Credit Fire Sales:

Captive Lending as Liquidity in Distress*

Matteo Benetton¶ Sergio Mayordomo § Daniel Paravisini ‡

August 2022

Abstract

We study the impact of vertical integration of manufacturing and credit provision on the propagation of financial shocks in durable good markets. Captive lending enables a manufacturer affected by a financing shock to generate liquidity through a *credit fire sale*: a dislocation in lending terms and standards to increase the cash collected up front from the sale of car inventory. We show evidence of credit fire sales using a new multi-country dataset on securitized car loans, and exploiting quasi-exogenous variation the demand and cost of external financing from heterogeneity in manufacturers' fraction of long term bonds maturing during the Volkswagen emissions scandal. The credit fire sale raises cash at an opportunity cost lower than the cost of external financing and the cost of a regular fire sale. Also, the credit fire sale shifts car purchases and indebtedness from high income-low risk consumers to low income-high risk ones. Thus, the direction, magnitude and heterogeneity of financial shock transmission is substantially altered when financial intermediation is internalized by manufacturers.

JEL codes: G21, G23, G50.

Keywords: Captive Finance, Fire Sales, Vertical Integration, Liquidity, Car Loans.

*We thank our discussants Bronson Argyle, Nicola Cetorelli, Anna Costello, Stefan Lewellen, Yueran Ma, Justin Murfin, Christopher Palmer, Ryan Pratt, Rodney Ramcharan, Alessandro Scopelliti and Enrico Sette. We also thank Nicola Gennaioli, Tim McQuade, Adair Morse, Emi Nakamura and numerous seminar and conference participants for helpful comments and suggestions. We are indebted to Marco Angheben and Ludovic Thebault at European DataWarehouse for providing valuable comments. The views expressed are those of the authors and do not necessarily reflect those of the Banco de España or the Eurosystem. All errors are our own.

¶Haas School of Business, University of California, Berkeley. Email: benetton@berkeley.edu.

§Banco de España . Email: sergio.mayordomo@bde.es.

‡London School of Economics. Email: d.paravisini@lse.ac.uk

1 Introduction

GM Financial is "inherently cash generative during a downturn."

Dhivya Suryadevara, General Motors CFO (CNBC, May 11th 2020)

The role played by consumer leverage in the purchase of durable goods in the global financial crisis resurfaced a long-standing academic debate on the mechanisms through which financial shocks are transmitted to the economy (Bernanke, 2018; Gertler and Gilchrist, 2018; Mian and Sufi, 2018). Most of the extant work focuses on evaluating how much of boom and bust in leverage and economic activity can be explained by innovations in stand-alone financial institutions, such as securitization and the liability maturity shortening (Keys et al., 2010; Gorton and Metrick, 2012). The analysis thus largely ignores that the crisis developed in the wake of another secular trend in the market for consumer credit: the internalization of financial intermediation by durable good manufacturers (Banner, 1958; Greenwood and Scharfstein, 2013; Bodnaruk et al., 2016).

Real estate (Stroebel, 2016), auto (Benmelech et al., 2017), and equipment (Murfin and Pratt, 2019) manufacturers have, over the last 50 years, created subsidiaries that perform bank-like activities - so called "captive lenders".[1] In the vertically integrated units, lending standards are set to maximize the joint profits of lending and manufacturing, which can change substantially the real implications of financial shocks. For example, while a distressed stand-alone lender may reduce the supply of credit to risky borrowers, distressed lenders/manufacturers may relax lending standards to boost durable good demand, resulting in increased leverage by risky consumers during downturns.

[1] According to Benmelech et al. (2017) before the crisis nonbank lenders financed more than half of all new cars bought in the United States. General Motors used to run one of the nation's largest banks, General Motors Acceptance Corp, which "contributed the bulk of the auto maker's profits, leading critics to label General Motors a bank that happened to sell cars." (See: https://www.wsj.com/articles/gm-finance-arm-is-a-profitable-cushion-against-slowing-car-sales-1528023601). In 2019 captive lenders account for about 28% of total car financing in the United States (See: https://www.experian.com/content/dam/marketing/na/automotive/quarterly-webinars/credit-trends/q1-2019-safm-final-v2.pdf).

In this paper we assess empirically how vertically integrated durable good manufacturers/lenders propagate financial shocks to consumers. We show evidence that captive lending enables manufacturers to convert car inventory into cash by changing jointly credit terms and standards, a behavior that we label a *credit fire sale*. In addition to fire-selling car inventory (Shleifer and Vishny, 2011) or adjusting car prices (Chevalier and Scharfstein, 1996; Gilchrist et al., 2017), an integrated manufacturer/lender can also increase the cash generated via car sales by: 1) lowering loan amount and maturity, which brings forward cash payments by inframarginal buyers, and 2) relaxing lending standards to risky borrowers, which boosts purchases and cash down-payments from marginal buyers.[2]

Credit fire sales have novel implications for how financial shocks affect manufacturers and propagate to consumers. The costs of a credit fire sale of car inventory—lower interest revenues and larger default losses—are only realized in the future and difficult to evaluate by outsiders. Instead, the cost of liquidating inventory (or any asset) at fire-sale prices is reflected immediately on the manufacturer's balance sheet. Also, a credit fire sale shifts car purchases and credit from infra-marginal (safe) borrowers to marginal (risky) borrowers. This implies that the integrated manufacturer's response to a liquidity shortage may induce an increase in the leverage of risky borrowers (relative to safe ones), an effect that would be difficult to reconcile with a standalone manufacturer fire-selling inventory or adjusting product prices, or with a standalone lender cutting credit supply.

Using a new multi-country dataset on over a million securitized used auto loans in Europe, we show that integrated manufacturers/lenders that face a financing shock engage in credit fire sales. The European securitized used car loan market has four distinct features that are ideal for the empirical study of credit fire sales. First, traditional stand-alone banks are

[2]Anecdotal evidence during the Covid-19 Pandemic stresses the role of captive lenders for manufacturers cash management. For example, Ford Chief Operating Officer Jim Farley said Ford Credit "has been indispensable" during the pandemic, while GM's Suryadevara said GM Financial is "inherently cash generative during a downturn". In the first quarter of 2020, GM received a $400 million dividend from GM Financial, while Ford Credit distributed $275 million to its parent company (See: https://www.cnbc.com/2020/05/11/coronavirus-detroits-automakers-have-enough-cash-to-last-the-year-without-a-bailout.html).

active players in the market for financing used vehicles sold by integrated lenders.[3] The credit terms offered by stand-alone lenders provide a useful benchmark in the empirical analysis. Second, in the used car market we can ignore car manufacturing costs and focus on the transformation of car inventory into cash, the core mechanism behind credit fire sales. Third, .[4] Finally, securitization cannot generate cash immediately after issuing a loan (because car loans are securitized a year after issuance) and lenders internalize the financial costs of default (because lenders retain the equity tranche). As a result, auto-loan securitization is not a short-run substitute for credit fire sales, and it is unlikely to distort loan terms and lending standards through agency or asymmetric information considerations.

We begin our analysis by documenting how captive lenders adjust credit terms and standards—relative to terms offered by stand-alone banks, and to purchase the same model/make vehicle in the same location—when their associated manufacturer faces *financing distress*. Throughout the paper we define financing distress as the concurrent increase in the cost of, and the demand for, external funding.[5] Before addressing the issue of endogeneity, we document stylized facts consistent with integrated manufacturers/lenders using credit fire sales as a tool for liquidity management, remaining agnostic on the reasons for financing distress. We measure changes in the cost of external financing using the high frequency variation in credit default swap (CDS) spreads. We measure the demand for financing, or a manufacturer's liquidity needs, using the fraction of outstanding long term bonds maturing in a given month.

The stylized facts, derived from specifications that include car-model $\times$ geographical market $\times$ month fixed-effects, are as follows. In the intensive margin, captive lenders tighten loan terms (reduce loan amount and maturity, increase interest rates) relative to stand-alone banks when their associated manufacturer is in financing distress. In the extensive margin, captive lenders increase the proportion of credit issued to buyers without income

[3]According to a study by Roland Berger in 2016 the captive market share is around 36% in France, Italy and Spain, and 45% in Germany.

[4]According to Nurski and Verboven (2016), who study the impact of exclusive dealing on entry in the European car market, around 70% of European car dealers practice exclusive dealing.

[5]

verification or stable sources of income (e.g., students, self-employed, unemployed). The apparent contraction of credit supply in the intensive margin and increase in the extensive margin can be reconciled through the logic of a credit fire sale: both adjustments increase the cash generated up front from the sale of used car inventory. The changes in lending standards are associated with a significant and economically large increase in the probability of future repayment arrears, even after controlling for changes in observable borrower characteristics. These stylized facts are robust to alternative specifications (e.g., comparing captive and stand-alone within narrower market definitions, controlling for unobservable characteristics of the cars with bins of car values) and sample sub-periods (e.g., with or without large CDS price changes), which makes them difficult to reconcile with alternative interpretations.

We then provide evidence of a causal link between a manufacturer's financing distress and credit fire sales. We exploit the events surrounding the Volkswagen emissions scandal as a natural experiment that generated unexpected and exogenous variation in manufacturer financing distress. On September 18, 2015, the U.S. Environmental Protection Agency (EPA) found that approximately 500,000 Volkswagen diesel-engine vehicles sold in the US contained a defeat device that could detect when the car was being tested, changing its performance to improve the test result.[6] The days following the discovery, Volkswagen's CDS price quadrupled, and that of all other manufacturers increased by 50% on average. We posit that for manufacturers *excluding* Volkswagen with a large fraction of bonds maturing in the quarter after the event (high liquidity needs), the Volkswagen scandal triggered an exogenous financial distress event: the coincidence of an increase in the cost and demand of external financing unrelated to firm fundamentals. We use the auto manufacturers that also experienced a CDS price increase, but had a small fraction of bonds maturing in the quarter after the event (low liquidity needs), as a counterfactual in a difference-in-difference analysis.[7] We estimate specifications that compare credit terms and standards offered by

[6] A number of recent papers study the Volkswagen emission scandal and its implication for example for health outcomes (Alexander and Schwandt, 2019) and collective reputation (Bachmann et al., 2019).

[7] The research design is close to Almeida et al. (2009), who compare firms whose long-term debt was scheduled to mature early in 2007 (onset of the Financial Crisis) to matched firms whose debt was scheduled to mature after 2008. In our setting, manufacturers classified as having high liquidity needs are BMW,

captive lenders relative to stand-alone banks, during the two months before and after the scandal. As in the initial analysis, the baseline estimation includes car-model × geographical market × month fixed-effects. In robustness specifications we control for unobserved car characteristics using fixed effects for car value bins. [8]

The findings from the causal analysis echo the stylized patterns. Integrated manufacturers/lenders with high liquidity needs make cash-generating adjustments to the loan terms when in financial distress: the CDS price increase following the Volkswagen scandal (a 50 basis point increase) causes a 36 basis points increase in loan rates, and a decrease in loan maturity and amount of 8% and 10% respectively (relative to stand-alone lenders). Captive lenders also lower lending standards in response to financial distress: the fraction of loans with future arrears increases by 1.2 percentage points—about a third relative to the mean arrears—relative to loans issued by stand-alone banks, even after controlling for observable borrower characteristics. In contrast, placebo integrated manufacturers with low liquidity needs barely change credit terms or standards despite experiencing the same increase in funding costs. Combining the results on loan terms and credit standards, our estimates show that to gain one additional euro in cash today high-liquidity-need integrated manufacturers are willing to lose 20 cents in present value terms. Hence, credit fire sales allow raising cash at an opportunity cost of about 5% annualized.

Since a credit fire sale entails a contraction of credit to infra-marginal (safe) borrowers and an expansion of credit to marginal (risky) borrowers, in theory credit fire sales unambiguously affect the car buyer risk composition, but have an ambiguous effect on the quantity of cars financed. We use the Volkswagen events to verify these conjectures. After the Volkswagen emissions scandal, integrated manufacturers/lenders with high liquidity needs increase the

Mercedes and Renault, while those with low liquidity needs are Toyota, Fiat, Opel, Peugeot and Ford. The high liquidity needs manufacturers had on average five bond issuances in the two months after the Volkswagen emissions scandal, more than double the average issuances for the low liquidity needs manufacturers (1.2).

[8] Controlling for unobserved car characteristics does not affect the point estimates. This is expected given the ex ante plausibility of the identifying assumption of the difference-in-differences estimation (that the fraction of loans maturing in September 2015 is uncorrelated with the unobserved quality of the cars sold by a manufacturer after the Volkswagen scandal). Nevertheless, we provide the results in a robustness analysis since our data do not include some car attributes, such as engine size or add-ons.

share of originations to low income borrowers (relative to stand-alone lenders with high liquidity needs). Since buyer income is positively correlated with loan repayment probability (conditional on car model, location and month), the finding implies that the credit fire sale reallocates credit towards risky borrowers. We obtain corroborating evidence using the internal credit score data for the captive arm of one high-liquidity need manufacturer and one stand-alone lender. In this subsample, the captive lender increases the share of loans to low credit score borrowers relative to the stand-alone lender by almost 20%. In contrast to the results on the borrower risk composition, the increase in manufacturer CDS prices does not have a statistically significant differential impact on the total number of cars financed by high liquidity need and low liquidity need captive lenders (relative to stand-alone lenders).

In the last part of the paper we evaluate quantitatively the liquidity created by credit fire sales using a simple two-period model of borrowers' demand for cars and loans with stand-alone and captive lenders. In the stylized model calibrated to the micro-data, we find that captive lending can lead to a relaxation of lending standards even if the integrated manufacturer is not liquidity constrained, because the profits from marginal car sales outweigh the losses from marginal defaults. We then use the model to compute the cash generated by a credit fire sale and its "car fire sale equivalent" for a stand-alone manufacturer. In our baseline calibration, we find that the average credit fire sale observed in the data generates the same amount of cash as a €1,000-1,600 reduction in car sale price by a stand-alone manufacturer, which corresponds to approximately a 8-12% discount from the equilibrium car value. Through the lens of the model, we also compare the cost of credit fire sales *relative* to car fire sales. The latter is captured by the lower revenues on the cars that would have been sold absent the price decrease; the former is due to: 1) expected losses from lending to risky marginal borrowers; 2) lower interest rate revenues from inframarginal borrowers. Our calibrated model shows that to generate the same amount of cash a credit fire sale is about 60% cheaper than a traditional fire sale for the average manufacturer.

Related literature. Our work is related to the literature on captive finance, which has proposed different explanations for the existence of captive lenders: price discrimination

(Brennan et al., 1988); asymmetric information (Stroebel, 2016); commitment problems and the Coase conjecture (Murfin and Pratt, 2019). In this paper we show that captive lending adds a new tool for liquidity management for manufacturers in financing distress.

Thus our work is related to the vast literature on liquidity shocks and financial frictions. This literature has proposed two alternative mechanisms through which a financially distressed stand-alone manufacturers can raise internal liquidity. The first is a traditional fire sale (Pulvino, 1998; Benmelech and Bergman, 2008; Campbell et al., 2011). Shleifer and Vishny (2011) define a *fire sale* as "a forced sale of an *asset* at a dislocated *price*". Our paper extends this traditional definition: a *credit fire sale* is a forced sale of an *asset bundled with financing* at dislocated *contract terms*. The integration of manufacturing and financing broadens the set of contract terms that can be adjusted to create liquidity. The cost of credit fire sales—due to lower revenues from interest payments and increased risk-taking in lending—accrue in the future and can be substantially lower than the immediate and certain losses of a traditional fire sale.

The second mechanism, proposed by work in macroeconomics to explain why prices increase during recessions, argues that manufacturers can generate internal liquidity by raising product prices when consumers face switching costs or have preferences with habit formation (Chevalier and Scharfstein, 1996; Gilchrist et al., 2017). Since credit fire sales occur through the dislocation of financing terms, they can be used to generate liquidity even if consumers have standard preferences. More importantly, credit fire sales also have potential macroeconomic implications, although not on prices. Large scale credit fire sales by distressed integrated manufacturers/lenders can lead to a reallocation of credit from safe to risky borrowers during economic downturns, potentially exacerbating aggregate leverage cycles.

Hence, our findings imply that vertical integration between production and financing fundamentally alters the credit responses to financing shocks relative to the case in which the two functions are performed by separate entities. Existing literature documents how stand-alone lenders that face a liquidity shock tighten credit supply, especially to high-risk borrowers (Khwaja and Mian, 2008; Paravisini, 2008; Ivashina and Scharfstein, 2010; Amiti and Weinstein, 2011). This paper demonstrates that a liquidity shock to a captive lender may lead to the exact opposite: an expansion in credit to high-risk borrowers. These findings imply that the integration of manufacturing and financial intermediation can change the sign, magnitude, and timing of the real effects of liquidity shocks to lenders and manufacturers. These new insights complement existing work on the transmission of financing shocks to the real economy (Almeida et al., 2009; Paravisini et al., 2014, 2015; Costello, 2020).

Finally, our work also contribute to the literature that studies car finance (Attanasio et al., 2008; Adams et al., 2009; Argyle et al., 2017, 2018, 2019; Melzer and Schroeder, 2017). While most previous work has focused on the demand for car loans, we focus on the supply side. Thus, our paper is related to Salz et al. (2020) who study with a quantitative model the effects of dealers discretion when prime borrowers have different demand-side elasticities to rate and car prices. We complement their work focusing on discretion by vertically integrated manufacturers/lenders, when borrowers are heterogeneous on the risk dimension and manufacturers experience liquidity shocks. Hence, our paper is very related to the work by Benmelech et al. (2017) who study the effect of the collapse of the asset-baked commercial paper market on auto sales, through illiquidity of nonbank lenders. We complement their work by looking at how captive lenders can instead provide liquidity in the presence of shocks to the manufacturers. In this way, our paper is also related to Hortaçsu et al. (2013), who show that financial distress can decrease demand for the distressed firm products, thus affecting cash flows. We show how integrated car manufacturers manage cash flows in response to increase in external financing costs through their captive lending units.

Overview. The remainder of the paper is organized as follows. Section 2 describes the data sources and summary statistics for traditional banks and captive lenders. Section 3 shows stylized evidence on credit fire sales and in support of the liquidity creation channel. Section 4 discusses the identification strategy and presents the results from the Volkswagen emission scandal. Section 5 presents a simple model of a car and loan market with stand-alone and captive lenders, and show the results of the quantitative exercise. Section 6 concludes.

2 Data and Setting

2.1 Data

Sources. Our main dataset comprises car loans securitised by European banks and captive lenders over the period December 2013 to December 2017. These data are available through the European Data Warehouse (EDW) and are reported according to the Asset Backed Security (ABS) template used by ECB within the framework of the 100 percent transparent policy on securitized loans. EDW collects information on all outstanding car loan securitizations from 2013. We focus on loans originated between December 2013 and December 2017 for buying used cars.[9] For our analysis the advantage of focusing on used cars is twofold. First, the coverage of new cars is poor for diversified lenders. In the final sample, only 6% of the loans for the purchase of new cars are granted by diversified lenders, whereas this fraction is 41% for the used cars.[10] Second, in the used car market we can ignore car manufacturing costs and focus on the transformation of car inventory into cash, the core mechanism behind credit fire sales.

Our final sample consists of about 1.2 million car loans granted by stand-alone banks (Banco Santander, Bank Deutsches Kraftfahrzeuggewerbe, Bank 11, BNP Paribas, Socram Banque) and captive lenders from nine large parent manufacturers (BMW, Fiat Chrysler, Ford, Mercedes, Opel/GM, Peugeot, Renault, Toyota and Volkswagen) over the period December 2013 to December 2017 to individuals domiciled in France, Germany, Italy and Spain. These loans are part of the pool of 37 securitizations and are granted for the purchase of 25 different brands and 272 different models made by the nine manufacturers mentioned above. All the loans that form our final sample are fixed-rate loans with a monthly payment frequency. In terms of coverage, for three captive lenders in our sample that operate in

[9] In Appendix A we discuss in detail how we build the final dataset used in main analyses.

[10] Our identification strategy requires that for a brand-model in a market at a certain time we always observe at least a loan issued by a captive and a loan issued by a diversified lender. This requirement is even stronger in the several sample splits that we implement to understand the joint role of manufacturers' liquidity cost and need.

Spain we collected data from the Spanish credit register from January 2016 onward. For this subset of lenders, our initial sample of securitized loans represents more than 65% of the total amount of loans granted by the three captive lenders.[11]

Our analysis combines the previously described dataset and three additional ones. The information on the lender's balance sheet is obtained from SNL (at branch or subsidiary level) and include proxies for size (logarithm of total assets), risk (equity over total assets) and profitability (ROA). CDS prices for the underlying lenders' debt securities are obtained from Reuters. We use Dealogic to conduct the analysis based on the financing needs of manufacturers. More specifically, we use information on all individual debt securities issued by the parent firm or its subsidiaries (issuance and maturity dates and amount issued) to define the liquidity needs of manufacturers.

Summary statistics. Table 1 shows the main variables used in the analysis. Panel A shows the main contract characteristics. The average car loan in the sample has an interest rates of 6.2%, a maturity of 51 months and a loan-to-value of 73%. There is lots of variation in all contract dimensions with rates ranging from 3 to 10%, maturities from 14 to 84 months and loan-to-value from about 20 to more than 110%. The average car value is about €13 thousand and car values go from about €4 thousand to €25 thousand.[12]

Panel B and C of Table 1 show borrowers characteristics and performances, respectively. The average annual gross income is about €36 thousands and it goes from about €7 thousands to more than €60 thousands. About 81% of borrowers are paid employee, 6% are self-employed, 1% student or unemployed and 11% pensioners. Income is verified in about 62% of loans. Finally, about 5% of loans are in arrears.[13]

Panel D shows the average seasoning at the securitization level. The average seasoning

[11]Additionally, the maturity in our sample (51 months) is almost identical to the one for the universe of loans in the credit register (53 months).

[12]The car value reported in our data is the sale price of the car.

[13]The arrears dummy is defined combining four variables contained in our dataset. The arrears dummy is equal to one if after one year from origination the loan has been in arrears at any time, the number of months in arrears is higher than zero, the arrears balance at the cutoff date is positive or the loan is in default. Some of these variables are missing for one captive lender and two stand-alone banks and for this reason we remove them from the analysis on arrears.

Table 1: Summary statistics

	Mean	Median	SD	P5	P95	N
Panel A: Loan terms and car value						
Interest (%)	6.18	6.00	2.21	3.00	10.00	1,155,450
Maturity (Months)	50.95	49.00	18.79	14.00	84.00	1,155,450
Size (euro)	9,216	8,269	5,640	2,125	19,599	1,155,450
Car value (euro)	13,192	12,387	6,281	4,707	24,440	1,155,450
LTV (%)	72.79	80.00	30.37	17.65	112.36	1,155,450
Panel B: Ex - ante risk measures						
Income (euro)	35,855	24,000	7,192,142	7,200	63,000	1,113,559
Paid-employed (0/1)	0.81	1	0.39	0	1	1,155,450
Self-employed (0/1)	0.06	0	0.24	0	1	1,155,450
Unemployed (0/1)	0.01	0	0.12	0	0	1,155,450
Student (0/1)	0.01	0	0.08	0	0	1,155,450
Pensioner (0/1)	0.11	0	0.31	0	1	1,155,450
Verified (0/1)	0.62	1	0.49	0	1	1,155,450
Panel C: Ex - post risk measures						
In arrears (0/1)	0.05	0.00	0.22	0.00	1.00	708,470
Panel D: Security						
Avg seasoning (Months)	15	15	5	1	22	37
Panel E: Manufacturers						
CDS (%)	1.252	1.034	0.915	0.279	3.020	441
Maturing bonds (%)	11.205	9.719	9.357	0.000	30.486	441
Panel F: Lenders						
ROA (%)	0.919	0.910	0.692	0.000	1.970	763
Equity / TA (%)	11.070	10.550	8.789	6.750	13.730	763
Log(TA)	16.597	16.902	1.273	14.487	18.414	763

Note: Summary statistics for the main variables used in the analysis. Panel A shows the main contract characteristics. The interest rate is in percentage points; maturity is in months; the size of the loan and the car value is in euros; the loan-to-value is in percentage points. Panel B shows borrowers characteristics. Income is in euros; paid-employed, self-employed, unemployed, student, pensioner are dummies for the status of the borrower; verified is a dummy equal to one if the income in the application has been verified by the lender. Panel C shows the ex-post performances. Arrears is a dummy equal to one if the loan is late payment starting one year after origination. Panel D reports the average seasoning in months at the securitization level. Panel E reports the characteristics for the manufacturers. CDS is the credit default swap of the manufacturer the first day of each month t; maturing bonds is the face value of maturing bonds in each quarter as a percentage of total outstanding bonds value at the beginning of the quarter. Panel F reports the characteristics for the lenders. ROA is return on assets; TA is total assets. The tables reports the mean, the standard deviation, the median, and 5th and 95th percentile in the full sample. N is the number of observations.

is approximately 15 months. Hence there is a lag greater than a year between the date the loan is originated and the date the loan is added to the security pool. Additionally, while we do not observe in the data what fraction of the securitization is retained by the issuer, we used the International Securities Identification Number (ISIN) to manually check the securitization prospectus. For all securitization in our sample for which we found an available prospectus the issuing lender retained a material net economic interest which is never less than 5% in accordance with regulatory requirements.[14]

Panel E and F of Table 1 show manufacturers' and lenders' variables, respectively. The average CDS in the sample is 120 basis points, but there is a lot of variation with CDS as high as 300 basis points. The average value of maturing bonds as a fraction of the total outstanding value is about 11%. There are manufacturers-month pairs with no maturing bonds, and months in which a manufacturer has more than 30% of the value of outstanding bonds maturing. Finally, we report lenders controls that we use in our regressions. Lenders average return on assets is about one, while the ratio of equity over total assets is around 11%. The average lenders' (log) total assets are around 16 millions, ranging from one to more than 18 millions.

2.2 Captive Lenders VS Stand-alone Banks

To set the stage for our empirical strategy, in this section we provide stylized facts of the difference in car loan terms and lending standards between captive lenders and traditional stand-alone banks.[15] Table 2 shows the main variables used in the analysis by lender type.

Loans granted by captive lenders have on average a significantly higher interest rate (6.8%) than loans by traditional banks (5.2%). Captive lenders also offer on average shorter

[14]For example the prospectus of one of the securitization in our sample reads: "The Seller will retain for the life of the Transaction a material net economic interest of not less than 5 per cent in accordance with Article 405 of Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012 (the "CRR")."

[15]Figure A1 in Appendix B shows the share of loans made by two captive and two traditional lenders for approximately 25 different brands. Captive lenders fully specialize in their brands: approximately 45% of PSA loans are for Citroen and 55% for Peugeot; more than 60% of Volskwagen finance loans goes to Volskwagen and Seat, which is also part of the group. The cars purchased with the loans granted by a given captive lender are part of the inventory of the car manufacturer that belongs to the same business group as the captive lender. Diversified lenders spread their loans across different brands. Bank A has no share greater than 30% in any brand, while lender B is even more diversified with no single brands accounting for more than 15% of the loans.

maturities (48 months versus 55 months) and lower loan-to-values (64% versus 85%) than traditional banks. The LTV difference comes, both, from captive lenders financing on average relatively more expensive cars (€13.7 versus 12.4 thousands) and lending smaller amounts (€8.5 versus 10.2 thousands).

Table 2: Summary Statistics by Lender Type

	Captive lenders			Diversified banks			Difference
	Mean	SD	N	Mean	SD	N	
Panel A: Loan terms and car value							
Interest (%)	6.81	2.17	681,633	5.26	1.94	473,817	1.55***
Maturity (Months)	47.98	17.38	681,633	55.22	19.89	473,817	-7.24***
Size (euro)	8,508	5,304	681,633	10,235	5,945	473,817	-1,727***
Car value (euro)	13,711	6,094	681,633	12,445	6,469	473,817	1,265***
LTV (%)	65.22	30.41	681,633	85.13	25.71	473,817	-20.90***
Panel B: Ex - ante risk measures							
Income (euro)	36,352	9,479,542	640,971	35,180	69,096	472,588	1,172
Paid-employed (0/1)	0.82	0.38	681,633	0.80	0.40	473,817	0.03***
Self-employed (0/1)	0.04	0.19	681,633	0.10	0.30	473,817	-0.06***
Unemployed (0/1)	0.02	0.14	681,633	0.00	0.05	473,817	0.02***
Student (0/1)	0.01	0.09	681,633	0.01	0.07	473,817	0.00***
Pensioner (0/1)	0.11	0.31	681,633	0.10	0.30	473,817	0.01***
Verified (0/1)	0.35	0.48	681,633	1.00	0.02	473,817	-0.6***
Panel C: Ex - post risk measures							
In arrears (0/1)	0.06	0.23	452,497	0.05	0.21	255,973	0.01***

Note: Summary statistics for the main variables used in the analysis. Panel A shows the main contract characteristics. The interest rate is in percentage points; maturity is in months; the size of the loan and the car value is in euros; the loan-to-value is in percentage points. Panel B shows borrowers characteristics. Income is in euros; paid-employed, self-employed, unemployed, student, pensioner are dummies for the status of the borrower; verified is a dummy equal to one if the income in the application has been verified by the lender. Panel C shows the ex-post performances. Arrears is a dummy equal to one if the loan is late payment starting one year after origination. The tables reports the mean and the standard deviation for captive and diversified lenders in the full sample. N is the number of observations. The last column reports the difference in means between the means for captive and diversified lenders. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

In Panel B of Table 2 we look at borrowers characteristics at origination. Borrowers from captives and banks have similar income level. Captive lenders are more likely to lend to unemployed borrowers and pensioners, while diversified lenders are more likely to lend to self-employed borrowers. All loans issued by traditional banks have the borrower's income verified at origination, while only 35% of the loans issued by captive lenders have income verification.[16] Finally, borrowers from captive lenders are about 1 percentage point more likely to be in default than borrowers from banks, 6% relative to 5% respectively.

To summarize, captive lenders offer relatively worse financing conditions (higher rate, lower maturity, lower loan-to-value) and target a segment of the buyer population that is less likely to obtain bank credit. These differences are consistent with a segmented market for auto loans, where captive lenders have some market power over customers with high shopping costs, as captives provide a convenient one-stop shop alternative, and higher risk, as captives seem to be willing to lend without income verification. The existence of market power and segmentation implies that captive lenders can adjust loan terms and lending standard to create liquidity following shocks to their parent manufactures, which is the main object of our analysis.

3 Credit Fire Sales: Stylized Evidence

A stand-alone manufacturer without a captive lender can generate liquidity internally via a fire sale, which implies adjusting the car sale price.[17] When the manufacturer also provides captive finance, the possibility of a credit fire sale arises. The manufacturer/lender can adjust an array of credit contract terms to increase the cash flows received at the time of the car purchase. First, the manufacturer/lender can reduce the price of the loan (instead of the price of the car) to sell more cars. Second, the manufacturer/lender can reduce the loan amount, which increases the cash flow from the down payment at the time of the sale, at the cost of reducing future cash flows from interest and principal payment.[18] Third, the

[16]The difference can be partly due to a technological advantage of stand alone lenders, who have access to other information about their customers (e.g., mortgage borrowing, cash account balance and activity). Moreover, due to data protection, captive lenders may not be able to verify the income status of some borrowers. Potential difference in reporting between captive and standalone lenders are not a concern for our identification strategy, unless the reporting standards also change differentially for captive lenders when the parent manufacturer CDS and liquidity needs are high.

[17]Our focus in this paper is on internal liquidity creation. The manufacturer can also acquire liquidity externally by borrowing or drawing down on credit lines, if these options are available.

[18]We do not observe the presence and value of trade-in which might impact the final cash (= car price - loan amount - trade-in value) that the transaction generates. Aggregate statistics for the US market show that about 20% of all used-car sales involve a trade-in compared to more than 40% of new-car transactions

manufacturer/lender can adjust the extensive margin directly by relaxing lending standards, which increases car purchases through the loan approval rate of prospective buyers seeking financing.[19] Relaxing standards comes at the cost of future higher losses related to default. Finally, the manufacturer/lender can reduce the time until repayment by shortening loan maturity.

This section provides stylized evidence consistent with credit fire sales being used as a tool for liquidity management. We begin by discussing our manufacturers' distress measure and empirical framework. Then we show how captive lenders adjust loan terms and lending standards relative to stand-alone lenders when the parent manufacturer experiences distress. Finally, we show that captive lending liquidity creation through a credit fire sale is more prevalent for manufacturers facing high financing costs when liquidity needs are high.

3.1 Measures and Empirical Specification

We follow Hortaçsu et al. (2013) and measure financial distress using the car manufacturers credit default swaps (CDS).[20] While the parent manufacturer and the captive lending unit may have separate funding sources, we use the manufacturer CDS as a measure of distress for the entire vertically integrated producers (i.e., the manufacturer plus the captive finance arm). Panel (a) of Figure A3 in Appendix B shows the CDS separately for Ford and Ford Motor Credit. The two CDSs are almost identical with a correlation of about 0.98.[21]

We use the following baseline empirical model to evaluate how car loan contract terms

(See: https://askwonder.com/research/cars-sold-trade-in-deals-us-qfro7n8la#:~:text=The%20National%20Automobile%20Dealers%20Association,sales%20include%20a%20trade%2Din.). Therefore for the vast majority of old car sales in our analysis it is likely that we measure the true cash generated, while for the fraction with trade-in value greater than zero we overestimate the actual cash generated. Figure A2 in Appendix B shows the cash flows for an hypothetical one-period car loan in two cases: (a) with only traditional stand-alone lenders; (b) with captive lenders.

[19]In Section 5.1 we sketch a simple model to explore this important dimension.

[20]Throughout the paper we use the term financial distress and high financing costs interchangeably.

[21]For other car makers separate high frequency data on the CDS for both the parent manufacturer and the captive unit are not available. However, we also check the yields on comparable bonds issued by manufacturers and their captive unit and find on average a very high correlation. For example, Panel (b) of Figure A3 shows the yields on a bond issued in March 2014 by Renault and on a bond with the same maturity issued in the same month by RCI (Renault Credit International). The yields are very similar with a correlation of about 0.97.

change with manufacturer distress differentially between loans financed by captive lenders and those financed by stand alone banks:

$$y_{ilbmt} = \alpha Manuf.CDS_{bt} \times Captive_l + \theta X_{ilt} + \gamma_l + \gamma_{bmt} + \epsilon_{ilbmt}, \tag{1}$$

where y_{ilbmt} is outcome of interest y (e.g., interest rate, maturity, loan amount, car value, and borrower characteristics) for individual i borrowing from lender l and buying brand-model b in market m and period t; $Manuf.CDS_{bt}$ is the manufacturer's CDS at the beginning of period t; $Captive_l$ is a dummy equal to one if the lender is a captive firm; X_{ilt} are borrower and lenders controls; γ_l are lender fixed effects; and γ_{bmt} are interacted brand-model, market and time fixed effects. The coefficient of interest is α which captures the effect of variation in manufacturer CDS on loan terms and lending standard by captive lenders *relative* to stand-alone banks. Our stringent set of fixed effects implies α is estimated from variation between loans originated by captive relative to stand-alone lenders for the same brand-model in the same market and time.

We do not observe some relevant car characteristics such as engine type or year of manufacturing, which can affect the resale value upon default among other things. For this reason, when studying the effect on contract characteristics, we also add interactions with the quintile of borrowers' income to capture the car unobserved quality within brand-model. Our quintiles of borrowers income are defined within geographical market and year. We do not include the interaction with income bins when the dependent variables are capturing lending standards as the pool of borrowers might change. Finally, equation (1) includes lenders' fixed effects, thus removing time-invariant differences in loan terms between captive and stand-alone lenders. Thus we only use the variation over time and across manufacturers in financial distress *interacted* with the type of car loan provider (captive versus stand-alone) in the estimation.[22]

[22] Note that the use of lender fixed effects captures not only time-invariant differences between captive and stand-alone lenders, but also time-invariant differences across captive lenders of different manufacturers (and across different stand-alone lenders). Also, the car-model × geographical market × month fixed-effects absorb the direct effect of manufacturers CDS on loan terms and lending standards.

3.2 Facts: Captive Contract Terms and Lending Standards

Contract terms. The estimation results using loan terms as the dependent variable are presented in Table 3. We find that when the car manufacturer's CDS increases, its captive lenders increases the interest rate for car loans relative to stand-alone banks. Our basic specification indicates that a 100 basis point increase in a manufacturer's CDS spread is associated with a 13 basis points increase in the captive loan rate (relative to stand-alone), or about 2% of the average loan rate. This increase possibly reflects the passthrough of the higher financing costs faced by the manufacturer to borrowers. If the manufacturer/lender is using lower interest rates to spur car purchases, the effect is second order relative to the impact of the cost of capital. Additionally, lower interest rates may not be the most effective way to promote sales if consumer are less sensitive to interest rates than to car prices.[23]

At the same time, captive lenders shorten maturity and decrease loan amount relative to standard banks when the car manufacturer CDS increases. The decline in maturity is statistically significant, but small in magnitude around 0.8%, while loan size declines by almost 2%. These results are consistent with a credit fire sale. Finally, we do not find evidence of differential changes in the price of the car between captive lenders and traditional banks when the CDS of the manufacturers increase. This does not imply the absence of a traditional fire sale, only that traditional fire sales do not occur more prevalently amongst cars financed by captive lenders than among car financed by stand-alone banks.

Columns (5) to (8) of Table 3 report the estimates when we include income bins to the car-model × geographical market × month fixed-effects to control for unobservable car characteristics which may be correlated with borrower income. The estimates for interest rates are not affected, while the effects on maturity and loan size become statistically insignificant (even if the magnitudes are similar).

Lending standards. We measure lending standards in two ways. First, we use loan and borrower observable characteristics that can be associated with higher repayment risk (e.g.,

[23]For example, Salz et al. (2020) find that consumers are substantially more sensitive to changes in car prices than loan rates in the US.

Table 3: Distress and captive lending: contract terms

	Contract Terms							
	Rate	Maturity	Loan size	Car value	Rate	Maturity	Loan size	Car value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Manuf. CDS × Captive Lender	0.133***	-0.008**	-0.019**	-0.006	0.130**	-0.008	-0.013	-0.000
	[0.049]	[0.004]	[0.008]	[0.008]	[0.051]	[0.005]	[0.010]	[0.009]
Fixed effects:								
Model-Region-Time	YES	YES	YES	YES	NO	NO	NO	NO
Model-Region-Time-Income	NO	NO	NO	NO	YES	YES	YES	YES
Lender	YES	YES	YES	YES	YES	YES	YES	YES
Additional controls:								
Lender-time	YES	YES	YES	YES	YES	YES	YES	YES
Borrower	YES	YES	YES	YES	YES	YES	YES	YES
Avg Dep Var	6.177	3.868	8.940	9.372	6.177	3.868	8.940	9.372
R^2	0.780	0.334	0.464	0.586	0.819	0.451	0.554	0.662
Observations	906,085	906,085	906,085	906,085	611,108	611,108	611,108	611,108

Note: The Table shows the results from equation (1). The dependent variables are the interest rate in percentage points, maturity in log, loan size in log and car value in log. Manuf. CDS is the CDS of the manufacturer of the car. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Model, region and time fixed effect are interacted fixed effects for the brand-model, the region where the car was sold and the month and year in which it was sold. Model, region, time and income fixed effect include an additional interaction with income quintiles defined within geographical market and year. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

lack of income verification, low borrower income, borrower is unemployed, etc.). Second we use the realized loan default rate. We estimate equation (1) with these risk measures as dependent variables.

Table 4 shows the results. The results for demographics variables at origination suggest a relaxation of lending standard by the captive lender when the parent company is in distress. The average income of captive loan recipients decreases relative to traditional bank loan recipients, for the same brand-model in the same market, but the effects are imprecisely estimated. Also, the fraction of loans to unemployed, self-employed, students and pensioners by captive lenders increases, relative to stand-alone banks. The estimates are statistically significant and large in magnitude. A 100 basis points increase in the manufacturer's CDS spread can be associated with a 2 percentage point increase in the fraction of unemployed and self-employed captive auto loan recipients.

Table 4: Distress and captive lending: lending standards

	Lending standards			
	Income	Other employment	Income verified	Arrears
	(1)	(2)	(3)	(4)
Manuf. CDS × Captive Lender	-0.008	0.021***	-0.053***	0.017***
	[0.005]	[0.005]	[0.013]	[0.006]
Fixed effects:				
Model-Region-Time	YES	YES	YES	YES
Lender	YES	YES	YES	YES
Age-Time	NO	NO	NO	YES
Additional controls:				
Lender-time	YES	YES	YES	YES
Borrower	NO	NO	YES	YES
Avg Dep Var	10.058	.188	.615	.053
R^2	0.478	0.330	0.887	0.308
Observations	906,085	906,085	906,085	567,860

Note: The Table shows the results from equation (1). The dependent variables proxy for ex-ante risk are the borrower income in log, a dummy for borrowers who are student, pensioner, unemployed or self-employed, and a dummy for verified income. The dependent variable for ex-post risk is a dummy equal to one if the loan is late payment starting one year after origination. Manuf. CDS is the CDS of the manufacturer of the car. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Model, region and time fixed effect are interacted fixed effects for the brand-model, the region where the car was sold and the month and year in which it was sold. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Column (3) of Table 4 shows the estimation result using an indicator for verified income as the dependent variable. The sign of the estimate indicates that the captive lender of a manufacturing company in distress decreases the share of verified income loans relative to diversified banks. The point estimate implies that a 100 basis points increase in a manufacturer's CDS spread decreases the relative share of verified income by captive lender by 5 percentage points, or 15% of the unconditional income verification rate by captive lenders.

Column (4) of Table 4 shows the results using ex-post loan performance. Loans originated by captive lenders when manufacturer's CDS spread increases by 100 basis points are 1.7 percentage points more likely to be in arrears over the course of the loan relative to loans originated by stand-alone lenders. Given a baseline default probability of approximately 5 percentage points, this represents approximately a 30% increase in the probability of future arrears.

Liquidity needs. To evaluate whether the lending behavior by captive lenders is related to liquidity creation, we estimate our baseline empirical model given by equation (1) separately in two subsamples defined by the fraction of maturing loans. First, we compute for each manufacturer in each quarter the face value of manufacturer b expiring bonds over its total amount of outstanding bonds at the beginning of the quarter. Second, we classify a car manufacturer as facing high liquidity needs, if its fraction of maturing bonds is in the top quartile of the distribution of this ratio in a quarter. Based on this classification, all manufacturers in our sample belong to the high liquidity need group in at least one month.[24] We expect the coefficient α in equation (1) in the high liquidity needs sample to capture the effect of captive lenders as liquidity providers in distress.

Table 5 shows the results. Panel A reports the results obtained for the periods in which the car manufacturer has a high relative need of liquidity, while Panel B contains the results for the period in which the car manufacturer has relatively low liquidity needs. We find that the differential adjustment of loan terms by captive lenders when the manufacturer's CDS is high have a larger magnitude and statistical significance when the fraction of maturing bonds is high. Following a 100-basis-points increase in the parent manufacturer's CDS, captive lenders increase rate by about 30 basis points when they have high liquidity needs, while the increase is about 11 basis point when the manufacturer's liquidity needs are low. Both maturity and loan-to-value decrease by a significant and large amount when the manufacturers needs liquidity, while the effects are not significant and small in magnitude when liquidity needs are low.

In columns (5) to (8) of Table 5 we look at how captive lending standards adjust during financial distress for different manufacturers' liquidity needs. When the manufacturer is

[24] For a given manufacturer to be considered it should have at least three outstanding bonds, to discard that a manufacturer with just one or two outstanding bonds that mature in a given month are classified as high liquidity needs. Results are identical if we do not impose this constraint and robust if we require that the manufacturer has at least five outstanding bonds instead of three. Table A1 in Appendix B reports the results when we impose that manufacturers should have at least five outstanding bonds.

Table 5: Captive Lenders Liquidity Creation Channel

	Contract Terms				Lending standards			
	Rate	Maturity	Loan Size	Car value	Income	Other employment	Income verified	Arrears
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: High liquidity need manufacturers								
Manuf. CDS × Captive Lender	0.292***	-0.032**	-0.040*	-0.002	-0.042***	0.020*	-0.117***	0.030***
	[0.069]	[0.014]	[0.023]	[0.018]	[0.009]	[0.012]	[0.031]	[0.010]
Avg Dep Var	6.18	3.867	8.895	9.422	9.983	.185	.564	.060
R^2	0.808	0.476	0.548	0.666	0.442	0.319	0.836	0.313
Observations	144,407	144,407	144,407	144,407	220,563	220,563	220,563	118,476
Panel B: Low liquidity need manufacturers								
Manuf. CDS × Captive Lender	0.113***	-0.004	-0.012	-0.003	0.005	0.021***	-0.040***	0.005
	[0.043]	[0.006]	[0.010]	[0.009]	[0.005]	[0.006]	[0.008]	[0.006]
Avg Dep Var	6.124	3.868	8.954	9.349	10.083	.181	.636	.052
R^2	0.824	0.442	0.554	0.659	0.486	0.334	0.904	0.319
Observations	465,375	465,375	465,375	465,375	682,679	682,679	682,679	449,309
Fixed effects:								
Model-Region-Time-Income	YES	YES	YES	YES	NO	NO	NO	NO
Model-Region-Time	NO	NO	NO	NO	YES	YES	YES	YES
Lender	YES	YES	YES	YES	YES	YES	YES	YES
Age-Time	NO	NO	NO	NO	NO	NO	NO	YES
Additional controls:								
Lender-time	YES	YES	YES	YES	YES	YES	YES	YES
Borrower	YES	YES	YES	YES	NO	NO	YES	YES

Note: The Table shows the results from equation (1). Panel A reports the case when manufacturers face high liquidity needs; Panel B reports the case when manufacturers face low liquidity needs. For each manufacturer in each quarter we compute the ratio between the face value of manufacturer expiring bonds over its total amount of outstanding bonds at the beginning of the quarter. We classify a car manufacturer as high liquidity needs, if it lies in the top quartile of the distribution of this ratio in our sample. The dependent variables are the interest rate in percentage points, maturity in logs, car value in logs, loan size in logs, income in logs, a dummy variable denoting the employment situation (student, pensioner, unemployed or self-employed), a dummy variable denoting if the income is verified and a dummy equal to one if the loan is late payment starting one year after origination. Manuf. CDS is the CDS of the manufacturer of the car. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Model, region and time fixed effect are interacted fixed effects for the brand-model, the region where the car was sold and the month and year in which it was sold. Model, region, time and income fixed effect include an additional interaction with income quintiles defined within geographical market and year. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

in distress and has a large fraction of bonds maturing, captive lenders extend more loans to borrowers with relative lower income than stand-alone lenders. The effect is large in magnitude, as borrowers' income decline by about 4%. Furthermore, the income is less likely to be verified. When the car manufactures' CDS and liquidity needs are high, captive lenders reduce the relative share of verified income by 11 percentage points, while the decrease is about 4 percentage points when the manufacturers liquidity needs are low. Finally, when the car manufactures' CDS increases by 100 basis points and liquidity needs are high, we find that loans originated by captive lenders have a 3 percentage points higher probability of future arrears, while when the CDS increases but liquidity needs are low the increase in arrears is not significant and small in magnitude.

To summarize, our results show that the differential behavior of captive lenders relative to stand-alone lenders when the parent manufacturers experience distress is strongly associated with liquidity needs. In Appendix B we show that our facts on credit fire sales are robust to controlling for bins of car values, varying the number of outstanding bonds, and excluding the Volkswagen Emission Scandal event. '

4 Evidence from the Volkswagen Emission Scandal

The results so far represent stylized evidence of credit fire sales: captive lenders adjust loan terms and relax credit standards to increase the cash paid upfront when facing liquidity needs in distress. In this section, we establish a causal link between manufacturer financial distress, liquidity needs, and the documented credit fire sale behavior. The goal is to isolate changes in captive lending terms and standards due to manufacturer funding needs, and distinguish them from those driven by demand shocks, changes in price discrimination or the value of collateral.

4.1 Empirical Strategy

In an ideal setting identification of credit fire sales requires: (i) observing the *same individual borrower* buying two *identical cars* using financing from both a captive lender and a stand-alone lenders; (ii) exogenous variation in both manufacturers' CDS and liquidity needs, all else equal. To proxy the former, we include car-model $\times$ geographical market $\times$ month $\times$ income bin fixed-effects, thus using only the variation across captive and stand-alone lenders, for the same car-model in the same market at the same time for borrowers with similar income. With respect to the latter, we exploit as a source of time-series quasi-experimental variation the short-lived effect of the Volkswagen emissions scandal on car manufacturers' funding costs, as well as cross-sectional variation in liquidity needs of different manufactures based on the fraction of bonds maturing in the quarter after the Volkswagen emissions scandal.

On September 18, 2015, the U.S. Environmental Protection Agency (EPA) found that approximately 500,000 Volkswagen diesel-engine vehicles sold in the US contained a defeat device that could detect when the car was being tested, changing the performance accordingly to improve results. Figure A4 in Appendix B shows the CDS for Volkswagen and other car manufactures. We show both the level of CDS and a version normalized to 100 in September 2015. Before the scandal the different brands have a similar trend in CDS, with minor deviations and with Volkswagen having a lower average CDS than other manufacturers. After the onset of the scandal, we observe a huge increase in the CDS of Volkswagen, which quadruples in the month of September and remain more than twice higher than before the event for several months. Other car manufacturers also experienced large increases in their CDS although to a lower extent relative to Volkswagen.

Our main identification strategy combines time-series variation in the CDS of manufacturers *other* than Volkswagen with cross-sectional variation in liquidity needs. Most notably, we divide the brands in our sample into high and low liquidity needs based on the fraction of bonds maturing in the quarter after the event relative to the outstanding amount in September 2015. This is our ex-ante measure of cross-sectional exposure to the shock. We then rank carmakers according to their liquidity needs and split them into two groups: manufacturers with high liquidity need are BMW, Mercedes, Renault, and Volkswagen, while Fiat, Ford, Opel, Peugeot and Toyota have low liquidity needs. In our exercise we exclude on purpose loans for buying Volskwagen cars and other brands of the group (Audi, Porsche, Seat, and Skoda), given the largely different change in CDS, and to minimize direct demand effects.

To illustrate the liquidity needs of these carmakers we look at the average ratio of the bonds maturing in the quarter after the Volskwagen over the total amount of bonds outstanding in September 2015. The average ratio for the three carmakers with high liquidity needs is 10.1% whereas it is equal to 5.5% for the low liquidity need group. Despite the low number of observations, the difference between these two means is statistically different from zero. The difference between the two analogous means in the quarter before the event (6.5% and 6.8%, respectively) is not statistically different from zero. This implies the heterogeneity in the fraction of bonds expiring is not a fixed firm characteristic, driven, for example, by a propensity to issue short term debt. The fact that some firms have a high fraction of bonds maturing during the Volkswagen event appears to be purely coincidental, driven by borrowing decisions made well before the scandal unfolded.[25]

We also check the number of bonds issued in the quarter after the Volkswagen emissions scandal. We find that the average number of issuances for the group with high liquidity needs is seven, while the average number of issuances for the group with low liquidity needs is one. This fact corroborates firms tend to roll over expiring long term debt, which validates the use of the fraction of bonds expiring as a measure for the demand for funding that is unrelated to contemporaneous firm fundamentals.

Figure 1 shows that manufacturers with high and low liquidity needs face a very similar

[25]Figure A5 in Appendix B shows for each month the ranking of manufacturers by liquidity needs from one (highest liquidity need) to nine (lowest liquidity need). The liquidity need is measured as the fraction of bonds maturing in the same and subsequent two months relative to the outstanding amount at the end of the previous month. The grey vertical bar identifies the month after the Volskwagen emission scandal which we use for our classification of liquidity need in our identification strategy. Figure A5 shows that the ranking of manufacturers varies substantially month to month, supporting the view that our classification does not capture fundamental differences between high- and low-liquidity need manufacturers, but predetermined quasi-random variation in bonds maturing after the Volskwagen emission scandal.

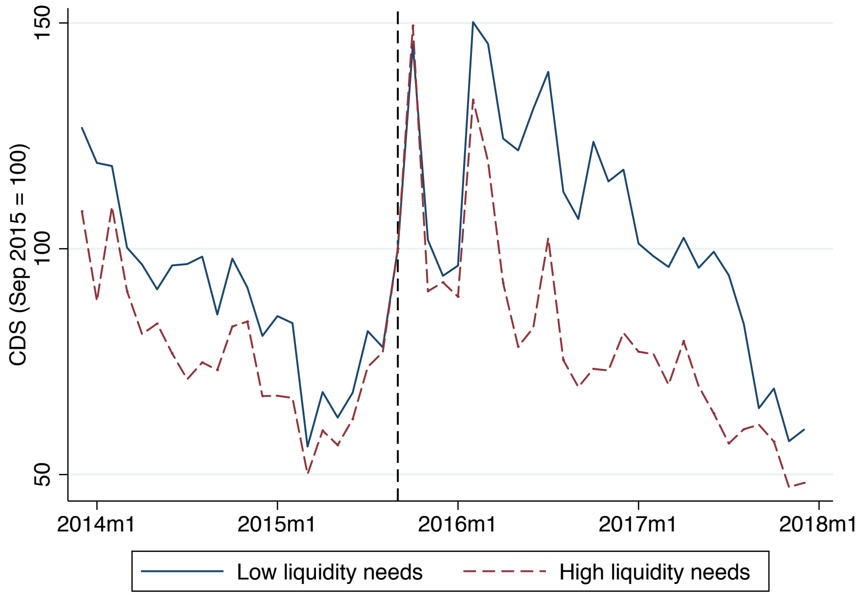


Figure 1: Volkswagen Emissions Scandal: CDS high and low liquidity manufacturers

Note: The figure shows the CDS for two groups of manufacturers which we classify based on their liquidity needs. We divide the brands in our sample into high and low liquidity needs based on the fraction of bonds maturing in the quarter after the event relative to the outstanding amount in September 2015 and we exclude on purpose loans for buying Volskwagen cars and other brands of the group (Audi, Porsche, Seat, and Skoda). BMW, Mercedes, Renault are in the high liquidity need group, while Fiat, Ford, Opel, Peugeot and Toyota are in the low liquidity need group. The figure plots the monthly averages of daily CDS from December 2013 to December 2017. The CDS values are normalized to 100 in September 2015.

pattern in terms of changes in CDS as a result of the scandal. The average CDS price of both groups increased by 50% on the date of the Volkswagen scandal, and returned to the pre-scandal level after a few months.[26] The identical reaction of CDS prices to the scandal across the two groups of firms suggests the change in the CDS prices was caused by an industry-wide shock, and not a firm-specific one. Thus, for firms with a high fraction of debt maturing, the Volkswagen scandal constitutes the double coincidence of a high demand for external funding and a sharp increase in the cost of external funding that is unrelated to firm fundamentals. Our research design exploits the increase in demand for internal liquidity due to this double coincidence as a natural experiment to look for evidence of credit fire sales.

We estimate a difference-in-difference empirical model separately for the high liquidity

[26]Also in levels the two groups experience a similar change around 50 basis point.

needs (treated) and low liquidity needs (control) manufacturers:

$$y_{ilbmt} = \alpha Post_t \times Captive_l + \theta X_{ilt} + \gamma_l + \gamma_{bmt} + \epsilon_{ilbmt}, \tag{2}$$

where y_{ilbmt} is the outcome of interest y for individual i borrowing from lender l and buying brand-model b in market m and period t; $Post_t$ is a dummy equal to one after the Volkswagen emissions scandal; and all other variables are as in equation (1). The coefficient of interest is α which captures the differential changes on loan terms and credit standards by captive lenders relative to stand-alone banks after the outbreak of the scandal. Our key estimates of interest are the αs for the manufacturers which are mostly exposed to the increase in CDS due to a high fraction of expiring bonds.

4.2 Results

Main result. Table 6 shows the results. For manufacturers with high liquidity needs, a 50 basis points increase in the CDS price leads to an increase in loan rates relative to stand-alone lenders by more than 35 basis points, a decrease in maturity by more than 9%, and in loan amounts by almost 10%. Low-liquidity-needs manufacturers, despite experiencing a similar increase in CDS, do not change loan terms relative to stand-alone lenders.

With respect to lending standards, we find that manufacturers which experience a 50 basis points increase in CDS with high liquidity needs originate loans to lower income borrower, who ex-post are 1.2 percentage points more likely to default relative to loans originated by stand-alone lenders. In contrast, placebo manufactures with low liquidity needs barely change credit terms or standards despite experiencing the same increase in CDS. If anything, placebo manufacturers increase significantly the share of borrowers with verified income relative to stand-alone lenders.

Overall, the loan terms results imply that a shock to manufacturers generates a response by captive lenders akin to a credit tightening by a traditional stand-alone lender: captive lenders increase rates, lower loan amounts and shorten maturities. Additionally, the larger

Table 6: Credit fire sales during the VW emission scandal

	Contract Terms				Lending standards			
	Rate	Maturity	Loan Size	Car value	Income	Other employment	Income verified	Arrears
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: High liquidity need manufacturers								
Post × Captive Lender	0.359***	-0.088***	-0.096**	-0.063	-0.025*	0.003	0.000	0.012**
	[0.094]	[0.022]	[0.045]	[0.044]	[0.013]	[0.015]	[0.000]	[0.006]
Avg Dep Var	5.716	3.916	8.918	9.279	9.987	.118	.453	.034
R^2	0.867	0.428	0.484	0.649	0.466	0.273	1.000	0.283
Observations	21,811	21,811	21,811	21,811	31,157	31,157	31,157	25,531
Panel B: Low liquidity need manufacturers								
Post × Captive Lender	0.013	-0.022	-0.019	0.003	-0.006	0.009	0.037***	-0.003
	[0.080]	[0.016]	[0.024]	[0.017]	[0.014]	[0.009]	[0.013]	[0.007]
Avg Dep Var	5.716	3.916	8.918	9.279	10.104	.195	.647	.052
R^2	0.763	0.409	0.540	0.635	0.463	0.266	0.781	0.318
Observations	28,549	28,549	28,549	28,549	41,888	41,888	41,888	30,811
Fixed effects:								
Model-Region-Time-Income	YES	YES	YES	YES	NO	NO	NO	NO
Model-Region-Time	NO	NO	NO	NO	YES	YES	YES	YES
Lender	YES	YES	YES	YES	YES	YES	YES	YES
Age-Time	NO	NO	NO	NO	NO	NO	NO	YES
Additional controls:								
Lender-time	YES	YES	YES	YES	YES	YES	YES	YES
Borrower	YES	YES	YES	YES	NO	NO	YES	YES

Note: The Table shows the results from equation (2) using a sample period of two months before and two months after the month of the Volkswagen Emission Scandal (September 2015). We divide the car manufacturers in our sample in two groups depending on whether they face high (Panel A) or low (Panel B) liquidity needs. This is done based on the fraction of bonds maturing in the quarter after the event relative to the outstanding amount if September 2015. High liquidity needs manufacturers include BMW, Mercedes, Renault and Volkswagen whereas Fiat, Ford, Opel, Peugeot and Toyota represent the groups with low liquidity needs. Volkswagen cars are excluded on purpose in this analysis. The dependent variables are the interest rate in percentage points, maturity in log, car value in log, loan size in log, income in logs, a dummy variable denoting the employment situation (student, pensioner, unemployed or self-employed), a dummy variable denoting if the income is verified and a dummy variable that is equal to one if the loan is in arrears starting one year after origination. Post is a dummy equal to one after the Volkswagen Emission Scandal. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Model, region and time fixed effect are interacted fixed effects for the brand-model, the region where the car was sold and the month and year in which it was sold. Model, region, time and income fixed effect include an additional interaction with income quintiles defined within geographical market and year. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

down payment and shorter maturity generate a reallocation of cash flows toward the present when liquidity is more costly, potentially avoiding the need to draw down liquidity or restore to fire sales. On the other hand, the lending standard results imply that a shock to manufacturers generates a response by captive lenders that is the opposite of a credit tightening by traditional stand-alone lenders. Captive lenders relax lending standards to promote sales and increase liquidity in the short term, at the cost of uncertain higher losses in the longer term. Both the loan terms and lending standard adjustments are consistent with the integrated manufacturer maximizing current liquidity.

We combine the results on loan terms and credit standards in Table 6 to compute a measure of the cost to generate an extra euro of cash today in terms of the net-present-value of future revenues from expected interest payments. Using the summary statistics in Table 1 and the statistically significant estimates for high-liquidity need manufacturers from Table 6, we compute the additional cash, the new monthly payment and the expected net-present-value.[27] High-liquidity-need manufacturers obtain approximately €820 in additional cash as a result of the larger down payment. Despite the significantly higher interest rate, the monthly payment for high-liquidity-need manufacturers decreases and the present value of expected revenues declines by about €1000 relative to the baseline. Putting together these numbers, our estimates show that to gain one additional euro in cash today, high-liquidity-needs manufacturers lose 20 cents in present value terms. Overall, credit fire sale allows raising cash at an opportunity cost of about 5% annualized.

Transmission. Having established a causal effect of manufacturers' distress on loan terms and lending standards via credit fire sales, we now characterize the transmission of financial shocks to consumers through an integrated manufacturer/lender. First, we look at total sales aggregating the number of cars financed in each market and month, for each

[27]Notice that for high-liquidity-needs manufacturers (the treated group) focusing on the significant coefficients is basically allowing all financial contract terms to change and keeping the car value unchanged. A reduction in the car value would imply more cash upfront if demand is elastic. By keeping the car value unchanged, we focus only on the cash generated via a credit fire sale through tightening of loan terms (the intensive margin). We compare the full credit fire sale (loan terms + lending standards) to a traditional fire sale via a price change in Section 5(R3-C2a). We discuss the calculation in detail in Appendix C.

brand-model by captive and stand-alone lenders. Second, we explore heterogeneous effects by borrowers ex-ante risk.

Columns (1) and (2) of Table 7 report the results of (log) total car financed for the low- and high-liquidity-needs manufacturers respectively. We find that after the Volkswagen emissions scandal captive lenders neither increase nor decrease the number of cars financed relative to stand-alone lenders. This result holds for both captives whose parent manufacturer has high and low liquidity needs. Hence, despite the worse financing terms (e.g., higher rates and larger down payment) the integrated manufacturer/lender does not lose volumes relative to stand-alone lenders.

A possible explanation could be that borrowers are not very sensitive to financing terms. For example Salz et al. (2020) find that consumers are less sensitive to changes in loan rates than car prices in the US. However, other financing terms such as lower loan amounts may reduce demand if car buyers are highly sensitive to down payment requirement, as Adams et al. (2009) find for subprime car borrowers in the US. A complementary explanation is that by relaxing lending standards and extending financing to marginal buyers, the captive lenders allows the manufacturers to extract liquidity from inframarginal buyers – via larger down payment, without losing aggregate volumes. We explore further this possibility by looking at the market share of low income borrowers in each market and month, for each brand-model by captive and stand-alone lenders.

Column (3) and (4) of 7 report the results. While the total number of cars does not change between captive and stand-alone lenders, we find that captive lenders with high liquidity needs increase their share of low income borrowers relative to stand-alone lenders. The higher overall lending to low income borrower is only marginally significant and large in magnitude for manufacturers with high liquidity needs, consistent with the results in Table 6. This result is suggestive that lax lending standards (and the induced increase in demand from marginal risky borrowers) allow captive lenders to offer worse loan contract terms to infra-marginal borrowers without sacrificing overall volumes. As a result of the negative shock, the behavior of the vertically integrated manufacturer/lender increase the leverage

Table 7: Effects on Total Sales and Share of Risky Borrowers

	Number of Cars (log)		Low income borrowers (%)		Low credit score borrowers (%)
Manufacturer liquidity need	Low	High	Low	High	
	(1)	(2)	(3)	(4)	(5)
Post × Captive Lender	0.028	0.019	0.004	0.025*	0.028**
	[0.023]	[0.020]	[0.014]	[0.015]	[0.011]
Fixed effects:					
Model-Region-Time	YES	YES	YES	YES	NO
Lender	YES	YES	YES	YES	YES
Model-Time	NO	NO	NO	NO	YES
Region-Time	NO	NO	NO	NO	YES
Additional controls:					
Lender-Time	YES	YES	YES	YES	YES
Borrower	NO	NO	NO	NO	YES
Avg Dep Var	.998	1.052	.484	.466	.158
R^2	0.681	0.711	0.601	0.625	0.209
Observations	11,755	7,393	11,755	7,393	10,781

Note: The Table shows the results from a variation of equation (2) using a sample period of two months before and two months after the month of the Volkswagen Emission Scandal (September 2015). The dependent variables are the logarithm of the total number of cars financed (columns (1) and (2)), the share of low income borrowers (columns (3) and (4)), which are those whose income is below the median in the region and month when they purchase the car, and the share of low credit score borrowers (columns (5)). The last column only refers to the one captive lender and one stand-alone lender for which we have credit score information. We divide the car manufacturers in our sample in two groups depending on whether the face high (Panel A) or low (Panel B) liquidity needs. This is done based on the fraction of bonds maturing in the quarter after the event relative to the outstanding amount if September 2015. High liquidity needs manufacturers include BMW, Mercedes, Renault and Volkswagen whereas Fiat, Ford, Opel, Peugeot and Toyota represent the groups with low liquidity needs. Volkswagen cars are excluded on purpose in this analysis. Post is a dummy equal to one after the Volkswagen Emission Scandal. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Brand-model, region and year-month fixed effect are interacted fixed effects for the brand-model, the region where the car was sold and the month and year in which it was sold. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

and durable consumption of ex-ante riskier individuals.

In the last column of Table 7 we provide further evidence on heterogeneous effects in the transmission of shocks through credit fire sales. For one captive lender and one stand-alone lender we obtained additional comparable information on the internal credit score for borrowers. Different lenders adopt different scoring systems (unobservable) which yield different ranks (observable) for borrowers' risk. In our context, the stand-alone lender classifies borrowers on a scale from 0 (highest risk) to 9 (lowest risk); while the captive lender classifies borrower on a scale from 1 (lowest risk) to 3 (highest risk). For comparability we create a dummy variable equal to one for borrowers with a low credit score.[28].

We estimate our difference-in-difference specification from equation (2) using as dependent variable the share of borrowers with low credit score and a slightly different set of fixed effects given the more limited sample based on only two lenders. In this case, we cannot distinguish between manufacturers with high and low liquidity needs, as we only have data on borrower credit scores for one captive lender (which in our case is in the group with high liquidity need). We can, however, study if when the parent manufacturer experiences financial distress as a result of the Volkswagen emissions scandal, the captive unit relaxes lending standard relative to a stand-alone lender financing similar cars. We find that the captive lender with high liquidity needs increases the share of loans to low credit score borrowers relative to the stand-alone lender by almost 3 percentage points. The effect are significant and large in magnitude. Given an average share of low credit score borrowers of 15%, our estimates imply an increase by almost 20%.

Overall, the findings from the causal analysis are qualitatively and quantitatively similar to the stylized aggregate patterns. Taken together, the results indicate that liquidity creation through credit fire sales is an important feature of the vertical integration of car manufacturers with auto lenders, with implications for the transmission of shocks to consumers with different risk profiles.

Robustness. In Appendix B we report the result of an additional tests and robustness checks which we only briefly discuss here. First, one possible concern with the results in Table 6 is that high liquidity need manufacturers and low liquidity need manufacturers are different for some unobservable reasons and these differences lead to different changes in contract terms and lending standards over time, irrespective of the change in CDS due to the Volkswagen scandal. We provide evidence that the outcome variables of interest (e.g., loan rates) had similar trend before the event for high and low liquidity need manufacturers. Table A5 shows the results. We cannot reject the null hypothesis of parallel trends, with the coefficient on the triple interaction term being close to zero, for all outcomes.

[28]Low credit score is defined as 1 to 7 for the stand-alone lender and 2 to 3 for the captive lender.

Second, as we discussed in Section 3, we do not observe some relevant car characteristics such as engine type or year of manufacturing. To address this limitation we control for car type with brand-model interacted with income bins fixed effects in all our baseline specifications studying loan terms. However, there could be unobservable characteristics that vary systematically between captive and traditional lenders and are correlated with both financing terms and manufacturers' distress. To lower the concern about omitted characteristics we re-estimate our difference-in-difference specification from equation (2) controlling within each brand-model for quartiles of the car value.[29] Table A6 shows the estimates of this robustness exercise. Our main results are robust to additional granular controls based on car values.

5 Quantification of Credit Fire Sales

We have shown that captive lenders decrease loan amounts and relax lending standards relative to stand-alone lenders to generate liquidity for the parent manufacturers, when the latter experience financial distress and liquidity needs are high. Additionally, we do not find differential effects on car values financed by captive lenders relative to stand-alone lenders. Thus, credit fire sales generate liquidity for the manufacturing company, without the need to adjust product prices.

In this section we develop a simple model of borrowers' demand for car loans with stand-alone and captive lenders, to gauge the importance of the new channel we document and compare it to more traditional asset fire sales. We then calibrate the model using our micro-data and perform a counterfactual analysis to quantify the effect of credit fire sales on manufacturers' liquidity.

[29] In this case we do not interact the car-model $\times$ geographical market $\times$ month fixed-effects also with the income bins because this will significantly drop the number of observations. The car value bins represent a more direct way to control for unobservable characteristics, but relative to the income bins that we use in our baseline specification they are endogenous and could in principle respond to the shocks and incentives that we analyze.

5.1 A Simple Model with Stand-alone and Captive Lenders

Car market. We model the car loan market following Perloff and Salop (1985). There are N differentiated cars producers indexed by j. We assume each manufacturer produces only one brand-model for simplicity. Manufacturers produce cars at common marginal cost k and incur a fixed cost K, and they set a price p_j for the car they sell. Manufacturer's j profits from selling the car are then given by:

$$\Pi_j(p_1, ..., p_N) = (p_j - \kappa)D_j(p_1, ..., p_N) - K, \tag{3}$$

where $D_j(p_1, ..., p_N)$ is the expected demand for manufacturer j.

Demand comes from M potential buyers indexed by i. We assume consumer i valuation for car j is given by v_{ij}, which is drawn from a distribution $F(v)$ with density $f(v)$. Consumer net surplus from purchasing car j is given by $b_{ij} = v_{ij} - p_j$. Consumer i will buy car j over car k if $b_{ij} > b_{ik}$ or $v_{ij} - p_j + p_k > v_{ik}$, which has a probability given by $F(v_{ij} - p_j + p_k)$. We assume valuations are independent and identically distributed across consumers. Thus, the fraction of consumer buying product j is given by:

$$Pr(b_{ij} \geq max_{k \neq j} b_{ik}) = \int \prod_{k \neq j} \left[F(p_k - pj + v)\right] f(v)dv. \tag{4}$$

Loan market. We assume that consumers need a loan to buy the car along the lines of Barron et al. (2008). A fraction γ of consumers is low risk (L), while a fraction $1 - \gamma$ is high risk (H). We assume that low risk consumers will always repay, while high risk will always default.

We make two simplifying assumptions on the supply side of car loans to avoid additional complications that are not central to the main channel we document in the empirical analysis. First, loans are provided in competitive markets by stand-alone banks and captive lenders. Second, a given fraction α of buyers goes to captive lenders and a fraction $1 - \alpha$ seeks a loan from stand-alone banks. In other words, credit markets are segmented.

We assume that all lenders borrow at rate r and incur a processing cost c per dollar loan. Lenders set an interest rate $i \leq \bar{i}$ based on the signal s from the consumer, which is below the maximum interest rate allowed in the car loan market $\bar{i}$.[30]

Lenders observe a signal about borrowers' type that is drawn from a normal distribution $G_L \sim N(\mu_L, \sigma)$ for low risk consumers, and $G_H \sim N(\mu_H, \sigma)$ for high risk consumers. We assume that $\mu_L > \mu_H$, i.e. low risky consumers generate higher signals on average. The per dollar profits from lending to consumer i an amount $l = \theta p$, where θ is the loan-to-value, are given by:

$$\pi_b(s_b) = P(L|s)(i - r) + (1 - P(L|s))(d - r) - c, \tag{5}$$

where $P(L|s)$ is the probability that the consumer is low risk given the signal and d is what the lender gets from the collection of the salvage value of the collateral.

Equilibrium. In Appendix C we solve the equilibrium of the model under different assumptions on the loan market. Most notably, we discuss the case when buyers do not require financing (i.e., only cash buyers); and the case when only stand-alone banks operate in the car loan market. In the main text we focus on the general case with both stand-alone and captive lenders, which is the baseline model that we calibrate with our data. First, we discuss lending standards of stand-alone banks and captive lenders. Then, we solve for the equilibrium car price and number of manufacturers.

The equilibrium interest rate is obtained by setting to zero the per-dollar profits for stand-alone banks given by equation (5):

$$i(s) = \frac{(r + c) - (1 - P(L|s))d}{P(L|s)}. \tag{6}$$

Note that if there are only low risk borrowers ($P(L|s) = 1$) we obtain the standard equation of price equal to marginal costs ($i = r + c$). Consumers with a better signal pay lower interest rates (i.e. $\frac{\partial i(s)}{\partial s} < 0$). The equilibrium signal threshold for stand-alone banks

[30] Usury limit are common in automobile lending, see for example Melzer and Schroeder (2017).

$\bar{s}_b$, below which they would not lend, is obtained by setting the per-dollar profits given by equation (5) to zero at the maximum interest rate $\bar{i}$:

$$P(L|\bar{s}_b) = \frac{c + r - d}{\bar{i} - d}. \tag{7}$$

The equilibrium signal threshold for captive lenders is obtained by looking at the joint profit from the car and loan sale, which are given by:

$$\overbrace{(p - \kappa)}^{\text{Profits from sales}} \quad + l \overbrace{\left[P(L|s)(\bar{i} - r) + (1 - P(L|s))(d - r) - c\right]}^{\text{Per dollar financing profits: } \pi_j(s_j)}. \tag{8}$$

Setting equation (8) equal to zero at the maximum interest rate $\bar{i}$, gives the optimal cutoff signal for the captive lender:

$$P(L|\bar{s}_j) = \frac{c + r - d - \frac{p-\kappa}{l}}{\bar{i} - d} \tag{9}$$

Note that $P(L|\bar{s}_j) < P(L|\bar{s}_b)$, where the latter is given by equation (7). Thus the captive lender has a lower signal threshold than the stand-alone lender $\bar{s}_j < \bar{s}_b$. The motivation behind the laxer lending standard is that the captive lender internalizes the profits from selling the car ($\frac{p-\kappa}{l}$).

The total fraction of buyers approved in the loan market is then given by:

$$(1 - \alpha) \overbrace{\left[\gamma(1 - G_L(\bar{s}_b)) + (1 - \gamma)(1 - G_H(\bar{s}_b))\right]}^{A(\bar{s}_b)\text{: Approval rate stand-alone lender}} + \alpha \overbrace{\left[\gamma(1 - G_L(\bar{s}_j)) + (1 - \gamma)(1 - G_H(\bar{s}_j))\right]}^{A(\bar{s}_b)\text{: Approval rate captive lender}}, \tag{10}$$

and the effective market size is $((1 - \alpha)A(\bar{s}_b) + \alpha A(\bar{s}_j))M$, which is strictly lower than M unless both stand-alone and captive lenders approve all buyers.

In the car market, we focus on a symmetric equilibrium where all manufacturers set the same price, i.e. $p_j = p \; \forall j = 1, ..., N$ (Perloff and Salop, 1985). Thus, each manufacturer receive a fraction $\frac{1}{N}$ of approved buyers. The total profits of manufacturer j are then given by:

$$\Pi(s_j) = \overbrace{\frac{M}{N}\left[(1-\alpha)A(\bar{s}_b) + \alpha A(\bar{s}_j)\right](p-\kappa)}^{\text{Total profits from sale}} + \overbrace{\alpha\frac{M}{N}(A(\bar{s}_j) - A(\bar{s}_b))(l\pi_j(\bar{s}_j))}^{\text{Losses from financing risky consumers}} - K = 0. \quad (11)$$

The equilibrium number of lender N is obtained by setting total profit given by equation (11) equal to zero:

$$N = \frac{\left[(1-\alpha)A(\bar{s}_b) + \alpha A(\bar{s}_j)\right] M(p-\kappa)}{K} + \frac{\alpha M(A(\bar{s}_j) - A(\bar{s}_b))(l\pi_j(\bar{s}_j))}{K}. \quad (12)$$

Finally, under the Bertrand-Nash assumption that each manufacturer chooses price to maximize its expected profits, the FOC from equation (11) is:

$$p = \kappa + \frac{1}{N(N-1)\int \left[F(v)\right]^{N-2} f(v)^2 dv} + \frac{\frac{\alpha(A(\bar{s}_j)-A(\bar{s}_b))}{\alpha A(\bar{s}_j)+(1-\alpha)A(\bar{s}_b)}\pi_j(\bar{s}_j)}{N(N-1)\int \left[F(v)\right]^{N-2} f(v)^2 dv}, \quad (13)$$

where the three terms on the right side represent the marginal costs of producing a car, the mark-up due to product differentiation, and the expected losses on the riskier buyers that captive lenders approve, respectively.

5.2 Credit Fire Sales VS Car Fire Sales

Our model is very stylized and leaves out several real world complexities. However, it allows us to highlight the key mechanism of the credit fire sales channel that we identify empirically. Most notably, through the lens of the model we quantify the effect of credit fire sales on manufacturers' liquidity, decompose the role of marginal and inframarginal borrowers, and compare our channel to a traditional car fire sale.

We calibrate the model leveraging the richness of our micro data. Table A8 in Appendix C shows the main parameters that we observe in the data or calibrate, as well as the endogenous outcomes of the model that we also observe in the data and use as target moments for our calibration. Our simple model can match quite closely the average price of the car and the number of manufacturers. We over-predict arrears, which are in the model higher on average than in the data. This result is driven by the simplifying assumption that all risky borrowers default, while in the data only a fraction of ex-ante risky borrowers end up in arrears.[31] Additionally, our simple model is able to generate a positive differential in arrears between captive and stand-alone lenders which is the main object of interest from our empirical specifications.

We then simulate the calibrated model in the baseline and two alternative scenarios. First, we calculate the equilibrium in the car loan market without captive lenders simply by setting the fraction of borrowers going to captive lenders (α) equal to zero. Second, we consider a counterfactual in which manufacturers have high liquidity needs. We proxy this case by lowering the loan-to-value (θ) for car loans originated by captive lenders by 5 percentage points, which is in line with our empirical estimates from the Volkswagen Emission Scandal.[32]

Table 8 shows the results for several variables of interest. Notice that the number of manufacturers and the price of the car exhibit only small variation across different scenarios, consistent with our empirical results that the action is taking place on the loan market. stand-alone banks' behavior is the same across scenarios, as the only difference is the exogenous fraction of borrowers that finance their cars purchases from them $(1-\alpha)$. stand-alone banks approve about 70% of borrowers, and approximately 5.7% of them end up in arrears.

First, we compare the baseline scenario to the case without captive lenders. Captive lenders have an approval rate of about 91%, or about 20 percentage points higher than stand-alone lenders. The key intuition is that captive lenders internalize the profit from the sell of the car by the parent manufacturing company. As a result of the higher approval

[31]Adding a probability of default conditional on the borrower type (safe or risky) would complicate the model without providing additional insights. If in reality safe borrowers almost never default and risky borrowers may also end up not defaulting, our estimates of the liquidity generated by credit fire sales represent a likely lower bound, as captive lenders have an even higher incentive to lend to risky borrowers who may not default than to risky borrower who always default.

[32]We obtain the loan-to-value counterfactual with high liquidity need by using the significant change in (log) quantity from column (3) of Table 5 and the price baseline price of the car (given the insignificant effect on car value in column (4) of Table 5). Hence in this second scenario we set $\theta = 0.60 < 0.65$.

Table 8: Credit fire sales VS car fire sales

	No captive lenders	Baseline	High liquidity need
Panel A: Car market			
Car price (euros)	13,180	13,166	13,166
Number of manufacturers	6	6	6
Panel B: Loan market			
Approved Buyers	24,817	29,012	29,052
Traditional Banks			
Fraction approved (%)	71	71	71
Number approved	24,817	10,423	10,423
Fraction default (%)	5.7	5.7	5.7
Captive lenders			
Fraction approved (%)		91	92
Number approved		18,589	18,692
Fraction default (%)		10.5	10.7
Average loss on high-risk loan (euros)		99	93
Δ approval rate captive - traditional		20	21
Extensive margin		4195	4298
Panel C: Credit fire sales			
Δ liquidity creation (%)		5.5	9.1
Marginal borrowers (%)		100	70
Inframarginal borrowers (%)		0	30
Car fire sale equivalent (euros)		-990	-1636
Car fire sale equivalent (% car price)		-7.5	-12.4
Cost of credit fire sale relative to car fire sale		0.37	0.35

Note: The Tables shows the several variables in three different scenarios. The Baseline scenario represents the full model described in Section 5 and calibrated using the parameters from Table A8. The "No captive lenders" assumes that in the model all borrowers go to stand-alone lenders (i.e. $\alpha = 0$). The details are discussed in Appendix C. The "High liquidity need" scenario represents the full model described in Section 5 and calibrated using the parameters from Table A8, but setting the loan-to-value by captive lenders to 0.60, rather than the baseline value of 0.65. Panel A shows the equilibrium car price in euros and number of manufacturers. Panel B shows the variables in the loan market. The total number of approved borrowers, and the fraction approved, number approved and fraction in default for stand-alone and captive lenders, respectively. Panel B also shows the average loss in euros for captive lenders on risky loans, that stand-alone lenders would not have approved. Panel C shows several variables related to the loan fire sale channel. The difference in approval rates between stand-alone and captive lenders and the extensive margin which is the extra number of borrowers approved by the captive lenders. The cash generated by the captive lenders through relaxing lending standard to marginal borrowers and changing loan-to-values to inframarginal borrowers. The car fire sale equivalent to a credit fire sale represents the decrease in car price that would generate the same cash flow as the loan fire sale expressed in euros and as a percentage of the car price. Finally, the cost of credit fire sale relative to car fire sale is the cost in terms of foregone revenues for creating the same amount of cash either by lowering the price of the car or by a credit fire sale.

rate, captive lenders experience higher average default rates at about 10%. The average loss for the defaulting high risky loans is however small given the low loan-to-value. The higher approval rate leads to almost 4.2 thousands more originations.

In Panel C of Table 8 we compute the cash that is generated by captive lenders. Given the average price of the car and the average loan-to-value by captive, the extra liquidity is computed as the down payment in euros by the buyers approved by captive lenders, who would not have been approved by stand-alone lenders. Lending to marginally riskier buyers generates approximately 5.5% in extra liquidity each month for the average manufacturer. We can then calculate the car fire sale that would generate the same amount of liquidity for the manufacturer as the credit fire sale. A decline in car price would increase liquidity for the manufacturers via additional sales, but also decrease the liquidity because of the lower price paid by buyers who would have bought at the original (higher) price. To obtain the change in sales as a result of a percentage change in prices we borrow from previous works in the IO literature, which find a demand elasticity around 4 (Goldberg, 1995; Goldberg and Verboven, 2001; Salz et al., 2020). Differently from the traditional case of cash buyers, the change in cash is the full price of the car when financed by a stand-alone lender, while it is only given by the down payment when financed by the captive lender.

The well-known trade-off though the lens of our model is captured by the following expression:

$$\overbrace{\Delta p \times \frac{M}{N} \alpha A(\bar{s}_j)(1-\theta)}^{\Delta p \times q\text{: Losses from inframarginal buyers}} \quad \overbrace{-\epsilon \times \Delta p \times \frac{M}{N} \alpha A(\bar{s}_j)(1-\theta)}^{\Delta q \times p\text{: Gains from marginal buyers}}, \tag{14}$$

where the second term is obtained by inverting the formula for the demand elasticity; and $\frac{M}{N}\alpha A(\bar{s}_j)(1-\theta)$ is the demand financed by captive lenders, which generate cash only through the fraction of the price that is paid upfront $(1-\theta)$.[33]

Thus, the change in car price for cars financed by captive lenders needed to generate

[33] We repeat the calculation assuming that fire sales occur in cars financed by, both, captive and stand-alone lenders. As expected, this requires a smaller car price decline to generate the same amount of liquidity as a credit fire sale. However, in terms of revenue losses, which we discuss below, the results are similar (because the smaller price decline is multiplied by a larger number of fire-sold vehicles).

the same amount of liquidity that is obtained through a loan fire sale can be calculated by setting (14) equal to the amount of liquidity and solving for Δp, as follows:

$$\Delta p = \frac{\text{Liquidity from credit fire sale}}{(1-\epsilon) \times \frac{M}{N} \alpha A(\bar{s}_j)(1-\theta)}. \tag{15}$$

Table 8 shows that the price of the car would have to decrease by about €990 to generate the same liquidity that captive lenders generate only via lending to marginally riskier borrower. This decline in price is equivalent to approximately 7.5% of the equilibrium car value.

Finally, the third column of Table 8 shows the case in which manufacturers have high liquidity needs. Relative to the baseline, the captive lenders approved a slightly higher number of consumers. The intuition is that the lower loan-to-value decrease the losses on the risky borrowers, who end up defaulting. Indeed we find that the average loss on high-risk loans decrease from €99 to €93. Lowering the loan-to-value generates an additional margin to create liquidity, which is now also operating via inframarginal borrowers. Lending to marginally risky buyers and asking for a larger down payment generate about 9% extra liquidity each month for the average manufacturer.[34]

We decompose increase in liquidity generated by the fire sale into the cash generated through the change in contract terms, and the cash generated though the change in lending standards. A 5-percentage-points lower loan-to-value increases monthly cash from inframarginal borrowers financed by the captive unit, accounting for 30% of the increase in liquidity. The additional cash coming from higher down payment is a likely upper bound to the cash generated via the intensive margin of credit fire sales, as the lower loan-to-value (higher down payment) may discourage some inframarginal purchases.[35] The extensive margin ac-

[34]This increase corresponds to approximately €5 millions in extra liquidity each month for the average manufacturer. This estimate pertains only the cash generated via the credit fire sale of used cars that are financed by a captive lender and then securitized. An estimate of the total amount of cash that a credit fire sale can generate to an integrated manufacturer/lender requires extrapolating our results to non-securitized used car loans and captive financed new cars, which requires stronger assumptions.

[35]In reality the fraction of borrowers financing a car and going to a captive lender (α) could be a complex function of (relative) car prices, financial contract characteristics such as interest rate, loan-to-value, and maturity, as well as other factors (e.g., proximity to a stand-alone bank brand relative to a exclusive dealer).

counts for about 70% of the increase in liquidity and it is also higher than in the baseline case. The reason for the increase is twofold. First, captive lenders are approving more borrowers than in the baseline, even if only slightly so (by about one percentage point). Second, each marginal borrower is borrowing less due to the lower loan-to-value, thus generating more liquidity upfront.

Overall, to generate the same cash of a credit fire sale, the manufacturers would have to decrease the price of the car by about €1600, or about 12.5% of its equilibrium value. In the last row of Table 8 we also report a measure of the cost of a credit fire sale *relative* to a car fire sale. The cost of lowering the price of the car is captured by lower revenues on the cars that would have been sold absent the price decrease. The cost of a credit fire sales comes from: 1) expected losses from lending to risky marginal borrowers; 2) lower interest rate revenues from inframarginal borrowers.[36] Using this simple measure, our calibration shows that to generate the same amount of cash a credit fire sale is about 60% cheaper than a traditional fire sale for the average manufacturer.

6 Conclusions

In this paper we study the role of captive finance in the car loan market when the parent manufacturing company's liquidity cost (CDS price) and need (large fraction of outstanding bonds expiring) are high. Using a new multi-country dataset on securitized car loans, we show that captive lending enables distressed manufacturers to create liquidity, at the cost of future losses, by lowering loan amounts to all borrowers and relaxing lending standards to high-risk borrowers relative to stand-alone lenders. We label this mechanism a *credit fire sale*.

While existing work has made significant progress in understanding car buyers' elasticities to down payment requirements (Adams et al., 2009), maturity and interest rates (Argyle et al., 2019), and car prices and interest rates (Salz et al., 2020), a comprehensive analysis of borrowers elasticities in segmented markets with multi-dimensional contracts would be an interesting area for future research.

[36] To compute the missed interest revenues in our simple one-period model we take a maturity of 4 years and an interest rate of 7% for loans originated by captive lenders consistent with our summary statistics in Table 2.

We quantify the mechanism by exploiting a funding shock to manufacturers resulting from the coincidence of a large fraction of maturing long-term bonds with the unexpected and temporary increase in manufacturers' CDS prices triggered by the Volkswagen emissions scandal. Taken together, the results indicate that liquidity creation through credit fire sales is an important feature of the vertical integration of car manufacturers with auto lenders.

Our mechanism has novel implications for the transmission of shocks to durable consumption and household leverage. Most notably, our findings imply that the integration of manufacturing and financial intermediation can change the sign, magnitude, and timing of the real effects of liquidity shocks to lenders and manufacturers. Finally, while our paper focuses on the auto market, our novel extended definition of fire sales may apply to many other settings where assets sales and financing are bundled together.

References

Adams, W., L. Einav, and J. Levin (2009): "Liquidity constraints and imperfect information in subprime lending," *American Economic Review*, 99, 49–84.

Alexander, D. and H. Schwandt (2019): "The Impact of Car Pollution on Infant and Child Health: Evidence from Emissions Cheating," .

Almeida, H., M. Campello, B. Laranjeira, and S. Weisbenner (2009): "Corporate debt maturity and the real effects of the 2007 credit crisis," Tech. rep., National Bureau of Economic Research.

Amiti, M. and D. E. Weinstein (2011): "Exports and financial shocks," *The Quarterly Journal of Economics*, 126, 1841–1877.

Argyle, B., T. Nadauld, and C. Palmer (2017): "Real effects of search frictions in consumer credit markets," .

Argyle, B., T. D. Nadauld, and C. Palmer (2019): "Monthly payment targeting and the demand for maturity," Tech. rep., National Bureau of Economic Research.

Argyle, B., T. D. Nadauld, C. Palmer, and R. D. Pratt (2018): "The capitalization of consumer financing into durable goods prices," Tech. rep., National Bureau of Economic Research.

Attanasio, O. P., P. Koujianou Goldberg, and E. Kyriazidou (2008): "Credit constraints in the market for consumer durables: Evidence from micro data on car loans," *International Economic Review*, 49, 401–436.

Bachmann, R., G. Ehrlich, Y. Fan, and D. Ruzic (2019): "Firms and collective reputation: a Study of the Volkswagen Emissions Scandal," Tech. rep., National Bureau of Economic Research.

Banner, P. H. (1958): "Competition, credit policies, and the captive finance company," *The Quarterly Journal of Economics*, 72, 241–258.

Barron, J. M., B.-U. CHONG, and M. E. Staten (2008): "Emergence of captive finance companies and risk segmentation in loan markets: theory and evidence," *Journal of Money, Credit and Banking*, 40, 173–192.

Benmelech, E. and N. K. Bergman (2008): "Liquidation values and the credibility of financial contract renegotiation: Evidence from US airlines," *The Quarterly Journal of Economics*, 123, 1635–1677.

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

Bernanke, B. (2018): "The real effects of the financial crisis," *Brookings Papers on Economic Activity*, 20.

Bodnaruk, A., W. O'Brien, and A. Simonov (2016): "Captive finance and firm's competitiveness," *Journal of Corporate Finance*, 37, 210–228.

Brennan, M. J., V. Maksimovics, and J. Zechner (1988): "Vendor financing," *The journal of finance*, 43, 1127–1141.

Campbell, J. Y., S. Giglio, and P. Pathak (2011): "Forced sales and house prices," *American Economic Review*, 101, 2108–31.

Chevalier, J. A. and D. S. Scharfstein (1996): "Capital-Market Imperfections and Countercyclical Markups: Theory and Evidence," *The American Economic Review*, 703–725.

Costello, A. M. (2020): "Credit market disruptions and liquidity spillover effects in the supply chain," *Journal of Political Economy*, 128, 3434–3468.

Gertler, M. and S. Gilchrist (2018): "What happened: Financial factors in the great recession," *Journal of Economic Perspectives*, 32, 3–30.

Gilchrist, S., R. Schoenle, J. Sim, and E. Zakrajšek (2017): "Inflation dynamics during the financial crisis," *American Economic Review*, 107, 785–823.

Goldberg, P. K. (1995): "Product differentiation and oligopoly in international markets: The case of the US automobile industry," *Econometrica: Journal of the Econometric Society*, 891–951.

Goldberg, P. K. and F. Verboven (2001): "The evolution of price dispersion in the European car market," *The Review of Economic Studies*, 68, 811–848.

Gorton, G. and A. Metrick (2012): "Securitized banking and the run on repo," *Journal of Financial economics*, 104, 425–451.

Greenwood, R. and D. Scharfstein (2013): "The growth of finance," *Journal of Economic Perspectives*, 27, 3–28.

Hortaçsu, A., G. Matvos, C. Syverson, and S. Venkataraman (2013): "Indirect costs of financial distress in durable goods industries: The case of auto manufacturers," *The Review of Financial Studies*, 26, 1248–1290.

Ivashina, V. and D. Scharfstein (2010): "Bank lending during the financial crisis of 2008," *Journal of Financial economics*, 97, 319–338.

Keys, B. J., T. Mukherjee, A. Seru, and V. Vig (2010): "Did securitization lead to lax screening? Evidence from subprime loans," *The Quarterly journal of economics*, 125, 307–362.

Khwaja, A. I. and A. Mian (2008): "Tracing the impact of bank liquidity shocks: Evidence from an emerging market," *American Economic Review*, 98, 1413–42.

Melzer, B. and A. Schroeder (2017): "Loan contracting in the presence of usury limits: Evidence from automobile lending," *Consumer Financial Protection Bureau Office of Research Working Paper*.

Mian, A. and A. Sufi (2018): "Finance and business cycles: the credit-driven household demand channel," *Journal of Economic Perspectives*, 32, 31–58.

Murfin, J. and R. Pratt (2019): "Who Finances Durable Goods and Why It Matters: Captive Finance and the Coase Conjecture," *The Journal of Finance*, 74, 755–793.

Nurski, L. and F. Verboven (2016): "Exclusive dealing as a barrier to entry? Evidence from automobiles," *The Review of Economic Studies*, 83, 1156–1188.

Paravisini, D. (2008): "Local bank financial constraints and firm access to external finance," *The Journal of Finance*, 63, 2161–2193.

Paravisini, D., V. Rappoport, and P. Schnabl (2015): "Specialization in bank lending: Evidence from exporting firms," Tech. rep., National Bureau of Economic Research.

Paravisini, D., V. Rappoport, P. Schnabl, and D. Wolfenzon (2014): "Dissecting the effect of credit supply on trade: Evidence from matched credit-export data," *The Review of Economic Studies*, 82, 333–359.

Perloff, J. M. and S. C. Salop (1985): "Equilibrium with product differentiation," *The Review of Economic Studies*, 52, 107–120.

Pulvino, T. C. (1998): "Do asset fire sales exist? An empirical investigation of commercial aircraft transactions," *The Journal of Finance*, 53, 939–978.

Salz, T., A. Grunewald, D. C. Low, and J. A. Lanning (2020): "Auto Dealer Loan Intermediation: Consumer Behavior and Competitive Effects," Tech. rep., National Bureau of Economic Research.

Shleifer, A. and R. Vishny (2011): "Fire sales in finance and macroeconomics," *Journal of Economic Perspectives*, 25, 29–48.

Stroebel, J. (2016): "Asymmetric information about collateral values," *The Journal of Finance*, 71, 1071–1112.

Online Appendix

The appendix is structured as follows. Section A discusses in detail how we construct our main dataset. Section B provides supplementary figures and tables with additional results and robustness checks. Section C provides additional derivations for the back-of-the-envelope calculation of Section 4 and the model of Section 5 in the main text.

A Data Construction

In this Appendix we discuss how we construct our main dataset. It comprises car loans securitised by European banks and captive lenders over the period December 2013 to December 2017. These data are available through the European Data Warehouse (EDW) and are reported according to the Asset Backed Security (ABS) template used by ECB within the framework of the 100 percent transparent policy on securitized loans. EDW collects information on all outstanding car loan securitizations from 2013. However, the information available in the first (and successive) reports of each securitization does not necessarily include all loans that were part of the pool of the securitization at origination, unless the first report is the one corresponding to the origination date. For instance, non-performing loans and loans maturing before the first reporting date could have been excluded. To avoid any bias due to this issue, we restrict our initial sample to those securitizations for which we observe the whole pool of securitized car loans over the entire life of the securitization (i.e., up to December 2017). Thus, we use information on all data reports (usually on a quarterly basis) corresponding to securitizations originated between December 2013 and December 2017.[37]

We focus on loans originated between December 2013 and December 2017 for buying used cars. For our analysis the advantage of focusing on used cars is twofold. First, the coverage of new cars is poor for diversified lenders. In the final sample, only 6% of the loans for the purchase of new cars are granted by diversified lenders in our data, whereas this fraction is 41% for the used cars.[38] Second, in the used car market we can ignore car manufacturing costs and focus on the transformation of car inventory into cash, the core mechanism behind credit fire sales.

[37]We screen all the reports available for each securitization given that new loans are added to the pool over time whereas some others disappear. Moreover, if any information is updated for any of the loans coming from a previous report, we use the new information to replace missing observations.

[38]Our identification strategy requires that for a brand-model in a market at a certain time we always observe at least a loan issued by a captive and a loan issued by a diversified lender. This requirement is even stronger in the several sample splits that we implement to understand the joint role of manufacturers' liquidity cost and need.

For the main analyses, we apply the following filters. First, we restrict our sample to amortizing car loans, which means that we discard leasing, balloon loans and any other type of non-standard car loans. Second, we consider just customers with the legal form of individuals such that we do not consider public and limited companies, partnerships, government entities and any other type of customers. Third, we restrict our sample to all loans for which we have information on the interest rate, the maturity, the amount granted at origination, the value of the car, and the car model. We also discard loans without information on borrower characteristics such as income, employment status, and region in which his/her domicile is located (i.e., NUTS codes). Fourth, our sample is winsorized at 0.1 and 99.9% levels for the car value of each specific model and the following loan characteristics: interest rate, maturity, and size. Fifth, we exclude duplicated loans given that although each loan and borrower has a unique identifier in each securitization, they could appear in more than one securitization of the same lender.[39] Sixth, we discard motorbikes, caravans, trucks; car models that appear less than 100 times and loans with a LTV below 10% at origination. Finally, we exclude from our sample brands of manufacturers without a captive lender in the group.[40]

Our final sample consists of about 1.2 million car loans granted by stand-alone banks (Banco Santander, Bank Deutsches Kraftfahrzeuggewerbe, Bank 11, BNP Paribas, Socram Banque) and captive lenders from nine large parent manufacturers (BMW, Fiat Chrysler, Ford, Mercedes, Opel/GM, Peugeot, Renault, Toyota and Volkswagen) over the period December 2013 to December 2017 to individuals domiciled in France, Germany, Italy and Spain.[41] These loans are part of the pool of 37 securitizations and are granted for the

[39]We consider that a loan is duplicated when there is more than one loan granted by the same lender at the same date for the same interest rate, amount, down-payment, and maturity; to individuals that buy the same car model at the same price and who are domiciled in the same region, with the same employment status, and the same income.

[40]These brands could belong to manufacturers with captive lenders not operating in Europe (e.g, Japanese brands) or not issuing Asset-backed securities (ABS) for financing.

[41]Note that within each group there are different subsidiaries and branches that operate in different countries: Banco Santander (Santander Consumer EFC, Santander Consumer Bank AG, Santander Consumer Bank S.p.A.), Bank Deutsches Kraftfahrzeuggewerbe GmbH, Bank11 fur Privatkunden und Handel GmbH, BNP Paribas Personal Finance, Socram Banque, BMW Bank, Fiat Chrysler (FCA Bank Deutschland GmbH, FCA Bank S.p.A., FCA Capital Espana, FGA Capital S.p.A.), Ford (FCE Bank German Branch), Mercedes-

purchase of 25 different brands and 272 different models made by the nine manufacturers mentioned above. All the loans that form of our final sample are fixed-rate loans with a monthly payment frequency.

Benz Bank, Opel/GM (GMAC Bank GmbH, Opel Bank GmbH), PSA (Banque PSA Finance, Banque PSA Finance Espana, BPF Italy, PSA Bank Deutschland GmbH, Credipar), Renault (RCI Banque, RCI Banque S.A. Niederlassung Deutschland), Toyota (TKG), Volkwagen (Volkswagen Bank GmbH, Volkswagen Bank Branch Italy, Volkswagen Finance S.A.).

B Additional Tables and Figures

In this Appendix we report the results of additional analyses and robustness checks.

First, a manufacturer is included in the main analysis if it has have at least three outstanding bonds in the given month. In this way we discard that a manufacturer with just one or two outstanding bonds that mature in a given month is classified as high liquidity needs. Table A1 reports the results when we impose that manufacturers should have at least five outstanding bonds. Results are identical if we do not impose the constraints with at least three bonds outstanding and robust if we require that the manufacturer has at least five outstanding bonds instead of three.

Second, in the baseline analysis we control for car type with brand-model interacted with income bins fixed effects. However, there could be unobservable characteristics that vary systematically between captive and traditional lenders and are correlated with both financing terms and manufacturers' distress. To lower the concern about omitted characteristics we re-estimate our model (1) controlling within each brand-model for quintiles of the car value.[42] Table A2 shows the estimates of this robustness exercise. Table A3 reports an additional robustness test which excludes the month of the Volkswagen Emission Scandal (September 2015) and the two months after. Our main results are robust to additional granular controls based on car values and the exclusion of extreme changes in manufacturers CDS.

Third, we also provide additional evidence on the lending standards margin of credit fire sales looking at borrowers' credit score. For one captive lender and one stand-alone lender we obtained additional comparable information on the internal credit score for borrowers. Different lenders adopt different scoring systems (unobservable) which yield different ranks (observable) for borrowers' risk. In our context, the stand-alone lender classifies borrowers on a scale from 0 (highest risk) to 9 (lowest risk); while the captive lender classifies borrower

[42]In this case we do not interact the car-model × geographical market × month fixed-effects also with the income bins because this will significantly drop the number of observations. The car value bins represent a more direct way to control for unobservable characteristics, but relative to the income bins that we use in our baseline specification they are endogenous and could in principle respond to the shocks and incentives that we analyze.

on a scale from 1 (lowest risk) to 3 (highest risk). For comparability we create a dummy variable equal to one for borrowers with a low credit score.[43]. We estimate our baseline model from equation (1) using as dependent variable the share of borrowers with low credit score and a slightly different set of fixed effects given the more limited sample based on only two lenders.

Table A4 shows the result. We find that when the car manufactures CDS increases by 100 basis points and liquidity needs are high, the captive lender increases its share of low credit score borrowers by about 2 percentage points. Given an average share of low credit score borrower of 15%, our estimates implies an increase by about 13%. The differential response by captive relative to stand-alone lenders to an increase in manufacturers' CDS is statistically insignificant and small in magnitude when manufactures' liquidity needs are low.

Finally, Table A6 shows the results of a robustness for the analysis exploiting the Volkswagen emission scandal. We estimate the difference-in-difference specification from equation (2) controlling within each brand-model for quartiles of the car value. In this case we do not interact the car-model $\times$ geographical market $\times$ month fixed-effects also with the income bins because this will significantly drop the number of observations. The car value bins represent a more direct way to control for unobservable characteristics, but relative to the income bins that we use in our baseline specification they are endogenous and could in principle respond to the shocks and incentives that we analyze. Our main results are robust to additional granular controls based on car values.

[43]Low credit score is defined as 1 to 7 for the stand-alone lender and 2 to 3 for the captive lender.

Table A1: Stylized evidence with at least 5 outstanding bonds

	Contract Terms				Lending standards			
	Rate	Maturity	Loan Size	Car value	Income	Other employment	Income verified	Arrears
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: High liquidity need manufacturers								
Manuf. CDS × Captive Lender	0.285***	-0.032**	-0.040*	-0.002	-0.042***	0.020*	-0.117***	0.030***
	[0.066]	[0.014]	[0.023]	[0.018]	[0.009]	[0.012]	[0.031]	[0.010]
Avg Dep Var	6.233	3.863	8.882	9.420	9.984	.183	.575	.061
R^2	0.771	0.476	0.542	0.666	0.443	0.320	0.829	0.313
Observations	139,769	139,769	139,769	139,769	213,229	213,229	213,229	114,097
Panel B: Low liquidity need manufacturers								
Manuf. CDS × Captive Lender	0.024	-0.004	-0.006	-0.002	0.005	0.023***	-0.019***	0.005
	[0.046]	[0.006]]	[0.010]	[0.010]	[0.006]	[0.006]	[0.005]	[0.006]]
Avg Dep Var	6.134	3.865	8.956	9.345	10.083	.179	.631	.052
R^2	0.831	0.441	0.553	0.659	0.487	0.335	0.910	0.319
Observations	454,677	454,677	454,677	454,677	666,200	666,200	666,200	449,309
Fixed effects:								
Model-Region-Time-Income	YES	YES	YES	YES	NO	NO	NO	NO
Model-Region-Time	NO	NO	NO	NO	YES	YES	YES	YES
Lender	YES	YES	YES	YES	YES	YES	YES	YES
Age-Time	NO	NO	NO	NO	NO	NO	NO	YES
Additional controls:								
Lender-time	YES	YES	YES	YES	YES	YES	YES	YES
Borrower	YES	YES	YES	YES	NO	NO	YES	YES

Note: The Table shows the results from equation (1) restricting to the sample with at least five outstanding bonds. Panel A reports the case when manufacturers face high liquidity needs; Panel B reports the case when manufacturers face low liquidity needs. For each manufacturer in each quarter we compute the ratio between the face value of manufacturer expiring bonds over its total amount of outstanding bonds at the beginning of the quarter. We classify a car manufacturer as facing high liquidity needs, if it lies in the top quartile of the distribution of this ratio in our sample. The dependent variables are the interest rate in percentage points, maturity in log, car value in log, loan size in log, income in logs, a dummy variable denoting the employment situation (student, pensioner, unemployed or self-employed), a dummy variable denoting if the income is verified and a dummy equal to one if the loan is late payment starting one year after origination. Manuf. CDS is the CDS of the manufacturer of the car. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Model, region and time fixed effect are interacted fixed effects for the brand-model, the region where the car was sold and the month and year in which it was sold. Model, region, time and income fixed effect include an additional interaction with income quintiles defined within geographical market and year. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A2: Stylized evidence controlling for bins of car value

	Contract Terms				Lending standards			
	Rate	Maturity	Loan Size	Car value	Income	Other employment	Income verified	Arrears
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: High liquidity need manufacturers				
Manuf. CDS × Captive Lender	0.293***	-0.023*	-0.037***	-0.007	-0.050***	0.015	-0.127***	0.046***
	[0.079]	[0.012]	[0.013]	[0.008]	[0.014]	[0.010]	[0.034]	[0.012]
Avg Dep Var	6.18	3.867	8.895	9.422	9.983	0.185	0.564	0.06
R^2	0.810	0.482	0.584	0.928	0.517	0.416	0.867	0.415
Observations	158,053	158,053	158,053	158,053	158,053	158,053	158,053	82,516
				Panel B: Low liquidity need manufacturers				
Manuf. CDS × Captive Lender	0.099*	-0.003	-0.016**	-0.006*	0.005	0.025***	-0.044***	0.009
	[0.053]	[0.005]	[0.006]	[0.003]	[0.007]	[0.007]	[0.009]	[0.007]
Avg Dep Var	6.124	3.868	8.954	9.349	10.083	0.181	0.636	0.052
R^2	0.830	0.464	0.635	0.930	0.564	0.437	0.925	0.412
Observations	499,949	499,949	499,949	499,949	499,949	499,949	499,949	317,245
Fixed effects:								
Model-Region-Time-CarValue	YES	YES	YES	YES	YES	YES	YES	YES
Lender	YES	YES	YES	YES	YES	YES	YES	YES
Age-Time	NO	NO	NO	NO	NO	NO	NO	YES
Additional controls:								
Lender-time	YES	YES	YES	YES	YES	YES	YES	YES
Borrower	YES	YES	YES	YES	NO	NO	YES	YES

Note: The Table shows the results from equation (1). Panel A reports the case when manufacturers face high liquidity needs; Panel B reports the case when manufacturers face low liquidity needs. For each manufacturer in each quarter we compute the ratio between the face value of manufacturer expiring bonds over its total amount of outstanding bonds at the beginning of the quarter. We classify a car manufacturer as facing high liquidity needs, if it lies in the top quartile of the distribution of this ratio in our sample. The dependent variables are the interest rate in percentage points, maturity in log, car value in log, loan size in log, income in logs, a dummy variable denoting the employment situation (student, pensioner, unemployed or self-employed), a dummy variable denoting if the income is verified and a dummy equal to one if the loan is late payment starting one year after origination. Manuf. CDS is the CDS of the manufacturer of the car. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Model, region, time and car-value fixed effect are interacted fixed effects for the brand-model, the region where the car was sold, the month and year in which it was sold, and quartiles of car value. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A3: Stylized evidence excluding Volkswagen emission scandal months

	Contract Terms				Lending standards			
	Rate	Maturity	Loan Size	Car value	Income	Other employment	Income verified	Arrears
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: High liquidity need manufacturers								
Manuf. CDS × Captive Lender	0.298***	-0.032**	-0.040*	-0.000	-0.037***	0.022*	-0.118***	0.031***
	[0.079]	[0.014]	[0.023]	[0.018]	[0.010]	[0.013]	[0.031]	[0.009]
Avg Dep Var	6.17	3.865	8.896	9.423	9.982	.184	.561	.058
R^2	0.808	0.475	0.548	0.666	0.441	0.320	0.842	0.311
Observations	141,618	141,618	141,618	141,618	216,042	216,042	216,042	115,226
Panel B: Low liquidity need manufacturers								
Manuf. CDS × Captive Lender	0.105	-0.004	-0.017	-0.012	0.013	0.035***	-0.060***	0.004
	[0.083]	[0.011]	[0.016]	[0.013]	[0.008]	[0.008]	[0.012]	[0.007]
Avg Dep Var	6.151	3.869	8.954	9.349	10.085	.184	.637	.052
R^2	0.824	0.442	0.557	0.661	0.488	0.339	0.902	0.319
Observations	424,216	424,216	424,216	424,216	622,731	622,731	622,731	408,106
Fixed effects:								
Model-Region-Time-Income	YES	YES	YES	YES	NO	NO	NO	NO
Model-Region-Time	NO	NO	NO	NO	YES	YES	YES	YES
Lender	YES	YES	YES	YES	YES	YES	YES	YES
Age-Time	NO	NO	NO	NO	NO	NO	NO	YES
Additional controls:								
Lender-time	YES	YES	YES	YES	YES	YES	YES	YES
Borrower	YES	YES	YES	YES	NO	NO	YES	YES

Note: The Table shows the results from equation (1) excluding the month of the Volkswagen Emission Scandal (September 2015) and the two months after. Panel A reports the case when manufacturers face high liquidity needs; Panel B reports the case when manufacturers face low liquidity needs. For each manufacturer in each quarter we compute the ratio between the face value of manufacturer expiring bonds over its total amount of outstanding bonds at the beginning of the quarter. We classify a car manufacturer as facing high liquidity needs, if it lies in the top quartile of the distribution of this ratio in our sample. The dependent variables are the interest rate in percentage points, maturity in log, car value in log, loan size in log, income in logs, a dummy variable denoting the employment situation (student, pensioner, unemployed or self-employed), a dummy variable denoting if the income is verified and a dummy equal to one if the loan is late payment starting one year after origination. Manuf. CDS is the CDS of the manufacturer of the car. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Model, region and time fixed effect are interacted fixed effects for the brand-model, the region where the car was sold and the month and year in which it was sold. Model, region, time and income fixed effect include an additional interaction with income quintiles defined within geographical market and year. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A4: ADDITIONAL STYLIZED EVIDENCE WITH BORROWERS CREDIT SCORES

	LOW CREDIT SCORE BORROWERS (%)	
Manufacturer liquidity needs	High	Low
	(1)	(2)
Manuf. CDS × Captive Lender	0.021**	0.003
	[0.010]	[0.002]
Fixed effects:		
Model-Time	YES	YES
Region-Time	YES	YES
Lender	YES	YES
Additional controls:		
Lender-Time	YES	YES
Borrower	YES	YES
Avg Dep Var	.153	.149
R^2	0.179	0.234
Observations	44,650	106,714

Note: The Table shows the results from a variation of equation (1) using a captive lenders and a stand-alone lender for which we obtained data on internal credit scoring for borrowers. The dependent variable is the fraction of low credit score borrowers. For the car manufacturer in each quarter we compute the ratio between the face value of manufacturer expiring bonds over its total amount of outstanding bonds at the beginning of the quarter. We classify the car manufacturer as facing high liquidity needs, if it lies in the top quartile of the distribution of this ratio in our sample. Manuf. CDS is the CDS of the car manufacturer. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Brand-model and year-month fixed effect are interacted fixed effects for the brand-model and the month and year in which it was sold. Region and year-month fixed effect are interacted fixed effects for the region where the car was sold and the month and year in which it was sold. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A5: Testing the parallel trend assumption

	Contract Terms				Lending standards			
	Rate	Maturity	Loan Size	Car value	Income	Other employment	Income verified	Arrears
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Captive Lender × High liquidity need × Month	-0.09	-0.03	-0.01	0.02	0.04	-0.01	-0.00	0.01
	(0.10)	(0.03)	(0.05)	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)
R^2	0.79	0.44	0.52	0.65	0.47	0.28	0.88	0.30
Observations	25,710	25,710	25,710	25,710	37,108	37,977	37,977	37,975
Fixed effects:								
Model-Region-Time-Income	YES	YES	YES	YES	NO	NO	NO	NO
Model-Region-Time	NO	NO	NO	NO	YES	YES	YES	YES
Lender	YES	YES	YES	YES	YES	YES	YES	YES
Age-Time	NO	NO	NO	NO	NO	NO	NO	YES
Additional controls:								
Lender-time	YES	YES	YES	YES	YES	YES	YES	YES
Borrower	YES	YES	YES	YES	NO	NO	YES	YES

Note: The Table shows the results from equation (2) replacing the interaction term $Post_t \times Captive_l$ with interactions $Month_t \times Captive_l$ and $Month_t \times Captive_l \times Highliquidityneed_m$, and using a sample period of two months before the month of the Volkswagen Emission Scandal (September 2015). We divide the car manufacturers in our sample in two groups depending on whether they face high or low liquidity needs. This is done based on the fraction of bonds maturing in the quarter after the event relative to the outstanding amount if September 2015. High liquidity needs manufacturers include BMW, Mercedes, Renault and Volkswagen whereas Fiat, Ford, Opel, Peugeot and Toyota represent the groups with low liquidity needs. Volkswagen cars are excluded on purpose in this analysis. The dependent variables are the interest rate in percentage points, maturity in log, car value in log, loan size in log, income in logs, a dummy variable denoting the employment situation (student, pensioner, unemployed or self-employed), a dummy variable denoting if the income is verified and a dummy variable that is equal to one if the loan is in arrears starting one year after origination. Post is a dummy equal to one after the Volkswagen Emission Scandal. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Model, region and time fixed effect are interacted fixed effects for the brand-model, the region where the car was sold and the month and year in which it was sold. Model, region, time and car-value fixed effect are interacted fixed effects for the brand-model, the region where the car was sold, the month and year in which it was sold, and quartiles of car value. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A6: Credit fire sales controlling for bins of car value

	Contract Terms				Lending standards			
	Rate	Maturity	Loan Size	Car value	Income	Other employment	Income verified	Arrears
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: High liquidity need manufacturers								
Post × Captive Lender	0.411***	-0.064***	-0.067***	-0.010	0.009	0.019	-0.000	0.022***
	[0.065]	[0.015]	[0.023]	[0.018]	[0.024]	[0.017]	[0.000]	[0.006]
Avg Dep Var	5.931	3.755	8.865	9.379	9.987	.118	.453	.034
R^2	0.864	0.421	0.528	0.916	0.549	0.387	1.000	0.374
Observations	23,719	23,719	23,719	23,719	23,719	23,719	23,719	18,973
Panel B: Low liquidity need manufacturers								
Post × Captive Lender	0.067	-0.015	-0.020	-0.002	0.001	0.005	0.033**	-0.004
	[0.083]	[0.015]	[0.016]	[0.008]	[0.019]	[0.012]	[0.013]	[0.010]
Avg Dep Var	5.716	3.916	8.918	9.279	10.104	0.195	0.647	0.052
R^2	0.775	0.484	0.676	0.937	0.552	0.376	0.830	0.415
Observations	30,432	30,432	30,432	30,432	30,432	30,432	30,432	21,544
Fixed effects:								
Model-Region-Time-CarValue	YES	YES	YES	YES	YES	YES	YES	YES
Lender	YES	YES	YES	YES	YES	YES	YES	YES
Age-Time	NO	NO	NO	NO	NO	NO	NO	YES
Additional controls:								
Lender-time	YES	YES	YES	YES	YES	YES	YES	YES
Borrower	YES	YES	YES	YES	NO	NO	YES	YES

Note: The Table shows the results from equation (2) using a sample period of two months before and two months after the month of the Volkswagen Emission Scandal (September 2015). We divide the car manufacturers in our sample in two groups depending on whether they face high (Panel A) or low (Panel B) liquidity needs. This is done based on the fraction of bonds maturing in the quarter after the event relative to the outstanding amount if September 2015. High liquidity needs manufacturers include BMW, Mercedes, Renault and Volkswagen whereas Fiat, Ford, Opel, Peugeot and Toyota represent the groups with low liquidity needs. Volkswagen cars are excluded on purpose in this analysis. The dependent variables are the interest rate in percentage points, maturity in log, car value in log, loan size in log, income in logs, a dummy variable denoting the employment situation (student, pensioner, unemployed or self-employed), a dummy variable denoting if the income is verified and a dummy variable that is equal to one if the loan is in arrears starting one year after origination. Post is a dummy equal to one after the Volkswagen Emission Scandal. Captive is a dummy equal to one if the lender originating the loan is a captive lender. Model, region and time fixed effect are interacted fixed effects for the brand-model, the region where the car was sold and the month and year in which it was sold. Model, region, time and car-value fixed effect are interacted fixed effects for the brand-model, the region where the car was sold, the month and year in which it was sold, and quartiles of car value. Region is defined as NUTS2. Lender-time controls are ROA, Equity as a fraction of total assets and the logarithm of total assets. Borrowers controls are income, employment status dummy and and dummy for verified income. Standard errors are double clustered at brand-model and region-lender levels. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

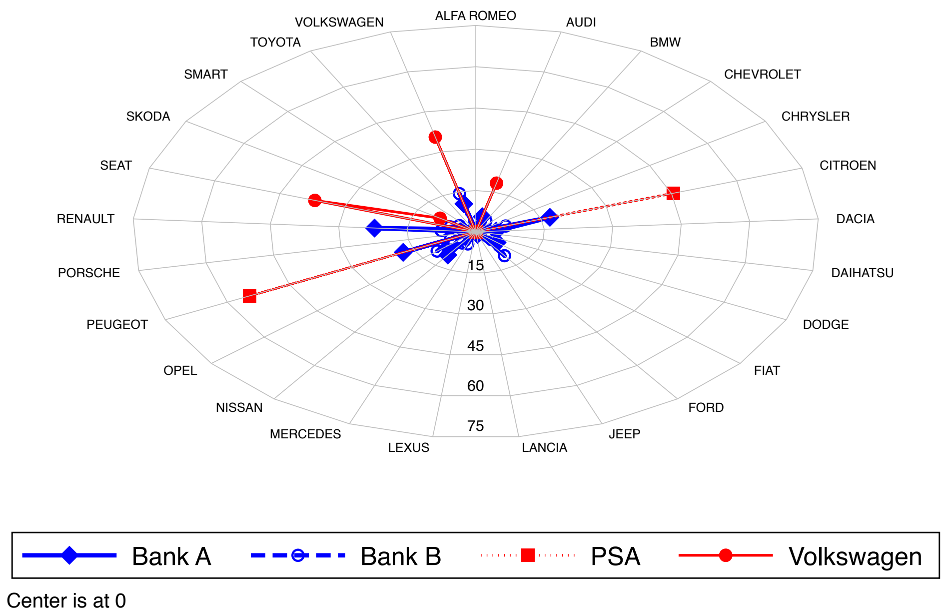
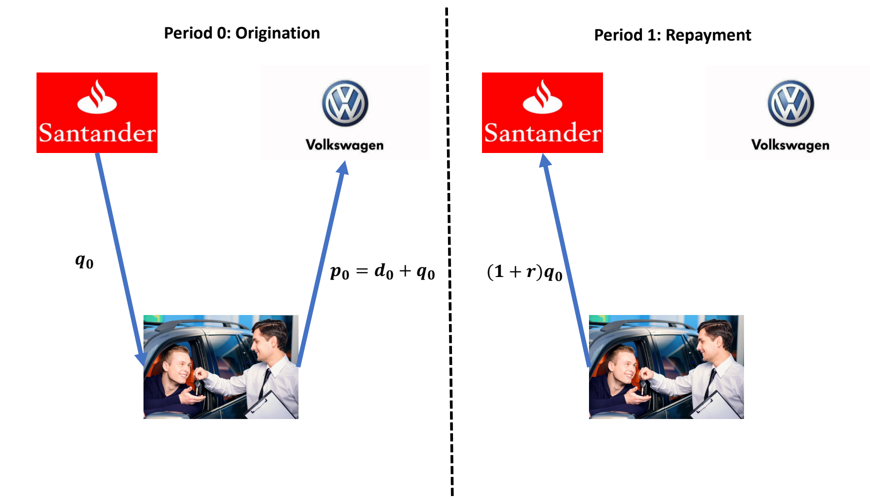
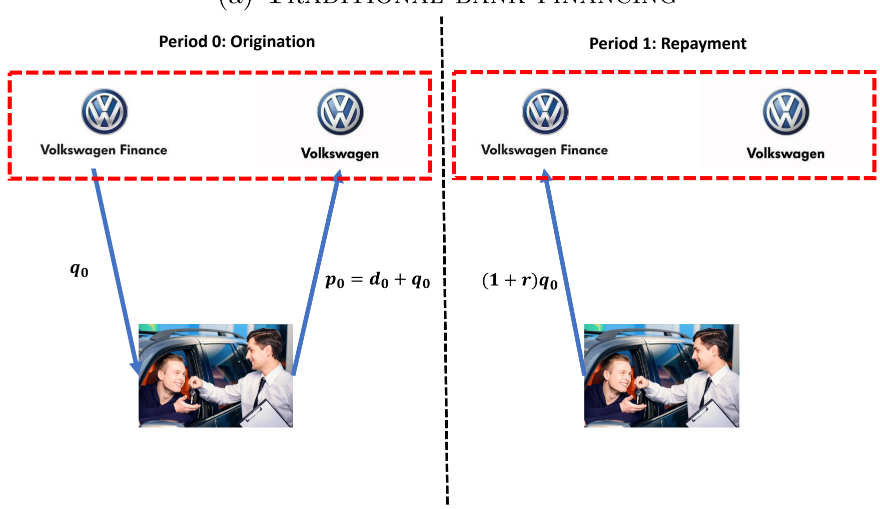


Figure A1: Specialization by brands

Note: The figure shows the share of loans made by two captive and two stand-alone lenders for approximately 25 different brands. The captive lenders are PSA finance and Volskwagen Finance. The stand-alone lenders are not reported to preserve confidentiality. The data comes from securitized loans issued by the four lenders between December 2013 and December 2017 in four European Countries (Spain, France, Germany and Italy).



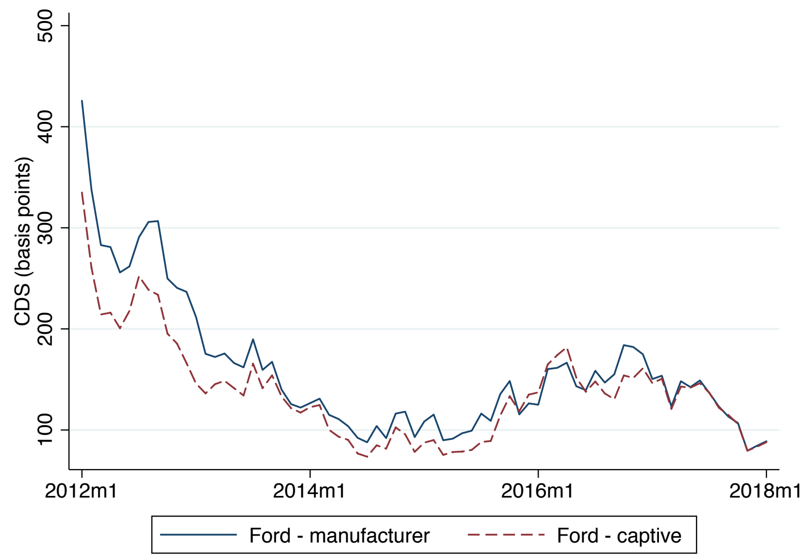
(a) Traditional bank financing



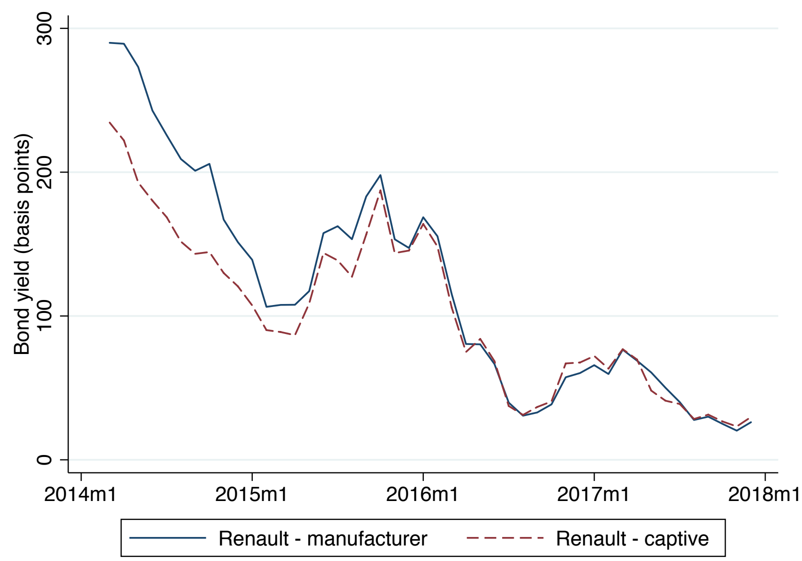
(b) Captive financing

Figure A2: Cash flows with traditional bank and captive lenders

Note: The figure shows the key flow and contract terms for a car purchase with financing at origination and repayment (assuming a one period contract). q_0 is the original loan amount, p_0 is the car value, d_0 is the down payment and r is the interest rate. Panel (a) shows the case with traditional bank financing, while panel (b) shows the case with captive financing. The red dotted line that circles the car maker and the captive lender indicates that they are part of the same group.



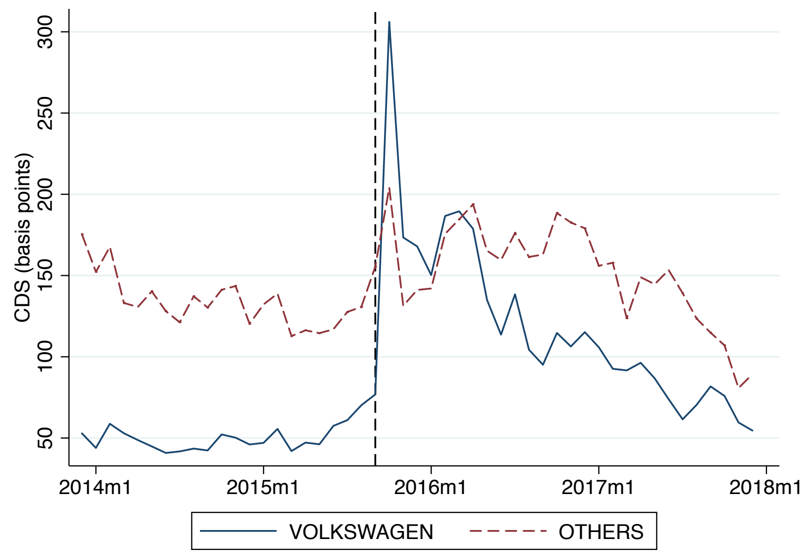
(a) CDS Ford



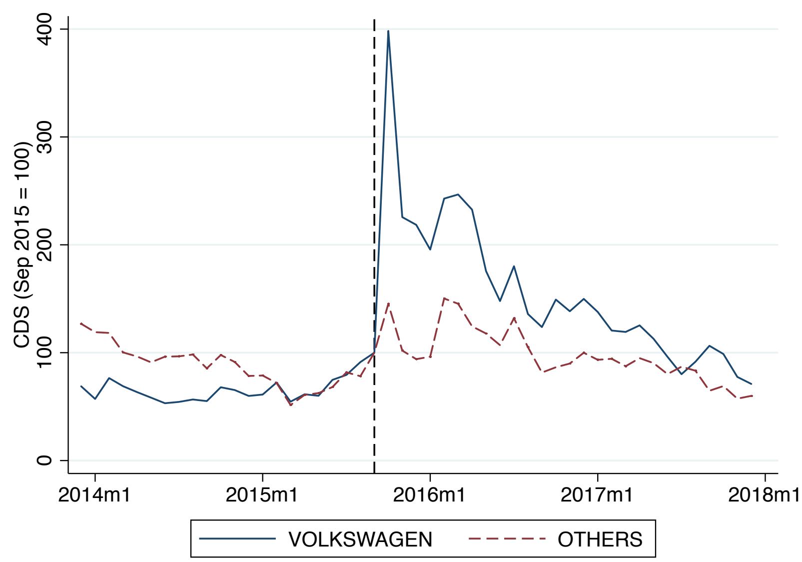
(b) Bond yields Renault

Figure A3: Financing of manufacturer and captive unit

Note: Panel (a) shows the CDS in basis points for Ford and Ford Motor Credit from December 2013 to December 2017. Panel (b) shows the yields on a bond issued in March 2014 by Renault and on a bond with the same maturity issued in the same month by RCI (Renault Credit International).



(a) CDS level



(b) CDS normalized

Figure A4: Volkswagen Emissions Scandal: CDS car manufacturers

Note: The figure shows the CDS for Volkswagen and the median across all other manufacturers. The figures plots the monthly averages of daily CDS from December 2013 to December 2017. The CDS values are in basis points in panel (a) and normalized to 100 in September 2015 in panel (b).

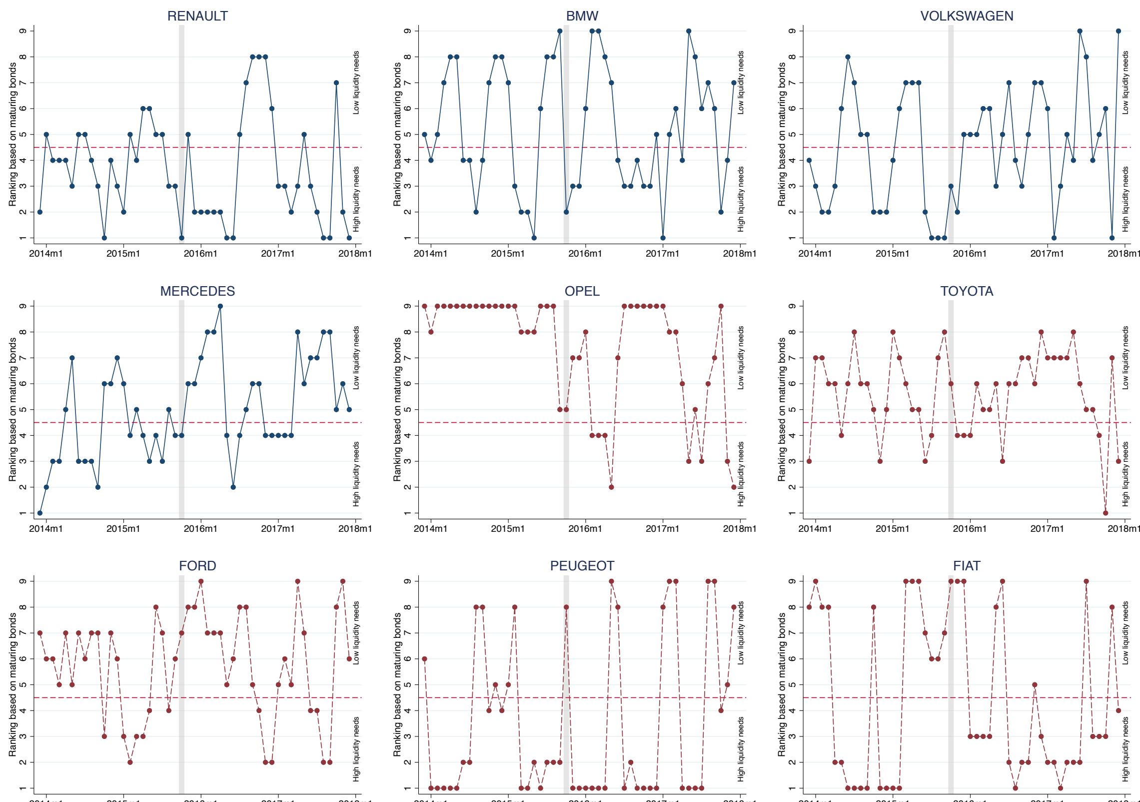


Figure A5: Ranking of Manufacturers by Liquidity Needs Over time

Note: The figure shows for each month the ranking of manufacturers by liquidity needs from one (highest liquidity need) to nine (lowest liquidity need). The liquidity need is measured as the fraction of bonds maturing in the current and subsequent two months relative to the outstanding amount at the end of the previous month. The grey vertical bar identifies the month after the Volskwagen emission scandal which we use for our classification of liquidity need in our identification strategy.

C Additional Derivations

C.1 Back-of-the-envelope Calculation

In this Appendix we discuss the calculation behind the back-of-the-envelope numbers that we present in Section 4. Table A7 reports the key inputs of and steps for the calculation. Contract terms and lending standards in column (1) are the average for captive lenders (See Table 2 in the main text). The coefficients in column (2) are the estimates for high liquidity need manufacturers following the Volkswagen emission scandal (See Panel A of Table 6 in the main text). Using the statistically significant coefficients in column (2) and the baseline levels in column (1) we compute the contract terms and fraction in arrears for high liquidity need manufacturers following the Volkswagen emission scandal, which we report in column (3).

We proxy the cost of funds as the sum of the average car manufacturer CDS plus the sovereign yield in our sample period. This gives a cost of funds of about 2%, which increases by about 50 basis points in the months following the Volskwagen emission scandal for the manufacturers in our sample (See Figure A4). We can then compute the cash manufacturers get upfront from the initial down payment and the expected net present value (NPV) of future revenues from expected interest payments both in the baseline scenario and in the high liquidity needs (and high CDS) scenario. High-liquidity-need manufacturers obtain approximately €820 in additional cash as a result of the larger down payment. Despite the significantly higher interest rate, the monthly payment for high-liquidity-need manufacturers decreases and the present value of expected revenues declines by about €1000 relative to the baseline. The latter is computed discounting the revenues from the monthly payments – including principal and interest – using the manufacturers cost of funds and multiplying by it by one minus the probability of arrears. The absolute value of the ratio of additional cash over lower expected present revenues is about 0.80. Hence, our estimates show that to gain one additional euro in cash today high-liquidity-need manufacturers loose 20 cents in

Table A7: Back-of-the-envelope calculation

	Baseline	High-liquidity needs		Difference
		Coefficient	Level	
	(1)	(2)	(3)	(4)
Contract terms:				
Interest (%)	6.81	0.359***	7.17	0.36
Maturity (Months)	47.98	-0.088***	43.76	-4.22
Size (euro)	8,508	-0.096**	5.34	-817
Car value (euro)	13,711	-0.063	13,711	0
Lending standards:				
In arrears (0/1)	0.06	0.012**	0.07	0.01
Cost of funds (%)	2.00		2.50	0.50
Cash today (euro)	5,203		6,020	817
Expected NPV (euro)	8,795		7,765	-1030
Expected NPV loss for 1 euro of cash (euro)				0.21
Annualized rate (%)				5.17

Note: Column (1) shows averages for captive lenders (See Table 2 in the main text). Column (2) shows the estimates for high liquidity need manufacturers following the Volkswagen emission scandal (See Panel A of Table 6 in the main text). Column (3) shows averages for high liquidity need manufacturers following the Volkswagen emission scandal combining columns (1) and (3), and column (4) shows the differences between column (3) and (1). The interest rate is in percentage points; maturity is in months; the size of the loan and the car value is in euros. Arrears is a dummy equal to one if the loan is late payment starting one year after origination. Cost of funds is in percentage points. Cash today is the difference between the car value and the loan amount. Expected NPV is the expected net present value of future revenues from expected interest payments.

present value terms. Overall, credit fire sale allows raising cash at an opportunity cost of about 5% annualized.

C.2 Model derivation and calibration

In this Appendix we also discuss the solutions of the model presented in Section 5.1 in two simpler cases. First, focusing only in the car market under the assumption that all buyers can purchase the car. Second, looking at both the car market and the loan market, when only stand-alone lenders offers financing.

Car market only (i.e., all cash buyers). The endogenous variables in the car market are the number of manufacturers N and the price of the cars p_j. Given a market size M and using (4), we can compute demand for manufacturer j as follows:

$$D_j(p_1,...,p_N) = M\int \left[F(p-p_j+v)\right]^{N-1} f(v)dv. \tag{16}$$

Under the Bertrand-Nash assumption that each supplier chooses price to maximize its expected profits, then the FOC from (3) is:

$$p_j = \kappa - \frac{D_j(p_1,...,p_N)}{\frac{\partial D_j(p_1,...,p_N)}{\partial p_j}}. \tag{17}$$

We focus on a symmetric equilibrium where all manufacturers set the same price, i.e. $p_j = p\ \forall j = 1,...,N$ (Perloff and Salop, 1985). Thus, each manufacturer receive a fraction $\frac{1}{N}$ of approved buyers. Combining (17) with (16) and using the symmetric equilibrium assumption, we get the optimal price:

$$p = \kappa + \frac{M\int \left[F(v)\right]^{N-1} f(v)dv}{(N-1)M\int \left[F(v)\right]^{N-2} f(v)^2 dv} = \kappa + \frac{1}{N(N-1)\int \left[F(v)\right]^{N-2} f(v)^2 dv}, \tag{18}$$

and the number of manufacturers is given by the zero profits conditions (3):

$$\frac{M}{N}(p-\kappa) - K = 0\ \rightarrow\ N^* = \frac{M(p-k)}{K}. \tag{19}$$

Loan market with only stand-alone banks. We now assume that in order to buy a car consumers need financing which is provided by stand-alone banks. The endogenous variables are now the number of manufacturers N and the price of the cars p_j as above, and also s_b, which is the optimally chosen lending signal threshold for stand-alone banks. The latter is obtained by setting lenders' profit to zero at the highest interest rate in the market as shown in (7). The approval rate by stand-alone banks is then given by:

$$A(\bar{s}_b) = \gamma(1-G_L(\bar{s}_b)) + (1-\gamma)(1-G_H(\bar{s}_b)). \tag{20}$$

Note that an increase in the signal threshold reduce the approval rate. Because now consumers who are denied a loan cannot buy the good, the effective market size becomes: $A(\bar{s}_b)M$. The latter is strictly lower than M unless stand-alone lenders approve all potential buyers. The new equilibrium number of manufacturers N is then given by:

$$A(\bar{s}_b)\frac{M}{N}(p-\kappa) - K = 0 \;\rightarrow\; N = \frac{A(\bar{s}_b)M(p-k)}{K}. \tag{21}$$

Unless traditional banks approve all consumers, we have a lower number of manufacturers than in the case in which all buyers can purchase a car irrespective of financing. And the new equilibrium price p is given by (18) with the new number of manufacturers from equation (21).

Calibration. Table A8 shows the main parameters that we observe in the data or calibrate, as well as the endogenous outcomes of the model that we also observe in the data and use as target moments for our calibration. Panel A shows the parameter of the model that we observe directly in our micro-data, namely the fraction α of borrowers going to captive lenders, the maximum rate $\bar{i}$, and the average loan-to-value by captive lenders θ.[44] We also observe in the data for a captive and a stand-alone lender the fraction of borrowers with a low credit score which we use to fix the proportion of low risk borrowers. Finally we proxy the cost of funds using the average car manufacturer CDS and the sovereign yield in our sample period.

Panel B shows the parameters that we have calibrated using the targeted endogenous outcomes of the model that we observe in the data and are reported in Panel C. To allow more flexibility in calibrating the model to the data, we allow processing cost c and collection rates upon default d to vary between stand-alone and diversified lenders.

[44] Given the assumption that loans are provided in competitive markets by stand-alone banks and captive lenders, we only need the loan-to-value by captive lenders. The latter is used to compute the losses on the risky loans approved by captive lenders, which would not have been approved by stand-alone lenders.

Table A8: Calibration

	Variables	Data	Model
Panel A: Parameters from the data			
Proportion of borrowers going to captive	α	0.58	0.58
Maximum loan rate	$\bar{i}$	0.13	0.13
Loan-to-value (captive)	θ	0.65	0.65
Proportion of low risk borrowers	γ	0.85	0.85
Cost of funds	r	0.02	0.02
Panel B: Parameters calibrated			
Marginal cost of producing car	κ		13,000
Fixed cost of producing car	K		800,000
Potential Buyers (monthly)	M		35,000
Support for uniform density function of car valuation	$f(v)$		15,000-16,000
Net collection rate upon default (standalone-captive)	d		0.01-0.02
Cost of processing loan (standalone-captive)	c		0.09-0.08
Panel C: Comparison data - model			
Car value	p	13,000	13,166
Number of car manufacturers	N	9	6
Arrears rate standalone	$\delta(s_b)$	0.05	0.06
Arrears rate captive	$\delta(s_j)$	0.06	0.10
Approved buyers (monthly)	$(1-\alpha)A(\bar{s}_b) + \alpha A(\bar{s}_j)$	30,000	29,012

Note: Panel A shows the parameters of the model that we observe directly in our micro-data. Panel B shows the parameters that we have calibrated. Panel C shows endogenous outcomes of the model that we also observe in the data and use as target to calibrate the parameters of the model.