Supplementary Appendix to the Paper "Markups and Financial Shocks"

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In this Supplementary Appendix, we present more information with respect to the analysis presented in the paper "Markups and Financial Shocks".

A Further information on the estimation of bank-loan supply shifters

Below, we provide further details with respect to the estimation of the bank-loan supply shocks by sketching the estimation approach of Amiti and Weinstein (2018, henceforth, AW). In addition, we discuss the underlying data used for this purpose, and provide further information on the ILSR dimension. At last, we present two plausibility exercises of the estimated bank-loan supply shifters.

A.1 Estimation details

AW's methodology relies on defining a bank's *total* loan growth D_{bt}^{B} as consisting of two parts; namely a bank's pre-existing loans D_{bt}^{B+} and its new loans D_{bt}^{BN}:

$$D_{bt}^{B} = \sum_{f \in G_{bt}} \left(\frac{L_{fbt} - L_{fb,t-1}}{L_{fb,t-1}} \right) \frac{L_{fb,t-1}}{\sum_f L_{fb,t-1}} + \frac{\sum_{f \notin G_{bt}} L_{fbt}}{\sum_f L_{fb,t-1}}, \tag{1}$$

where the first part of the right-hand side of equation (1) refers to D_{bt}^{B+} and the second part to D_{bt}^{BN}. Total growth of bank b's pre-existing loans is thus given by the weighted sum of the percentage growth rates of lending to firms present already in the previous period ($f \in G_{bt}$), with weights equal to the share of loans given to firm f in a bank's total outstanding loans in $t-1$ ($\sum_f L_{fb,t-1}$). Note that by defining the growth rate in percentage terms (instead of log changes), D_{bt}^{B+} can also account for terminated lending relationships. New lending is measured as the sum of loans related to a bank's new lending relationships in t ($\sum_{f \notin G_{bt}}$) over its total outstanding loans in the previous period. Equivalently, we can define a firm's *total* borrowing growth as: $D_{ft}^{F} = D_{ft}^{F+} + D_{ft}^{FN}$:

$$D_{ft}^{F} = \sum_{b \in G_{ft}} \left(\frac{L_{fbt} - L_{fb,t-1}}{L_{fb,t-1}} \right) \frac{L_{fb,t-1}}{\sum_b L_{fb,t-1}} + \frac{\sum_{b \notin G_{ft}} L_{fbt}}{\sum_b L_{fb,t-1}} \tag{2}$$

AW provide moment conditions that can be used to recover estimates of β_{bt} and α_{bt} consistent with D_{bt}^{B} and D_{ft}^{F}. Notice that a bank's total loan growth can be expressed as :

$$D_{bt}^{B} = \beta_{bt} + \sum_{f} \phi_{fb,t-1} \alpha_{ft}, \text{ with } \phi_{fb,t-1} = \frac{L_{fb,t-1}}{\sum_f L_{fb,t-1}}, \tag{3}$$

where $\phi_{fb,t-1}$ refers to the lagged share of a bank's lending to firm f in the bank's total lending. Similarly, firm-level total borrowing growth is given by:

$$D^F_{ft} = \alpha_{ft} + \sum_b \theta_{fb,t-1}\beta_{bt}, \text{ with } \theta_{fb,t-1} = \frac{L_{fb,t-1}}{\sum_b L_{fb,t-1}}, \tag{4}$$

with weight $\theta_{fb,t-1}$ measuring the lagged share of firm f's loans from bank b in its total borrowing. Since the weights ($\phi_{fb,t-1}$ and $\theta_{fb,t-1}$) are predetermined,[1] we can find β_{bt}'s and α_{ft}'s such that equations (3) and (4) hold.[2] The moment conditions uniquely determine the bank and firm shocks up to the choice of a numeraire ($F + B$ equations and $F + B$ unknowns). In a supplementary appendix, AW detail how one can solve the system of equations and recover the bank-loan supply shifters for all banks. It is worth noting that, in the absence of new lending relationships, the estimated parameters will be identical to weighted least squares (see also Tielens and Van Hove, 2017, for a formal proof). Furthermore, if we additionally apply equal weights, the approach yields parameter estimates that are equivalent to those obtained by OLS. Finally, it is worth noting that in their proposition 1, AW point out that their setup is equivalent to a model with a bank-firm interaction if the components of such an interaction term that vary only at the bank or firm level are part of the bank- and firm-specific effects.[3]

A.2 Details on loan-level data (MiMiK) and sample selection

As mentioned in the main text, MiMiK provides information about the universe of credit exposures amounting to at least 1.5 million Euro per borrower or borrower unit in Germany on a quarterly basis. There are two reasons that justify the fact that we observe lending relationships below this threshold. First, borrower units are defined as mutually dependent legal entities which may run into problems if one firm belonging to the entity faces finan-

[1] So that $E[\sum_f \phi_{fb,t-1}\epsilon_{fbt}] = \sum_f \phi_{fb,t-1}E[\epsilon_{fbt}] = 0$

[2] Note that we drop observations referring to firms with $D_{ft} > 5$ or banks with $D_{bt} > 2$. This approximates to removing the top percentile from the distribution of the respective variable.

[3] In this context, Manaresi and Pierri (2018) compare estimates of bank-loan supply shifters in line with AW's setup (see equation 1 in our paper) to those obtained from a model which also contains relationship-specific variables and find that the two types of estimates are highly correlated. They also argue that the baseline setup does not factor in potential substitution patterns and suggest that loan supply shocks of other banks may also be included in the model. However, their findings suggest that this adjustment has negligible effects on the estimated bank-loan supply shifters.

cial distress. Hence, reported lending relationships may in fact be below 1.5 million Euro; for instance, if a firm belongs to a borrower unit for which only the sum of credits across all firms (or only one loan) exceeds the reporting threshold. Another reason is that loans have to be reported if they exceed the threshold once during a quarter. For example, a loan that amounts to 2 million Euro at the beginning of the quarter may be repaid within that quarter by 90%. The credit exposure in this period would then be reported as 0.2 million Euro (see Schmieder, 2006, for more details regarding the reporting requirements of MiMiK).

Despite the reporting threshold, coverage of this data set is quite high. In particular, in 2005, it covered around 70% of the total credit volume in Germany. While the coverage is almost complete for the interbank market, reaching approximately 60% for corporate credit and 20% for household debt (see Schmieder, 2006). Note that we focus our analysis on banks' direct on-balance-sheet credit receivables from non-financial enterprises and thus exclude off-balance-sheet activities, e.g., related to derivatives and guarantees. Moreover, we only consider firms' direct credit relations in order to avoid double-counting of indirect relations in the case of affiliated enterprises. In addition, we drop inter-bank credit relations from the sample, in order to avoid reverse-causality issues. At last, we drop credit institutions with only a few lending relationships to ensure consistent estimates of the bank-supply shifters. Specifically, we remove banks with less than three borrowers at the *ILSR*-level in t and $t-1$. Finally, note that we adjust the growth rate of lending to account for M&A activities in the financial sector. We do so by forming "temporary banks", consisting of the acquired and acquiring bank one year before the takeover takes place.

A.3 Details on the ILSR dimension

As mentioned in the main paper, the *ILSR*-level refers to the following observable firm-level characteristics: sector affiliation (i.e. *I*ndustry), regional location (i.e. *L*ocation), indicators of group membership of firms as well as their total bank debt (as indicators of *S*ize), information about the number of banks a firm borrows from (i.e., number of bank *R*elations), and its legal form. Note that we consider 49 economic sectors and 200 regions. The sectors correspond to NACE 2-digit level of aggregation with some exceptions. Some 2-digit sectors were aggregated to form larger groups in order to concord NACE rev. 1 and rev. 2 classifications over time. Moreover, we consider ten firm types according to the number of banks that they borrow from, ten firm types according to their total bank debt and four firm types according to their legal form. All characteristics are fixed in the pre-sample year 2005, or the first year of their appearance for firms entering the sample later. In sum, we distinguish between more than 90,000 firm types.

A.4 Plausibility of shock estimates

In this section, we provide two types of plausibility exercises regarding the bank-loan supply shifters.

A.4.1 Controlling for credit demand with observable firm characteristics

We analyze the ability of our *ILSR* approach to account for demand effects by estimating two sets of bank-loan supply shocks on a sample comprising multi-bank firms only. Specifically, we estimate equation (1) in the main paper and vary the type of demand control. Starting with firm-time effects (α_{ft}) as the benchmark case, we then control for credit demand using observable firm-level characteristics as outlined above and compare this with bank shocks obtained when neglecting any demand control.[4] We then evaluate the extent to which bank shocks, estimated using observable firm characteristics, as demand controls correspond to bank shocks applying firm-time effects, by regressing the former on the latter, while controlling for year fixed effects.[5]

The results in columns 1 and 2 of Table A1 suggest that observable firm-level characteristics indeed perform well as a control for the borrowing channel. In particular, the coefficients imply that changes in these bank shocks translate almost one-to-one into changes in the bank shocks obtained when controlling for firm-time effects. Moreover, the R-squared is high, implying that bank shocks derived from the *ILSR* approach can explain close to 90% of the variation in shocks based on firm-time fixed effects. Note that the R-squared drops to less than 60% in a model that does not contain

[4] Note that we consider 49 economic sectors and 200 regions. The sectors usually relate to NACE 2-digit sectors, while some 2-digit sectors had to be aggregated to form larger groups in order to concord NACE rev. 1 and rev. 2 sectors over time. Moreover, we consider ten firm types according to the number of banks that they borrow from, ten firm types according to their total bank debt and four firm types according to their legal form. As noted above, all characteristics are fixed in the pre-sample year 2005, or for firms entering the sample later, in the first year of their appearance. In sum, we distinguish between more than 90,000 firm types.

[5] Note that we obtain the bank shocks by way of weighted regressions where the weights are based on a loan's value in the previous period. Hence, this is equivalent to the AW approach, while ignoring the creation and destruction of lending relationships. Other recent papers also weight the sample when estimating models like equation (1) in the main paper to ensure that an observation's influence is proportional to its relevance in terms of total credit (see e.g., Greenstone, Mas and Nguyen, 2020).

any control for demand factors (column 2). In column 3 of Table A1, we also aim at understanding if bank shocks estimated using the *ILSR* demand controls differ when single-bank firms are added to the sample. We thus compute an alternative set of bank-loan supply shifters using the *ILSR* approach estimated on a sample containing all firms. Regressing these fixed effects on those obtained from the sample comprising multi-bank firms only, we find that the estimated coefficient is considerably lower than one and the R-squared amounts to around 60%. Hence, these results suggest that there is a significant difference between these two shock estimates.

Consistently with DJJMS, we thus find that accounting for single-bank firms implies substantially different estimates of the bank-loan supply shifters. For this reason, in this paper, we always include single-bank firms when estimating the bank-loan supply shocks, by applying the AW estimation approach to the data set collapsed to the bank *ILSR*-time dimension.

Table A1: Bank shocks with different demand controls and sample size

	(1) *BankShock* firm fe (mb-firms)	(2) *BankShock* firm fe (mb-firms)	(3) *BankShock* ILSR fe (mb-firms)
BankShock - ILSR fe (mb-firms)	1.000***		0.534***
	(0.009)		(0.026)
BankShock - NO fe (mb-firms)		0.988***	
		(0.018)	
Observations	7,231	7,231	7,254
Banks	1,294	1,294	1,295
R^2	0.88	0.58	0.62
Year FE	Yes	Yes	Yes

Notes: Regressions contain year dummies. Robust standard errors in parentheses. mb-firms refers to firms with multiple bank relationships, all firms refers to all firms independent of the number of bank relationships (i.e. also including single-bank firms). ILS fe stands for industry-location-size fixed effects and ILSR fe industry-location-size-relationship fixed effects; "size" refers to a dummy indicating that a firm belongs to a larger group, and "relationship" refers to the number of banks from which a firm borrows.

A.4.2 External validity of shock estimates

One major advantage of the adopted approach to estimating bank-loan supply shifters is that it does not require any type of exogenous bank shock for identification. Nevertheless, the presence of potentially exogenous events can be useful for assessing the external validity of these shifters. For instance, AW show that their bank-loan supply shifters are meaningfully correlated with proxy variables for bank health frequently used in studies based on Japanese data.

We consider two potential sources of exogenous variation suggested by earlier work for Germany over this period. First, Puri, Rocholl and Steffen (2011) use shocks to certain federal state banks ("Landesbanken") and savings banks in Germany in the course of the financial crisis between 2007 and 2008. Federal state banks in some regions of Germany were severely affected by the US subprime crisis, which had consequences for savings banks located in the same federal states due to their holdings in these banks.[6] In particular, Puri et al. (2011) show that such savings banks significantly reduced retail lending relative to savings banks from other regions during 2007 and 2008 (i.e., they rejected relatively more loan applications). Second, Dwenger, Fossen and Simmler (2018) provide evidence that banks in Germany which engaged in proprietary trading during 2005 or 2006 significantly cut corporate lending relative to non-trading banks during the period 2007 to 2010. They explain this observation by arguing that the financial crisis caused losses for trading banks, which then had to scale back lending in order to meet capital adequacy requirements.[7] Moreover, Dwenger et al. (2018) point out that healthy banks may also have had an incentive to cut lending in order to take advantage of opportunities related to fire sales. Indeed, in a recent paper Abbassi, Iyer, Peydró and Tous (2016) find that some trading banks in Germany leveraged such opportunities during the crisis period and that these banks reduced lending to non-financial firms relative to non-trading banks.[8]

Thus, one would expect savings banks in regions with federal state banks exposed to the US subprime crisis and banks active in proprietary trading during 2005/06 to have more negative bank-loan supply shifters in our data. We investigate these relationships in Table A2. First, we regress the estimated bank-loan supply shifters on a dummy variable indicating federal state banks and savings banks located in the relevant regions, focusing on the years 2007 and 2008. Indeed, we obtain the expected negative coefficient (column 1). Instead of a dummy variable indicating the affected savings banks, in column 2 we consider a dummy for federal state banks and savings banks located in other regions, and we do not obtain a significant coefficient. The results also hold when adding both dummies simultaneously to

[6] The point to note is that federal state banks (“Landesbanken”) are owned by the respective federal state as well as by savings bank associations in that state. Hence, the ownership of a federal state bank is fully determined by its location. In 2007 and 2008 federal state banks in Saxony, Bavaria, and North Rhine-Westphalia were severely affected by the US subprime crisis, which in turn impacted the savings banks in these regions since they had to make guarantees or equity injections.

[7] They further note that even banks not falling short of the capital adequacy requirements may have opted to reduce lending in the event of losses due to internal risk management considerations.

[8] In a recent study, Huber (2018) finds that the estimated relationship of Dwenger et al. (2018) is primarily due to one large bank that cut lending during the period under investigation. Note that our bank loan supply shocks also capture the effects related to this bank.

the model in column 3. Second, we focus on the period 2007-2010 and regress the bank-loan supply shifters on a dummy variable signalling banks that engaged in proprietary trading during 2005 or 2006. Once more, we estimate a negative and significant coefficient, suggesting that these banks, on average, have more negative bank-loan supply shocks (column 4). Moreover, we obtain similar results when using the share of (absolute) net profits or losses from proprietary trading, instead of a dummy variable (columns 5). Hence, we conclude that the estimated bank-loan supply shifters display reasonable correlations with other proxy variables from the literature used to identify credit supply shocks in Germany during our sample period.

Table A2: External validity of bank shocks

	(1) *BankShock*	(2) *BankShock*	(3) *BankShock*	(4) *BankShock*	(5) *BankShock*
Affected saving banks	-0.125***		-0.123***		
	(0.034)		(0.039)		
Unaffected saving banks		0.037	0.007		
		(0.033)	(0.037)		
Propretary trading (dummy)				-0.155***	
				(0.036)	
Propretary trading (share)					-0.244**
					(0.111)
Observations	2,645	2,645	2,645	5,226	5,226
Banks	1,372	1,372	1,372	1,434	1,434
R^2	0.004	0.003	0.004	0.008	0.004
Year FE	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Period	2007-2008	2007-2008	2007-2008	2007-2010	2007-2010

Notes: Regressions contain year dummies as well as controls for the size of the banks' balance sheets and their capital ratios. Clustered (bank-level) standard errors in parentheses.

B Further information on the estimation of markups

B.1 General framework

Below, we provide a description of the underlying approach to estimate firm-level markups and refer the reader to the corresponding cited papers for further details.

De Loecker and Warzynski (2012) provide a framework for estimating firm-specific and time-varying markups, which does not depend on a particular type of competition or functional form of demand. This framework relies heavily on the production function estimation literature and in particular the control function approach (following the work of Ackerberg, Caves and Frazer, 2015; Olley and Pakes, 1996; Levinsohn and Petrin, 2003). This approach is widely adopted in order to address the so-called transmission bias that translates the fact that productivity is unobserved to the econometrician, while managers likely make input decisions based on their current level of productivity.

Firm f in period t is assumed to minimize costs given the production function which combines inputs into quantity of output Q_{ft}, using production technology $F_{ft}(\cdot)$:

$$Q_{ft} = F_{ft}(X^V_{ft}, K_{ft}, \Omega_{ft}),$$

where variable inputs are collected in the vector X^V_{ft} and dynamic inputs like capital in K_{ft}, while Ω_{ft} is a Hicks-neutral productivity term productivity. Assuming that there is at least one truly variable input factor that adjusts frictionlessly within one period, cost minimization implies that optimal input demand is satisfied when a firm equalizes the output elasticity of the variable input X^V_{ft} to its costs share:

$$\frac{P^{X^V}_{ft} X^V_{ft}}{MC_{ft} Q_{ft}} = \frac{\partial Q_{ft}}{\partial X^V_{ft}} \frac{X^V_{ft}}{Q_{ft}}, \text{ with } \frac{\partial Q_{ft}}{\partial X^V_{ft}} \frac{X^V_{ft}}{Q_{ft}} = \psi^{X^V}_{ft},$$

where $P^{X^V}_{ft}$ is the price of input X^V_{ft}, MC_{ft} denotes the firm's marginal costs, and $\psi^{X^V}_{ft}$ is the output elasticity of X^V. Defining markups μ_{ft} as the price to marginal cost ratio and rearranging yields:

$$\mu_{ft} = \frac{P_{ft}}{MC_{ft}} = \frac{\psi^{X^V}_{ft}}{\tau^{X^V}_{ft}} = \text{ with } \tau^{X^V}_{ft} = \frac{P^{X^V}_{ft} X^V_{ft}}{P_{ft} Q_{ft}},$$

where $\tau^{X^V}_{ft}$ refers to the expenditure share of input X^V in firm f's total sales ($P_{ft}Q_{ft}$). Hence, markups can be derived from the ratio of the output elasticity of a variable input to its revenue share. $\psi^{X^V}_{ft}$ is typically obtained by estimating a production function, as described below.

First of all, it is important to note that given the still rather regulated nature of the German labour market during the period under investigation, we assume that intermediate inputs (M) is the only input factor that is free of adjustment costs.[9] Hence, we rely on a gross output production function for each industry s specified as follows:

$$q_{ft} = f(l_{ft}, m_{ft}, k_{ft}) + \omega_{ft} + \epsilon_{ft}, \tag{5}$$

where lower case letters denote logs and l_{ft} refers to labor, m_{ft} to intermediate goods, k_{ft} to capital and ω_{ft} to firm-specific productivity. The estimation

[9] This assumption is consistent with other recent studies for Germany (e.g., Mertens, 2020) and also with OECD indicators on labour market regulation. In addition, as recently pointed out by Liu and Mao (2019), intermediates are less likely to reflect measurement error, which also makes the choice of this input more appropriate in our context.

approach is implemented in two stages under proxy methods. The first stage relies on two key assumptions regarding the input demand of intermediate inputs. First, scalar unobservability implies that productivity is the only unobservable factor which determines a firm's input demand, such that:

$$m_{ft} = m_t(k_{ft}, l_{ft}, \omega_{ft}, z_{ft}), \tag{6}$$

where z_{ft} is a vector containing additional observables which may impact a firm's optimal input demand. The second assumption implies that the intermediate input demand is monotone in productivity (conditional on other arguments of equation 6).[10] Based on these assumptions, it is possible to invert m_{ft} for ω_{ft} such that $\omega_{ft} = h_t(k_{ft}, l_{ft}, m_{ft}, z_{ft})$, which provides us with a control function for productivity.

De Loecker and Warzynski (2012) emphasise the importance of including in z_{ft} factors that may drive the intermediate input demand of the firm in the context of the respective application. We include in z_{ft} firm-level wages, which should help address identification issues related to the estimation of a gross output production function.[11] Moreover, we account also for the possibility that financial variables can affect the input demand of the firm by including in z_{ft} the bank credit supply shock and the lagged share of bank loans in total assets. This is consistent with the approach by Cao and Leung (2019) who introduce collateral constraints affecting firms' investment and hiring decisions in the estimation framework. Manaresi and Pierri (2018) further discuss assumptions required to allow intermediate input demand to be directly affected by financial factors in the context of the control function approach. In particular, they assume that these constraints are also a function of the productivity of the firm, which is consistent with the idea that more productive firms can generally be considered as more reliable borrowers so that – all else equal – they can borrow more. This is consistent with size-dependent financial constraints as introduced by Gopinath, Kalemli-Özcan, Karabarbounis and Villegas-Sanchez (2017) to characterize financial frictions in Spain.

The first stage of the estimation approach consists of a non-parametric regression that purges output from unanticipated shocks to production and

[10] Levinsohn and Petrin (2003) show that this holds in the case of perfect competition. Maican and Orth (2017) further show that this condition holds for a static input like intermediate inputs in the case of imperfect competition as long as more productive firms do not charge disproportionately higher markups than less productive firms.

[11] In particular, De Loecker and Scott (2016) propose to include firm-level wages in the control function to address identification problems of the output elasticities raised by Gandhi, Navarro and Rivers (2020). Firm-level wages are serially correlated and vary across firms for reasons that are at least in part due to exogenous factors such as geographic or temporal differences in local labour markets.

measurement error:[12]

$$q_{ft} = h(x_{ft}, z_{ft}) + \epsilon_{ft}, \tag{7}$$

where inputs are collected in x_{ft} and the function $h(\cdot)$ is approximated by a second order polynomial of its arguments. The second stage of the estimation approach relies on a first order Markov process as law-of-motion for productivity, which we modify to allow productivity to be potentially affected by bank-loan supply shocks: $\omega_{ft} = g(\omega_{ft-1}) + BankShock_{ft-1} + \xi_{ft}$.[13] This productivity process yields the moment conditions required to obtain the output elasticities of the production function using a General Methods of Moments (GMM) estimator.[14] The functional form of the production function is specified above in general terms. In our baseline setup, we consider a Cobb-Douglas production function, implying that we do not have to run the second stage of the estimation approach since we can control for the output elasticity using appropriate fixed effects. In addition, we relax this assumption and adopt a translog specification defined as follows:

$$\begin{aligned} q_{ft} = \kappa_0 + \kappa_l l_{ft} + \kappa_m m_{ft} + \kappa_k k_{ft} + \kappa_{ll} l_{ft}^2 + \kappa_{mm} m_{ft}^2 + \kappa_{kk} k_{ft}^2 \\ \kappa_{lk} l_{ft} k_{ft} + \kappa_{lm} l_{ft} m_{ft} + \kappa_{km} k_{ft} m_{ft} + \kappa_{kml} k_{ft} m_{ft} l_{ft} + \omega_{ft} + \epsilon_{ft} \end{aligned} \tag{8}$$

This functional form is widely adopted given its appealing nature as output elasticities become firm and time specific as formally specified in the main text. This specification nests also the Cobb-Douglas functional form by dropping the interaction terms and also the squared terms.

B.2 Details on firm-level data (USTAN) and sample selection

The Deutsche Bundesbank data set known as "USTAN" contains information on corporate annual accounts (Becker, Biewen, Neulen, Schultz and Weisbecker, 2017). The data are collected within the framework of the Bundesbank's refinancing operations. Specifically, domestic credit institutions report annual financial statements of non-financial enterprises (their clients)

[12] In terms of timing, it is assumed that capital and labor are dynamic inputs. At the beginning of the period, firms observe ω and the components of z_{ft} and then decide on borrowing requirements and set their inputs. ϵ_{ft} is observed only at the end of the period.

[13] See Manaresi and Pierri (2018) and Loecker (2013).

[14] As noted by De Loecker, Eeckhout and Unger (2020), the output elasticity of a variable input is identified under the assumption that the use of variable inputs responds to productivity shocks contemporaneously and that lagged variable input use is related to the current use of variable inputs due to the productivity process.

to the Bundesbank for the determination of collateral and credit ratings. This data set has been used extensively for research purposes (see, e.g., Goldbach, Nagengast, Steinmüller and Wamser, 2019), also along with its merge with MiMiK (see, e.g., Haselmann, Schoenherr and Vig, 2018).

Our sample selection criteria are the following. First, we drop observations if information for relevant variables is missing. Second, we remove micro firms from the sample; i.e. firms with less than ten employees. Third, we adjust variables for extreme values. In particular, we trim the first and last percentiles of the markup ratios (computed by industry).[15] When the dependent variable is a growth rate, we drop observations that deviate from the median growth rate by more than four times the standard deviation (computed on a yearly basis). Furthermore, we exclude observations for other ratios in the empirical analysis (e.g. labor productivity and the loan share) that deviate from the median by more than four times the standard deviation (computed by industry). Finally, we include only firms for which there are at least two periods of observations in order to be able to include firm fixed effects.

In order to construct an annual matched loan-firm-level data set for the German manufacturing sector, we merge firms present in the data source MiMiK to the ones in USTAN, exploiting a mapping between the firms in both data sets (Schild, Schultz and Wieser, 2017). We can match credit information from MiMiK to roughly half of the manufacturing firms present in USTAN.

B.3 Further empirical evidence regarding markups

Table B1 presents summary statistics for the various markups proxies that are consistent with a translog functional form; i.e, for which we estimate the output elasticity, to ease comparisons with other studies. The estimates suggest average markups range from 1.27 to 1.29 across the various specifications and estimation frameworks. These numbers seem plausible and are in line with estimates found in other studies (e.g., De Loecker and Warzynski, 2012, estimate that average markups of Slovenian firms amount to 28% when considering a translog production function). Table B2 additionally presents the estimated production function coefficients obtained by NACE chapter under a translog specification.

Finally, Table B3 shows that these markup proxies display correlations with firm-level characteristics that are consistent with recent evidence for a

[15] Note that when we consider a translog functional form, we drop observations with implausible intermediate input coefficients; i.e., coefficients below zero or above one.

large set of countries provided by Díez, Fan and Villegas-Sánchez (2021). In particular, we find a non-linear relationship between markups and firms' market shares, suggesting that especially very large firms charge higher markups. Moreover, we find a positive relationship between markups and both firm productivity and intangible assets as a share on total assets.

Table B1: Summary statistics for various markup measures

	obs	mean	sd	p5	p25	p50	p75	p95
μ^{tl} - base	12607	1.29	0.24	1.03	1.14	1.24	1.36	1.70
μ^{tl} - CPI	12361	1.27	0.20	1.03	1.14	1.23	1.36	1.64
μ^{tl} - other market share	12589	1.28	0.22	1.03	1.14	1.24	1.36	1.70
μ^{tl} - industry-year FE	12379	1.27	0.21	1.02	1.14	1.24	1.36	1.64
μ^{tl} - exports	12545	1.30	0.24	1.03	1.15	1.25	1.38	1.73
μ^{tl} - marketing proxy	12486	1.29	0.24	1.02	1.13	1.23	1.38	1.71
μ^{tl} - no. of banks	12555	1.27	0.19	1.02	1.14	1.24	1.36	1.63
μ^{tl} - OP	11741	1.29	0.23	1.03	1.15	1.25	1.37	1.68
μ^{tl} - Wooldridge	12403	1.27	0.20	1.03	1.15	1.24	1.36	1.63

Notes: The table presents summary statistics for various markup proxies, consistent with a translog functional form.

Table B2: Markup and production function coefficients - translog (ACF)

NACE 4 digit	Designation	Obs.	μ^{tl}	coeff b_l^{tl}	se b_l^{tl}	coeff ${b_k}^{tl}$	se b_k^{tl}	coeff b_m^{tl}	se b_m^{tl}
1012	Manu. of food products etc.	447	2.14	0.33	0.114	0.01	0.097	0.93	0.338
1315	Manu. of textiles, apparel etc.	1230	1.23	0.28	0.099	0.01	0.021	0.73	0.164
1618	Manu. of wood and paper products,	2316	1.24	0.30	0.016	0.02	0.010	0.69	0.012
2021	Manu. of chemical product and pharmaceuticals	1439	1.26	0.33	0.072	0.02	0.036	0.68	0.152
2200	Manu. of rubber and plastic products	2193	1.22	0.30	0.090	0.05	0.030	0.66	0.095
2300	Manu. of other non-metallic mineral products	1086	1.32	0.32	0.018	0.05	0.016	0.64	0.018
2400	Manu. of basic metals	1559	1.14	0.24	0.038	0.04	0.020	0.72	0.091
2500	Manu. of fabricated metal products,	3832	1.20	0.35	0.016	0.03	0.011	0.60	0.014
2600	Manu. of computer, electronic, optical products	1315	1.28	0.38	0.030	0.01	0.014	0.60	0.028
2700	Manu. of electrical equipment	1024	1.32	0.29	0.037	0.01	0.013	0.70	0.020
2800	Manu. of machinery and equipment n.e.c.	4909	1.27	0.37	0.014	0.01	0.006	0.63	0.009
2930	Manu. of transport equipment	1303	1.19	0.26	0.037	0.03	0.024	0.72	0.048
3133	Other manufacturing	1289	1.30	0.38	0.021	0.03	0.010	0.64	0.018

Notes: The table presents median markups and production function coefficients that are consistent with a translog functional form. Standard errors are derived from 200 bootstrap draws.

Table B3: Markup premium regressions

	(1) $\ln(\mu^{cd})$ - base	(2) $\ln(\mu^{tl})$ - base	(3) $\ln(\mu^{tl})$ - Wooldridge	(4) $\ln(\mu^{tl})$ - OP
Log market share	0.016	0.032***	0.020**	0.038***
	(0.013)	(0.008)	(0.009)	(0.008)
Log market share squared	0.007***	0.005***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Log productivity	0.037*	0.097***	0.104***	0.101***
	(0.019)	(0.011)	(0.011)	(0.011)
Log intangibles in total assests	0.023***	0.010***	0.011***	0.010***
	(0.003)	(0.002)	(0.001)	(0.002)
Observations	12,541	11,576	12,434	10,860
Firms	2,858	2,658	2,842	2,567
R^2	0.345	0.430	0.315	0.377
Industry-year FE	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects. Dependent variable shown in the second row of the table. Productivity is approximated by total factor productivity using an index number approach for gross output and assuming constant returns results.

C Other complementary results

This section presents a series of complementary results. First, we present more evidence on firm characteristics, according to the distributions of bank-loan supply shifters. Second, we investigate in more detail the relationship between bank-loan-supply shifters and firms' loans. Third, we consider various robustness checks regarding the main findings. Finally, we present some additional results regarding the role of bank-loan supply shocks for other firm-level outcomes.

C.1 Descriptive statistics

In Table C1, we show how additional firm-level characteristics vary over the quintile of the bank-shock distribution. As mentioned in the main text, there is some evidence that larger firms (here in terms of turnover, value added or tangible assets) experience, on average, more favourable bank-loan supply shocks during the sample period.

C.2 Firm-level loans and bank loan-supply shocks

In Table C2, we provide additional evidence on the impact of bank-loan supply shocks on firm-level loans. Looking first at the odd numbered columns of the Table, we find that a firm's bank loans decrease in response to a negative bank-loan supply shock also when scaling them by total assets (columns 1). This also holds when considering bank loans as a share of total debt (columns

3). Moreover, we do not find clear evidence for a stronger effect on short-term relative to long-term loans, when considering the effect on short-term loans as a share of total loans as the dependent variable (columns 5). Furthermore, we present a Placebo-type exercise by estimating the effect of bank-loan supply shocks on lagged loans over total assets (columns 7), which yields a small and statistically insignificant coefficient. In the evenly numbered columns of the Table, we present similar regressions, while including an interaction term between BankLoansDue and the BankShock variable. This interaction is mostly insignificant (the only exception is column 2, where the coefficient reaches a statistical significance of 10%).

C.3 Sensitivity analysis regarding the effects on markups

We consider alternative markup proxies, adjustments to the baseline empirical model specifications, and the sensitivity of the results to using weighted regressions.

C.3.1 Alternative markup proxies

We consider a set of alternative markup proxies. First, we use a markup measure that relies on firm specific and time varying output elasticities by estimating the second stage of the production function. We refer to this markup proxy as μ^{tl}_{ft}. Second, we consider a measure, where the input share is no longer adjusted for unobserved shocks to production (μ^{ne}_{ft}). Third, we derive a proxy from a firm's Lerner index, which is defined as $LI_{ft} = (Rev_{ft} - Wages_{ft} - Mat_{ft})/Rev_{ft}$, where Rev_{ft}, $Wages_{ft}$, and Mat_{ft} refer to firm f's revenue, wage bill, and intermediate inputs.[16]

Table C3 shows the estimation results using these alternative measures. As before, we find that markup responses of the firm to bank-loan supply shocks vary according to its reliance on short-term bank credit. This holds for all markup measures when considering the lagged exposure variable and for all measures except for μ^{pcm}_{ft} when considering the pre-sample values. Hence, qualitatively, these results are broadly consistent with our previous findings.

Moreover, we investigate whether the main results are sensitive to different specifications of the input demand equation in the estimation of the markup proxies and to different estimation methods. In particular, we consider various adjustments of the specification of the material demand function (equation 6). In our baseline specification, the vector z_{ft} includes firm-level wages, bank-loan supply shocks, lagged bank-loans in total assets, market

[16] We obtain an expression consistent with our firm-level markup measures from $\mu^{pcm}_{ft} = (1 - LI_{ft})^{-1}$.

shares (defined at the 4-digit industry level), 4-digit industry dummies, region dummies, and year fixed effects. To ensure that our results are robust, we first add information on regional producer prices, which may capture further local input cost shocks (Manaresi and Pierri, 2018). Second, following the approach adopted by several authors, we include export dummies to account for potentially varying input demand across exporting and non-exporting firms. Third, we define market shares at a narrower (3-digit) industry level in line with sensitivity checks adopted by De Loecker et al. (2020). Fourth, we include interactions between 3-digit industry and year dummies, e.g., in order to capture potential changes in customer market features and to absorb any other potential changes related to demand and supply that are sector-specific. Fifth, we include a variable that captures firms' expenses not related to wages, materials or rents which thus accounts, e.g., for marketing expenses of the firm.[17] The introduction of this variable aims at controlling for remaining sources of unobserved demand heterogeneity that are firm and time specific, which might not be captured by the remaining control variables. The theoretical literature has highlighted the role of advertising in shaping the price elasticity of demand (Bagwell, 2007). In fact, Blum, Claro, Horstmann and Rivers (2018) use advertising expenditures as demand shifters which they relate to "prestige" and "information effects". They find that these expenditures are strongly and positively correlated with demand heterogeneity measures obtained in their setting. Sixth, we add firms' lagged number of bank relations to the control function. Finally, we report results derived from a framework in the spirit of Olley and Pakes (1996), where we use investment as proxy for productivity.[18] Table C4 reports the corresponding estimation results and shows that our main results are hardly affected by these adjustments of the control function and alternative estimation setups.

We consider corresponding adjustments also for markups derived using the translog production function. Moreover, in this case, we also adopt a Wooldridge (2009)-type estimation approach. The main results are robust to these checks, as shown in Table C5.

C.3.2 Variable transformations, large firms, and controls

In Table C6, we present another set of sensitivity checks. First, we empirically test if our results hold under different transformations of the dependent

[17] More specifically, we compute this proxy as the difference between the two variables "other operating charges" and "operating expenses relating to other periods", which are both reported in USTAN.

[18] Ackerberg et al. (2015) discuss the investment proxy also in the context of their estimation framework.

variable. In particular, in column 1 we do not log transform the markup proxy and in column 2 we also use the growth rate of the markup as dependent variable ($\Delta\ln(\mu_{ft})$). Our main results are robust to these adjustments.

Second, column 3 presents estimation results obtained by excluding firms that belong to the 90th percentile of the total asset distribution. This exercise aims to address any remaining concerns in relation to potential reverse causality issues. For instance, banks may have more information about the future developments of their largest borrowers and change their lending to all firms accordingly. In our case, such concerns are mitigated since the *ILSR* accounts for the size of the borrower and, indeed, our main results are hardly affected by the exclusion of these firms from the estimation sample.

At last, in the subsequent two columns of Table C6, we add to the regressions location-year and size-class-year dummies, respectively. Location refers to a federal state and we distinguish between four size classes according to quartiles of the distribution of total assets (lagged). Berton, Mocetti, Presbitero and Richiardi (2018) mention that banks may specialize in supplying credit to firms of a certain size, and that the sensitivity of demand for the products of such firms to the business cycle may vary. For instance, some banks may lend especially to large firms and these firms may be more reliant on the business cycle. If these banks also cut lending relatively more during the sample period, then this may lead to spurious correlations in relation to the $BankShock_{ft}$ variable. While we argue that our *ILSR* approach largely accounts for such concerns due to its size controls, including size-class-year dummies can act as an additional robustness exercise. Indeed, we find that neither the inclusion of location-year nor of size-clear-fixed dummies qualitatively affect the main results. We simultaneously account for both types of shocks in the last column of the table (column 5), but our results are again hardly affected.

C.3.3 Weighted vs. unweighted regressions

In the main paper, we discuss markup cyclicality in the context of the economic implications of our findings, using weighted regressions. In Table C7, we first show that our main findings are robust to using weighted regressions, where weights refer to firms' intermediate input expenditures fixed during the pre-sample period. Second, in Table C8, we present results regarding the implications of our findings for the cyclicality of markups, using unweighted regressions. Our findings broadly remain, even though they are reinforced when based on weighted regressions.

C.3.4 Persistence of the effects on markups

Moreover, we investigate whether the effect of bank-credit supply shocks on markups occurs with a lag or rather materializes contemporaneously. To do so, we include lagged bank-shock variables in the model. Table C9 shows that the effect of the bank-credit supply shocks occurs, on average, contemporaneously over this period. This finding is consistent with recent empirical evidence such as the one presented by Lenzu, Rivers and Tielens (2019), who find largely contemporaneous price reactions of Belgium firms to credit supply shocks linked to the European sovereign debt crisis.

C.3.5 Effects by quintile of bank loans due

Finally, in Table C10, we present results using quantile dummies of *BankLoansDue*, interacted with the *BankShock* variable (where the first quantile is the reference group). The results suggest that firms in the first quantile of *BankLoansDue* lower markups after a negative credit supply shock. Firms in the second quantile of *BankLoansDue* lower markups by less, while those in higher quantiles rather tend to raise them. Hence, firms with low exposure to the *BankShock* (due to the virtual absence of short-term bank loans in their balance sheets) lower markups, while firms more exposed to these shocks raise them relatively to these firms, but also absolutely if heavily relying on short-term bank loans. The results further imply that firms with limited exposure in terms of *BankLoansDue* have higher sales after a negative shock, while the remaining, more exposed firms, have lower sales.

C.4 Results for other outcome variables

We also consider the role of bank-loan supply shocks for other outcome variables. In particular, we are interested in a potential trade trade-off between firms' short-term liquidity needs and medium-term market share considerations, as suggested by the theoretical framework by Gilchrist, Schoenle, Sim and Zakrajšek (2017). To this end, we consider the role of current and lagged bank-loan supply shocks on firms' markups and market shares. In Table C11, we present results using markups and sales as outcome variables in a specification such as the one in our baseline model. Since the model contains 3-digit industry-year fixed effects, the results for firms' sales correspond to effects on market shares. The results suggest that the effects on market shares are indeed more persistent, while the effect on markups largely occurs contemporaneously (as shown also above). Hence, these results corroborate the presence of such a trade-off predicted by the theoretical framework. Note that we obtain similar results when adding 4-digit industry-year fixed effects to the model in order to allow for different definitions of the relevant market. Thus, we ensure that the previous findings are not driven by this choice.

Finally, in Table C12 we present some results for firms' investment, employment and sales which generally yield contractionary effects on these variables.

Table C1: Mean firm characteristics by quintile of $BankShock_{ft}$

	Quintile of *BankShock*				
	1	2	3	4	5
$\ln(\mu^{tl})$	-0.010	-0.002	0.003	0.002	0.007
	(-2.48)	(-0.42)	(0.69)	(0.47)	(1.74)
$\ln\Delta(\mu^{tl})$	-0.000	-0.001	-0.003	0.001	0.002
	(-0.11)	(-0.69)	(-1.79)	(0.92)	(1.70)
Log of turnover	-0.002	-0.216	-0.165	0.066	0.317
	(-0.06)	(-6.67)	(-5.09)	(2.02)	(9.83)
Log of value added	-0.025	-0.212	-0.149	0.081	0.305
	(-0.81)	(-6.76)	(-4.73)	(2.58)	(9.75)
Log tangible assets	-0.039	-0.278	-0.153	0.101	0.367
	(-0.93)	(-6.65)	(-3.65)	(2.42)	(8.83)
$\ln(tfp^{tl})$	0.001	-0.046	-0.065	0.019	0.092
	(0.03)	(-2.57)	(-3.61)	(1.05)	(5.11)
$\Delta(tfp^{tl})$	0.000	-0.001	-0.001	-0.001	0.002
	(0.02)	(-0.10)	(-0.16)	(-0.16)	(0.40)

Notes: The table presents average values of firm characteristics by quintile of the $BankShock_{ft}$ distribution. Note that $BankShock_{ft}$ is purged from industry-year fixed effects before computing quintiles. Similarly, the firm characteristics are purged from industry fixed effects. This is carried out since in baseline specification of the main paper contains industry-year fixed effects. Further note that the firm characteristics are computed as mean values of pre-sample years (2004-2006), or, where a firm joins the sample in 2007, they relate to the year 2007. T-statistics presented in parentheses inform about differences in means with respect to the remaining observations in the sample.

Table C2: Effect of bank loan supply shocks on firms' loans

	Bank loans over assets		Loans over debt		SR loans over loans		Lagged loans over assets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BankShock	0.003***	0.005***	0.003**	0.005**	-0.003	-0.005	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.001)	(0.001)
BankShock × *Bank loans due*		-0.018*		-0.015		0.012		-0.003
		(0.009)		(0.012)		(0.025)		(0.009)
Observations	8,377	8,377	8,377	8,377	8,377	8,377	8,377	8,377
Firms	2,634	2,634	2,634	2,634	2,634	2,634	2,634	2,634
R^2	0.131	0.135	0.111	0.113	0.028	0.028	0.263	0.262
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain year fixed effects and controls for credit demand ($\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), lagged leverage, and lagged number of bank relations. R-squared refers to the (adjusted) within R-squared. Dependent variable shown in the second row of the table.

Table C3: Alternative markup proxies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\ln(\mu^{tl})$	$\ln(\mu^{tl})$	$\ln(\mu^{tl})$	$\ln(\mu^{ne})$	$\ln(\mu^{ne})$	$\ln(\mu^{ne})$	$\ln(\mu^{pcm})$	$\ln(\mu^{pcm})$	$\ln(\mu^{pcm})$
BankShock	0.000	0.003***	0.003***	0.001	0.005**	0.005**	-0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
BankShock × *Bank loans due (t-1)*		-0.020***			-0.029**			-0.015*	
		(0.006)			(0.012)			(0.008)	
BankShock × *Bank loans due*			-0.021***			-0.032**			-0.009
			(0.007)			(0.015)			(0.008)
Observations	7,573	7,903	7,573	8,308	8,671	8,308	8,276	8,639	8,276
Firms	2,418	2,579	2,418	2,626	2,801	2,626	2,625	2,801	2,625
R^2	0.230	0.232	0.232	0.174	0.174	0.174	0.065	0.069	0.066
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects and controls for credit demand (i.e., $\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), leverage (lagged total debt in total assets), and lagged number of bank relations. Additionally, we add firms' labor and capital inputs as well as a corresponding interaction term to the models in columns 4 to 6. R-squared refers to the (adjusted) within R-squared. Dependent variable shown in the second row of the table.

Table C4: Control function adjustment - CD

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$
	CPI	Market share	Industry × year FE	Exports	Marketing	No. of banks	OP
BankShock	0.005***	0.006***	0.006***	0.006***	0.006***	0.005***	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
BankShock × *Bank loans due*	-0.027***	-0.027***	-0.026***	-0.026***	-0.027***	-0.025***	-0.018*
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)
Observations	8,190	8,199	8,181	8,198	8,189	8,213	7,663
Firms	2,601	2,601	2,598	2,604	2,602	2,605	2,539
R^2	0.340	0.343	0.358	0.325	0.298	0.342	0.339
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects and controls for credit demand (i.e., $\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), leverage (lagged total debt in total assets), and lagged number of bank relations. Additionally, we add firms' labor and capital inputs as well as a corresponding interaction term to the models. R-squared refers to the (adjusted) within R-squared. Dependent variable shown in the second row of the table. Third row indicates the adjustment applied to the control function.

Table C5: Control function adjustment - TL

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(\mu^{tl})$	$\ln(\mu^{tl})$	$\ln(\mu^{tl})$	$\ln(\mu^{tl})$	$\ln(\mu^{tl})$	$\ln(\mu^{tl})$	$\ln(\mu^{tl})$	$\ln(\mu^{tl})$
	CPI	Market share	Industry × year FE	Exports	Marketing	No. of banks	OP	Wooldridge
BankShock	0.003**	0.003***	0.003***	0.003***	0.004***	0.002*	0.002	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BankShock × *Bank loans due*	-0.021**	-0.018**	-0.021***	-0.019***	-0.025***	-0.013**	-0.019**	-0.015**
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.006)	(0.009)	(0.007)
Observations	7,423	7,732	7,442	7,580	7,550	8,180	7,004	8,122
Firms	2,364	2,471	2,372	2,428	2,408	2,603	2,327	2,589
R^2	0.221	0.242	0.323	0.201	0.168	0.252	0.207	0.221
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects and controls for credit demand (i.e., $\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), leverage (lagged total debt in total assets), and lagged number of bank relations. R-squared refers to the (adjusted) within R-squared. Dependent variable shown in the second row of the table. Third row indicates the adjustment applied to the control function or the estimation setup.

Table C6: Variable transformation, firm size, and controls

	(1) (μ^{cd})	(2) $\Delta\ln(\mu^{cd})$	(3) $\ln(\mu^{cd})$	(4) $\ln(\mu^{cd})$	(5) $\ln(\mu^{cd})$	(6) $\ln(\mu^{cd})$	(7) $\ln(\mu^{cd})$
BankShock	0.016***	0.005**	0.005***	0.005***	0.006***	0.005***	0.005***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
BankShock × *Bank loans due*	-0.067***	-0.027**	-0.025**	-0.027***	-0.027***	-0.025***	-0.026***
	(0.021)	(0.013)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	8,200	7,397	7,252	8,200	8,200	8,200	8,200
Firms	2,602	2,573	2,322	2,602	2,602	2,602	2,602
R^2	0.295	0.426	0.349	0.343	0.344	0.343	0.345
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	No	Yes	Yes	Yes
No large firms	No	No	Yes	No	No	No	No
Region × year FE	No	No	No	No	Yes	No	Yes
Size class × year FE	No	No	No	No	No	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects and controls for credit demand (i.e., $\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), leverage (lagged total debt in total assets), and lagged number of bank relations. Additionally, we add firms' labor and capital inputs as well as a corresponding interaction term to the models. R-squared refers to the (adjusted) within R-squared. Dependent variable shown in the second row of the table.

Table C7: Main Results using weighted regressions

	(1) $\ln(\mu^{cd})$	(2) $\ln(\mu^{cd})$	(3) $\ln(\mu^{cd})$	(4) $\ln(\mu^{cd})$	(5) $\ln(\mu^{cd})$	(6) $\ln(\mu^{cd})$
BankShock	0.005***	0.005**	0.006***	0.008***	0.007***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
BankShock × *Bank loans due*			-0.039***			-0.065***
			(0.012)			(0.013)
Observations	13,580	13,580	13,580	8,181	8,181	8,181
Firms	2,993	2,993	2,993	2,593	2,593	2,593
R^2	0.472	0.487	0.489	0.528	0.546	0.551
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	Yes	No	Yes	Yes
Period	2007-2013	2007-2013	2007-2013	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects and controls for credit demand (i.e., $\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), leverage (lagged total debt in total assets), and lagged number of bank relations. Additionally, we add firms' labor and capital inputs as well as a corresponding interaction term to the models. Regressions are weighted according to firms' pre-sample intermediate input expenditure. R-squared refers to the (adjusted) within R-squared. Dependent variable shown in the second row of the table.

Table C8: Markup cyclicality - unweighted

	All	Elasticity of substitution		Persistence of market shares		R&D intensity	
		High (≥p66)	Low (<p66)	High (≥p33)	Low (<p33)	High (≥p33)	Low (<p33)
		$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BankShock	0.006***	0.003	0.007***	0.007***	0.003	0.006***	0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
BankShock × *Bank loans due*	-0.031***	-0.019	-0.039***	-0.038***	-0.006	-0.038***	-0.008
	(0.010)	(0.015)	(0.012)	(0.011)	(0.019)	(0.012)	(0.014)
BankShock × *Industry gowth*	-0.007	-0.004	-0.008	-0.007	-0.007	-0.004	-0.025
	(0.010)	(0.019)	(0.013)	(0.012)	(0.019)	(0.012)	(0.017)
BankShock × *Bank loans due* × *Industry gowth*	0.125**	0.042	0.141*	0.119*	0.149	0.128*	0.129
	(0.061)	(0.109)	(0.076)	(0.070)	(0.126)	(0.070)	(0.087)
Observations	8,200	2,743	5,399	5,799	2,397	6,084	2,116
Firms	2,602	876	1,722	1,851	765	1,919	687
R^2	0.344	0.360	0.337	0.328	0.365	0.344	0.327
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects and controls for credit demand (i.e., $\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), leverage (lagged total debt in total assets), and lagged number of bank relations. R-squared refers to the (adjusted) within R-squared.

Table C9: Persistence of effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$
BankShock	0.002*	0.005***					-0.000	0.004*
	(0.001)	(0.002)					(0.002)	(0.002)
BankShock (t-1)			-0.005	-0.006			-0.017	-0.011
			(0.006)	(0.010)			(0.011)	(0.016)
BankShock (t-2)					-0.001	-0.006	-0.012	-0.022
					(0.007)	(0.010)	(0.010)	(0.014)
BankShock × *Bank loans due*		-0.027***						-0.035***
		(0.009)						(0.012)
BankShock (t-1) × *Bank loans due*				0.004				-0.048
				(0.053)				(0.079)
BankShock (t-2) × *Bank loans due*						0.037		0.065
						(0.055)		(0.072)
Observations	8,200	8,200	7,207	7,207	6,660	6,660	6,186	6,186
Firms	2,602	2,602	2,558	2,558	2,362	2,362	2,216	2,216
R^2	0.342	0.343	0.349	0.350	0.348	0.348	0.348	0.351
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects and controls for credit demand (i.e., $\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), leverage (lagged total debt in total assets), and lagged number of bank relations. Additionally, we add firms' labor and capital inputs as well as a corresponding interaction term to the models. R-squared refers to the (adjusted) within R-squared. Dependent variable shown in the second row of the table.

Table C10: Effects conditional on quantile of SR loan share

	(1)	(2)	(3)	(4)	(5)
	$\ln(\mu^{cd})$	$\ln(\mu^{tl})$	$\ln(\mu^{ne})$	$\ln(\mu^{pcm})$	ln(sales)
BankShock	0.008***	0.004***	0.008**	0.003	-0.010*
	(0.002)	(0.001)	(0.003)	(0.002)	(0.005)
BankShock × 1(*Bank loans due*| 2nd quantile)	-0.005*	-0.003*	-0.007	-0.005*	0.005
	(0.003)	(0.002)	(0.004)	(0.003)	(0.007)
BankShock × 1(*Bank loans due*| 3rd quantile)	-0.010***	-0.006***	-0.010**	-0.005	0.014*
	(0.003)	(0.002)	(0.004)	(0.003)	(0.007)
BankShock × 1(*Bank loans due*| 4th quantile)	-0.008***	-0.006***	-0.010**	-0.004	0.015**
	(0.003)	(0.002)	(0.004)	(0.003)	(0.007)
Observations	8,200	7,573	8,308	8,276	8,378
Firms	2,602	2,418	2,626	2,625	2,634
R^2	0.343	0.232	0.175	0.067	0.358
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain year fixed effects and controls for credit demand ($\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), lagged leverage, and lagged number of bank relations. R-squared refers to the (adjusted) within R-squared. Dependent variable shown in the second row of the table.

Table C11: Persistence of effects: markups and market share

	Markups				Sales (market shares)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	$\ln(\mu^{cd})$	ln(sales)	ln(sales)	ln(sales)	ln(sales)
BankShock	0.005***			0.004*	-0.007**			-0.006
	(0.002)			(0.002)	(0.004)			(0.005)
BankShock (t-1)		-0.006		-0.011		-0.011		-0.007
		(0.010)		(0.016)		(0.022)		(0.035)
BankShock (t-2)			-0.006	-0.022			0.034	0.047
			(0.010)	(0.014)			(0.024)	(0.032)
BankShock × *Bank loans due*	-0.027***			-0.035***	0.048**			0.084***
	(0.009)			(0.012)	(0.022)			(0.031)
BankShock (t-1) × *Bank loans due*		0.004		-0.048		0.265**		0.433**
		(0.053)		(0.079)		(0.123)		(0.189)
BankShock (t-2) × *Bank loans due*			0.037	0.065			-0.242*	-0.147
			(0.055)	(0.072)			(0.137)	(0.175)
Observations	8,200	7,207	6,660	6,186	8,200	7,207	6,660	6,186
Firms	2,602	2,558	2,362	2,216	2,602	2,558	2,362	2,216
R^2	0.343	0.350	0.348	0.351	0.380	0.404	0.409	0.412
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects and controls for credit demand (i.e., $\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), leverage (lagged total debt in total assets), and lagged number of bank relations. R-squared refers to the (adjusted) within R-squared.

Table C12: Effects on other outcome variables

	Log of investment			Log of employment			Log of output		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BankShock	0.023*	0.002	-0.043*	0.003*	0.000	0.003	-0.002	-0.009**	-0.009*
	(0.013)	(0.019)	(0.024)	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)	(0.005)
BankShock × *Bank loans due*		0.171			0.021*			0.056**	
		(0.121)			(0.013)			(0.023)	
BankShock × *Bank loans total*			0.248***			0.001			0.026*
			(0.078)			(0.008)			(0.015)
Observations	7,829	7,829	7,829	8,378	8,378	8,378	8,378	8,378	8,378
Firms	2,569	2,569	2,569	2,634	2,634	2,634	2,634	2,634	2,634
R^2	0.144	0.144	0.145	0.144	0.144	0.144	0.358	0.358	0.358
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demand control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010	2007-2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered (firm-level) standard errors in parentheses. All regressions contain (3-digit) sector-year fixed effects and controls for credit demand (i.e., $\tilde{\alpha}_{ILSR,t}$), size (lagged assets), productivity (lagged value added per employee), leverage (lagged total debt in total assets), and lagged number of bank relations.

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