dean Corbae, Makoto Nakajima, and José-Víctor Ríos-Rull, 2007, A quantitative theory of unsecured consumer credit with risk of default, *Econometrica* 75, 1525–1589.

Chen, Kaiji, Jue Ren, and Tao Zha, 2018, The nexus of monetary policy and shadow banking in China, *American Economic Review* 108, 3891–3936.

Chen, Long, Lin William Cong, and Yizhou Xiao, 2021, A brief introduction to blockchain economics, in Kashi R Balachandran, ed., *Information for E cient Decision Making: Big Data, Blockchain and Relevance*, 1–40 (World Scientific, Singapore).

Chiu, Jonathan, and Thorsten V. Koeppl, 2019, Blockchain-based settlement for asset trading, *The Review of Financial Studies* 32, 1716–1753.

Cloyne, James, Clodomiro Ferreira, Maren Froemel, and Paolo Surico, 2018, Monetary policy, corporate finance and investment, Working Paper 25366, NBER.

Cloyne, James, Clodomiro Ferreira, and Paolo Surico, 2020, Monetary policy when households have debt: New evidence on the transmission mechanism, *The Review of Economic Studies* 87, 102–129.

Cong, Lin William, and Zhiguo He, 2019, Blockchain disruption and smart contracts, *The Review of Financial Studies* 32, 1754–1797.

Cong, Lin William, Zhiguo He, and Jiasun Li, 2021, Decentralized mining in centralized pools, Working Paper 25592, NBER.

Cornaggia, Jess, Brian Wolfe, and Woongsun Yoo, 2017, Crowding out banks: Credit substitution by peer-to-peer lending, SSRN Working Paper 3000593.

Cravino, Javier, Ting Lan, and Andrei A. Levchenko, 2020, Price stickiness along the income distribution and the effects of monetary policy, *Journal of Monetary Economics* 110, 19–32.

Danisewicz, Piotr, and Ilaf Elard, 2018, The real effects of financial technology: Marketplace lending and personal bankruptcy, SSRN Working Paper 3208908.

De Roure, Calebe, Loriana Pelizzon, and Anjan V. Thakor, 2018, P2P lenders versus banks: Cream skimming or bottom fishing?, SSRN Working Paper 3174632.

Di Maggio, Marco, Amir Kermani, Benjamin Keys, Tomasz Piskorski, Rodney Ramcharan, Amit Seru, and Vincent Yao, 2017, Interest rate policy pass-through: Mortgage rates, household consumption and voluntary deleveraging, *American Economic Review* 107, 3550–3588.

Di Maggio, Marco, Amir Kermani, and Christopher Palmer, 2020, How quantitative easing works: Evidence on the refinancing channel, *The Review of Economic Studies* 87, 1498–1528.

Di Maggio, Marco, Dimuthu Ratnadiwakara, and Don Carmichael, 2022, Invisible primes: Fintech lending with alternative data, Working Paper 29840, NBER.

Di Maggio, Marco, and Vincent Yao, 2021, Fintech borrowers: Lax screening or cream-skimming?, *The Review of Financial Studies* 34, 4565–4618.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2017, The deposits channel of monetary policy, *The Quarterly Journal of Economics* 132, 1819–1876.

Egan, Mark, Ali Hortaçsu, and Gregor Matvos, 2017, Deposit competition and financial fragility: Evidence from the US banking sector, *American Economic Review* 107, 169–216.

Eichenbaum, Martin, Sergio Rebelo, and Arlene Wong, 2022, State-dependent effects of monetary policy: The refinancing channel, *American Economic Review* 112, 721–61.

Enkhbold, Amina, 2021, Monetary policy transmission, bank market power, and wholesale funding reliance.

Foohey, Pamela, 2021, Consumers' declining power in the fintech auto loan market, *Brooklyn Journal of Corporate, Financial & Commercial Law* 15, 5–47.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery, 2019, The role of technology in mortgage lending, *The Review of Financial Studies* 32, 1854–1899.

Gertler, Mark, and Peter Karadi, 2015, Monetary policy surprises, credit costs, and economic activity, *American Economic Journal: Macroeconomics* 7, 44–76.

Gilchrist, Simon, and Egon Zakrajšek, 2013, The impact of the federal reserve's large-scale asset purchase programs on corporate credit risk, *Journal of Money, Credit and Banking* 45, 29–57.

Gopal, Manasa, and Philipp Schnabl, 2022, The rise of finance companies and fintech lenders in small business lending, *The Review of Financial Studies* 35, 4859–4901.

Gürkayanak, Refet, Brian Sack, and Eric T. Swanson, 2005, Do actions speak louder than words? The response of asset prices to monetary policy actions and statements, *International Journal of Central Banking* 1, 55–93.

Havrylchyk, Olena, Carlotta Mariotto, Talal-Ur Rahim, and Marianne Verdier, 2019, The expansion of the peer-to-peer lending, SSRN Working Paper 2841316.

Hertzberg, Andrew, Andres Liberman, and Daniel Paravisini, 2018, Screening on loan terms: Evidence from maturity choice in consumer credit, *The Review of Financial Studies* 31, 3532–3567.

Iyer, Rajkamal, Asim Ijaz Khwaja, Erzo F. P. Luttmer, and Kelly Shue, 2016, Screening peers softly: Inferring the quality of small borrowers, *Management Science* 62, 1554–1577.

Jiang, Erica, 2020, Financing competitors: Shadow banks' funding and mortgage market competition, Working paper, Available at SSRN 3556917.

Johnson, Mark J., Itzhak Ben-David, Jason Lee, and Vincent Yao, 2022, Fintech lending with lowtech pricing, Available at SSRN.

Jordà, Òscar, Moritz Schularick, and Alan M Taylor, 2020, The effects of quasi-random monetary experiments, *Journal of Monetary Economics* 112, 22–40.

Keys, Benjamin J., Devin G. Pope, and Jaren C. Pope, 2016, Failure to refinance, *Journal of Financial Economics* 122, 482–499.

Krishnamurthy, Arvind, and Annette Vissing-Jorgensen, 2011, The effects of quantitative easing on interest rates: Channels and implications for policy, *Brookings Papers on Economic Activity* 2011, 215–287.

Liu, Yukun, and Aleh Tsyvinski, 2021, Risks and returns of cryptocurrency, *The Review of Financial Studies* 34, 2689–2727.

Luck, Stephan, and Tom Zimmermann, 2020, Employment effects of unconventional monetary policy: Evidence from QE, *Journal of Financial Economics* 135, 678–703.

Nakamura, Emi, and Jón Steinsson, 2018a, Identification in macroeconomics, *Journal of Economic Perspectives* 32, 59–86.

Nakamura, Emi, and Jón Steinsson, 2018b, High-frequency identification of monetary non-neutrality: The information effect, *The Quarterly Journal of Economics* 133, 1283–1330.

Peydró, José Luis, David Elliott, Ralf Meisenzahl, and Bryce C. Turner, 2020, Nonbanks, banks, and monetary policy: U.S. loan-level evidence since the 1990s, Working Paper DP14989, CEPR.

Philippon, Thomas, 2016, The fintech opportunity, Discussion Paper 14989, NBER.

Rodnyansky, Alexander, and Olivier M Darmouni, 2017, The effects of quantitative easing on bank lending behavior, *The Review of Financial Studies* 30, 3858–3887.

Romer, Christiana, and David Romer, 2004, A new measure of monetary shocks: Derivation and implications, *American Economic Review* 94, 1055–1084.

Scharfstein, David, and Adi Sunderam, 2016, Market power in mortgage lending and the transmission of monetary policy, Working Paper, Harvard University.

Swanson, Eric T., 2021, Measuring the effects of federal reserve forward guidance and asset purchases on financial markets, *Journal of Monetary Economics* 118, 32–53.

Tang, Huan, 2019, Peer-to-peer lenders versus banks: Substitutes or complements?, *The Review of Financial Studies* 32, 1900–1938.

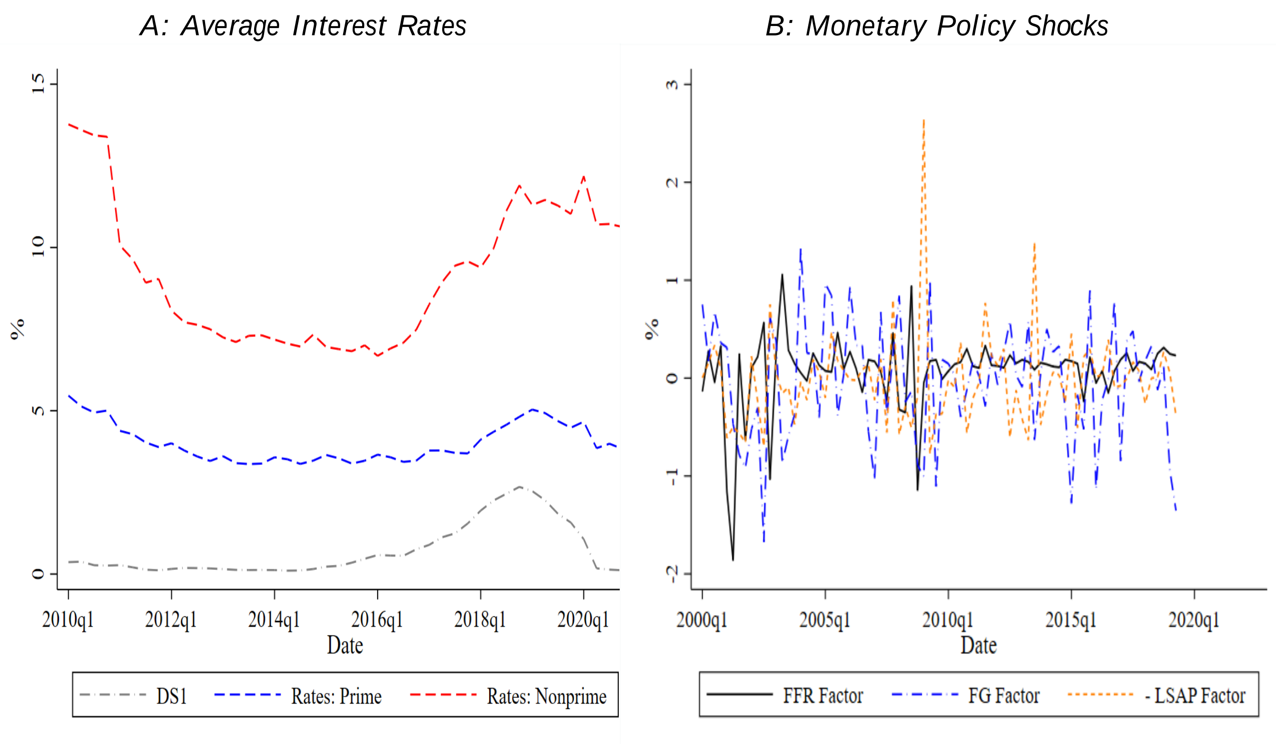
Vallée, Boris, and Yao Zeng, 2019, Marketplace lending: A new banking paradigm?, *The Review of Financial Studies* 32, 1939–1982.

Wang, Yifei, Toni M Whited, Yufeng Wu, and Kairong Xiao, 2020, Bank market power and monetary policy transmission: Evidence from a structural estimation, Working Paper 27258, NBER.

Wright, Jonathan H., 2012, What does monetary policy do to long-term interest rates at the zero lower bound?, *The Economic Journal* 122, F447–F466.

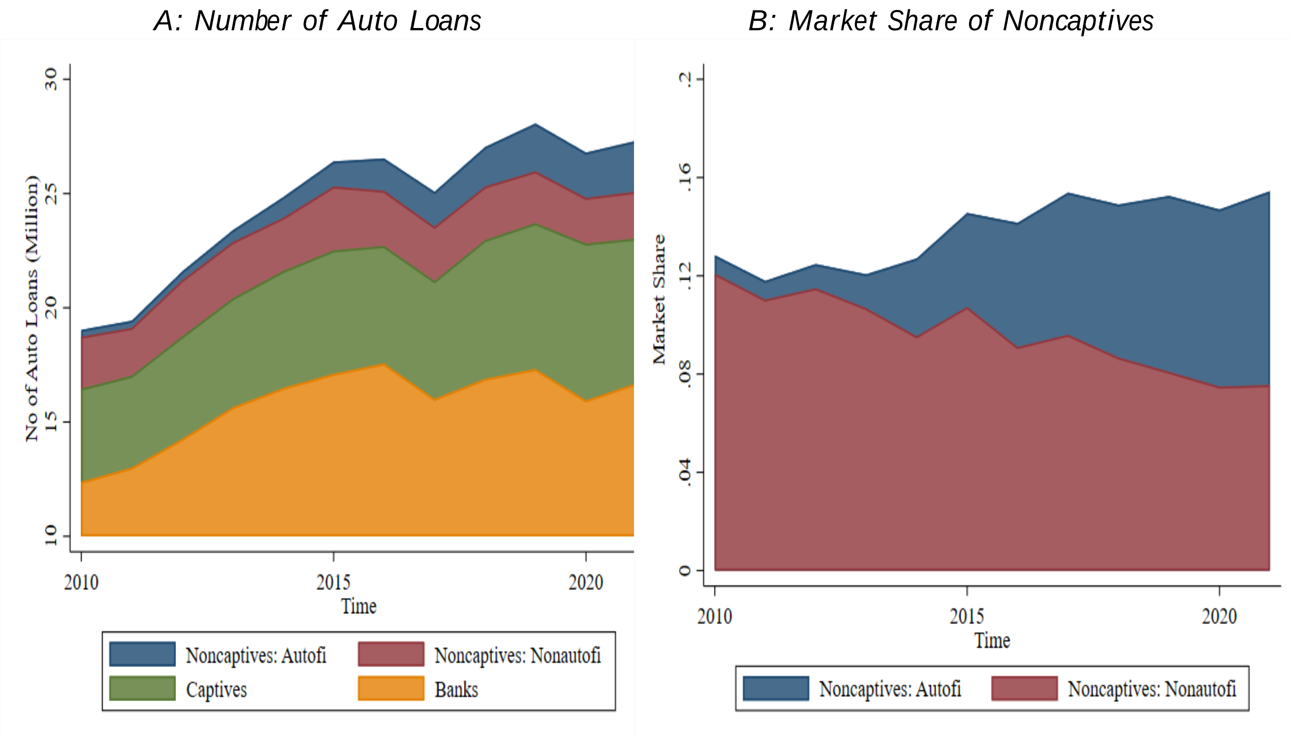
Xiao, Kairong, 2020, Monetary transmission through shadow banks, *Journal of Monetary Economics* 33, 2379–2420.

Figure 1. Monetary Policy Shocks and Rates



This figure plots the time series of monetary policy shocks and interest rates. Panel A plots one-year Treasury rate (DS1), average rates on prime auto loans, and those on nonprime auto loans in 2010q1{2020q4. Loan rates are calculated from the universe of automobile loans, weighted by loan balance. Panel B plots three monetary policy shocks in 2010q1{2019q2, estimated by Swanson (2021) using high-frequency (30-minute) financial data.

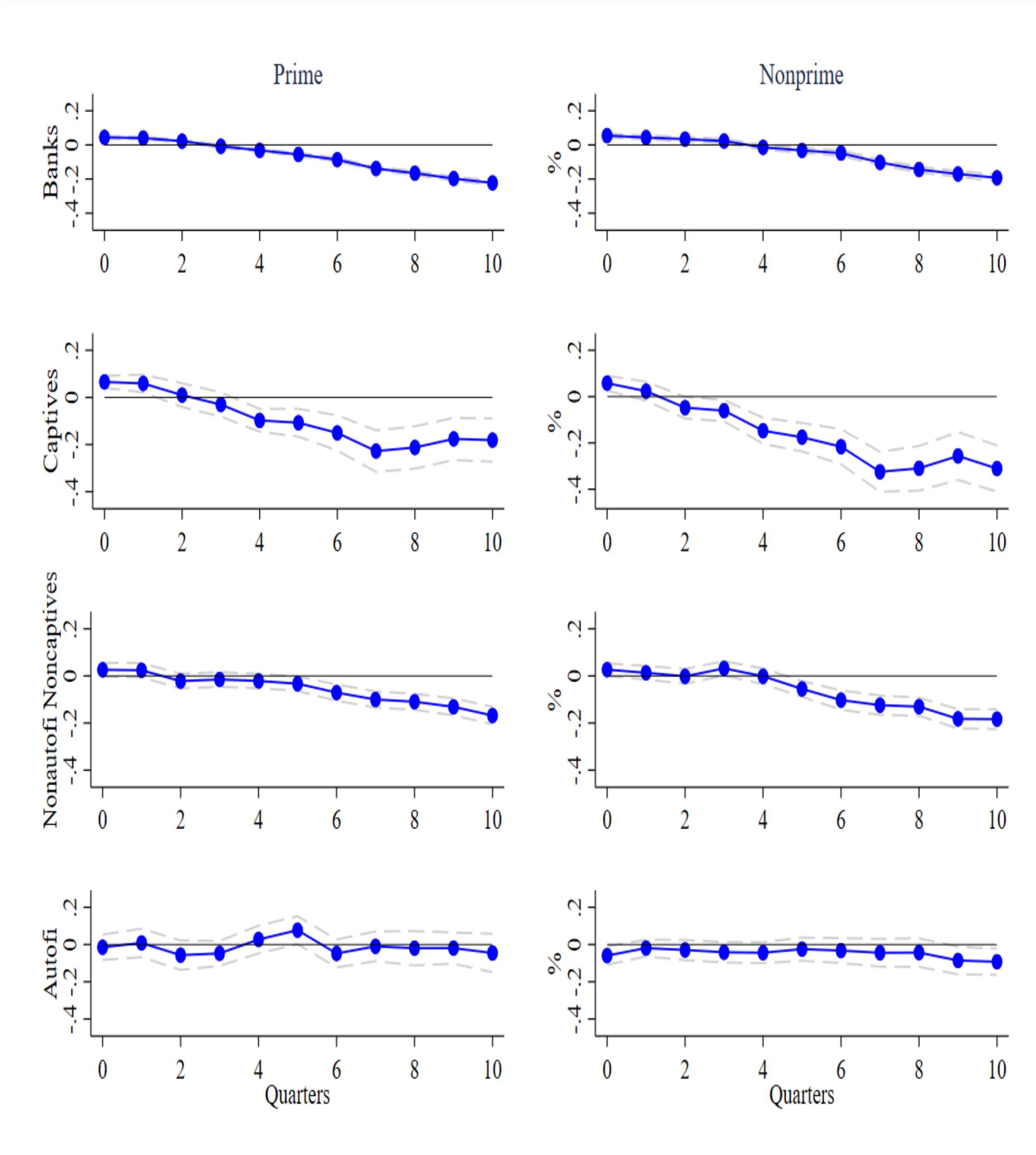
Figure 2. Auto Loan Market



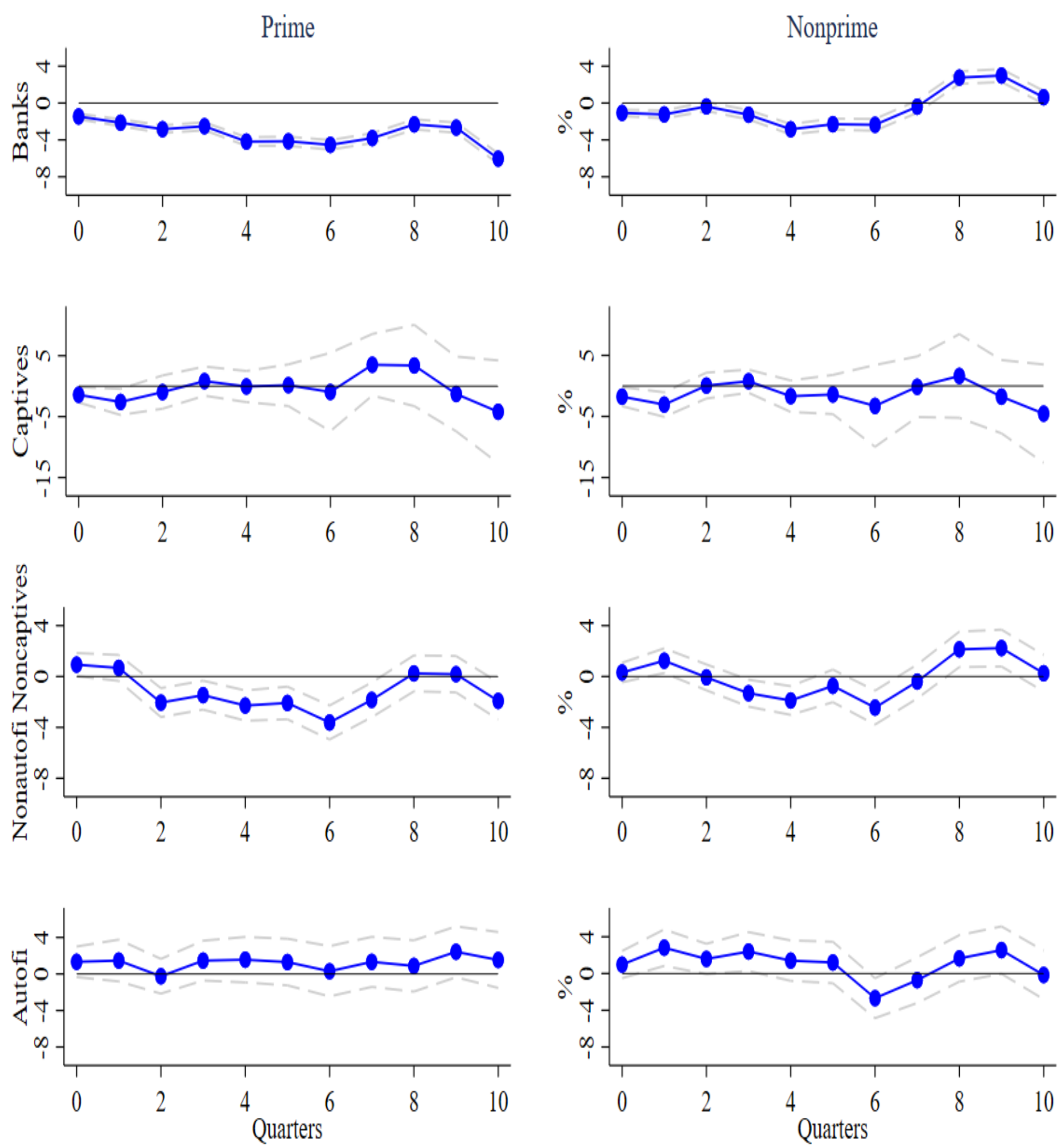
This figure plots the time series of trends in the automobile credit markets. Panel A plots the automobile loan originations by four lender types from 2010 to 2020 in an area chart. Panel B plots the market share of auto and other noncaptives in the automobile loan originations in 2010{2020.

Figure 3. Heterogeneous IRFs of Auto Lending

A: Rates



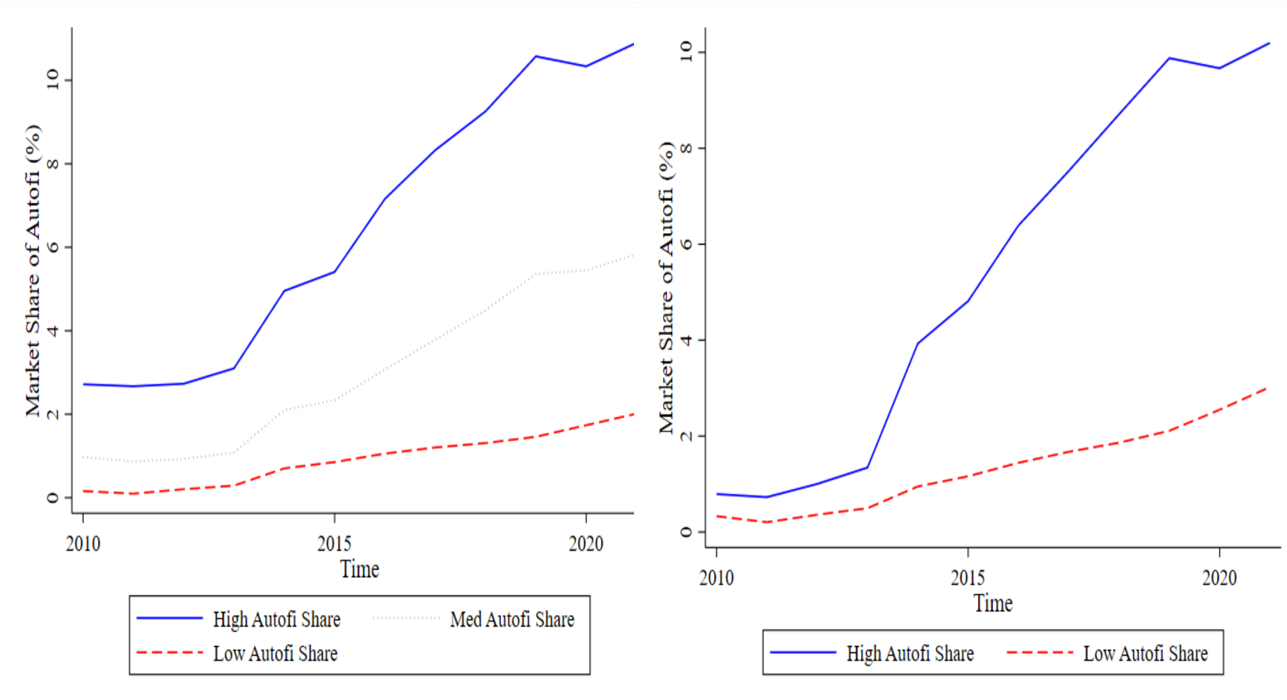
B: Volume



This gure shows the IRFs for the auto-lending rates (Panel A) and volume (Panel B) following a 25 bps increase in the one-year interest rate. We run separate sets of regressions per each row based on di erent subsamples containing cohort-quarter data based on automobile loans originated by a particular lender type in 2010{2019. The left column shows the response of changes in rates or volume of prime loans while the right column shows the response of changes in rates or volume of nonprime loans. The rst row in both panels shows the response of auto-lending rate or volume for banks; the second row in both panels shows the response of auto-lending rate or volume for captives; the third row in both panels shows the response of auto-lending rate or volume for nonauto noncaptives; the last row in both panels shows the response of auto-lending rate or volume for auto . The IRFs are estimated using the LP-IV method described in the text. Dotted lines are 90% standard error bands. Standard errors are computed using the Driscoll-Kraay method, clustering by lender and time.

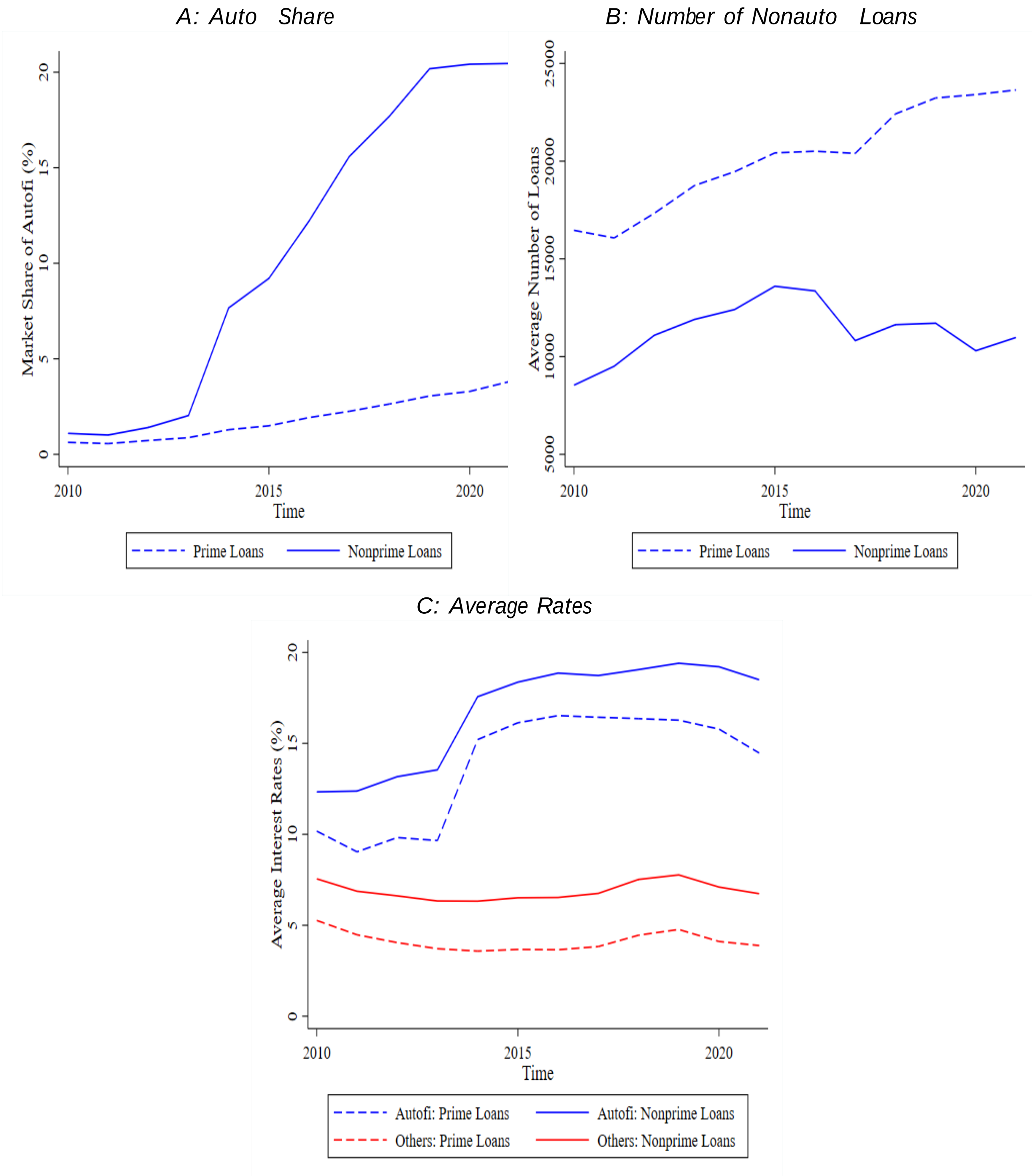
Figure 4. Entry of Autofi Lenders

A: Auto Share in All Counties   *B: Auto Share in Matched Counties*



This gure plots the market share of automobile loans originated by auto in 2010{2020. Panel A plots the time series of market share by high, medium, and low auto -share counties, de ned based on the average share in 2010{2020. Panel B plots the time series of market share for high and low auto -share counties restricted to only matched counties using a PSM procedure described in the text.

Figure 5. Market Dynamics in the Treated Counties



This gure plots several time series by prime and nonprime loans originated in the treated counties in 2010{2020. Panel A plots the auto share in the prime and nonprime segments separately. Panel B plots the county-level average number of prime and nonprime automobile loans originated by nonauto lenders (banks, captives, and other noncaptives). Panel C plots the average rates on prime and nonprime loans by auto and nonauto lenders.

Table 1: Summary of Statistics

Panel A: Lender YQ Sample

	Banks		Captives		Noncaptives: Nonautofi		Noncaptives: Autofi	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Rates: All	4.961	3.876	4.134	2.930	12.335	9.969	19.753	5.460
Rates: Prime	4.207	4.655	3.364	2.401	11.989	11.057	19.309	6.060
Rates: Nonprime	6.784	6.282	5.946	3.559	13.228	9.749	19.886	5.351
ΔRates: All	-0.076	3.142	-0.041	0.677	-0.014	5.287	0.052	1.893
ΔRates: Prime	-0.076	4.947	-0.039	0.765	-0.030	7.117	0.022	3.561
ΔRates: Nonprime	-0.084	6.280	-0.032	0.677	-0.013	6.026	0.051	1.907
Balance: All ($M)	37.80	335.00	1210.00	1760.00	13.70	121.00	27.70	174.00
Balance: Prime ($M)	27.50	228.00	855.00	1270.00	7.94	68.10	8.58	86.50
Balance: Nonprime ($M)	10.30	132.00	357.00	538.00	5.74	76.70	19.10	107.00
ΔBalance: All	0.873	58.455	0.398	58.130	-0.431	63.623	-2.436	65.490
ΔBalance: Prime	1.029	65.770	0.752	59.390	0.196	87.350	0.351	98.474
ΔBalance: Nonprime	0.340	75.712	-0.068	61.596	-0.766	76.646	-3.108	68.280
Loan Counts: All	1,699	14,414	52,288	66,451	705	5,640	1,750	10,372
Loan Counts: Prime	1,193	9,261	37,134	47,980	351	2,561	476	4,528
Loan Counts: Nonprime	506	6,170	15,153	20,816	353	4,156	1,273	7,132
1 Year Rate	0.656	0.765	0.693	0.795	0.566	0.698	0.803	0.846
MP Shock: FFR	0.142	0.108	0.141	0.110	0.146	0.103	0.141	0.112
MP Shock: FG	-0.064	0.519	-0.067	0.539	-0.050	0.477	-0.109	0.576
MP Shock: LSAP	-0.005	0.381	-0.010	0.376	0.001	0.391	0.005	0.349
N	50,314		779		12,948		2,022	

Panel B: Lender County YQ Sample

	Banks		Captives		Noncaptives: Nonautofi		Noncaptives: Autofi	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Rates: All	5.400	3.987	5.482	3.462	10.634	8.607	17.289	5.967
Rates: Prime	4.545	11.848	4.153	2.827	9.479	8.269	15.525	6.857
Rates: Nonprime	7.113	10.011	7.978	4.377	11.833	8.574	18.286	5.012
ΔRates: All	-0.043	1.772	-0.049	1.707	-0.055	2.640	-0.071	1.467
ΔRates: Prime	-0.039	3.262	-0.045	1.804	-0.039	4.094	-0.095	2.885
ΔRates: Nonprime	-0.043	2.940	-0.039	2.686	-0.044	4.141	-0.038	1.670
Balance: All ($M)	4.207	10.700	4.286	10.200	2.746	8.518	2.198	4.465
Balance: Prime ($M)	3.062	8.152	3.022	7.325	1.590	5.828	0.683	2.226
Balance: Nonprime ($M)	1.145	3.547	1.263	3.267	1.155	3.962	1.515	2.865
ΔBalance: All	0.400	43.121	0.403	43.063	-0.333	43.938	0.252	41.594
ΔBalance: Prime	0.429	53.899	0.802	53.879	0.173	71.485	2.526	83.078
ΔBalance: Nonprime	0.076	75.368	-0.186	70.200	-0.812	71.322	-0.280	50.854
Loan Counts: All	189.478	487.029	185.035	456.110	141.715	370.206	138.725	260.596
Loan Counts: Prime	133.160	362.073	131.400	337.976	70.310	233.198	37.921	117.287
Loan Counts: Nonprime	56.318	164.835	53.636	137.831	71.405	207.314	100.804	183.503
1 Year Rate	0.689	0.788	0.699	0.793	0.672	0.766	0.865	0.868
MP Shock: FFR	0.138	0.112	0.138	0.112	0.139	0.111	0.138	0.120
MP Shock: FG	-0.070	0.540	-0.072	0.546	-0.070	0.532	-0.148	0.612
MP Shock: LSAP	-0.009	0.380	-0.011	0.374	-0.008	0.377	-0.005	0.307
Noncaptives Share	0.125	0.071	0.125	0.069	0.145	0.074	0.148	0.067
Autofi Share	0.014	0.021	0.014	0.021	0.015	0.021	0.021	0.024
N	428,615		137,622		63,871		23,666	

Panel C: Matched Sample for Autofi Entry Analysis

	Treated Counties		Control Counties		Difference
	Mean	SD	Mean	SD	
Rates: All	7.312	5.891	6.348	5.148	0.964
Rates: Prime	6.190	13.519	5.344	5.050	0.846
Rates: Nonprime	8.983	5.971	8.200	8.017	0.783
ΔRates: All	-0.047	1.786	-0.045	1.743	-0.002
ΔRates: Prime	-0.045	4.575	-0.043	2.148	-0.003
ΔRates: Nonprime	-0.041	2.610	-0.043	2.782	0.002
Balance: All ($M)	4.426	10.400	3.015	6.561	1.411
Balance: Prime ($M)	2.929	7.351	2.266	5.477	0.663
Balance: Nonprime ($M)	1.497	4.093	0.749	1.467	0.747
ΔBalance: All	0.303	42.521	0.322	43.699	-0.019
ΔBalance: Prime	0.706	58.267	0.480	57.946	0.226
ΔBalance: Nonprime	-0.140	68.875	0.068	74.962	-0.208
Loan Counts: All	203.976	465.085	142.869	317.638	61.107
Loan Counts: Prime	128.272	323.655	103.123	256.732	25.149
Loan Counts: Nonprime	75.704	192.808	39.746	80.278	35.958
1 Year Rate	0.705	0.796	0.695	0.790	0.010
MP Shock: FFR	0.139	0.112	0.138	0.112	0.000
MP Shock: FG	-0.075	0.546	-0.073	0.544	-0.002
MP Shock: LSAP	-0.009	0.373	-0.009	0.377	0.000
Noncaptives Share	0.151	0.058	0.100	0.066	0.051
Autofi Share	0.009	0.010	0.003	0.007	0.006
N	172,563		131,153		303,716

This table reports a summary of statistics for all the variables used in the analysis. Panel A reports statistics for variables in the lender quarter sample by four lender types; Panel B reports statistics for variables in the lender county quarter sample by four lender types; Panel C reports statistics for variables in the matched lender county quarter sample by treated and control counties. The rate, balance, and loan counts variables are the average interest rates, total balances, and total number of loans counts calculated from all auto loans originated from 2010 to 2019 available at one of the credit bureaus. One-year U.S. Treasury rate is obtained from FRED. Three monetary policy shock series, estimated by Swanson (2021), are updated through June 2019. Noncaptives and auto shares are also calculated from all auto loans originated from 2010 to 2019.

Table 2: Responses of Auto Lending by Lenders

Dep Var	$\Delta Rates_{i;t}$					$\Delta Volume_{i;t}$				
Sample	All Lenders	Banks	Captives	Noncaptives		All Lenders	Banks	Captives	Noncaptives	
				Nonautofi	Autofi				Nonautofi	Autofi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$GS1_t$	0.171***	0.202***	0.256***	0.099**	-0.218*	-4.096***	-5.189***	-5.727*	0.139	3.702
	(10.47)	(11.58)	(3.64)	(2.02)	(-1.77)	(-6.54)	(-7.40)	(-1.89)	(0.09)	(1.12)
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	66063	50314	779	12948	2022	66063	50314	779	12948	2022
Adj. R^2	0.272	0.294	0.136	0.229	0.304	0.324	0.320	0.294	0.328	0.418

This table reports the estimated response of the auto-lending rates and volume by di erent lender types following a 100 bps increase in the one-year interest rate. Columns (1) and (6) are based on the entire lender quarter sample while all the other columns are based on the subset of lender quarter sample for a particular lender type (i.e., banks, captives, nonauto , or other noncaptives), containing automobile loans originated in 2010{2019. The dependent variable is $Rates_{i;t}$ in Columns (1){(5) and $Volume_{i;t}$ in Columns (6){(10). The main explanatory variable is the one-year policy rate instrumented by the three monetary policy shocks. The responses are estimated using the LP-IV method described in the text. We control for the lender xed e ects, four lags of the dependent variable, and four quarterly dummies to capture the seasonality. Standard errors are computed using the Driscoll-Kraay method, clustering by lender and time. t-statistics are shown in parentheses. Statistical signi cance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 3: Responses of Auto Lending by Lenders and Borrower Segments

Panel A: Rates

Dep Var	$\Delta Rates_{i;t}$							
Sample	Prime Loans				Nonprime Loans			
	Banks	Captives	Noncaptives		Banks	Captives	Noncaptives	
			Nonautofi	Autofi			Nonautofi	Autofi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GS1_t$	0.180***	0.264***	0.116*	-0.060	0.219***	0.229***	0.101	-0.235*
	(9.99)	(4.27)	(1.78)	(-0.36)	(7.83)	(2.98)	(1.54)	(-1.95)
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	50314	779	12948	2022	50314	779	12948	2022
Adj R^2	0.324	0.131	0.344	0.340	0.345	0.125	0.275	0.329

Panel B: Volume

Dep Var	$\Delta Volume_{i;t}$								
Sample	Prime Loans					Nonprime Loans			
	Banks	Captives	Noncaptives			Banks	Captives	Noncaptives	
			Nonautofi	Autofi				Nonautofi	Autofi
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
$GS1_t$	-5.884***	-5.603*	2.077	5.370		-4.218***	-7.104*	1.442	3.919
	(-7.93)	(-1.84)	(1.02)	(1.42)		(-5.04)	(-1.92)	(0.79)	(1.10)
Lender FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
N	50314	779	12948	2022		50314	779	12948	2022
Adj R^2	0.331	0.295	0.363	0.419	0.298	0.267	0.328	0.412	

This table reports the estimated response of the auto-lending rates and volume by di erent lender types and borrower segments following a 100 bps increase in the one-year interest rate. Regressions reported in each column are based on the subset of lender quarter sample for a particular lender type (i.e., banks, captives, nonauto , or other noncaptives), containing automobile loans originated in 2010-2019. Panel A presents the regression results using $Rates_{i;t}$ as the dependent variable, while Panel B presents the regression results using $Volume_{i;t}$ as the dependent variable. Columns (1){(4) in both panels use rate and volume variables for prime loans, while Columns (5){(8) in both panels use rate and volume variables for nonprime loans. The main explanatory variable is the one-year policy rate instrumented by the three monetary policy shocks. The responses are estimated using the LP-IV method described in the text. We control for the lender xed e ects, four lags of the dependent variable and four quarterly dummies to capture the seasonality. Standard errors are computed using the Driscoll-Kraay method, clustering by lender and time. t-statistics are shown in parentheses. Statistical signi cance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

Table 4: Responses of Auto Lending by Market Share of Noncaptives

Panel A: Rates

Dep Var	$\Delta Rates_{i;t}$							
Sample	Prime Loans				Nonprime Loans			
	Banks	Captives	Noncaptives		Banks	Captives	Noncaptives	
			Nonautofi	Autofi			Nonautofi	Autofi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GS1_t \times$ Noncaptives Share$_i$: Q1	0.166***	0.364***	0.799*	0.067	0.188***	0.482***	0.601	0.263
	(8.18)	(7.70)	(1.66)	(0.21)	(6.56)	(6.75)	(1.08)	(1.40)
$GS1_t \times$ Noncaptives Share$_i$: Q2	0.163***	0.475***	0.171	0.223***	0.210***	0.478***	0.286**	0.045
	(11.46)	(21.30)	(1.60)	(3.26)	(12.57)	(14.35)	(2.55)	(0.72)
$GS1_t \times$ Noncaptives Share$_i$: Q3	0.169***	0.496***	0.218***	0.372***	0.205***	0.477***	0.072	0.142***
	(10.43)	(23.02)	(4.57)	(6.54)	(11.95)	(15.75)	(1.37)	(2.89)
$GS1_t \times$ Noncaptives Share$_i$: Q4	0.193***	0.469***	0.355***	0.489***	0.255***	0.477***	0.296***	0.326***
	(13.88)	(22.41)	(5.90)	(8.10)	(14.09)	(18.29)	(3.89)	(8.08)
Lender $\times$ County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	428615	137622	63871	23666	428615	137622	63871	23666
Adj R^2	0.293	0.303	0.321	0.325	0.326	0.335	0.305	0.305

Panel B: Volume

Dep Var	$\Delta Volume_{i;t}$							
Sample	Prime Loans				Nonprime Loans			
	Banks	Captives	Noncaptives		Banks	Captives	Noncaptives	
			Nonautofi	Autofi			Nonautofi	Autofi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GS1_t \times$ Noncaptives Share$_i$: Q1	-2.938***	-0.147	-13.765**	9.362	-2.578***	1.679	-4.621	-5.464
	(-4.38)	(-0.10)	(-2.52)	(0.70)	(-2.79)	(0.80)	(-0.66)	(-0.88)
$GS1_t \times$ Noncaptives Share$_i$: Q2	-1.605***	-0.774	-4.309***	-6.021**	-3.677***	-2.999***	-7.975***	2.952
	(-3.62)	(-1.14)	(-2.68)	(-2.42)	(-6.95)	(-3.41)	(-4.51)	(1.36)
$GS1_t \times$ Noncaptives Share$_i$: Q3	-1.578***	-1.940***	-5.889***	-6.455***	-5.964***	-2.735***	-5.961***	-3.101*
	(-3.50)	(-3.14)	(-4.87)	(-3.23)	(-10.83)	(-3.37)	(-4.55)	(-1.92)
$GS1_t \times$ Noncaptives Share$_i$: Q4	-2.056***	-1.786***	-5.725***	-2.935*	-6.600***	-2.280***	-6.810***	-0.676
	(-4.61)	(-3.13)	(-6.24)	(-1.82)	(-13.11)	(-3.05)	(-6.76)	(-0.56)
Lender $\times$ County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	428615	137622	63871	23666	428615	137622	63871	23666
Adj R^2	0.275	0.342	0.322	0.397	0.295	0.355	0.288	0.340

This table reports the role of noncaptives' market power in lenders' responses following a 100 bps increase in the one-year interest rate. Regressions reported in each column are based on the subset of lender $\times$ county $\times$ quarter sample for a particular lender type (i.e., banks, captives, nonautofi, or other noncaptives), containing automobile loans originated in 2010–2019. Panel A presents the regression results using $\Delta Rates_{i;t}$ as the dependent variable, while Panel B presents the regression results using $\Delta Volume_{i;t}$ as the dependent variable. Columns (1)–(4) in both panels use rate and volume variables for prime loans, while Columns (5)–(8) in both panels use rate and volume variables for nonprime loans. The main explanatory variable is the one-year policy rate, instrumented by the three monetary policy shocks, interacted with the quartile dummies of the county-level share of loans originated by noncaptives in 2010–2019. The responses are estimated using the LP-IV method described in the text. We control for the lender by county fixed effects, four lags of the dependent variable, and four quarterly dummies to capture the seasonality. Standard errors are computed using the Driscoll-Kraay method, clustering by lender and time. t-statistics are shown in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 5: Responses of Auto Lending by Market Share of Autofi

Panel A: Rates

Dep Var	$\Delta Rates_{i;t}$					
Sample	Prime Loans			Nonprime Loans		
	Banks	Captives	Noncaptives Nonautofi	Banks	Captives	Noncaptives Nonautofi
	(1)	(2)	(3)	(4)	(5)	(6)
$GS1_t \times$ Autofi Share$_i$: Low	0.158***	0.408***	0.268***	0.194***	0.457***	0.200**
	(11.58)	(17.86)	(3.88)	(11.33)	(12.79)	(2.45)
$GS1_t \times$ Autofi Share$_i$: Med	0.183***	0.467***	0.277***	0.208***	0.504***	0.209**
	(11.75)	(20.18)	(3.44)	(11.51)	(15.51)	(2.07)
$GS1_t \times$ Autofi Share$_i$: High	0.183***	0.516***	0.297***	0.254***	0.475***	0.264***
	(14.80)	(28.20)	(4.90)	(16.35)	(21.09)	(3.71)
Lender $\times$ County FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	428615	137622	63871	428615	137622	63871
Adj R^2	0.293	0.303	0.321	0.326	0.335	0.305

Panel B: Volume

Dep Var	$\Delta Volume_{i;t}$					
Sample	Prime Loans			Nonprime Loans		
	Banks	Captives	Noncaptives Nonautofi	Banks	Captives	Noncaptives Nonautofi
	(1)	(2)	(3)	(4)	(5)	(6)
$GS1_t \times$ Autofi Share$_i$: Low	-2.050***	-0.012	-6.335***	-4.119***	-2.066**	-5.488***
	(-5.28)	(-0.02)	(-4.02)	(-8.20)	(-2.12)	(-3.46)
$GS1_t \times$ Autofi Share$_i$: Med	-0.750	-1.238*	-5.620***	-3.484***	-1.793**	-6.661***
	(-1.50)	(-1.75)	(-4.11)	(-6.06)	(-2.00)	(-4.60)
$GS1_t \times$ Autofi Share$_i$: High	-2.487***	-2.428***	-4.358***	-7.104***	-2.844***	-7.426***
	(-6.35)	(-5.08)	(-4.26)	(-15.79)	(-4.59)	(-7.50)
Lender $\times$ County FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	428615	137622	63871	428615	137622	63871
Adj R^2	0.275	0.342	0.325	0.295	0.355	0.288

This table reports the role of autofi's market power in lenders' responses following a 100 bps increase in the one-year interest rate. Regressions reported in each column are based on the subset of lender $\times$ county $\times$ quarter sample for a particular lender type (i.e., banks, captives, nonautofi, or other noncaptives), containing automobile loans originated in 2010–2019. Panel A presents the regression results using $\Delta Rates_{i;t}$ as the dependent variable, while Panel B presents the regression results using $\Delta Volume_{i;t}$ as the dependent variable. Columns (1)–(4) in both panels use rate and volume variables for prime loans, while Columns (5)–(8) in both panels use rate and volume variables for nonprime loans. The main explanatory variable is the one-year policy rate, instrumented by the three monetary policy shocks, interacted with the tercile dummies of the county-level share of loans originated by autofi in 2010–2019. The responses are estimated using the LP-IV method described in the text. We control for the lender by county fixed effects, four lags of the dependent variable, and four quarterly dummies to capture the seasonality. Standard errors are computed using the Driscoll-Kraay method, clustering by lender and time. t-statistics are shown in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table 6: Responses of Auto Lending Using an Event Study

Panel A: Rates

Dep Var		$\Delta Rates_{i;t}$					
Sample		Prime Loans			Nonprime Loans		
		Banks	Captives	Noncaptives Nonautofi	Banks	Captives	Noncaptives Nonautofi
		(1)	(2)	(3)	(4)	(5)	(6)
$GS1_t$	Autofi Entry: Year -2	-0.473***	0.115***	-0.346***	-0.286***	-0.041	-0.492***
		(-23.25)	(4.13)	(-4.62)	(-11.01)	(-1.11)	(-6.94)
$GS1_t$	Autofi Entry: Year -1	-0.248***	0.057**	-0.831***	-0.217***	0.069*	-0.055
		(-12.64)	(2.00)	(-9.43)	(-8.20)	(1.72)	(-0.89)
$GS1_t$	Autofi Entry: Year +1	0.129***	0.164***	0.395***	0.200***	0.229***	-0.254***
		(7.83)	(5.51)	(5.98)	(8.70)	(5.18)	(-3.69)
$GS1_t$	Autofi Entry: Year +2	0.153***	0.012	0.597***	0.217***	0.182***	0.286***
		(11.04)	(0.43)	(9.81)	(10.97)	(4.28)	(5.09)
$GS1_t$	Autofi Entry: Year +3	0.394***	0.243***	0.368***	0.514***	-0.000	0.071
		(19.42)	(6.50)	(4.99)	(19.09)	(-0.00)	(0.93)
$GS1_t$	Autofi Entry: Year +4	0.298***	0.509***	0.394***	0.338***	0.594***	0.181***
		(21.77)	(21.07)	(8.34)	(17.36)	(16.29)	(3.59)
$GS1_t$	Autofi Entry: Year +5	0.646***	0.653***	0.592***	0.626***	0.622***	0.226***
		(55.23)	(27.94)	(12.55)	(38.66)	(19.72)	(5.16)
$GS1_t$	Autofi Entry: Year +6	0.296***	0.417***	0.356***	0.278***	0.233***	0.077*
		(27.20)	(18.55)	(7.56)	(18.38)	(7.93)	(1.65)
Lender County FE		Yes	Yes	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes	Yes	Yes
N		203376	68814	31526	203376	68814	31526
Adj R^2		0.310	0.308	0.349	0.330	0.331	0.319

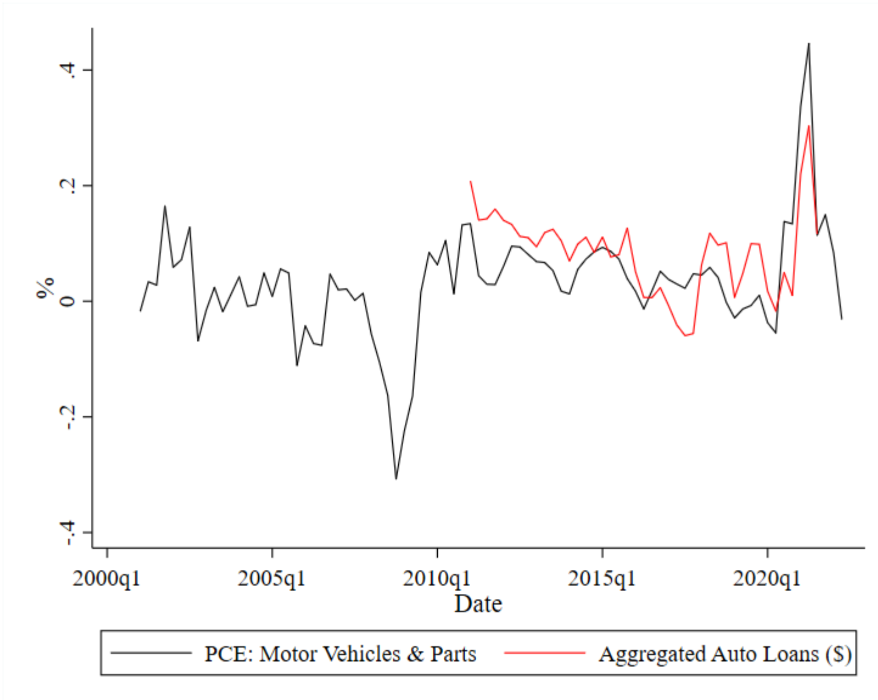
Panel B: Volume

Dep Var		$\Delta Volume_{i;t}$					
Sample		Prime Loans			Nonprime Loans		
		Banks	Captives	Noncaptives Nonautofi	Banks	Captives	Noncaptives Nonautofi
		(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{GS1}_t$	Autofi Entry: Year -2	3.753***	-11.948***	4.512***	5.475***	3.407***	8.719***
		(6.35)	(-15.20)	(2.90)	(7.11)	(3.47)	(6.16)
$\widehat{GS1}_t$	Autofi Entry: Year -1	-1.872***	3.173***	19.105***	2.284***	6.988***	14.000***
		(-3.43)	(3.34)	(9.68)	(3.24)	(6.27)	(8.32)
$\widehat{GS1}_t$	Autofi Entry: Year +1	1.206**	-4.604***	6.901***	-5.072***	-0.926	-2.920
		(2.02)	(-4.80)	(3.58)	(-6.95)	(-0.78)	(-1.63)
$\widehat{GS1}_t$	Autofi Entry: Year +2	-0.299	1.735**	0.739	-8.115***	1.422	2.984*
		(-0.56)	(2.10)	(0.43)	(-12.68)	(1.47)	(1.81)
$\widehat{GS1}_t$	Autofi Entry: Year +3	-9.962***	-15.115***	-1.011	-15.304***	-18.586***	-12.424***
		(-12.28)	(-11.59)	(-0.43)	(-15.55)	(-13.00)	(-4.75)
$\widehat{GS1}_t$	Autofi Entry: Year +4	-0.426	-4.445***	-10.087***	-16.217***	-9.294***	-27.903***
		(-0.59)	(-5.58)	(-6.64)	(-22.88)	(-10.19)	(-16.99)
$\widehat{GS1}_t$	Autofi Entry: Year +5	-4.894***	-0.284	2.086	-13.511***	-2.840***	-10.151***
		(-10.22)	(-0.38)	(1.58)	(-22.45)	(-3.15)	(-6.55)
$\widehat{GS1}_t$	Autofi Entry: Year +6	-2.696***	-3.569***	-2.354**	-8.349***	-6.119***	-6.980***
		(-5.94)	(-5.14)	(-2.04)	(-15.47)	(-8.19)	(-5.93)
Lender County FE		Yes	Yes	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes	Yes	Yes
N		203376	68814	31526	203376	68814	31526
Adj R^2		0.271	0.348	0.334	0.297	0.355	0.301

This table reports the role of auto 's market power in lenders' responses following a 100 bps increase in the one-year interest rate using an event study approach. Regressions reported in each column are based on the subset of the matched lender county quarter sample for a particular lender type (i.e., banks, captives, nonauto , or other noncaptives), containing automobile loans originated in 2010{2019. Panel A presents the regression results using $Rates_{i;t}$ as the dependent variable, while Panel B presents the regression results using $Volume_{i;t}$ as the dependent variable. Columns (1){(3) in both panels use rate and volume variables for prime loans, while Columns (4){(6) in both panels use rate and volume variables for nonprime loans. The main explanatory variable is the one-year policy rate, instrumented by the three monetary policy shocks, interacted with relative year dummies de ned based on origination time and the entry year of auto . The responses are estimated using the LP-IV method described in the text. We control for the lender by county xed e ects, four lags of the dependent variable, and four quarterly dummies to capture the seasonality. Standard errors are computed using the Driscoll-Kraay method, clustering by lender and time. t-statistics are shown in parentheses. Statistical signi cance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

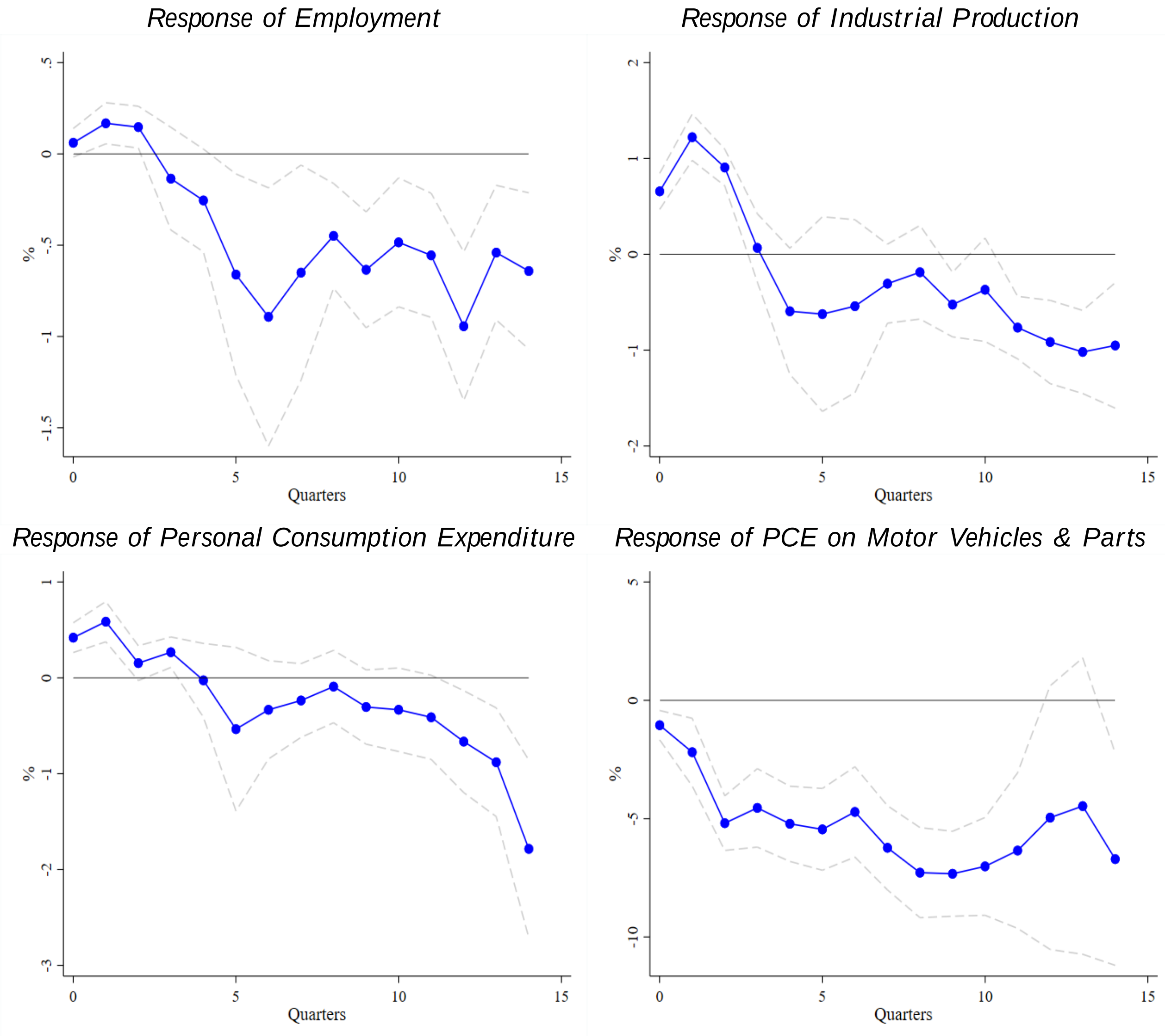
Online Appendix

Figure A.1. Auto Consumption: Aggregated Micro Data vs. National Statistics



The gure plots the time series of PCE on motor vehicles and parts from NIPA in 2001{2021 and total number of automobile loans aggregated from our sample in 2010{2020.

Figure A.2. Cumulative Effect of Monetary Policy Shocks on Selected National Statistics Data



This gure shows the IRFs for the macroeconomic variables following a 25 bps increase in the one-year interest rate. The dependent variable is the changes in employment, industrial production, total PCE, and PCE on motor vehicles and parts in the four panels, respectively. The IRFs are estimated using the LP method described in the text. Dotted lines are 90% standard error bands. Standard errors are computed using the Driscoll-Kraay method, clustering by time.

Table A.1: Monetary Responses in the Increasing or Decreasing Rate Environment

Panel A: 2010-2015

Dep Var	$\Delta Rates_{i;t}$							
Sample	Prime Loans				Nonprime Loans			
	Banks	Captives	Noncaptives		Banks	Captives	Noncaptives	
			Nonautofi	Autofi			Nonautofi	Autofi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{GS1}_t$	0.972***	-1.491**	2.729***	-2.620	0.613	-1.325	1.316	0.939
	(3.90)	(-2.32)	(3.17)	(-1.21)	(1.63)	(-1.33)	(1.53)	(0.73)
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	50314	779	12948	2022	50314	779	12948	2022
Adj R^2	0.328	0.135	0.334	0.423	0.342	0.111	0.263	0.473

Panel B: 2016-2019

Dep Var	$\Delta Rate_{i;t}$							
Sample	Prime Loans				Nonprime Loans			
	Banks	Captives	Noncaptives		Banks	Captives	Noncaptives	
			Nonautofi	Autofi			Nonautofi	Autofi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{GS1}_t$	0.252***	0.255***	0.223***	-0.120	0.237***	0.151**	0.196***	-0.178*
	(19.17)	(3.28)	(5.08)	(-0.79)	(11.27)	(2.50)	(4.16)	(-1.75)
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	50314	779	12948	2022	50314	779	12948	2022
Adj R^2	0.372	0.149	0.469	0.272	0.401	0.123	0.418	0.276

This table reports di erences in the estimated response of the auto-lending rates between di erent monetary policy regimes following a 100 bps increase in the one-year interest rate. Panel A presents the regression results based on loans originated in 2010{2015, while Panel B presents the regression results based on loans originated in 2016{2019. $Rates_{i;t}$ is the dependent variable in all regressions. Regressions reported in each column are based on the subset of lender quarter sample for a particular lender type (i.e., banks, captives, nonauto , or other noncaptives), containing automobile loans originated in 2010{2019. Columns (1){(4) in both panels use rate and volume variables for prime loans, while Columns (5){(8) in both panels use rate and volume variables for nonprime loans. The main explanatory variable is the one-year policy rate instrumented by the three monetary policy shocks. The responses are estimated using the LP-IV method described in the text. We control for the lender xed e ects, four lags of the dependent variable, and four quarterly dummies to capture the seasonality. Standard errors are computed using the Driscoll-Kraay method, clustering by lender and time. t-statistics are shown in parentheses. Statistical signi cance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Table A.2: PSM Estimation

Dep Var	I(High Autofi County$_i$)		
	(1)	(2)	(3)
Log(HHI)$_{i;0}$	-0.907***	-0.703***	-0.413**
	(-5.53)	(-4.13)	(-1.97)
Log(Average Number of Auto Loans)$_{i;0}$	-0.237*	-0.223*	-0.273*
	(-1.90)	(-1.79)	(-1.77)
Log(Median Income)$_{i;0}$	-0.614***	-0.797***	-1.324***
	(-3.78)	(-4.68)	(-6.08)
Unemployment Rate$_{i;0}$	0.202***	0.183***	0.195***
	(5.23)	(4.72)	(4.11)
Log(Population)$_{i;0}$	0.916***	0.956***	1.228***
	(5.55)	(5.74)	(5.83)
Pct_Bachelor$_{i;0}$	0.031***	0.031***	0.011
	(2.79)	(2.83)	(0.75)
Pct_Poverty$_{i;0}$	0.082***	0.069***	0.129***
	(4.29)	(3.59)	(5.44)
Noncaptives Share$_{i;0}$		3.043***	0.742
		(3.84)	(0.69)
Autofi Share$_{i;0}$			127.194***
			(11.14)
N	993	993	993
Log Likelihood	-515.237	-508.151	-355.604
χ^2	214.288	223.856	261.791

This table reports the logit regression used in the PSM procedure to match high auto -share counties to low auto -share counties. It is based on county-level data containing variables capturing the local automobile market conditions based on data in automobile loan originations in 2010 and economic conditions from Census 2010. Columns (3) with full speci cation is the one used in nal matching. The dependent variable is the indicator of counties with high auto share. We exclude counties that have medium auto share. Columns (1){(3) use rate variables for prime loans, while Columns (4){(6) use rate variables for nonprime loans. HHI is also calculated based on all automobile loans originated by all lenders in each county. t-statistics are shown in parentheses. Statistical signi cance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.