# Credit supply shocks and prices: Evidence from Danish firms*

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**Abstract**

We study the response of firms' output prices to a cut in credit supply. We combine data on loans between Danish firms and banks with survey-based producer prices and transaction-based export unit values. Exploiting banks' heterogeneous exposure to the global financial crisis, we show that loans to firms with relationships to exposed banks drop and lending rates increase. In response, firms raise prices by 3–5%. This effect is decreasing in the elasticity of firms' demand but positive for most industrial production. Our results support the idea that firms use price increases to raise cash when external sources of liquidity dry up.

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*Keywords*: price-setting, liquidity, bank lending, inflation, demand elasticity

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# 1 Introduction

In this paper, we study the relationship between loan supply and firms' output prices in the aftermath of the 2007–2008 global financial crisis. During the Great Recession triggered by the financial crisis, inflation did not fall as much as many economists would have expected based on the historic relationship between output and prices.[1] A natural explanation for this "missing disinflation" is that the financial crisis had a direct impact on prices through bank lending markets. Such a channel is an important component of efforts to model price developments over the Great Recession (see Christiano et al. (2015), Gilchrist et al. (2017)), but direct evidence on the effect of loan supply on prices remains scarce.

We aim to provide such evidence in this paper. We identify the causal effect of loan supply on prices using a strategy based on firms' pre-existing relationships with banks who are more or less exposed to the financial crisis, depending on banks' pre-crisis funding strategy through either deposits or wholesale interbank loans. Our empirical analysis is based on a new dataset covering all loan relationships between Danish firms and banks, combined with price information from producer price index (PPI) survey data and transaction-based export unit values. We show that the loan balances of firms with pre-existing relationships with "wholesale-funded" banks decrease sharply after 2007, while the interest rates they pay on the remainder increase. At the same time, these firms raise their domestic and export prices by 5% and 3% relative to other firms in the same sector. Our IV estimates of the loan supply elasticities of domestic and export prices amount to between -0.06 and -0.26. We find that the short-term profitability of exposed firms increases, while their longer-run market share falls. Overall, our results are consistent with an important role of the liquidity channel of Gilchrist et al. (2017), who suggest that liquidity-constrained firms trade off short-term profits against longer-term market share.

Our identification strategy follows Jensen and Johannesen (2017) and is similar to identification schemes based on U.S. banks' exposure to the financial crisis, such as Chodorow-Reich (2014). Like Jensen and Johannesen, we distinguish between banks who rely more on deposits ("deposit-funded") and banks who rely more on interbank wholesale markets ("wholesale-funded") for funding before the financial crisis. After the interbank market froze up at the end of 2007, wholesale-funded banks faced a severe funding shortage and reduced their loan supply relative to deposit-funded banks. This results in substantial variation in firms' access to credit over the crisis depending on their pre-crisis banking relationships. We find that after 2007, the loan balances of firms with pre-crisis relationships with wholesale-funded banks decrease by roughly 20-30%, while the interest rate paid on the remainder increases by up to 0.5pp relative to other firms.

The main challenge to our identification strategy is the possibility of sorting between firms and

[1] See e.g. Hall (2011) for a discussion of the U.S. case, Friedrich (2016) for a cross-country perspective and Appendix D.1 for the Danish case.

banks—wholesale-funded banks could attract customer firms who are more exposed to the Great Recession through other channels as well. We address this concern in several ways: First, we show that firms borrowing from deposit-focused and wholesale-funded banks are very similar in terms of observable characteristics. Second, we show that prior to the crisis, price and loan outcomes of both groups of firms align very closely. Third, we show that our results are robust to controlling for the dynamic impact of firm characteristics over the crisis by controlling for the dynamic impact of ex-ante selected controls and picking controls using the PDSLASSO method proposed by Belloni et al. (2014, 2017) in robustness checks.

Our main contribution to the existing literature are causally identified estimates of the effect of loan supply on producer prices of a diverse and broadly representative sample of firms. Kim (2021) uses a similar identification strategy to identify the effect of credit supply on prices of U.S. consumer packaged goods producers—mostly large food manufacturing firms—and finds that a negative credit supply shock leads to lower prices in this sample. Our analysis is based on prices of firms that participate in the Danish PPI survey—which is representative of the sectoral composition of Danish manufacturing—and export unit values for the universe of Danish exporters in manufacturing sectors. In contrast to Kim (2021) we find that negative credit supply shocks lead to price increases. We reconcile these two different results through differences in the elasticity of market demand between consumer packaged goods producers and manufacturing overall. We show that the price effect of a negative credit supply shock decreases with the elasticity of market demand, and that consumer packaged goods producers face much more elastic demand than manufacturing firms overall. For the high demand elasticities faced by consumer packaged goods producers, our estimates imply a modestly negative effect consistent with Kim (2021). However, given the distribution of demand elasticities in Danish and European manufacturing, our estimates imply that negative credit supply shocks lead to price increases for most firms.

Our results are consistent with the evidence in Gilchrist et al. (2017), who show that U.S. manufacturing firms with lower initial liquidity buffers (who are more likely to hit liquidity constraints) increase prices relative to other firms over the course of the Great Recession. They are also consistent with Montero and Urtasun (2021), who show that estimated markups of Spanish manufacturing firms in sectors with higher initial average debt-to-cash flow ratios increase over the Great Recession, and Duca et al. (2018) who provide survey evidence that Italian firms who report financial constraints are also more likely to report increases in markups. These contributions present results consistent with ours, but are subject to important endogeneity concerns that our identification strategy is designed to address: initial liquidity reserves and debt correlate with access to external financing (see e.g. Bates et al. (2009)), and firms that hold little liquidity or high debt initially may also have easier access to credit during the financial crisis.

Our second contribution is evidence of the relevance of different channels behind the overall positive effect we find. The two mechanisms consistent with a positive relationship between credit supply and prices are the "liquidity channel" of Gilchrist et al. (2017) and Chevalier and Scharfstein (1996) and the "working capital channel" (see e.g. Christiano and Eichenbaum (1992), Christiano et al. (2015), Bigio (2015)). The working capital channel is based on the idea that when firms have to pre-finance part of their variable production cost, an increase in interest rates can affect marginal cost beyond what is implied by the rental cost of physical capital. Such a cost increase would then be passed through into prices. The "liquidity channel" is based on the idea that firms operate in markets where short-run demand elasticities are lower than the longer-run demand elasticities—for example, due to habits or search frictions. In this context, firms can raise internal liquidity by increasing their markups when external credit becomes more costly or difficult to obtain. This leads to an increase in short-run profits at the cost of a loss of future market share. Our results suggest an important role for the liquidity channel: we find that the gross profit margin of firms exposed to a negative credit supply shock increases by around 3pp, while their European market share decreases by about 10% in the longer run. This is inconsistent with the pass-through of higher working capital cost alone, which would imply constant (full pass-through) or lower (incomplete pass-through) profitability. We do find that exposed firms that use more working capital initially raise their prices more strongly than other firms, suggesting that pass-through of working capital cost adds to the liquidity channel. However, in back-of-the-envelope calculations we can attribute at most one tenth of the price increase to a higher cost of working capital.

In addition to the micro-econometric evidence already discussed above, our results relate to recent macro-econometric work that has integrated measures of financial shocks into structural VARs. The results in this literature are mixed and depend on the identifying restrictions imposed on the data. For example, Gilchrist and Zakrajšek (2012) find insignificantly negative effects of a financial shock on inflation in a VAR identified through imposing a zero effect on impact. Several other papers identify the effects of financial shocks on inflation through sign restrictions on the relationship between output and inflation (Hristov et al. (2012), Darracq-Paries and De Santis (2015), Gambetti and Musso (2017), Furlanetto et al. (2019)). While the main focus of these papers lies in estimating the impact of financial shocks on output, they also tend to find that financial shocks decrease inflation. In contrast, Abbate et al. (2020) present evidence based on a structural VAR that leaves the response of inflation unrestricted, and find that negative financial shocks raise prices. Compared to the macro-econometric approach, we do not rely on structural restrictions but instead work under the assumption that pre-crisis banking relationships are independent of exposure to the Great Recession through non-financial channels.

Our results on the relationship between loan supply and prices also contribute more broadly to understanding the unusual price dynamics over the Great Recession. We show that in a partial equilibrium counterfactual scenario in which the credit supply of all Danish banks mirrors the credit supply of the deposit-funded banks less exposed to the financial crisis, the aggregate producer price index would have fallen about 3% below its actual values over the 2008–2010 period. This brings the behavior of aggregate prices closer to a conditional forecast based on a simple VAR estimated on pre-crisis data and can explain some of the missing disinflation in Denmark. Moreover, our results contribute to the discussion of the interaction between macro-prudential policy measures, traditional monetary policy, and real economic activity. In the aftermath of the financial crisis, Farhi and Werning (2016) and Korinek and Simsek (2016) argue that policies that limit borrowing during a boom and support lending during recessions could improve welfare due to aggregate demand externalities. We show that such policies can be in conflict with price-stability targets of traditional monetary policy: restricting credit availability can be inflationary during a boom, and supporting credit supply during the bust enhances deflationary tendencies.

The rest of the paper is structured as follows. In Section 2 we present the data we use in our analysis. We discuss estimation and identification assumptions in Section 3. Section 4 shows that our measure of exposure to bank-level shocks substantially affected loan balances and interest rates paid by firms. In Section 5 we present the main results on the effects on prices. In Section 6 we discuss evidence for the importance of the liquidity and working capital channels. Section 7 discusses the aggregate importance of our results. Finally, Section 8 concludes the paper.

# 2 Data

Our analysis is based on several administrative and survey-based datasets collected by Statistics Denmark. The core data match the universe of bank loans between Danish banks and firms with banks' balance sheets on the one hand and manufacturing firms' output prices on the other hand.

## 2.1 Loan data

Our data on lending is based on Danish banks' annual account-level reports of all loans and deposits to the Danish Tax Authority ("Skat"). We use the part of this dataset that covers firms. All bank loan relationships are reported, including regular loans, syndicated loans, credit card debt, and accounts with variable utilization such as revolving loans or overdraft deposit accounts. The notable exception are mortgages, which in Denmark are provided outside the banking system by specialized mortgage institutions.[2] The primary variables reported by banks are the account balance per December 31st and interest paid over the year. Loan accounts can be linked to banks as well as the borrowing firms through bank register numbers and unique identifiers of all firms taxed in Denmark.

We combine this dataset with bank balance sheet data provided by the Danish Financial Supervisory

[2]Danish mortgage institutions are highly regulated and fund themselves through bonds that exactly match the maturity of their mortgages. As a result, they did not experience a funding shortage comparable to the Danish banking sector.

Authority ("Finanstilsynet") and the Monetary and Financial (MFI) statistics of the Danish central bank, which cover loans and deposits to non-financial firms and in total for each bank. The sum of loans in the micro data closely follows aggregate bank lending from balance sheets for the 2005–2010 period, as we show in Figure A.2 in the Appendix.

In addition to outstanding loans and interest payments, the loan data also covers loan maturity and the contractual interest rate for some observations. However, these variables are not systematically reported by most banks. We therefore calculate an average interest rate for each firm $i$ from end-of-year loan balances and total interest payments over a year:

$$i_{i,t} = \frac{\text{Interest payments}_{i,t}}{\frac{1}{2}(\text{Loans}_{i,t-1} + \text{Loans}_{i,t})}. \tag{1}$$

For low- and medium-level interest rates, this average interest rate measure lines up well against the contractual rates when both are available in the data (Figure A.3 in the Appendix). It fails to capture very high interest rates above 10%, which are typically associated with short-run loans—such as overdraft accounts and credit cards—that are often settled within a year and hence not adequately captured by the average end-of-year balance we use in our calculation. The coefficient from a regression of average interest rate measure on the contractual interest rate is 0.91 for contractual interest rates below 10% and 0.41 overall.

### 2.2 Price data

**Producer price index survey** We combine the loan data with two sources of price data. First, we use survey data underlying the Producer Price Index (PPI). The Danish PPI micro data provides a very clear picture of the price developments of large Danish manufacturing firms, with the disadvantage that it covers relatively few firms. It is based on a monthly survey in which firms report prices for a persistent selection of their product portfolio. On average, the data covers about 3,500 price quotes from about 500 firms. Products are classified using 8-digit Harmonized System (HS) codes. Firms also report whether goods are sold domestically or exported, and in our baseline results we only include domestic prices. The reported prices are transaction prices in Danish kroner and include temporary sales and discounts.[3] The survey is designed to allow adjustments for quality changes and product substitutions. The dataset is strongly balanced, with very few gaps in price series. We perform quality adjustments and winsorize price changes at $\pm 1$ log points in the monthly data.[4] We then transform the dataset to quarterly frequency by keeping the price in the first month of each quarter. The Danish PPI survey has been previously used in Dedola et

[3]When applying the sales filter of Nakamura and Steinsson (2008), we detect that a share of 0.31% of price observations and 3.5% of price decreases are sales. Therefore, sales are not a prominent feature in the Danish PPI data.

[4]This truncates 0.61% of price changes in the raw data.

al. (2019), who provide important price-setting moments and show that the data is comparable to other European producer price datasets.

**Export unit values** To complement the PPI data, we use export unit values calculated from data collected by Danish customs. Compared to prices reported in the PPI data, unit values are a relatively noisy measure of prices. However, they are available for all goods exporters above a small annual export threshold. Customs data cover firms' export sales and quantities at the level of destination countries and 8-digit Combined Nomenclature (CN) product codes. The data are reported at monthly frequency. We sum sales and quantities over countries and months, and calculate yearly unit values for 8-digit CN categories $c$ for each firm:

$$P_{i,c,t} = \frac{\text{Sales}_{i,c,t}}{\text{Quantity}_{i,c,t}} \tag{2}$$

The CN classification is subject to frequent adjustment of product categories. We construct unit value indices for each firm and 2-digit CN category based on consistent combinations of 8-digit CN categories. We describe this procedure in more detail in Appendix A. These unit value indices are a noisy measure of underlying prices: there may be unobserved composition changes within reported 8-digit category sales, and firms may mis-classify some products in some years. In Figure B.1 in the Appendix, we benchmark changes in export unit value indices against changes in PPI prices in the same CN2 category for firms that appear in both datasets. Summing over the contemporaneous coefficient plus one lag and lead, the correlation between PPI prices and export unit values amounts to roughly 0.4.

## 2.3 Other data

In addition to price and lending data, we use several other register datasets. First, we use the Danish firm register, which contains yearly data on industry codes, legal form, firm age, total wage bill, and employment for each firm active in Denmark. Second, we use the Danish accounting statistics. This annual dataset contains important balance sheet items such as sales, profits and total assets for most Danish firms. In addition, it contains more detailed balance sheet items such as inventories based on a survey taken by a large sample of Danish firms.

## 2.4 Sample

The starting point for our sample is the 2007 Danish firm register, which includes the population of Danish firms. It contains 7,281 active manufacturing firms, which account for about 24% of private sector employment. Based on practical considerations and our identification strategy, we

Table 1: 2007 sample characteristics

| | All firms | | PPI match | | Export unit values match | |
|---|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Mean | Median |
| Employment | 98.4 | 38.0 | 367.8 | 154.0 | 131.6 | 53.0 |
| Ann. employment growth 04-07 (%) | 6.5 | 3.0 | 2.7 | 0.8 | 5.5 | 2.6 |
| Ann. employment growth 08-10 (%) | -7.4 | -7.1 | -8.8 | -7.9 | -7.6 | -7.1 |
| Firm age (years) | 20.7 | 18.7 | 30.2 | 26.8 | 22.6 | 20.3 |
| Sales (mio DKK) | 169.0 | 42.7 | 791.9 | 224.9 | 236.8 | 68.3 |
| Ann. sales growth 04-07 (%) | 17.0 | 8.9 | 10.9 | 6.6 | 15.7 | 8.6 |
| Ann. sales growth 08-10 (%) | -1.9 | -3.3 | -3.0 | -3.6 | -1.8 | -2.9 |
| Profits (% of sales) | 5.4 | 5.5 | 5.2 | 4.5 | 5.2 | 5.2 |
| Bank loans (% of sales) | 18.9 | 14.0 | 20.9 | 15.1 | 19.3 | 14.9 |
| Bank loans (% of debt) | 47.7 | 44.0 | 47.7 | 42.5 | 47.7 | 43.6 |
| Avg. interest rate (%) | 5.8 | 5.6 | 5.1 | 5.1 | 5.5 | 5.4 |
| Bank connections (incl. deposits) | 2.9 | 3.0 | 3.9 | 4.0 | 3.2 | 3.0 |
| Bank connections (only loans) | 2.3 | 2.0 | 3.0 | 3.0 | 2.6 | 2.0 |
| Share of loans from prim. bank (%) | 88.3 | 99.2 | 82.3 | 91.6 | 86.1 | 98.0 |
| Share of short-maturity loans (%) | 77.4 | 100.0 | 72.1 | 87.1 | 76.2 | 100.0 |
| Equity share (%) | 29.1 | 28.4 | 35.8 | 34.7 | 31.2 | 31.0 |
| Deposits (% of sales) | 2.4 | 0.3 | 2.4 | 0.5 | 2.4 | 0.4 |
| Inventories (% of sales) | 14.3 | 12.5 | 17.5 | 15.5 | 16.6 | 14.8 |
| Avg. ann. price change 04-07 (%) | | | 2.7 | 1.3 | 1.7 | 1.8 |
| Avg. ann. price change 08-10 (%) | | | 1.8 | 0.8 | 2.2 | 1.4 |
| Avg. demand elasticity | | | 3.5 | 2.4 | 3.6 | 2.4 |
| Observations | 1,753 | | 213 | | 1,176 | |

*Notes*: Summary statistics for the population and the matched samples conditional on sampling restrictions. Unless stated otherwise, variables are measured in 2007. Growth rates of employment and sales are winsorized at the 1st and 99th percentile. The variables displayed in the last three rows are firm-level averages of good-level information. Demand elasticity denotes the estimated price elasticity of demand estimated for categories of goods by Broda and Weinstein (2006), which we will use in Section 5.2.

impose several restrictions on this population—Table A.1 in the Appendix illustrates the bite of each restriction. We exclude small firms with less than 10 employees or less than 1,000,000 DKK (roughly 135,000 EUR) in sales, and condition on continuous activity between 2005 and 2010. Since our identification strategy requires an active lending relationship with at least one bank, we also exclude firms with bank loans of less than 1% of sales in 2007, or less than 100,000 DKK (about 13,500 EUR) in 2006 or 2007. This leaves us with 1,753 firms that represent 47% of manufacturing employment. Of these firms, we can link 213 firms to the PPI survey, and 1,176 to export data. These matched firms account for 21% and 42% of total manufacturing employment.

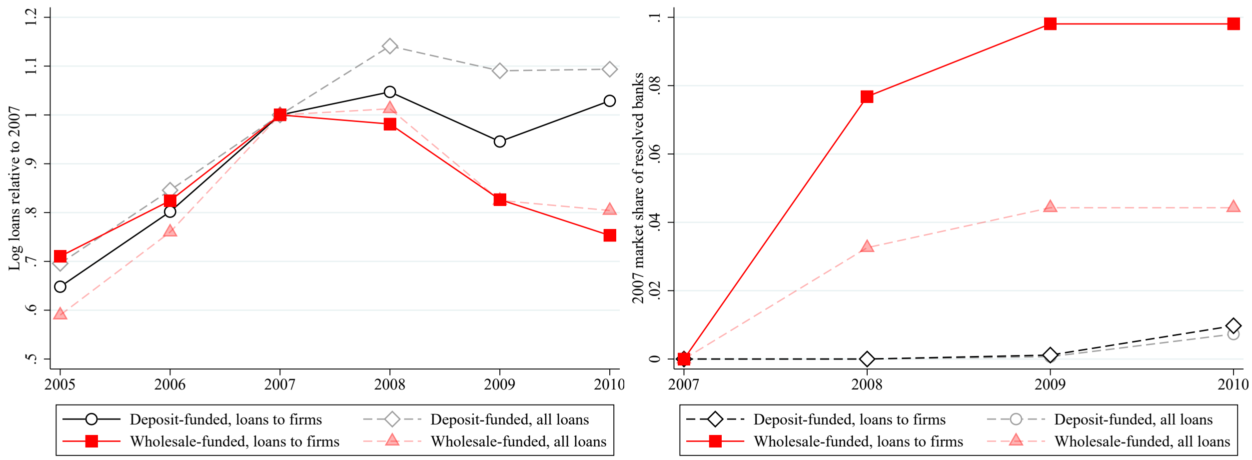
In Table 1 we present a summary of firm characteristics in the matched PPI and export unit value datasets, compared to the full population of manufacturing firms that fulfil all sample restrictions. Firms in the PPI dataset are substantially larger and older than firms in the larger unit value dataset, who in turn are slightly larger and older than the population. Firms' reliance on bank loans, measured as percentages of sales or overall debt, is similar across the samples. Even though many firms have multiple banking connections, the share of a firm's primary bank in pre-crisis lending is high (around 0.85) and similar in all three groups, and even firms with multiple loan relationships should thus still be affected by a decrease in their primary bank's loan supply.

## 3 Identification strategy and empirical specification

**Identification strategy** Our identification strategy uses heterogeneous exposure of Danish banks to the 2007–2008 global financial crisis as a source of exogenous variation in the loan supply to borrower firms. During the early 2000s, aggregate lending of Danish banks grew rapidly. Deposits were not growing at the same pace, and some banks relied heavily on funds borrowed in the inter-bank wholesale funding market to fund this expansion. When inter-bank lending markets froze up at the end of 2007, these "wholesale-funded" banks faced a severe funding shortage and were forced to cut their lending compared to "deposit-funded" banks. This pattern has been used in Jensen and Johannesen (2017) as a source of exogenous variation in the credit supply to Danish households. It is similar to identification strategies that use heterogeneity in US banks' exposure to the financial crisis as source of variation in credit supply to firms (e.g. Chodorow-Reich (2014)).

We follow Jensen and Johannesen and divide Danish banks into a wholesale-funded and a deposit-funded group based on the ratio of loans on the asset side of their balance sheets to deposits on the liability side. We use the 2007 loans-weighted median loan-to-deposit ratio of 1.37 as a cutoff. Of the 145 banks in our sample in 2007, this puts 31 banks in the wholesale-funded and 131 banks in the deposit-funded group. Wholesale-funded banks include two out of the largest five, and 9 out of the largest 15 banks in terms of corporate lending. The difference in lending dynamics between the two groups is apparent in Figure 1, panel (a). Aggregate lending of both groups grows rapidly in the years leading up to the crisis. Starting in 2008, lending of wholesale-funded banks drops relative to deposit-funded banks. This pattern is evident in total loans, as well as when only looking at loans to Danish non-financial firms. By the end of 2010, the gap in outstanding loans relative to 2007 amounts to about 25%. Moreover, as suggested by panel (b), banks in the exposed group are substantially more likely to be resolved over the course of the crisis. By the end of 2010, banks from the exposed group accounting for about 10% of 2007 corporate loans have ceased to exist as independent entities or transferred substantial shares of their loan portfolio into bad banks. This includes the resolution of 4 out of the largest 15 banks. In contrast, bank failures in the deposit-funded group are rare, and the 2007 market share of resolved banks in that group amounts to roughly 1%.

Figure 1: Deposit-funded vs. wholesale-funded banks




(a) Total loans

(b) Share of resolved banks in 2007 loans

*Notes*: Panel (a): Outstanding loans by banks with a 2007 loan-to-deposit ratio below (deposit-funded) and above (wholesale funded) the loans weighted median, normalized to 2007. The solid lines sum loans to Danish non-financial firms, the dashed lines sum all loans (including households). Panel (b): 2007 market share of deposit- and wholesale-funded banks that are resolved by a given year. The solid lines sum over market shares in the market for loans to non-financial firms, the dashed lines in the overall loan market.

**Firm exposure** Our main analysis proceeds at the firm level. To map bank-level to firm-level shocks, we define firms' exposure to loan supply shocks as the share of loans with wholesale-funded banks in their total 2007 bank lending relationships, i.e., the part of bank loans that is extended by high loan-to-deposit banks prior to the crisis.

$$\text{Exposure}_i = \frac{\sum_{b\in B} \text{Loans}_{i,b,2007} \times \text{Wholesale-funded}_b}{\sum_{b\in B} \text{Loans}_{i,b,2007}} \tag{3}$$

Firm exposure commonly takes values 0 or 1, but may take values in between as well, since some firms have multiple banking relationships. Of the firms with price information, slightly below 35% have loans with wholesale-funded banks only, and slightly above 35% have loans with deposit-funded banks only. The distribution of exposure of the 30% remaining firms is roughly uniform. The full distribution of our exposure measure is shown in Figure A.4 in the Appendix.

Several closely related papers, most importantly Chodorow-Reich (2014) and Kim (2021) use Bartik-style instruments that are constructed from the weighted average change in banks' lending or other measures of bank health during the financial crisis, where the weights reflect the importance of each bank in firms' pre-crisis loan relationships. We instead directly use variation in exposure (i.e what would be the weights in a Bartik instrument) as our source of identification. As discussed in Borusyak et al. (2018) and Goldsmith-Pinkham et al. (2020), the exclusion restrictions of Bartik-style instruments rely on either independence of the weights (i.e. our exposure measure) or a large number of independent aggregate (in this case bank-level) shocks. We think that the former assumption is appropriate in our case, and we prefer to directly use exposure as the basis for our estimation, since mergers and absorption of parts of some banks' loan portfolio into bad banks make it difficult to construct loan supply measures for some of the most exposed banks after 2007.

**Estimation** Our baseline estimates for price outcomes come from variants of the following dynamic difference-in-difference specification:

$$\log \text{Price}_{i,p,t} = \Lambda_{i,p} + \Gamma_{s(i),t} + \sum_{\substack{k=2005 \\ k\neq 2007}}^{2010} 1(t=k) \times (\beta_k \text{Exposure}_i + \gamma_k X_i) \tag{4}$$

This specification estimates the dynamic effect of exposure of firm $i$ on the price of product $p$ relative to its value in the 2007 base period. We include observations from the 2005–2010 period and estimate one coefficient for each year except 2007. The price in the 2007 base period is absorbed in the firm-product fixed effect $\Lambda_{i,p}$.[5] We include sector-time fixed effects $\Gamma_{s(i),t}$ that ensure estimates are identified from variation of exposure within sectors. Moreover, in our main specification we control for dynamic effects of a number of constant 2007 firm characteristics $X_i$ (see e.g. Bentolila et al. (2018) for a similar application). These controls include the average interest rate, the short-term loan share, and the deposit-to-sales and loans-to-sales ratios.

We estimate Equation (4) using OLS for PPI prices and loan outcomes. For export unit values, we use an approach that puts less weight on more volatile series. Unit values are prices measured with error, and we expect the variance of this measurement error to vary between different series. For example, some firms may be more careful in correctly classifying their exports, while others may frequently misclassify products. Within-category composition changes, for example between customers who are charged different prices, are another possible source of measurement error, and likely especially affect lower-volume unit value series. Other contributions working with unit values, such as Broda and Weinstein (2006) or Amiti et al. (2019) weight unit value regressions by sales volume to deal with the resulting inefficiency. We implement an iterated FGLS estimator when using unit value outcomes: we estimate Equation (4) using OLS first, calculate the variance of the regression residuals for each series, and then use the inverse variance as weight in the next iteration. We repeat this step until the weights converge. We present alternatives to this procedure in robustness checks discussed below—in general, alternative estimates are comparable in magnitude, but less precise than our FGLS estimates.

[5] For firm outcomes such as loans, the dependent variable is at the firm level, i.e. $Y_{i,t}$, and we include firm fixed effects instead.

Our baseline results are reduced-form coefficients—i.e. we separately show that exposure has an effect on loan outcomes and prices by estimating Equation (4) with credit and price outcomes. We also provide estimates of the elasticity of prices to the supply of loans. These estimates are obtained from instrumental variable estimates of the following specification:

$$\log \text{Price}_{i,p,post} = \Lambda_{i,p} + \Gamma_{s(i),post} + \beta \log \text{Loans}_{i,post} + \gamma X_i \tag{5}$$

We estimate this equation on samples including observations from the base period in 2007 and a post-period that is either 2008, 2009 or 2010. We always use 2008 levels of loans for the post period, i.e. we estimate the dynamic response of prices over different horizons to the 2007–2008 drop in loans. We use $\text{Exposure}_i \times \text{Post}_t$ as an instrument for $\log \text{Loans}_{i,t}$. Since our instrument does not vary over time, we cannot clearly distinguish between time variation in the extent of the credit supply shock and a possibly delayed dynamic response to it.

**Identification** A causal interpretation of our estimates requires exposure to other shocks that affect prices to be independent of firm exposure to wholesale-funded banks. This could be violated if there is sorting between banks and firms along observeable or unobserveable dimensions that correlate with exposure to the Great Recession through channels other than the supply of bank loans. Our dynamic diff-in-diff estimates show that there is no significant difference between exposed and non-exposed firms in the development of loan or price outcomes prior to 2007, and that firms behave very similarly during normal times.

Moreover, we show that exposed and non-exposed firms are very similar according to observable characteristics, and that the modest differences in firm characteristics do not impact firms' response to the credit supply shock. We show in Table A.2 in the Appendix that there are no substantial differences in a large number of firm characteristics between firms who borrow from wholesale-funded or deposit-funded banks. There are some systematic differences between firms with partial exposure (i.e. exposure between 0.02 and 0.98) and firms with full (>0.98) or no exposure (<0.02). These differences arise since larger firms are more likely to have multiple banking relationships and hence to exhibit intermediate exposure. Therefore, we report Kolmogorov-Smirnov test statistics comparing the distribution of pre-crisis characteristics between firms with no or full exposure, and separately firms with low (0.02–0.5) and high (0.5–0.98) partial exposure. With respect to most characteristics, the respective p-values do not indicate any systematic differences in firm characteristics by exposure.

The only consistently significant difference between exposed and non-exposed firms is the reported share of short-term loans in total loans—exposed firms seem to have more longer-term loans than non-exposed firms. However, there are important inconsistencies in the maturity variable included in the loan data: except for the three largest banks, banks report all loans as short-term loans.

It therefore seems likely that the distribution reflects differences in reporting standards between different banks rather than actual differences in loan maturity. We control for the dynamic impact of the short-term loan share in all our regressions. Since the terms of longer-term loans are more difficult to adjust, a lower short-term share of exposed firms would reduce the extent to which bank-level shocks are transmitted to exposed firms and reduce the power of our identification strategy, but not affect its validity.

In our baseline regressions, we control for three additional pre-crisis firm characteristics which that exhibit modest differences of firms by exposure. The share of bank deposits in sales prior to 2008 is higher for firms with high partial exposure than those with low partial exposure, although the difference between firms with no and full exposure is small and of the opposite sign. Furthermore, we include the 2007 loans-to-sales ratio and the 2007 average interest rate as controls. The p-values for Kolmogorov-Smirnov tests of equality of distributions of these firm characteristics between firms with low and high exposure are 0.13 and 0.07, respectively. We show in numerous robustness checks that our results are not sensitive to the inclusion of additional controls. We estimate specifications that exclude all control variables, pick covariates from the firm characteristics in Table A.2 using the post-double selection LASSO[6] methodology proposed in Belloni et al. (2014, 2017), or include all firm characteristics in Table A.2 as controls. Our results are not affected by any of these variations. Furthermore, all our regressions include sector-time fixed effects and coefficients are identified from within-sector variation, so modest differences in the distribution of firms over sectors (see Figure A.5 in the Appendix), are not a concern for identification.

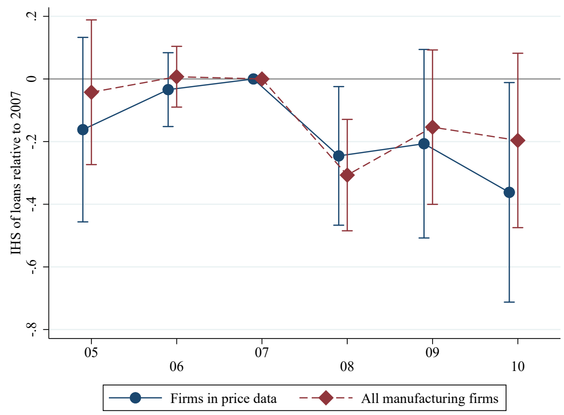
## 4 Cross-sectional variation in loan supply

**Baseline "first stage" result** We first document the dynamic effect of firm exposure on loan outcomes. As expected from a negative credit supply shock, we find that firms' exposure has a large negative effect on outstanding loan balances, and a large positive effect on the average interest rate paid on the remaining loans. We use the inverse hyperbolic sine (IHS) transform of loans as our baseline outcome to deal with zeros and right-skewness of loan balances. Like with log outcomes, one can interpret estimates with IHS outcomes as approximate elasticities.[7] We find that full exposure decreases outstanding loans by about 20-30% (panel (a) of Figure 2). The effect on loan balances is similar regardless of whether we include firms for which we observe prices or all manufacturing firms. Panel (b) illustrates the effect for the average interest rate, which increases by 0.25-0.5pp between 2008 and 2010. Given a 2007 mean interest rate of about 5.4%, this effect

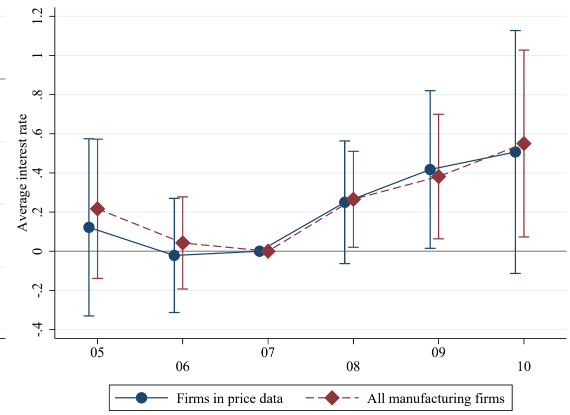
[6] The PDSLASSO procedure includes controls if they predict firms exposure, or if they predict the development of outcome variables over the 2005–2010 period.

[7] The inverse hyperbolic sine function (IHS) is defined as $\log(x+\sqrt{x^2+1})$. For most of its range it is approximately equal to $IHS(X) \approx \log(2x)$ and regressions with IHS outcomes can be interpreted similarly to regressions with log outcomes. The advantage of the IHS is that it is defined at zero, with $IHS(0) = 0$.

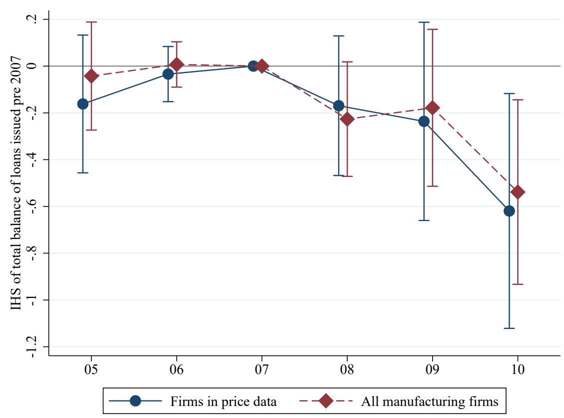
Figure 2: Effects of firm exposure on loan outcomes



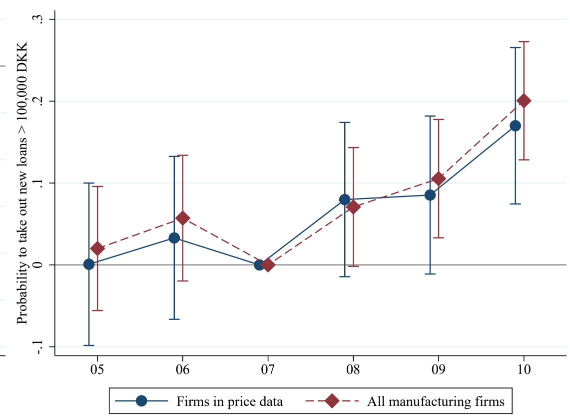

(a) Total loan balance



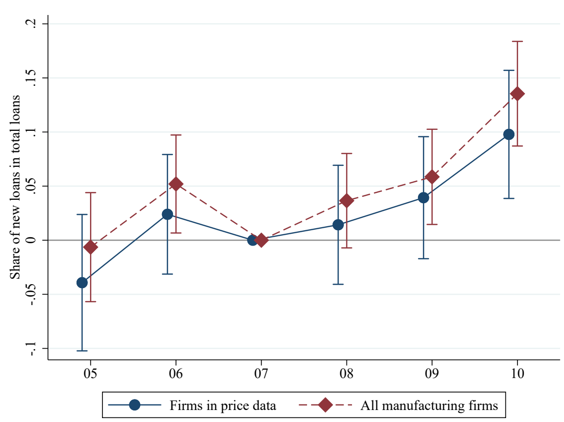

(b) Average interest rate



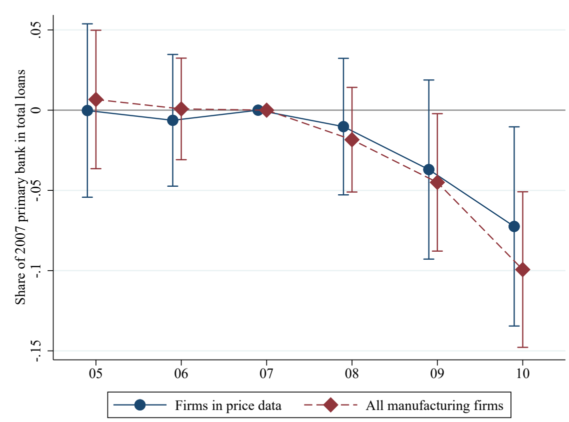

(c) Balance of loans originated up to 2007




(d) Propensity to take out new loans




(e) Share of new loans in total loans




(f) 2007 primary bank share in total loans

*Notes*: The figures show estimates of the effect of exposure to wholesale-funded banks in 2007 on loan market outcomes 2005–2010. The dynamic difference-in-difference specification we estimate follows Equation (4). The sample includes all firms firms that fulfil sampling criteria (diamonds) and the subset that can be matched to a price in either the PPI or unit value dataset (circles). The figures include 95% confidence intervals based on standard errors clustered at the firm level.

corresponds to a relative increase of 5-10%. For both loans and interest rates, we do not find significant differences by exposure prior to the onset of the financial crisis.

**Mechanism** In the last four panels of Figure 2 we illustrate the mechanism behind the decrease in loan balances in more detail. Exposed firms repay loans that were originated up to 2007 faster than other firms (panel (c)), but are more likely to take out new loans after 2007 (d). These additional new loans amount to 5–10% of firms' total loans in 2009 and 2010 (e). New loans are often taken out from banks that are not firms' 2007 "primary bank" (i.e. the largest bank in terms of 2007 loan volume)—the share of exposed firms' 2007 primary bank in firms' loans decreases by 5 to 10pp by the end of 2010 (e). These patterns are inconsistent with a demand-driven differential decrease in bank lending, and lend further support to our identification strategy.

**Robustness** We present important robustness checks to these results in Tables A.3, A.4 and A.5 in the Appendix. Table A.3 shows results for outcomes that deal with the issue of zeros and right-skewed loan growth rates in different ways. The results are robust to using either logarithms or growth rates of loan balances relative to 2007, winsorized at the 5th and 95th percentile, as outcome variables. All specifications show a strong drop in loan balances after 2007. In Table A.4 we present additional robustness checks for the loan volume results: The large drop in loan balances by the end of 2008 is robust to controling for sparser 2-digit industry-year fixed effects or linear firm-level trends. The results do not substantially change if we add additional dynamic control variables or pick controls for the diff-in-diff using the PDSLASSO method. Analogous robustness checks for the interest rate results are provided in Table A.5.

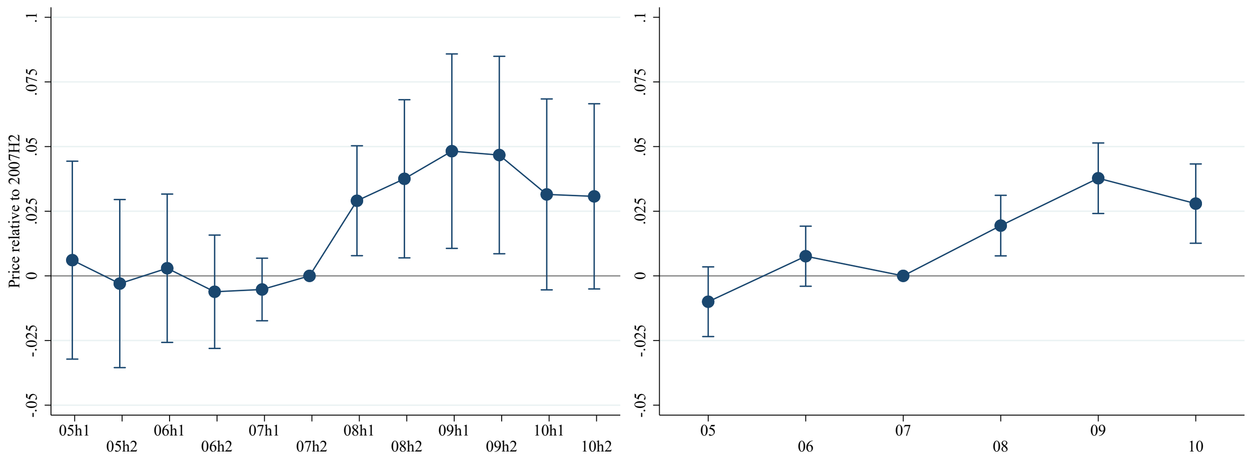
# 5 The effect of credit supply shocks on prices

## 5.1 Baseline result

We now turn to effects of firms' exposure on their output prices. We estimate reduced-form results using variants of Equation (4) with log prices and unit values as dependent variables. For PPI prices, the data is in quarterly frequency and we estimate one coefficient for each half-year (in figures) or year (in tables). For unit values indices, which are constructed at yearly frequency, we estimate one coefficient for each year.

Exposed firms increase their domestic PPI prices by roughly 3.5% relative to non-exposed firms in 2008. We find a peak effect of 5% in 2009 (Figure 3, panel(a)). Prior to the global financial crisis, prices of exposed and non-exposed firms evolve in parallel. Similarly, unit values of goods exported by exposed firms increase by 2% in 2008 relative to unexposed firms, and the difference

Figure 3: Effect of firm exposure on prices




(a) Domestic prices in PPI

(b) Export unit values

*Notes*: The figure shows estimates of the effect of exposure to wholesale-funded banks in 2007 on PPI prices and export unit values 2005–2010. The dynamic difference-in-difference specification we estimate follows Equation (4), but with a dynamic effect estimated for each half-year in the case of the quarterly PPI data. The figures include 95% confidence intervals based on standard errors clustered at the firm level.

peaks at 3.8% in 2009 (Figure 3, panel(b)). Prior to the global financial crisis, unit values of both groups of firms evolve roughly in parallel. Despite the differences in the underlying data source and firm samples, both unit values and prices exhibit very similar dynamics. Estimated coefficients and standard errors for the years 2008–10 are provided in the tables in Appendix A.5.

**Robustness of reduced form results** We present results for different specifications and samples using PPI prices in Tables A.6 and A.7. In column (2) of Table A.6 we include linear firm trends, in column (3) we add fixed effects for each year-2-digit CN product category combination (in addition to sector-time fixed effects). Both do not substantially alter the estimated coefficients. In column (4) we omit all control variables and in column (5) we choose control variables out of a larger set of 12 variables using the PDSLASSO methodology proposed in Belloni et al. (2014, 2017). The controls selected by this procedure include our baseline controls used in all specifications, the logarithm of 2007 employment, the 2007 market share of a firm and the profit-to-sales ratio in 2007. In column (6) we include all 12 variables that we allow the LASSO to pick from. In Table A.7 we vary the sample used to estimate the effects. In column (1) we restrict the sample to firms with exposure below 0.02 or above 0.98, and in column (2) we restrict the sample to firms with only one important lending relationship. The effects are very similar in this smaller sample. In columns (3) to (6) we relax the baseline sample restrictions. The results are not affected by including products that exit the PPI sample between 2007 and 2010.[8] In column (4) we include export prices reported in the PPI, which reduces the magnitude of the effects, in line with the lower estimates we find for export unit values more generally. In column (5) we include firms with low levels of loans. As one would expect, this reduces the size of the coefficients further. Finally, if we relax all three restrictions at the same time—i.e. we include all price series with an observation in 2007—the coefficients become substantially smaller but remain positive.

In Tables A.8 and A.9 we present analogous robustness checks for export unit values. Our main finding is robust to including trends, product category-time fixed effects, dropping controls, picking them via PDSLASSO or including a larger set of control variables. Estimated effects are similar when we drop firms with partial exposure or only include firms with one major bank. They are robust to including products that enter between 2005 and 2007 or exit between 2008 and 2010, and to including firms with low loans. Like for domestic prices, estimated effects are smaller when we drop all sampling restrictions at the same time. Finally, in Figure A.6 we provide two robustness checks with respect to the FGLS estimation. First, the estimated peak effect in 2009 is significant and similar in magnitude if we estimate the effect using unweighted OLS but exclude the 20% most volatile unit value series instead. Moreover, we show that the iterated FGLS quickly converges to stable coefficients and standard errors and changes little after two iterations.

**IV estimates** Our results so far provide reduced form evidence that firms with loan relationships to wholesale-funded banks see their loan balances decrease and increase their prices relative to other firms. Here, we provide direct instrumental variable estimates for the loan supply elasticity of firms' prices. We estimate three elasticities based on specification (5) over the 2007 to 2008, 2007 to 2009 and 2007 to 2010 horizons. All three specifications use the 2007–2008 drop in lending as the endogenous variable and exposure to wholesale-funded banks interacted with a time dummy as an instrument. Panel (II) of Table 2 presents our baseline IV estimates. The elasticity estimates for PPI prices lie between -0.04 and -0.06. As expected, the IV estimates are less precise than the reduced form estimates but significant at 5% or 10% confidence levels for the 2007 to 2008 and 2007 to 2009 horizons, respectively. The analogous estimates for the export unit values, using the variance of FGLS residuals from Equation (4) as weights, are larger but insignificant.

The IV estimates are based on a somewhat weak first stage. The F-statistic in the PPI sample indicates a significant first stage relationship, but the F-statistic in the unit value sample indicates an insignificant first stage relationship. Both are below common critical values for worst-case scenario upper bounds on the bias of the IV estimator under weak instruments provided by Olea and Pflueger (2013). We deal with this issue in several ways. First, weak instruments always bias IV estimates toward the OLS estimate, which we provide in panel (I) of Table 2. All OLS estimates

[8] Products may exit due to substitutions and firms due to panel rotation—we do not include firms that become inactive in the firm register.

Table 2: IV estimates of loan supply elasticity of prices

| | (I) OLS | | | | | |
|---|---|---|---|---|---|---|
| | Domestic prices in PPI | | | Export unit values | | |
| | 2007–08 | 2007–09 | 2007–10 | 2007–08 | 2007–09 | 2007–10 |
| Log Loans | -0.021*** | -0.013* | -0.016*** | 0.000 | 0.001 | -0.001 |
| | (0.006) | (0.007) | (0.006) | (0.002) | (0.003) | (0.003) |
| Observations | 5,682 | 5,673 | 5,548 | 5,730 | 5,730 | 5,730 |
| Firms | 213 | 213 | 213 | 1,080 | 1,080 | 1,080 |
| | (II) Baseline IV - first stage regression at product level | | | | | |
| | Domestic prices in PPI | | | Export unit values | | |
| | 2007–08 | 2007–09 | 2007–10 | 2007–08 | 2007–09 | 2007–10 |
| Log Loans | -0.054** | -0.061* | -0.041 | -0.108 | -0.207 | -0.150 |
| | (0.025) | (0.037) | (0.030) | (0.088) | (0.164) | (0.122) |
| 1st stage F-stat. | 4.522 | 4.522 | 4.522 | 1.727 | 1.727 | 1.727 |
| (p-value) | (0.035) | (0.035) | (0.035) | (0.189) | (0.189) | (0.189) |
| Anderson-Rubin stat. | 7.071 | 4.457 | 2.235 | 10.559 | 28.927 | 12.032 |
| (p-value) | (0.008) | (0.036) | (0.136) | (0.001) | (0.000) | (0.001) |
| Observations | 5,682 | 5,673 | 5,548 | 5,730 | 5,730 | 5,730 |
| Firms | 213 | 213 | 213 | 1,080 | 1,080 | 1,080 |
| | (III) Two-sample IV - first stage regression at firm level | | | | | |
| | Domestic prices in PPI | | | Export unit values | | |
| | 2007–08 | 2007–09 | 2007–10 | 2007–08 | 2007–09 | 2007–10 |
| Log Loans | -0.184** | -0.267** | -0.170** | -0.105** | -0.205** | -0.151** |
| | (0.080) | (0.116) | (0.075) | (0.047) | (0.089) | (0.067) |
| 1st stage F-stat. | 5.454 | 5.454 | 5.454 | 5.454 | 5.454 | 5.454 |
| (p-value) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) |
| Anderson-Rubin stat. | 7.071 | 4.457 | 2.235 | 10.559 | 28.927 | 12.032 |
| (p-value) | (0.008) | (0.036) | (0.136) | (0.001) | (0.000) | (0.001) |
| Observations | 5,730 | 5,721 | 5,593 | 5,762 | 5,762 | 5,762 |
| Firms | 213 | 213 | 213 | 1,089 | 1,089 | 1,089 |

*Notes*: Loan supply elasticity of prices estimated from Equation (5). For each column, we include observations from the base period 2007 and a post-period (any year from 2008 to 2010), instrumenting log loans with an exposure×post interaction. Observations in the export unit values are weighted with the inverse variance of reduced form OLS residuals for each series. Standard errors clustered at the firm level in parentheses.

are smaller (in absolute terms) than the baseline IV estimates, suggesting that our IV estimates are a lower bound. Second, we follow the recommendation of Andrews et al. (2019) and provide an Anderson-Rubin test of the null hypothesis that the loan supply elasticity of prices is zero. This test is fully robust to weak instruments and the null is rejected with high confidence, even in the unit value sample.[9]

Finally, we estimate a specification with an alternative first stage in panel (III) of Table 2 to address to possible issues with the baseline IV. First, while we observe prices at the product-level, the first-stage regressions only involve firm-level variables. Because we estimate the baseline IV regressions at the product level, the estimator overweights the first stage of firms with many products, which is likely inefficient. Second, the baseline IV estimates are based on first-stage regressions using the separate samples of firms in the PPI and the export unit values instead of using the full set of firms like we did in Section 4. To address these two problems, we use a two-sample IV approach following (Angrist and Krueger, 1992) ( with cluster-robust standard errors following Pacini and Windmeijer (2016)) and estimate the unweighted first-stage regression at the firm level on the full sample of manufacturing firms. The second stage is the same product level regression run on the respective data set as in the baseline IV. Panel (III) of Table 2 presents the results for this two-sample IV estimator. The two-sample first stage is stronger and by construction identical between the PPI and export unit value samples. The resulting IV estimates for the loan supply elasticity of prices are similar between the two samples, larger, and all significant. They vary between -0.11 and -0.27.

### 5.2 Effect heterogeneity

Do the price-increasing effects vary for different types of products? The answer to this question can potentially reconcile our main result with Kim (2021). We focus on two product characteristics that are closely related to the demand response to price changes: the elasticity of a product's demand and the degree of strategic complementarity in prices between competitors in a product market. We estimate treatment effect heterogeneity by augmenting our baseline model with additional interaction terms:

$$\begin{aligned}\log \text{Price}_{i,p,t} =& \Lambda_{i,p} + \Gamma_{s(i),t} + \sum_{\substack{k=2005 \\ k\neq 2007}}^{2010} 1(t=k) \times (\beta_k \text{Exposure}_i + \eta_k X_i + \\ & \gamma_k z_p + \delta_k [\text{Exposure}_i \times z_p])\end{aligned} \tag{6}$$

$z_p$ is a standardized, time-invariant product characteristic such as the price elasticity of demand or the degree of strategic complementarity.

[9] The Anderson-Rubin test is based on the reduced form regression, which is strongly significant for both the PPI and unit value sample.

Table 3: Price outcomes: Heterogeneity by product characteristics

| Interaction with: | Domestic prices in PPI | | | Export unit values | | |
|---|---|---|---|---|---|---|
| | (1) Demand elasticity | (2) —, alt. definition | (3) Strategic complem. | (4) Demand elasticity | (5) —, alt. definition | (6) Strategic complem. |
| 2008 | 0.023 | 0.035*** | 0.039** | 0.020*** | 0.020*** | 0.021** |
| | (0.015) | (0.014) | (0.017) | (0.006) | (0.006) | (0.008) |
| 2009 | 0.042* | 0.053** | 0.053** | 0.029*** | 0.028*** | 0.037*** |
| | (0.022) | (0.021) | (0.024) | (0.007) | (0.007) | (0.009) |
| 2010 | 0.034 | 0.044** | 0.034 | 0.026*** | 0.022** | 0.030*** |
| | (0.025) | (0.020) | (0.028) | (0.009) | (0.009) | (0.011) |
| 2008 × Interaction | -0.024 | -0.004 | -0.017*** | 0.001 | 0.002 | -0.002 |
| | (0.017) | (0.008) | (0.004) | (0.005) | (0.004) | (0.005) |
| 2009 × Interaction | -0.044** | -0.014 | -0.016** | -0.013*** | -0.010** | -0.014** |
| | (0.019) | (0.013) | (0.007) | (0.004) | (0.005) | (0.006) |
| 2010 × Interaction | -0.043** | -0.026** | -0.007 | -0.013** | -0.005 | -0.011 |
| | (0.020) | (0.013) | (0.008) | (0.006) | (0.006) | (0.007) |
| Firm-product | Yes | Yes | Yes | Yes | Yes | Yes |
| time-product | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 16,366 | 14,400 | 16,438 | 16,968 | 16,560 | 17,220 |
| Firms | 212 | 200 | 213 | 1,081 | 1,068 | 1,089 |
| Interact.: Centered | 2.40 | 3.40 | 0.00 | 2.38 | 3.94 | 0.00 |
| Interaction: Std. dev. | 2.74 | 7.78 | 0.16 | 2.57 | 9.75 | 0.16 |

*Notes*: Credit shock exposure interacted with product-level characteristics as in Equation (6): (1) demand elasticities from Broda and Weinstein provided at 4-digit SITC Rev. 3 level (see Appendix C.1 for details). (2) demand elasticities from the same source at much finer 10-digit Harmonized System code disaggregation. (3) Own estimates of strategic complementarities, proxied by the exchange-rate pass-through into domestic-currency prices (see Appendix C.3). Interaction variables are normalized to unit variance, the first two centered around the sample median and the latter around zero (no strategic complementarities). A few observations are dropped because we do not have an estimate of the respective product-level characteristic. All models contain firm-product and time-product sector fixed effects. Standard errors clustered at the firm level in parentheses.

In Table 3 we present evidence that the effect of a negative credit supply shock on prices is smaller for products with more elastic demand. We use demand elasticities estimated in Broda and Weinstein (2006) from data on U.S. imports. We use two levels of product definitions: one over 958 and a finer one one over 13,972 product categories.[10] We standardize the measure by subtracting the median across goods in the data because the distribution is heavily right-skewed and dividing by the standard deviation. In the domestic PPI, price increases of goods with a demand elasticity that is 1 standard deviation higher than the median are 1.4 to 4.4% lower in the medium run. In the

[10]Product substitutability increases with the level of disaggregation and thus the estimated level of the elasticity of demand is generally higher in the latter case. Details on the way we match both Broda and Weinstein elasticities to our data are provided in Appendix C.1.

export unit value data, the interaction coefficients are somewhat smaller, but they are significantly negative in both samples for at least one year during the recession. This result is consistent with the idea that increasing prices to raise liquidity is less attractive when customers are more likely to switch to other suppliers.

The second set of interactions included in Table 3 measure strategic complementarity at the good level, i.e. the average responsiveness of prices to relative price differences with competitors. We estimate this parameter from exchange-rate pass-through into domestic-currency export unit values prior to the Great Recession at the 2-digit CN level following Amiti et al. (2014). The details of the pass-through estimation are deferred to Appendix C.3. As one would expect, we find that the increase in prices after a credit supply shock is lower for products with higher strategic complementarity.[11]

### 5.3 Reconciling results with Kim (2021)

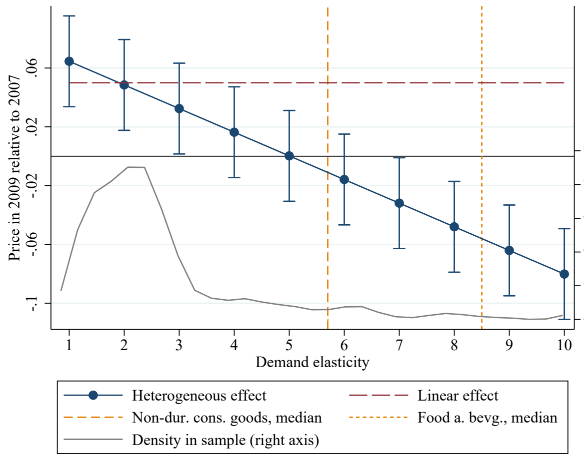
In contrast to our results, Kim (2021) finds that negative loan supply shocks lead to lower prices in a sample of producers of consumer packaged goods, mostly in food manufacturing. This effect is driven by a fire-sale of firms' inventories. Such a fire-sale should be a viable strategy to raise cash only for firms who face relatively elastic short-run demand. Indeed, both Kim (2021) and this paper find that the effect of a negative credit supply shock on prices is smaller (less positive) for products facing more elastic demand. In the lower half of Figure 4 we show cumulative densities of the coarser definition of Broda-Weinstein demand elasticities used above. The distribution in our sample (solid line) is similar to the distribution for Danish and European Union manufacturing firms overall, with a median between 2 and 3 for all three groups.[12] In contrast, the median demand elasticity for firms in sectors that produce non-durable consumption goods lies at about 5.7, and for firms in manufacturing of food and beverages at about 8.6.[13] The latter two sectors are similar to the sample of Kim (2021), and one would expect that it is easier for these firms to sell off inventory by lowering their prices, but more costly to generate internal liquidity by raising prices.

[11]The size of the interaction coefficient is such that only for goods with the highest strategic complementarities is the effect of a credit supply shock on prices potentially negative. The concept is invariably linked to the variability of markups, where the variability of markups increases with strategies complementarity. We present evidence below that support the view that firms temporarily increase their markups when they cannot access external liquidity.

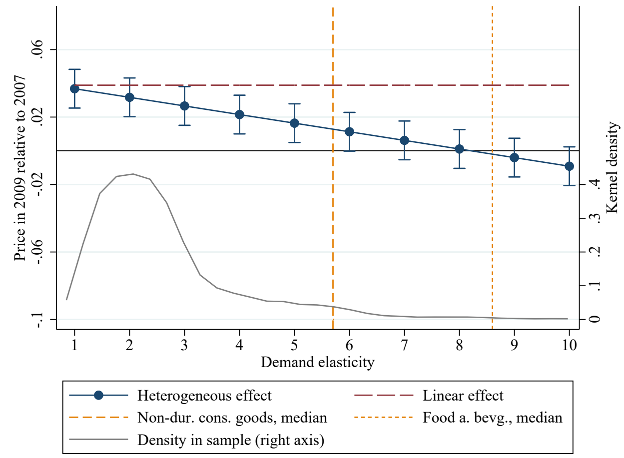
[12]For the distribution in our sample, we merge demand elasticities to the products in our data, average over goods in a firm and further aggregate using firms' sales as weights. For the reference distribution in total industrial output, we use Eurostat's Prodcom Annual Data of 2007 sales in Denmark and the European Union, respectively, at the 8-digit product code level. We first translate Prodcom product codes (the first four digits of which describe industries) to the 6-digit Combined Nomenclature we have for products in the sample using Eurostat's correspondence tables and then merge demand elasticities, which are defined by SITC code. This way, we match at least one demand elasticity for Prodcom product codes representing 93% of Danish industrial production (92% of non-durable consumer goods and 100% of food and beverages).

[13]We obtain these estimates by subsetting the Prodcom data to a basket of goods that is defined in Appendix C.1. The full cumulative densities are shown in Figure 4(c).

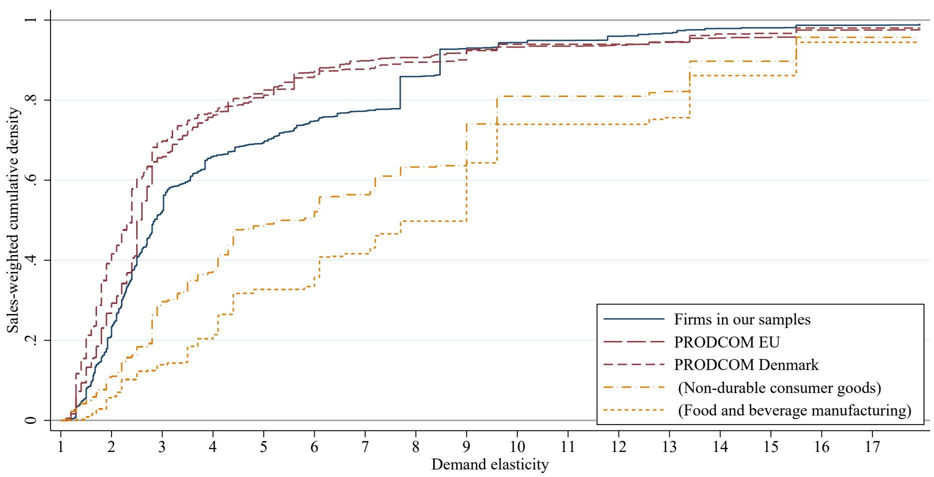
Figure 4: Marginal effects of credit supply shock by demand elasticity




(a) Domestic prices in the PPI




(b) Export unit values




(c) Distribution of Broda-Weinstein demand elasticities

*Notes*: Blue connected dots in panels (a) and (b): Effect of exposure to credit supply shock on prices in 2009 evaluated at different levels of demand elasticities (Broda and Weinstein, 2006) (90% confidence intervals). Estimates based on Equation (6). Red dashed line: Linear estimate based on Equation (4). The grey lines show kernel densities of product-level demand elasticities in the estimation sample. Vertical lines: Sales-weighted median of elasticities among non-durable consumer goods and foods and beverages. Panel (c) shows cumulative densities of the firms in our sample compared to four benchmarks: Red lines show distributions in total industrial production in European and Danish industrial production according to Eurostat Prodcom sales weights from 2007. Orange lines show distributions in the Prodcom data of two sub-samples of products consisting only of consumer packaged goods. See Appendix C.1 for our definition of the two sub-samples.

In the top panel of Figure 4 we relate the predicted effect for different demand elasticities from the linear interaction model described in Section 5.2 to the distribution of demand elasticities in our sample. The bulk of firms in our sample sell products with demand elasticities for which a negative credit supply shock increases prices. However, for the median demand elasticity in manufacturing of non-durable consumption goods and food and beverage manufacturing shown by the dashed vertical lines, our estimates imply a much lower or negative response of prices after a negative credit supply shock.[14] Our results are thus at least qualitatively consistent with the estimates in the narrower sample of Kim (2021). One implication of this result is that negative credit supply shocks may increase or decrease aggregate prices depending on the composition of market demand elasticities in an economy. Our estimates suggest a positive effect for the bulk of manufactured output, and we thus view a positive relationship as the relevant case for aggregate prices.

## 6 Working Capital and Liquidity Channels

The two channels consistent with an increase in prices after a negative loan supply shock are the liquidity channel of Gilchrist et al. (2017) and Chevalier and Scharfstein (1996) and the working capital channel (see e.g. Christiano and Eichenbaum (1992), Bigio (2015), Christiano et al. (2015)). The two channels differ in terms of their prediction for firms' price-cost markup. In the case of the liquidity channel, firms raise liquidity internally when external credit becomes more difficult to obtain by increasing short-run profits through higher prices, at the cost of a lower market share in the future. This suggests that measures of profitability should increase. In contrast, the working capital channel works through pass-through of higher marginal cost and consequently the price-cost markup and profitability should decline or stay constant. We provide evidence for an important role of the liquidity channel.

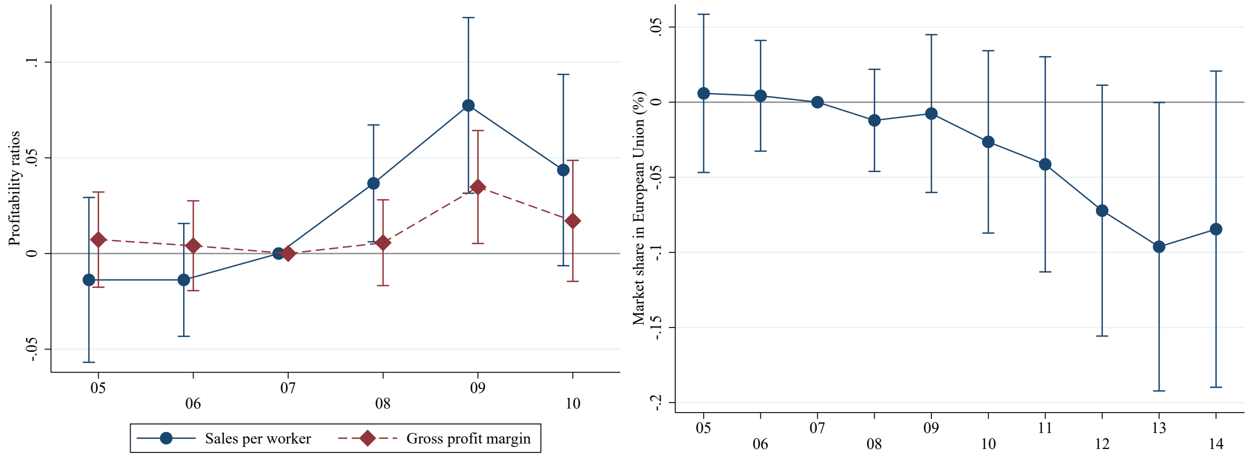
**Liquidity channel** In Figure 5(a) we show the response of two proxies for markups we can obtain in the data: the amount of sales per worker and the gross operating margin, defined as sales minus purchases and labor cost relative to sales. Both measures point to an increase in price-cost markups after the shock. The gross operating margin of exposed firms increases by 3pp in 2009 relative to unexposed firms.[15] We also find that in the longer run, the market share of exposed manufacturing firms in total sector sales in the European Union declines.[16] The latter effect appears gradually and

[14] The median demand elasticity reported in Kim (2021), based on Hottman et al. (2016) is 3.9—which would still be in the right tail of our data—but these demand elasticities are estimated at the UPC-firm level in Hottman et al. (2016) and hence not directly comparable to elasticities at the good-country level in Broda and Weinstein (2006).

[15] Point estimates and standard errors are very similar if we also subtract interest expenses on bank loans when computing this margin. Additionally, Table A.10 shows that even accounting profits after interest, taxes and depreciation, which include many (quasi-)fixed costs, increase by around 1.4%.

[16] The market shares are based on annual sales in the micro data and nominal market size in the annual EU Prodcom statistics.

Figure 5: Effects on profit and market shares




(a) Profitability ratios

(b) EU market share

*Notes*: Firm-level outcomes by exposure estimated from Equation (4). The gross profit margin is calculated as sales minus the wage bill and purchases relative to sales. Market shares are calculated as firms' sales divided by total European Union sales in the corresponding 4-digit NACE sector. The source of the latter data are PRODCOM statistics. 95% confidence intervals based on standard errors clustered at the firm level.

amounts to one tenth of firms' 2007 market share by 2013 (Figure 5(b)). The increase in measures of profitability in response to the loan supply shock and the longer-run decrease in market share is strong evidence for the liquidity channel.

The response of prices to the credit supply shock for firms with different levels of cash holdings lends further support to the importance of liquidity. In Table 4 we show price outcomes interacted with the ratio of firms' 2007 bank deposits to sales. At least in the unit value data with a broader set of firms, firms with more pre-crisis cash holdings respond less to the credit supply shock, which is consistent with a liquidity-generating motive for price increases.

We provide estimates of additional firm-level outcomes in Table A.10. Consistent with Chodorow-Reich (2014) and Züllig (2021), we find that cutting labor input cost is another important margin for exposed firms to improve their cash flow situation. We find no significant response of inventories, consistent with a limited importance of the inventory-fire-sale channel of Kim (2021) in our sample. Additionally, in Appendix Figure A.7 we show that firms facing relatively elastic demand, i.e., firms who we find increase prices less in response to a credit supply shock, have a stronger drop in their wage bill. This indicates that firms selling products with lower demand elasticities temporarily boost their operating cash flow by increasing prices, whereas others do so by decreasing labor cost. Overall, these findings are consistent with firms trading off short-run profit margin against long run market share as predicted by the liquidity channel if the demand they face allows them to do so.

Table 4: Price outcomes: Heterogeneity by firm balance sheets

| | Domestic prices in PPI | | Export unit values | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Interaction with: | Liquidity | Working capital | Liquidity | Working capital |
| 2008 | 0.038*** | 0.048*** | 0.021*** | 0.019*** |
| | (0.013) | (0.012) | (0.006) | (0.007) |
| 2009 | 0.051*** | 0.071*** | 0.037*** | 0.029*** |
| | (0.018) | (0.017) | (0.007) | (0.008) |
| 2010 | 0.038** | 0.054*** | 0.028*** | 0.024*** |
| | (0.018) | (0.016) | (0.008) | (0.009) |
| 2008 × Interaction | 0.015 | 0.023* | -0.016** | -0.002 |
| | (0.019) | (0.013) | (0.006) | (0.004) |
| 2009 × Interaction | 0.008 | 0.042* | -0.020** | 0.017*** |
| | (0.038) | (0.023) | (0.008) | (0.005) |
| 2010 × Interaction | 0.032 | 0.046** | -0.014 | 0.030*** |
| | (0.036) | (0.022) | (0.009) | (0.006) |
| Firm-product | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes |
| Observations | 16,439 | 15,773 | 17,286 | 14,016 |
| Firms | 213 | 202 | 1,089 | 794 |
| Interact.: Centered around | 0.02 | 0.32 | 0.02 | 0.32 |
| Interaction: Standard dev. | 0.06 | 0.18 | 0.04 | 0.22 |

*Notes*: Credit shock exposure interacted with standardized firm-level balance sheet information from 2007 (Equation (6)). Before standardization, balance sheet information are winsorized at the 99th percentile. Liquidity is measured by the deposit-to-sales ratio in 2007, whereas deposits are measured directly in the bank loan data. Working capital is defined as total inventories and accounts receivable net of accounts payable, following Barth and Ramey (2002), relative to sales in 2007. The latter is not available for all firms. All models contain firm-product and time-sector fixed effects. Standard errors clustered at the firm level in parentheses.

**Working capital channel** The increase in gross profit suggests an important role for the liquidity channel, but does not rule out that firms also pass-through increased cost of financing. The working capital channel is based on the idea that firms need to pre-finance input expenses prior to production. In a highly stylized model of production with working capital, marginal cost $MC$ is a product of the input unit cost $C$ and the cost for pre-financing a share $\psi$ of that cost at the interest rate $r^w$.

$$MC_t = ((1-\psi) + \psi(1+r_t^w))C_t \tag{7}$$

With a credit supply shock, $r_t^w$ increases the marginal cost of production, potentially leading to cost-driven price increases.

We first provide evidence that firms with more working capital do increase their prices more after a credit supply shock. We measure working capital as the sum of inventories and accounts receivable

Table 5: Working capital loans and marginal cost

| Predicted marginal cost increase | | | |
|---|---|---|---|
| | Pre-finance share | Lending rate increase | Marginal cost increase |
| Stylized Christiano et al. | 0.56 | 0.14pp | 0.08% |
| Working capital share, sample mean | 1.28 | | 0.17% |
| —, p10 | 0.52 | | 0.07% |
| —, p90 | 1.95 | | 0.26% |
| **Estimated price increase between 2007 and 2010** | | | |
| PPI prices | | | 3.38% |
| Export unit values | | | 2.79% |

*Notes*: The first row provides an estimate of marginal cost changes if firms borrow 56% of their production expenses at the beginning of each quarter, as estimated by Christiano et al. and the annualized (quarterly) interest rate to do so increases by 0.55pp p.a. (0.14pp at a quarterly rate). This is the largest response of the interest rate we estimate to the credit supply shock (see Figure 2b), namely for 2010. The semi-elasticity we use is $\frac{\psi}{(1-\psi)+\psi(1+r_t^w)}$, where $r_t^w$ is the quarter-equivalent of the firm's 2007 effective interest rate, which is on average 1.43%. Rows 2-4 use the working capital ratio (inventories + accounts receivable - accounts payable divided by a fourth of annual sales) from our own micro data to proxy for the pre-finance share. It can have values larger than 1 if production is financed more than a quarter in advance. The lower panel provides the estimated effects on prices for reference.

net of payable relative to sales as in Barth and Ramey (2002). The idea is that a high level of current assets reflect a longer gap between cash in- and outflows. Table 4 shows that firms with higher levels of working capital indeed increase prices more after a credit supply shock. However, the working capital share correlates with numerous other firm characteristics—as an example, by construction working capital correlates with the level of inventories, which may reflect differences in the working-capital intensity of production, but also the history of a firm's demand shocks. We thus recommend caution with a causal interpretation of this coefficient.

We also provide a back-of-the envelope calculation suggesting that higher cost of working capital can explain only a small part of price increases. With marginal cost given by Equation (7), the semi-elasticity with respect to the lending rate is given by $\frac{\psi}{(1-\psi)+\psi(1+r_t^w)}$. This provides an upper bound for effects on prices under full pass-through. Our estimates suggest annual lending rates of exposed firms increase by up to 0.55pp (see Figure 2b), which corresponds to 0.14pp in quarterly terms. We use this figure to calculate a rough estimate of the corresponding increase in marginal cost.

The calculation depends crucially on the share of expenses that are pre-financed. Christiano et al. (2015) estimate this share to be 0.56 of quarterly cost in the U.S.[17] This implies an increase in marginal cost far below the estimated price increase, as shown in the first row of Table 5. In Danish data, the mean ratio of measured working capital to annual sales is 0.32, corresponding to pre-financing of 1.28 quarters of cash flow. At the 10th and 90th percentiles, working capital ratios imply pre-financing of about 0.5 and 2 quarters of cash flow. Using these values, we calculate a marginal cost increase of 0.17% for the average firm and 0.26% for firms at the 90th percentile. Such an increase would account for a minor share of the price increase we estimate. Consistent with the increase in profitability measures, we conclude that the major part of price increases is due to firms raising liquidity from higher profits, rather than cost pass-through.

# 7 Aggregate Implications

How important is the effect of loan supply on aggregate inflation during the Great Recession? We calculate a partial equilibrium counterfactual of PPI dynamics in a scenario in which wholesale-funded banks' loan supply follows the same path as deposit-funded banks'. This counterfactual can be easily obtained from our difference-in-difference estimates as follows:

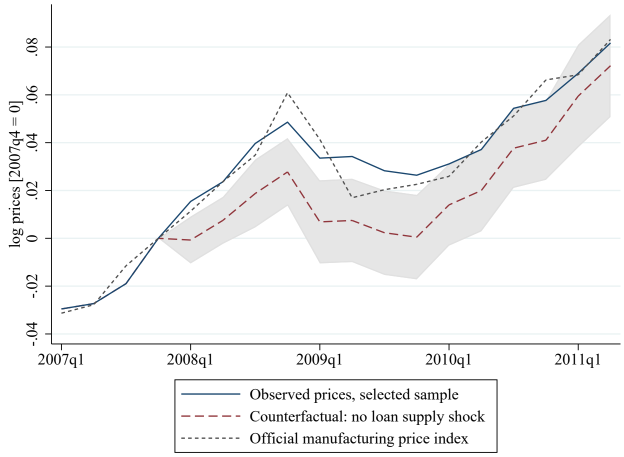
$$\log \widehat{\text{Price}}_{i,p,t}(\text{Exposure}_i = 0) = \log \text{Price}_{i,p,t} - \sum_{\substack{k=2005 \\ k \neq 2007}}^{2010} 1(t = k) \times (\widehat{\beta}_k \text{Exposure}_i) \tag{8}$$

We aggregate observed and predicted prices to a sales-weighted aggregate price index that follows the construction of the official PPI. For firms that do not fulfil our sample restrictions because of small lending relationships, we use observed prices in the counterfactual calculation. The solid line in Figure 6 plots actual the index of observed prices. It can deviate from the price index of manufacturing output published by Denmark Statistics (the dotted line) because we do not know the exact product- and firm-level weights for the aggregation, but it tracks the medium run dynamics of prices rather well. The counterfactual index based on predicted values implied by our regression drops in 2008 and remains around 3% below the index based on observed prices in 2009, after which the difference becomes statistically insignificant.

How much of the "missing disinflation" can our estimates explain? In Appendix D.1 we estimate a VAR model on time series of GDP and the PPI up to 2007. We then generate a benchmark prediction for manufacturing PPI dynamics over the Great Recession as a forecast of the price series conditional on the observed developments of real output. Given the 9% contraction of GDP,

[17] More concretely, they estimate the parameters of a DSGE model in which the final goods producer borrows to finance a fraction $\psi$ of its expenditure on inputs and repays the loan at the end of the period with interest $r_t^w$. The model is estimated on pre-crisis quarterly data and matched to a set of impulse responses to three identified shocks from a VAR. We use their resulting posterior mean.

Figure 6: Counterfactual path of producer prices without differential credit supply shock




*Notes*: The figure depicts a sales-weighted PPI index constructed from PPI micro data, compared to a counterfactual in which wholesale-funded banks' loan supply follows the same path as deposit-funded banks' loan supply. The counterfactual scenario is based on the coefficient estimates in Figure 3. (90% confidence intervals in grey).

the VAR predicts a medium-run price level around 7% below the observed one.[18] Our counterfactual therefore closes around closes around 40% of the medium-run gap between actual price developments and the conditional forecast.

Our counterfactual does not take into account any general equilibrium effects, but we think that such effects would likely further reduce prices. First, the counterfactual PPI assumes that prices of firms dropping out of the treatment effect estimation due to the restrictions made in Table A.1 were unaffected. Second, if firms compete for funds in the lending market, a higher loan supply from wholesale-funded banks would have reduced congestion for funds from deposit-funded banks, and thereby lowered prices of their borrowers as well. Furthermore, in the presence of strategic complementarities, lower prices of exposed firms would likely also lead to lower prices of non-exposed competitors.

# 8 Conclusions

In this paper we estimate the effect of a large credit supply shock on firms' output prices. We find that firms with pre-crisis lending relationships to banks who are particularly exposed to the global financial crisis decrease their loan balances and pay higher interest rates during the recession. In turn, they raise their prices and increase their profits in the short-run, but lose market share in the

[18]The actual price index fell around 2%. A detailed description of aggregation to the PPI index and the computation of the counterfactual can be found in Appendix D.1. The VAR-based estimate has relatively strong inertia, which is why we focus on the comparison of the medium-run price levels only.

longer run. The estimated effects decline in the elasticity of demand for goods, but are positive for the vast majority of industrial output.

Our results are consistent with the idea that firms face a trade-off between short-run profits and longer-run market share, and that price increases are a viable and important strategy to raise cash in the short-run when other sources of liquidity dry up. They support prior work that incorporates liquidity constraints and customer markets into macroeconomic models of price-setting, such as Gilchrist et al. (2017), and suggest that credit supply can explain an important part of the "missing disinflation".

Our work also suggests that policies that affect banks' credit supply have a direct impact on inflation. In the aftermath of the global financial crisis, many regulators have introduced macro-prudential policy tools such as counter-cyclical capital buffers that do exactly that. The interaction of such policies with central banks' traditional price stability targets have not been broadly discussed and analyzed in the literature, and we hope that our work contributes to inspiring further work in this direction.

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# Appendices

# A Supplementary Figures and Tables

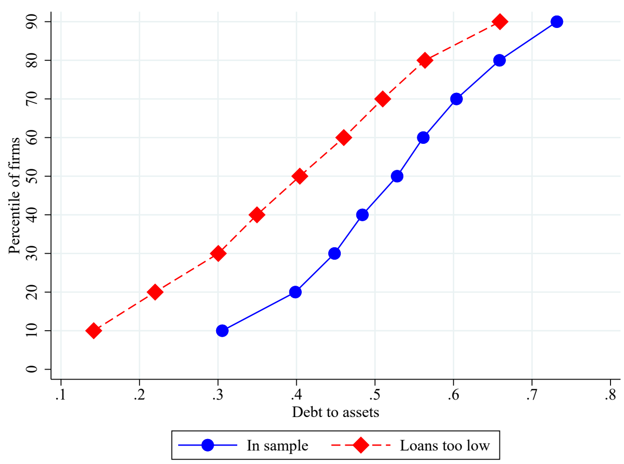
## A.1 Sample

Table A.1: Sample construction

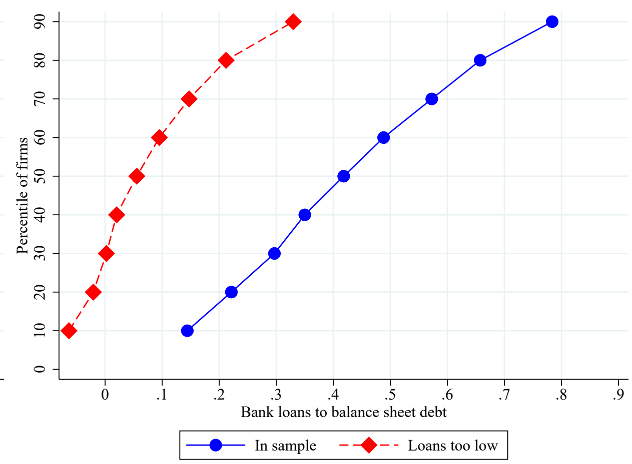
| Restriction | All firms | | PPI match | | Export unit values match | |
|---|---|---|---|---|---|---|
| | Firms | Empl (of initial) | Firms | Empl (of matched) | Firms | Empl (of matched) |
| Active manuf. firms | 7,281 | 1.00 | 380 | 0.34 | 2,852 | 0.82 |
| >10 employees | 3,322 | 0.90 | 366 | 0.37 | 2,122 | 0.88 |
| $\geq$ 1 bank connection | 3,295 | 0.89 | 364 | 0.37 | 2,110 | 0.88 |
| Survival 2005–2010 | 2,703 | 0.79 | 344 | 0.40 | 1,788 | 0.89 |
| Loans>100,000 DKK, loan-to-sales>0.01 | 1,753 | 0.47 | 213 | 0.45 | 1,176 | 0.90 |

*Notes*: Starting with the complete 2007 Danish firm register, we cumulatively apply the restrictions listed in column 1. The number of firms in the population and their share in total manufacturing employment is in columns 2–3. For reference, the amount of workers in manufacturing in 2007 was 366,000, according to our micro data. Columns 3–4 and 5–6 contain the number of firms matched to the PPI and export unit value datasets and their employment share in the population conditional on restrictions. While most restrictions are inconsequential, imposing a minimum loan volume excludes a fairly large set of firms. The data is based on administrative tax records and matches aggregate bank lending nearly perfectly (see Figure A.2). The sizeable number of firms with no or minimal bank lending relationships thus reflects firm practices rather than a measurement problem. Moreover, we require a positive amount of outstanding loans in both 2007 and 2006 to compute 2007 average interest rates using Equation (1), which we will use as a control. In Figure A.1, we compare the liabilities of firms below the minimum loan requirement to firms in either the matched PPI or unit value sample. Firms that fall below have less overall debt (reported in balance sheets), and a much lower share of bank loans in their debt. We conclude that the debt of firms with small bank loan relationship consists mostly of other forms of debt, such as bonds, mortgages or loans from non-banks.

Figure A.1: Sample vs. firms below minimum bank loan requirements




(a) Debt to assets

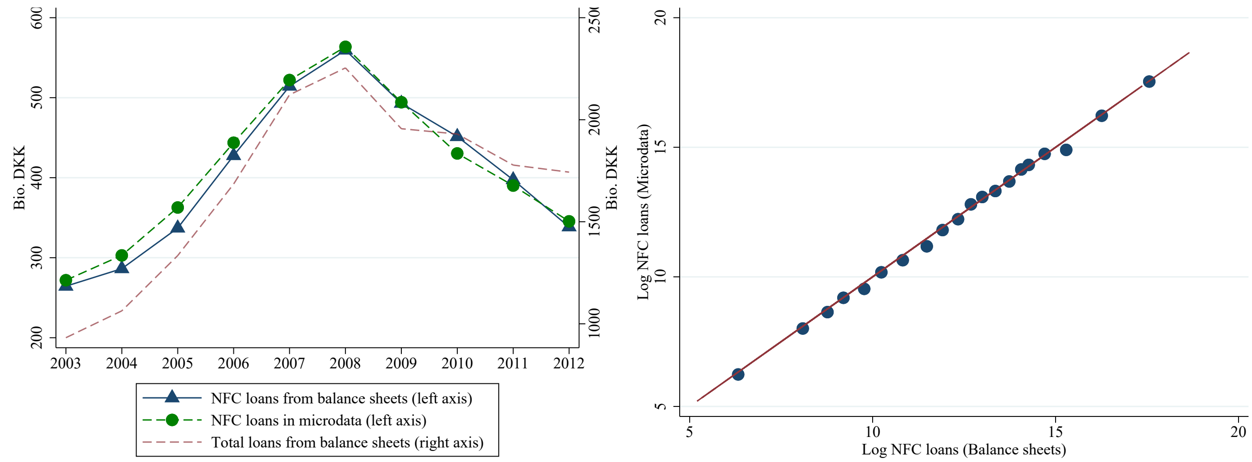



(b) Bank loans to debt

*Notes*: Our sample excludes firms with below 0.01 2007 loan-to-sales ratios and firms with loans below 100,000 DKK in 2006 or 2007 (see section 2.4). The figure compares the distributions of debt and bank loans between firms excluded from the sample on this ground and firms in the sample. Firms excluded from the sample have somewhat less debt in their balance sheets, but mostly they are excluded because the composition of their debt is different. The debt of excluded firms is mostly with non-bank lenders, and their exposure to bank loan supply shocks is limited.

## A.2 Verification of loan data

Figure A.2: Aggregate lending to Danish firms in bank balance sheets and loan micro data

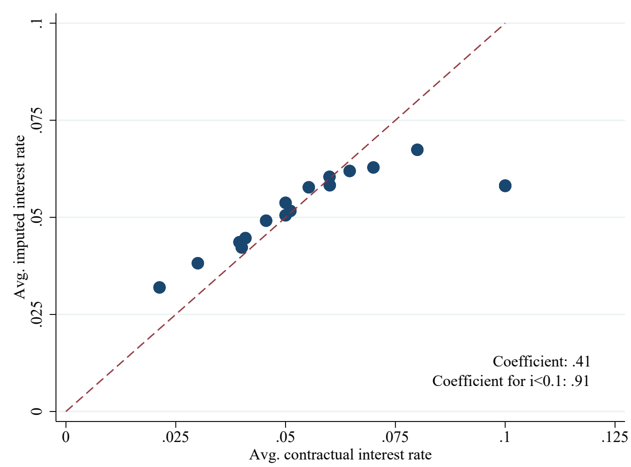



(a) Aggregate lending over time

(b) Bank level correlation 2005–2010

*Notes*: Panel (a): Bank lending to Danish non-financial firms (in Danish kroner) from the Monetary and Financial statistics and the sum of loans to non-financial firms in the micro data. Panel (b): Binned scatter plot of total bank-level loans in the bank-borrower micro data and loans to non-financial corporations in the bank-level Monetary and Financial statistics (pooled data 2005–2010), with 45 degree line in red. The correlation between yearly log loans in balance sheets and the micro data is 0.986. We attribute slight discrepancies between the balance sheets and the aggregated micro data to differences between tax reporting rules and accounting standards.

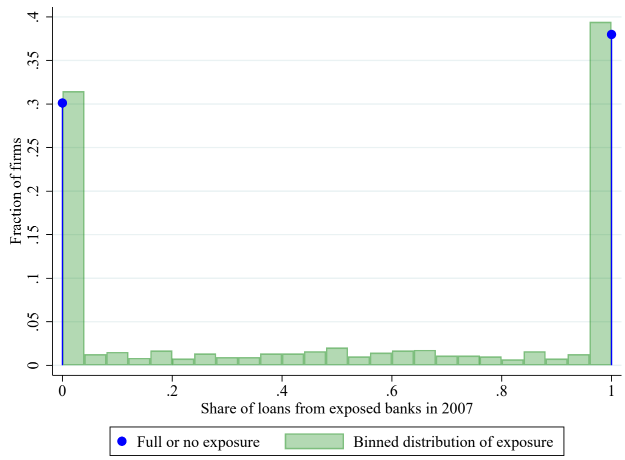
Figure A.3: Calculated average and reported contractual interest rate




*Notes*: Because contractual interest rates are often not reported in the loan micro data, we use a calculated average interest rate instead. The Figure compares the two when both are available in a binned scatter plot. The average interest rate is calculated as interest paid divided by the average of the current and lagged end-of-year loan balance, as described in equation (1). The coefficient of a regression of the average interest rate on the contractual interest rate is 0.91 for interest rates below 0.1 and 0.4 overall.

## A.3 Firm characteristics by credit supply shock exposure

Figure A.4: Distribution of firms' loan exposure to wholesale-funded banks




*Notes*: The figure depicts the distribution of exposure to wholesale-funded banks in the pooled sample of firms in either the PPI or export unit value data. Exposure is defined as the share of wholesale-funded banks in a firm's 2007 loan portfolio. Bars illustrate the fraction of firms in exposure bins. The blue spikes illustrate the share of firms with exposure of exactly 0 or 1.

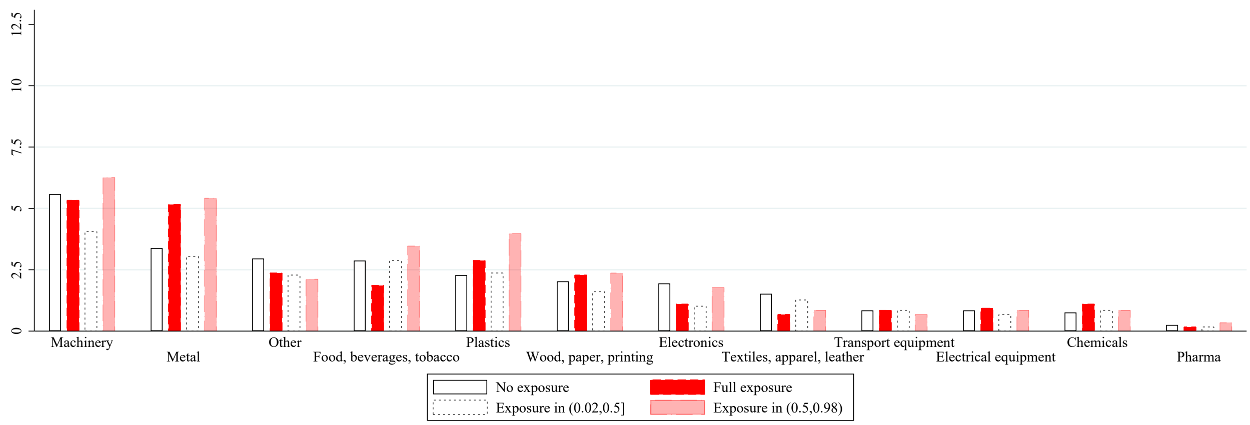
Table A.2: Sample characteristics by exposure to wholesale-funded banks

| | High primary bank share | | | | | Low primary bank share | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | No exposure | | Full exposure | | KS-test | Low exposure | | High exposure | | KS-test |
| | Mean | Med. | Mean | Med. | p-val. | Mean | Med. | Mean | Median | p-val. |
| Employment | 81.9 | 42.0 | 82.0 | 42.0 | 0.95 | 192.9 | 71.0 | 171.8 | 65.5 | 0.79 |
| Ann. empl. growth 04-07 (%) | 6.9 | 3.4 | 5.8 | 2.6 | 0.30 | 5.2 | 2.0 | 4.2 | 2.3 | 0.10 |
| Firm age (years) | 19.8 | 17.4 | 22.1 | 20.3 | 0.02 | 24.1 | 20.7 | 24.4 | 22.7 | 0.10 |
| Sales (mio DKK) | 123.9 | 53.8 | 119.7 | 53.6 | 0.55 | 363.5 | 91.6 | 341.5 | 81.8 | 0.37 |
| Ann. sales growth 04-07 (%) | 19.4 | 8.9 | 16.7 | 8.7 | 0.45 | 13.4 | 7.8 | 13.2 | 8.7 | 0.50 |
| Profits (% of sales) | 5.4 | 5.5 | 5.5 | 5.7 | 0.85 | 4.8 | 4.5 | 5.2 | 5.3 | 0.72 |
| Bank loans (% of sales) | 16.0 | 12.5 | 15.9 | 12.0 | 0.81 | 21.5 | 16.6 | 23.5 | 18.7 | 0.13 |
| Bank loans (% of debt) | 45.0 | 39.3 | 43.0 | 38.4 | 0.99 | 50.1 | 48.5 | 51.1 | 48.3 | 0.67 |
| Avg. interest rate (%) | 5.3 | 5.2 | 5.6 | 5.3 | 0.11 | 5.5 | 5.4 | 5.8 | 5.6 | 0.07 |
| Bank connections (incl. deposits) | 2.8 | 3.0 | 2.7 | 3.0 | 0.29 | 3.8 | 4.0 | 3.6 | 4.0 | 0.41 |
| Bank connections (only loans) | 2.0 | 2.0 | 2.0 | 2.0 | 0.22 | 3.2 | 3.0 | 3.1 | 3.0 | 0.70 |
| Share of loans from prim. bank (%) | 99.7 | 99.9 | 99.7 | 100.0 | 0.73 | 74.2 | 75.8 | 71.3 | 69.4 | 0.19 |
| Share of short-maturity loans (%) | 92.3 | 100 | 75.2 | 100 | 0.00 | 80.7 | 93.0 | 59.6 | 60.0 | 0.00 |
| Equity share (%) | 30.9 | 30.6 | 32.8 | 33.2 | 0.32 | 30.2 | 29.2 | 31.0 | 31.1 | 0.69 |
| Deposits (% of sales) | 2.6 | 0.4 | 2.3 | 0.4 | 0.49 | 1.8 | 0.3 | 2.8 | 0.5 | 0.03 |
| Inventories (% of sales) | 16.5 | 15.1 | 16.5 | 15.0 | 0.72 | 17.3 | 15.0 | 16.4 | 14.6 | 0.52 |
| Avg. ann. price chg. 04-07 (PPI*) | 2.5 | 1.7 | 2.7 | 1.0 | 0.34 | 2.6 | 1.1 | 3.0 | 1.3 | 0.25 |
| — (export unit values) | 2.1 | 2.0 | -0.2 | 0.6 | 0.19 | 1.4 | 1.6 | 3.1 | 3.3 | 0.23 |
| Demand elasticity (PPI goods*) | 4.0 | 2.5 | 3.7 | 2.5 | 0.52 | 2.9 | 2.2 | 3.3 | 2.4 | 0.73 |
| — (export unit values) | 4.0 | 2.4 | 3.6 | 2.4 | 0.58 | 3.4 | 2.4 | 3.5 | 2.5 | 0.15 |
| Observations | 299 | | 292 | | | 249 | | 342 | | |

*Notes*: See next page.

*Notes to Table A.2:* Summary statistics for the matched sample conditional on sampling restrictions. Unless stated otherwise, variables are measured in 2007. Growth rates of pre-crisis employment and sales are winsorized at the 1st and 99th percentile. We report means and medians of four groups of firms by exposure to wholesale-funded banks in 2007: No exposure (¡ 0.02), low exposure (0.02-0.5), high exposure (0.5-0.98) and full exposure (¿0.98). Firms with intermediate exposure levels differ significantly from firms with no/full exposure because, by definition, they were lending from multiple banks in 2007 (primary bank share of 0.75 instead of 0.99), are larger and older. To test for the equality of distributions of firm characteristic by exposure, we therefore report Kolmogorov-Smirnov p-values comparing firms with no/full exposure and those with low/high intermediate exposures. The variables displayed in the last four rows are firm-level averages of good-level information. Demand elasticity denotes the estimated price elasticitz of demand estimated for categories of goods by Broda and Weinstein (2006), which we use in Section 5.2. *Notice also that the last four rows report information based on price changes in the PPI and export unit value samples, respectively. As is shown in Table A.1, these sample sizes can be considerably smaller than what is reported as observations at the bottom of the table.

Figure A.5: Sectoral distribution




*Notes*: Share of sector–exposure cells in the sample. We distinguish between no exposure (<0.02), full (>0.98), low (0.02–0.5) and high (0.5–0.98) partial exposure. The sample includes firms with price information (either in the PPI or export unit value sample) that fulfill sampling criteria of Table A.1.

## A.4 Additional results for loan outcomes

Table A.3: Loan volume: alternative outcome transformations

| | Firms in price data | | | All manufacturing firms | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | IHS | Log | Growth rel. to 2007 | IHS | Log | Growth rel. to 2007 |
| 2008 | -0.25** | -0.18* | -0.03 | -0.31*** | -0.18** | -0.04 |
| | (0.11) | (0.10) | (0.04) | (0.09) | (0.08) | (0.03) |
| 2009 | -0.21 | -0.24* | -0.10** | -0.15 | -0.19* | -0.10** |
| | (0.15) | (0.14) | (0.05) | (0.13) | (0.10) | (0.04) |
| 2010 | -0.36** | -0.35** | -0.06 | -0.20 | -0.20* | -0.08* |
| | (0.18) | (0.16) | (0.05) | (0.14) | (0.12) | (0.04) |
| Firm | Yes | Yes | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,888 | 6,810 | 6,888 | 10,350 | 10,198 | 10,350 |
| Firms | 1,148 | 1,148 | 1,148 | 1,725 | 1,725 | 1,725 |

*Notes*: Effects of exposure on end-of-year loan balances. Fixed effects at the firm and 4-digit-NACE×year level are included, standard errors clustered at the firm level in parentheses. "IHS" and "Log" use inverse hyperbolic sine and logarithmic transformations of loans as outcome. Columns (3) and (6) use growth rates of loans relative to 2007 as outcome, winsorized at the 5th and 95th percentile and estimate recentered influence functions.

Table A.4: Loan volume: other robustness checks

| | Firms in price data | | | | |
|---|---|---|---|---|---|
| | (1) 2d Nace | (2) Trend | (3) No controls | (4) PDSLASSO | (5) All controls |
| 2008 | -0.26** | -0.34** | -0.08 | -0.24** | -0.26** |
| | (0.11) | (0.17) | (0.11) | (0.11) | (0.11) |
| 2009 | -0.17 | -0.38 | -0.04 | -0.21 | -0.24 |
| | (0.14) | (0.26) | (0.15) | (0.15) | (0.15) |
| 2010 | -0.34** | -0.62* | -0.20 | -0.35* | -0.36** |
| | (0.17) | (0.35) | (0.17) | (0.18) | (0.18) |
| Firm | No | Yes | No | No | No |
| time-4d NACE | No | Yes | Yes | Yes | Yes |
| time-2d NACE | Yes | No | No | No | No |
| Firm trend | No | Yes | No | No | No |
| Observations | 7,092 | 6,888 | 6,888 | 6,888 | 6,888 |
| Firms | 1,182 | 1,148 | 1,148 | 1,148 | 1,148 |
| | All manufacturing firms | | | | |
| | (6) 2d Nace | (7) Trend | (8) No controls | (9) PDSLASSO | (10) All controls |
| 2008 | -0.32*** | -0.34** | -0.19** | -0.30*** | -0.33*** |
| | (0.09) | (0.13) | (0.08) | (0.09) | (0.09) |
| 2009 | -0.16 | -0.21 | -0.02 | -0.15 | -0.19 |
| | (0.12) | (0.21) | (0.12) | (0.13) | (0.12) |
| 2010 | -0.21 | -0.27 | -0.08 | -0.18 | -0.21 |
| | (0.14) | (0.27) | (0.13) | (0.14) | (0.14) |
| Firm | No | Yes | No | No | No |
| time-4d NACE | No | Yes | Yes | Yes | Yes |
| time-2d NACE | Yes | No | No | No | No |
| Firm trend | No | Yes | No | No | No |
| Observations | 10,518 | 10,350 | 10,350 | 10,350 | 10,350 |
| Firms | 1,753 | 1,725 | 1,725 | 1,725 | 1,725 |

*Notes*: Effects of exposure on IHS transformation of end-of-year loan balances following eq. (4). Except for (3)-(5), regressions include interactions of year dummies with 2007 values of: interest rate, loans-to-sales and deposits-to-sales, the short-term loan share. Fixed effects at the firm and 4-digit NACE×year level are included, except for "2d NACE", where the fixed effect controls for 2-digit NACE × year variation. A small number of firms is dropped due to no variation in exposure within sectors. Standard errors clustered at the firm level in parentheses. Trend includes linear firm-level trend. "No controls" omits controls except FE. "PSDLASSO" selects as controls (2007 values interacted w. year dummies): short-term loan share, loans-to-sales, interest rate, equity share, primary bank share, and in the sample of all firms the avg. wage, "All controls" controls for a total of 19 firm-level covariates.

Table A.5: Interest rate

| | Firms in price data | | | | |
|---|---|---|---|---|---|
| | (1) Baseline | (2) Trend | (3) No controls | (4) PDSLASSO | (5) All controls |
| 2008 | 0.25 | 0.34 | 0.28* | 0.25 | 0.28* |
| | (0.16) | (0.25) | (0.16) | (0.16) | (0.16) |
| 2009 | 0.42** | 0.57 | 0.29 | 0.42** | 0.44** |
| | (0.21) | (0.41) | (0.22) | (0.21) | (0.20) |
| 2010 | 0.51 | 0.72 | 0.12 | 0.51 | 0.56* |
| | (0.32) | (0.60) | (0.31) | (0.32) | (0.32) |
| Firm | Yes | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,888 | 6,888 | 6,888 | 6,888 | 6,888 |
| Firms | 1,148 | 1,148 | 1,148 | 1,148 | 1,148 |
| | All manufacturing firms | | | | |
| | (6) Baseline | (7) Trend | (8) No controls | (9) PDSLASSO | (10) All controls |
| 2008 | 0.27** | 0.40** | 0.24* | 0.26** | 0.28** |
| | (0.12) | (0.20) | (0.13) | (0.12) | (0.12) |
| 2009 | 0.38** | 0.62** | 0.22 | 0.37** | 0.37** |
| | (0.16) | (0.32) | (0.17) | (0.16) | (0.16) |
| 2010 | 0.55** | 0.90* | 0.22 | 0.54** | 0.57** |
| | (0.24) | (0.46) | (0.23) | (0.24) | (0.24) |
| Firm | Yes | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,350 | 10,350 | 10,350 | 10,350 | 10,350 |
| Firms | 1,725 | 1,725 | 1,725 | 1,725 | 1,725 |

*Notes*: Effects of exposure on avg. borrowing interest rate in pp. Except for (3)-(5), regressions include interactions of year dummies with 2007 values of: interest rate, loans-to-sales and deposits-to-sales, the short-term loan share. Fixed effects at the firm and 4-digit NACE×year level are included. A small number of firms is dropped due to no variation in exposure within sectors. Standard errors clustered at the firm level in parentheses. Baseline: see Equation (4). Trend includes a linear firm-level trend. "No controls" omits controls except fixed effects. "PSDLASSO" selects as controls (2007 values interacted with year dummies): short-term loan share, loans-to-sales, interest rate, log revenue, and in the sample of firms in the price data the equity share, "All controls" controls for a total of 19 firm-level covariates.

## A.5 Additional results for price outcomes

Table A.6: Domestic prices in PPI, alternative specifications

| | (1) Baseline | (2) Incl. trend | (3) Incl. CN FE | (4) No controls | (5) PDS-LASSO | (6) All controls |
|---|---|---|---|---|---|---|
| 2008 | 0.036*** | 0.036*** | 0.026** | 0.031** | 0.039*** | 0.040*** |
| | (0.012) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) |
| 2009 | 0.050*** | 0.052** | 0.046** | 0.045** | 0.055*** | 0.052*** |
| | (0.018) | (0.024) | (0.019) | (0.018) | (0.019) | (0.019) |
| 2010 | 0.034* | 0.036 | 0.028 | 0.040** | 0.044** | 0.044** |
| | (0.017) | (0.024) | (0.017) | (0.017) | (0.018) | (0.017) |
| Firm-product | Yes | Yes | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes | Yes | Yes |
| time-2d CN | No | No | Yes | No | No | No |
| Firm trend | No | Yes | No | No | No | No |
| Observations | 16,439 | 16,439 | 16,439 | 16,439 | 16,439 | 16,439 |
| Firms | 213 | 213 | 213 | 213 | 213 | 213 |

*Notes*: Effects of exposure on domestic PPI prices. Except for (4)-(6), regressions control for interactions of year dummies with 2007 values of: interest rate, loans-to-sales and deposits-to-sales, the short-term loan share. Fixed effects at the firm and 4-digit NACE×half-year level are included. (2) includes a linear firm trend, (3) includes 2-digit CN×year fixed effects, (4) omits all controls except fixed effects. In (5) PSDLASSO selects as controls (2007 values interacted with year dummies): short-term loan share, log employment, market share, loans-to-sales, deposits-to-sales, interest rate. (6) includes all 19 control variables PDSLASSO picks from. A small number of firms is dropped because of lack of variation in exposure within sectors. Standard errors clustered at the firm level in parentheses.

Table A.7: Domestic prices in PPI, alternative (sub-)samples

| | (1) Full/No Exposure | (2) High prim. bank share | (3) Include entry/exit | (4) Include exports | (5) Include low loans | (6) No sample restrictions |
|---|---|---|---|---|---|---|
| 2008 | 0.021 | 0.053** | 0.029*** | 0.024** | 0.033*** | 0.014* |
| | (0.014) | (0.022) | (0.011) | (0.011) | (0.011) | (0.008) |
| 2009 | 0.049** | 0.072** | 0.043** | 0.033** | 0.029 | 0.015 |
| | (0.020) | (0.030) | (0.017) | (0.016) | (0.018) | (0.014) |
| 2010 | 0.031 | 0.044 | 0.029* | 0.022 | 0.007 | 0.011 |
| | (0.019) | (0.028) | (0.017) | (0.017) | (0.022) | (0.017) |
| Firm-product | Yes | Yes | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 9,279 | 6,523 | 20,188 | 26,932 | 24,651 | 49,156 |
| Firms | 124 | 90 | 269 | 273 | 335 | 519 |

*Notes*: Effects of exposure on domestic PPI prices. Regressions control for interactions of year dummies with 2007 values of: interest rate, loans-to-sales and deposits-to-sales, the short-term loan share. Fixed effects at the firm and 4-digit NACE×half-year level are included. (1) only includes firms with exposure $< 0.02$ or $> 0.98$, (2) includes only firms with a 2007 primary bank share higher than 0.98, (3) does not condition on the continuation of products until 2010, (4) includes export prices and (5) does not impose the minimum loan/sales requirement from Table A.1. (6) removes restrictions (3) to (5) at the same time. A small number of firms is dropped because of lack of variation in exposure within sectors. Standard errors clustered at the firm level in parentheses.

Table A.8: Export unit values, alternative specifications

| | (1)<br>Baseline | (2)<br>Incl.<br>trend | (3)<br>Incl.<br>CN FE | (4)<br>No<br>controls | (5)<br>PDS-<br>LASSO | (6)<br>All<br>controls |
|---|---|---|---|---|---|---|
| 2008 | 0.019*** | 0.015** | 0.018*** | 0.018*** | 0.020*** | 0.022*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| 2009 | 0.038*** | 0.023*** | 0.037*** | 0.028*** | 0.040*** | 0.037*** |
| | (0.007) | (0.007) | (0.007) | (0.006) | (0.007) | (0.007) |
| 2010 | 0.028*** | -0.002 | 0.032*** | 0.026*** | 0.029*** | 0.033*** |
| | (0.008) | (0.008) | (0.007) | (0.007) | (0.008) | (0.008) |
| Firm-product | Yes | Yes | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes | Yes | Yes |
| time-2d CN | No | No | Yes | No | No | No |
| Firm trend | No | Yes | No | No | No | No |
| Observations | 17,286 | 17,286 | 17,220 | 17,286 | 17,286 | 1,7286 |
| Firms | 1,089 | 1,089 | 1,089 | 1,089 | 1,089 | 1,089 |

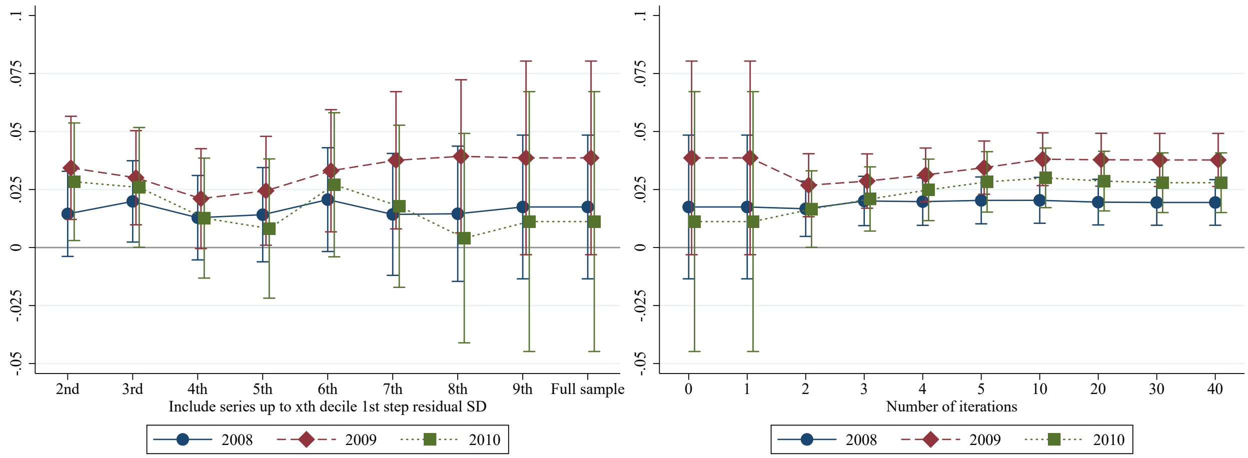
*Notes*: Evolution of export unit values (relative to 2007) conditional on the firms' lending portfolio exposure. Estimation based on Equation (4). All regressions include firm×product and 4-digit NACE×year fixed effects as well as controls for 2007 firm characteristics. Column (2) additionally controls for a linear firm trend, (3) 2-digit Combined Nomenclature×-year fixed effects and (5) the following additional variables chosen by the PDSLASSO procedure: log of 2007 employment, market share and profit-to-sales ratio. (6) includes all 19 control variables PDSLASSO picks from. A small number of firms is dropped because of lack of variation in exposure within sectors. Standard errors clustered at the firm level in parentheses.

Table A.9: Export unit values, alternative (sub-)samples

| | (1) Full/No Exposure | (2) Only 1 bank | (3) Include entry/exit | (4) Include low loans | (5) No sample restrictions |
|---|---|---|---|---|---|
| 2008 | 0.019*** | 0.018* | 0.021*** | 0.018*** | 0.019*** |
| | (0.007) | (0.009) | (0.006) | (0.006) | (0.004) |
| 2009 | 0.025*** | 0.037*** | 0.031*** | 0.031*** | 0.017*** |
| | (0.008) | (0.010) | (0.007) | (0.007) | (0.004) |
| 2010 | 0.012 | 0.027** | 0.024*** | 0.021*** | 0.018*** |
| | (0.010) | (0.012) | (0.008) | (0.007) | (0.005) |
| Firm-product | Yes | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,626 | 7,428 | 20,529 | 19,152 | 50,302 |
| Firms | 724 | 524 | 1,161 | 1,169 | 1,989 |

*Notes*: Evolution of export unit values (relative to 2007) conditional on the firms' lending portfolio exposure. Estimation based on Equation (4). All regressions include firm×product and 4-digit NACE×year fixed effects as well as controls for 2007 firm characteristics. Columns exclude/include additional firms/products: (1) only includes firms with exposure of $< 0.02$ or $> 0.98$, (2) only firms with a 2007 primary bank share higher than 0.98, (3) does not condition on the survival of the firm, (4) does not impose the minimum loan/sales requirement from A.1. (5) removes restrictions (3) and (4) at the same time. A small number of firms is dropped because of lack of variation in exposure within sectors. Standard errors clustered at the firm level in parentheses.

Figure A.6: Effects of exposure on export unit values: Robustness of FGLS estimator




(a) Unwgt. effect by SD of 1st-step FGLS resid.

(b) FGLS estimates by number of iterations

*Notes*: The volatility of unit value series varies widely, which can result from re-classifications, misreporting or within-category composition changes. We address this noise in the data by iteratively weighting each series of unit values with the inverse of the variance of residuals until they converge. We show two of the conducted robustness checks. In (a) we estimate coefficients using OLS while excluding the most volatile series as measured by the variance of OLS residuals. The figure shows OLS estimates that restrict the samle to deciles of unit value series with the lowest volatility: The coefficients for "p2" show estimates of $\beta_k$ in Equation (4) for the least volatile 20% unit value series. The figure includes 90% confidence intervals based on standard errors clustered at the firm level. The effects are positive throughout but insignificant when we include all unit value series. The estimate for 2009 becomes consistently significant if we exclude the 20% least volatile series. (b) shows the estimated effect of exposure on export unit values after each iteration in the FGLS estimator. While the first two iterations reduce noise in the data considerably, the exact number of iterations thereafter leaves size and significance of the effects broadly unchanged.

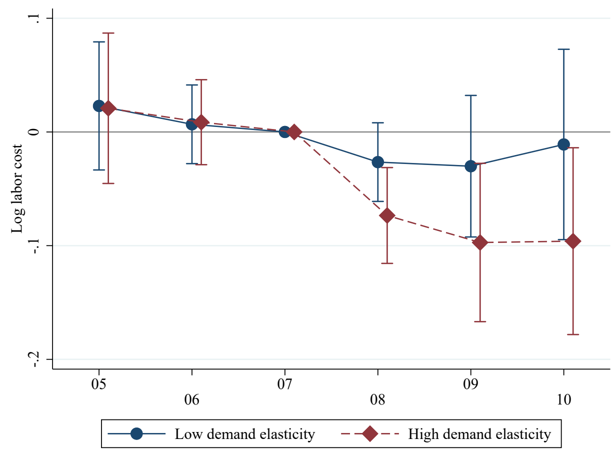
## A.6 Additional firm outcomes

Table A.10: Other firm outcomes

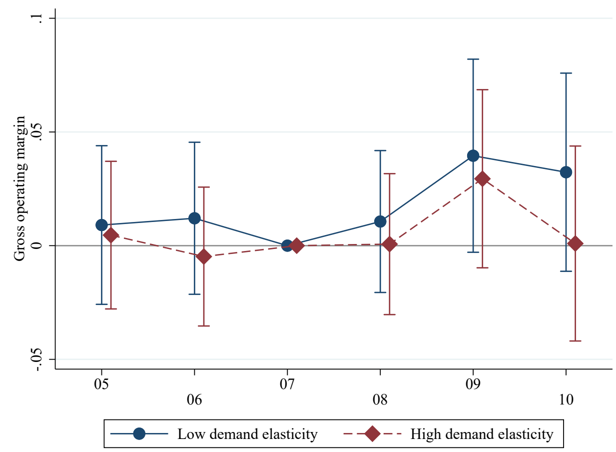
| | (1) Sales per worker | (2) Gross op. margin | (3) —, excl. int. paym. | (4) Sales | (5) Domestic sales | (6) Exports |
|---|---|---|---|---|---|---|
| 2008 | 0.037** | 0.006 | 0.006 | -0.014 | 0.009 | -0.017 |
| | (0.016) | (0.011) | (0.012) | (0.017) | (0.036) | (0.037) |
| 2009 | 0.077*** | 0.035** | 0.036** | 0.009 | -0.017 | -0.028 |
| | (0.023) | (0.015) | (0.015) | (0.030) | (0.049) | (0.051) |
| 2010 | 0.044* | 0.017 | 0.019 | -0.009 | -0.000 | 0.023 |
| | (0.025) | (0.016) | (0.016) | (0.037) | (0.059) | (0.071) |
| Firm | Yes | Yes | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,888 | 6,888 | 6,888 | 6,888 | 6,875 | 6,606 |
| Firms | 1,148 | 1,148 | 1,148 | 1,148 | 1,148 | 1,120 |
| | (7) Labor cost | (8) Employ-ment | (9) Profits to sales | (10) Total invent. | (11) Final invent. | (12) —, more balanced |
| 2008 | -0.048*** | -0.050*** | 0.004 | -0.016 | -0.194 | -0.284 |
| | (0.014) | (0.013) | (0.006) | (0.028) | (0.297) | (0.323) |
| 2009 | -0.060** | -0.068*** | 0.014* | -0.002 | 0.086 | 0.154 |
| | (0.024) | (0.023) | (0.008) | (0.047) | (0.388) | (0.455) |
| 2010 | -0.050* | -0.052* | -0.001 | -0.061 | 0.014 | -0.152 |
| | (0.031) | (0.030) | (0.007) | (0.049) | (0.445) | (0.491) |
| Firm | Yes | Yes | Yes | Yes | Yes | Yes |
| time-4d NACE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,888 | 6,888 | 6,888 | 6,424 | 4,207 | 3,144 |
| Firms | 1,148 | 1,148 | 1,148 | 1,146 | 990 | 596 |

*Notes*: Firm-level outcomes by exposure estimated from Equation (4). Gross operating margins in (2) are calculated as (sales - labor cost - purchases)/sales; (3) additionally subtracts interest payments to banks in the loan data. Accounting profits in (9) are after interest, taxes and depreciation. Total inventories (10) include inventories of raw/intermediate inputs and pre-payments of purchases, whereas final goods inventories (11) only include produced goods. This variable is based on a survey with infrequent sampling and has a lot of bunching at zero. Transformed using the inverse hyperbolic sine and additionally, (12) shows the subset of firms with non-missing final goods inventories in at least 50% of active years. All regressions include firm and 4d-NACE sector × year fixed effects as well as controls for 2007 firm characteristics. Standard errors clustered at the firm level in parentheses.

Figure A.7: Effects on firm outcomes by demand elasticity




(a) Wage bill




(b) Gross profits to sales

*Notes*: Firm-level outcomes by exposure estimated from Equation (6) with a three-way interaction of year dummies, exposure to wholesale-funded banks and a dummy for whether the average demand elasticity of the firms' products is above or below the median. We aggregate Broda and Weinstein's demand elasticities from the good to the firm level using 2007 nominal revenue shares as weights. Low-elasticity firms have a composite of goods with a demand elasticity of less than 2.4. The gross operating margin is calculated as sales minus labor cost and purchases divided by sales. 95% confidence intervals based on standard errors clustered at the firm level.

## B Construction of unit value indices

Our starting point are annual unit values for 8-digit combined nomenclature goods at the firm leve, calculated by dividing export revenue by export quantities. A common problem in using time-variation in such unit values is that the combined nomenclature is frequently revised. During such revisions, existing categories may be split up into separate new categories (one-to-many mapping), several existing categories may be combined into a single one (many-to-one mapping), or definitions may be reshuffled in a way that combines both (many-to-many mapping). We construct firm level 2-digit unit value indices from firm-level 8-digit export data. These indices are based on changes in unit values that are consistent between two consecutive years at the firm level.

We first identify one-to-one, many-to-one and one-to-many and many-to-many mappings in the CN classification and identify the sets of connected 8-digit CN categories between every two consecutive years. In particular, we identify for each mapping $m$ that maps categories in year $y-1$ to categories in year $y$ the sets $I_{m,y-1}$ and $J_{m,y}$ that ensure that each category in $I_{m,y-1}$ only maps to categories in $J_{m,y}$ and that each category in $J_{m,y}$ is only mapped to from categories in $I_{m,y-1}$. We then join the firm-level data to this set of potential mappings. Many complicated mappings in the combined nomenclature reduce to simple one-to-one mappings at the firm level—for example, even if category A in year 0 maps to B, C, and D in year 1, many firms will only report one of the new categories in year 1.

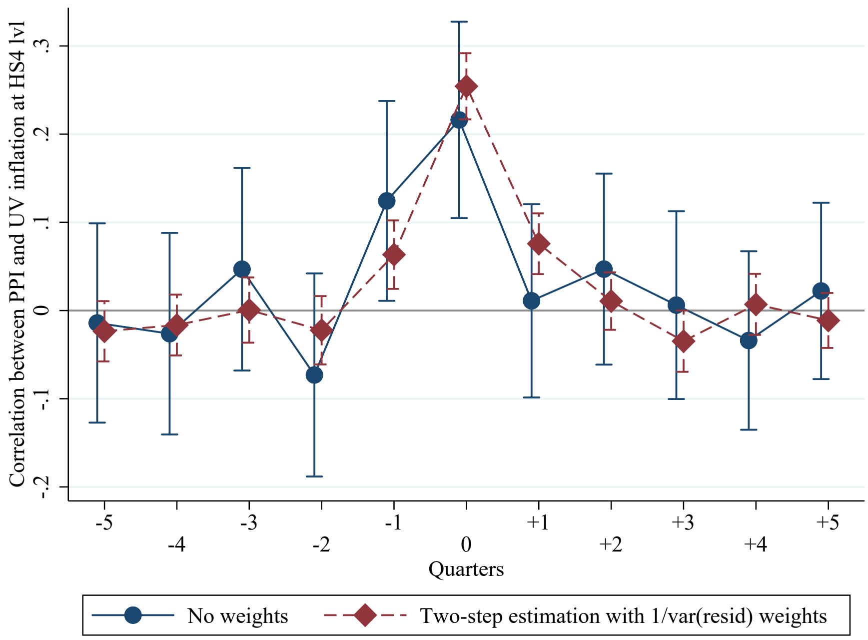
We then calculate changes in log unit values for firm $f$, year $y$ and mapping $m$

$$\Delta uv_{f,y,m} = \log\left(\frac{\sum_{j\in J_{y,m}} \text{Value}_{j,y}}{\sum_{j\in J_{y,m}} \text{Quantity}_{j,y}}\right) - \log\left(\frac{\sum_{i\in I_{y-1,m}} \text{Value}_{i,y-1}}{\sum_{i\in I_{y-1,m}} \text{Quantity}_{i,y-1}}\right) \tag{B.1}$$

We ensure that all quantities in $I$ and $J$ are measured in the same unit. When this is not the case, we use physical weight, which is provided for all goods, for all categories in the mapping. We then calculate a geometric mean price index at the level of 2-digit CN categories. Weights for each mapping are based on the total sales in year $y-1$. Mappings between different 2-digit CN codes are rare, but when they do occur we assign series to categories based on the CN codes in year $y$. In the case where a mapping points to different 2-digit CN codes in year $y$, we assign weights proportionally to all year $y$ 2-digit CN codes:

$$\Delta uv_{f,y,c} = \sum_{m\in c} w_{m,y-1}\Delta uv_{f,y,m} \quad \text{with} \quad w_{m,y-1} = \sum_{i\in I_{y-1,m}} \text{Value}_{i,y-1} \tag{B.2}$$

Figure B.1: Relationship between export unit values and PPI prices




*Notes*: The figure plots coefficients from a regression of changes in 2-digit CN log export unit value indices on current, leading and lagged average change of log prices in the same product category at the same firm. Matching unit values and prices at more detailed CN levels produces many non-matches, because CN classifiers in PPI and customs data often do not coincide. PPI prices include both domestic and export prices. The blue dots depict OLS coefficients, the red dots show FGLS coefficients, where we first regress changes in unit values on price changes using OLS and use the inverse variance of first step residuals as weights for each unit value series in the second step.

# C Construction of demand elasticity and strategic complementarity measure

## C.1 Demand elasticity

We estimate the heterogeneity of price effects of a loan supply shock by the price elasticity of demand of goods in Section 5.2. This subsection describes the source of the data and how we match it to our PPI goods and export unit values.

Broda and Weinstein (2006) use a demand system based on a CES utility function estimated on trade flows. The data are import quantities and prices at the product-origin-time level from 1990 to 2001 and published at two levels of disaggregation:

- 4-digit Standardized International Trade Classification (SITC) Rev. 3 codes (958 product codes): To merge these estimates onto our data, we first have to match 4-digit SITC Rev. 3 codes to 6-digit product codes of the Harmonized System. This gives us an estimate of the price elasticity of demand for 94% of products in the PPI data. For the few products we do not match, we add the average demand elasticity at the 4-digit level instead, giving us 98.9% coverage. In the unit value data, we computed unit value indices at the 2-digit CN level, so we use the volume-weighted mean of the known elasticities within a firm's 2-digit cell. This way, we match 98.5% of unit value observations in the baseline regression to a demand elasticity.
- 10-digit Harmonized System codes (13,972 product codes): Estimates of the elasticity of demand are available by 10-digit HS category from the same source. Notice that this is a much finer grid. Because product substitutability increases with the level of disaggregation, the estimated level of the elasticity of demand is generally higher in this data. Due to frequent re-classifications of products at this fine level of disaggregation, we match a lower share of our sample, namely 86.4% in the PPI and 96% in the unit value data.

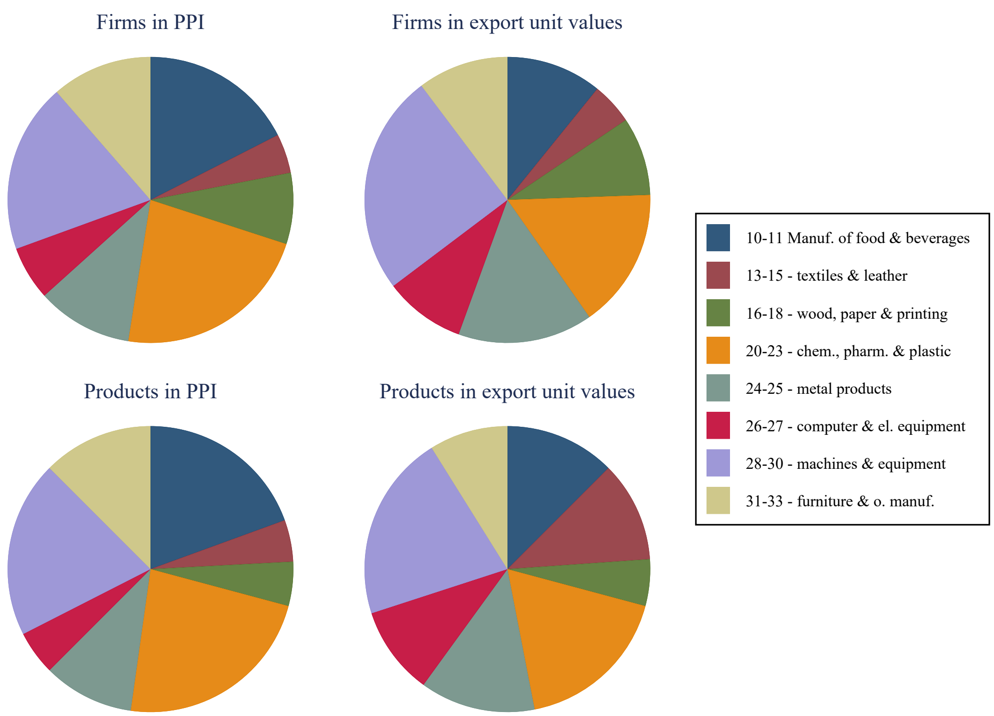
## C.2 Consumer packaged goods

We argue that this difference in the sample of products is important to understanding the difference between our results consisting on a sample of firms in all manufacturing sectors and those of Kim (2021), who looks at consumer packages goods. This includes foods and beverages, but also clothing and toiletries. We argue in Figure 4(c) that products which can be classified as consumer packaged goods differ from the broader industrial output in the price elasticity of demand, among other things. This subsection provides some details.

First, we show the industry distribution of firms and their products in our sample in Figure C.1. 19.42% (in the PPI) and 12.46% (in the trade data) of firms operate in food and beverage manufacturing, respectively.

We know the distribution of demand elasticities–estimated by Broda and Weinstein– in our data. But what would the distribution look like if our sample looked similar to the basket used by Kim (2021)? To answer this question we take data on industrial output values by Eurostat and merge the demand elasticities onto each product code. We then consider all industries defined by Eurostat as producing non-durable consumer goods (Eurostat). The respective basket is summarized in Table C.1. The last column shows the elasticity of demand translated from 4-digit SITC to the respective Eurostat prodcode of the average good in the respective category. Most categories have significantly higher demand elasticities than the goods in our sample (see Table 1). Weighted by the appropriate weights–the value of Danish production in 2007–the median elasticity of demand of that basket is 5.7. A second basket considers the subset of food and beverage manufacturing only, i.e. 10.1-11 in the table. The median demand elasticity, again weighted by the respective subsector's production values, for food and beverages is 8.6. Goods in both these reference baskets are much more price sensitive than industrial output as a whole.

Figure C.1: Industry composition of firms and products in price datasets




*Notes*: Pie chart of industry composition in the PPI survey used in the regression (left-hand side panels) and equivalent for the export unit values (right-hand side). The 2-digit NACE industries have been slightly aggregated to 9 categories for ease of illustration.

Table C.1: Consumer packaged goods

| NACE level | Code | Description | Share | Demand elasticity |
|---|---|---|---|---|
| 3 | 10.1 | Proc. and pres. of meat and meat products | 21.75% | 13.1 |
| 3 | 10.2 | — fish, crustaceans and molluscs | 5.32% | 5.0 |
| 3 | 10.3 | — fruit and vegetables | 2.32% | 5.1 |
| 3 | 10.4 | Manufacture of vegetable and animal oils and fats | 4.42% | 5.0 |
| 3 | 10.5 | — dairy products | 15.10% | 15.9 |
| 3 | 10.7 | — bakery and farinaceous products | 5.61% | 13.4 |
| 3 | 10.8 | — other food products | 9.52% | 5.3 |
| 2 | 11 | — beverages | 2.25% | 7.9 |
| 2 | 12 | — tobacco products | 0.98% | 5.7 |
| 3 | 13.9 | — other textiles | 6.22% | 2.9 |
| 2 | 14 | — wearing apparel | 3.72% | 3.3 |
| 2 | 15 | — leather and related products | 0.63% | 3.8 |
| 2 | 18 | Printing and reproduction of recorded media | 7.25% | 1.2 |
| 3 | 20.4 | Manufacture of soap and detergents, cleaning and polishing prep., perfumes and toilet prep. | 2.92% | 3.4 |
| 2 | 21 | — basic pharmaceutical prod. and pharm. prep. | 10.16% | 2.3 |
| 3 | 32.3 | — sports goods | 0.26% | 1.9 |
| 3 | 32.4 | — games and toys | 0.43% | 2.4 |
| 3 | 32.9 | — n.e.c. | 1.16% | 1.6 |

*Notes*: Approximation of consumer packaged goods basket using non-durable consumer goods industries, as classified by Eurostat's Prodcom product codes (which are consistent with NACE industry definitions). The second last column shows 2007 nominal production values of the respective industries in relation to the sum of the total of non-durable consumer goods (Source: Prodcom/Eurostat). The last column shows the average Broda and Weinstein 4-digit SITC Rev. 3 demand elasticity estimates of all the products within that country (unweighted).

## C.3 Exchange-rate pass-through and strategic complementarities

This subsection describes how we estimate strategic complementarities for product categories in our own data on exports.

Let $p_{i,t}$ be the producer's desired log price in the domestic currency. The price that governs demand optimization, i.e. in the currency of the export market, is $p^*_{i,t} \equiv p_{i,t} - e_t$. An appreciation shock $\Delta e_t < 0$ increases the foreign price if the domestic one is kept unchanged. Further, define the aggregate log price level in a product market as $p_t$. If the firm sets a price above that level, it will lose market share and the impact of the firm's price on the market index decreases, implying a flatter, more elastic demand curve (Atkeson and Burstein, 2008, Amiti et al., 2014).[19] Put differently, the desired markup above the firm's marginal cost is a function of its own relative price with an elasticity $-\Gamma_{i,t}$.

$$\begin{aligned}\Delta p_{i,t} &= -\Gamma_{i,t}\left(\Delta p_{i,t} - \Delta e_t - \Delta p_t\right) + \Delta mc_{i,t} \\ &= \frac{\Gamma_{i,t}}{1+\Gamma_{i,t}}\Delta e_t + \frac{\Gamma_{i,t}}{1+\Gamma_{i,t}}\Delta p_t + \frac{1}{1+\Gamma_{i,t}}\Delta mc_{i,t} \end{aligned} \tag{C.1}$$

If $\Gamma = 0$, pass-through of marginal cost shocks into output prices is always complete and unconstrained markups constant. At the same time, domestic prices are unaffected by exchange-rate fluctuations, so the foreign-currency price absorbs the shock entirely. With $\Gamma > 0$, shocks to marginal cost (and also demand) are partially absorbed by variable markups, for which there is evidence in the Danish PPI (Dedola et al., 2019). An appreciation of the producer's currency will move the foreign-currency price into territory where the demand curve is more elastic and the desired markup lower; The optimal domestic-currency price will decrease by the same amount as it reacts to the average price in the economy, namely $\frac{\Gamma}{1+\Gamma}$. Therefore, estimates of exchange-rate pass-through into domestic prices can directly inform the degree of strategic complementarities in a given market and by extension the degree to which firms pass on idiosyncratic shocks.

**Estimation** To estimate the average $\frac{\Gamma_i}{1+\Gamma_i}$ for each 2-digit product category in our data, we use the 1995-2007 vintages of the customs data on Danish exporters. The only difference is that we use the information of the destination of the exported product, over which we have aggregated in the data used throughout the rest of the paper (see Appendix A). It contains export values (in Danish kroner) and quantities of exported goods for each firm-product-destination cell by which we compute the unit value $P_{i,p,d,t} = \frac{\text{Export value}_{i,p,d,t}}{\text{Export quantity}_{i,p,d,t}}$, where $i$ indicates the firm, $p$ the product (defined as an 8-digit code in the Combined Nomenclature), $d$ the export destination and $t$ the

[19] The framework crucially depends on two assumptions: Firms compete oligopolistically, internalizing the effect of their price-setting on the market index, and that substitution within industries is easier than across. The concavity of the demand curve can also come directly from the formulation of consumer preferences (Kimball, 1995, Gopinath and Itskhoki, 2010).

year. We estimate

$$\Delta p_{i,p,d,t} = \beta^{SC}_{c(p)} \Delta e_{d,t} + \gamma_{i,t} + \zeta_{p,t} + \varsigma_{p,d} + \Gamma X_{d,t} + u_{i,p,d,t}. \tag{C.2}$$

$\Delta e_{d,t}$ is the change in the average nominal exchange rate relative to the year prior and defined such that positive values indicate a depreciation of the Danish currency. $\beta^{SC}_{c(p)}$ is the product category-specific pass-through to the domestic-currency price $p_{i,p,d,t}$. Crucially, we include a firm-time fixed effect $\gamma_{it}$, which will absorb marginal cost shocks common to products within a firm, including those coming from exchange-rate fluctuations for firms that simultaneously import and export. We further include product-time fixed effects and product-destination fixed effects to account for the (unobserved) prices of competitors and destination-specific conditions for each product. We cannot include destination-time fixed effects, so we instead control for local conditions in the destination market by including growth rates of real GDP, exports, imports and the difference in the unemployment rate in the vector $X_{d,t}$. Identification of $\beta^{SC}_{c(p)}$ in Equation (C.2) comes from the fact that a firm sells multiple products in multiple destination markets with potentially different developments in the bilateral exchange rates. On the destination side, we consider the 45 countries for which we can merge the change in the annual average of the bilateral exchange rate (including national European currencies prior to the introduction of the euro). They cover 89% of export values over the time period.

**Results** To benchmark results against the literature, we first estimate a uniform $\beta^{SC}$ on the combined sample, shown in Table C.2. The estimated reaction of domestic prices is 0.18 (i.e., a pass-through to export prices of 0.82). Denmark's central bank has followed a credible fixed exchange-rate policy vis-à-vis the German mark and later on the Euro. Fluctuations of the exchange rate are to be kept within a 2.25pp band around 7.46038 DKK/EUR, but have been much closer in practice. Estimating Equation (C.2) only on exports to destinations with which there was no fixed exchange rate does not yield statistically significant differences. Column (3) includes the recession and subsequent recovery up to 2017. The evidence for strategic complementarities in the export data is even stronger in this case, although the baseline estimate lies within the confidence interval. Our estimates are slightly higher compared to the version in Amiti et al. (2014) controlling for imports more explicitly to account for the marginal cost channel. Columns (4) and (5) show versions of the baseline estimate first without fixed effects to control for marginal costs, in which case the estimate is expectedly higher, and finally a version with a firm-product-time fixed effect. The estimated pass-through coefficient of this very saturated model is almost identical to the baseline, which is why we consider the firm-time fixed effect sufficient to control for marginal cost when estimating $\beta^{SC}$ separately for each 2-digit category of the Combined Nomenclature. According to our estimation, there is considerable heterogeneity across the 96 categories. Their mean and median are 0.13 and 0.20, respectively, with an interquantile range between 0.02 and 0.31. 66 cases are

Table C.2: Exchange rate pass-through to home currency prices

| | (1) Baseline | (2) Excl. $\bar{E}$ destinations | (3) Incl. post-GFC | (4) No marg. cost control | (5) More marg. cost control |
|---|---|---|---|---|---|
| Pass-through | 0.176*** | 0.185*** | 0.199*** | 0.241*** | 0.178*** |
| | (0.031) | (0.038) | (0.016) | (0.049) | (0.032) |
| Firm-time | Yes | Yes | Yes | No | No |
| Product-time | Yes | Yes | Yes | No | No |
| Firm-product-time | No | No | No | No | Yes |
| Observations (in 1000) | 1,332 | 560 | 3,699 | 1,332 | 1,332 |
| Firms | 10,846 | 9,324 | 14,505 | 10,846 | 10,846 |
| Destinations | 45 | 26 | 49 | 45 | 45 |

*Notes*: Estimation of Equation (C.2) for a nominal exchange rate change depreciation on export prices in the domestic currency. Data in growth rates of annual averages. All regressions include an additional destination-product fixed effect, as well as the following destination-specific control variables: the growth rate of annual real GDP, aggregate exports and imports, as well as the difference in the destination's unemployment rate. Standard errors clustered by destination-year in parentheses.

statistically significantly higher than zero at the 95% confidence level. We winsorize the estimated levels of strategic complementarities at 0 and 1 and merge them onto the price data to study the heterogeneity of the credit supply shock in Section 5.2.

# D Time series correlations

## D.1 Missing disinflation of output prices in Denmark

Friedrich (2016) shows that surprisingly high inflation rates during the bust (and low inflation during the subsequent recovery) were a global phenomenon, including in Denmark. To quantify missing disinflation of Danish producer prices during the Great Recession, we estimate dynamic correlations of output and prices on the pre-crisis sample, based on which we compute forecasts of prices conditional on the observed path of output (equivalent to Bobeica and Jarociński (2019), who do not find that U.S. inflation was puzzlingly low during the recession).

**VAR specification** We estimate a 2-variable reduced-form vector autoregression:

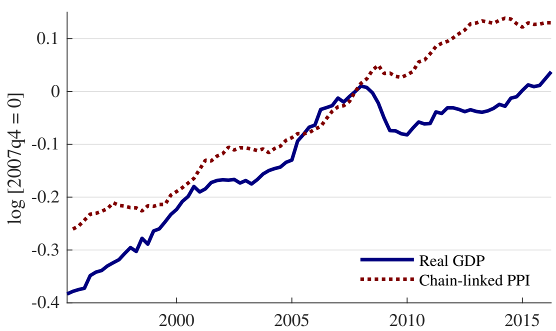
$$\begin{bmatrix} y_t \\ p_t \end{bmatrix} = c + \sum_{j=1}^{l} A_j \begin{bmatrix} y_{t-j} \\ p_{t-j} \end{bmatrix} + u_t, \qquad E(u_t) = 0, E(u_t u_t') = \Omega \tag{D.1}$$

$y$ is the log of real GDP and $p$ the log price level. $c$ are variable-specific constants, $A_j$ matrices of dynamic coefficients as a function of $l$ lags, and $u$ the vector of reduced-form residuals with variance-covariance matrix $\Omega$. The estimation sample includes data up to 2007. For subsequent periods, we generate forecasts of output and prices, calibrating the (correlated) reduced-form residuals to match the path of actual GDP after 2007.

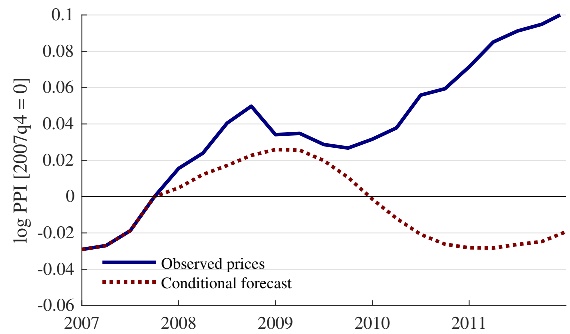
**Data** Since we want to quantify the extent of missing disinflation *in the relevant series of prices*, the series entering as $p_t$ is computed directly from the PPI micro data used throughout the paper. When the Danish statistical office calculates and publishes the PPI index, it does so in a hierarchical fashion: First it constructs indices of each 6-digit HS code product category from (cleaned) item-level price changes. The indices are aggregated to arithmetic Laspeyres indices at the sector level, and finally to the headline PPI ($PPI_t = \sum_s \omega_{s,0} \frac{PPI_{s,t}}{PPI_{s,0}}$). While the weights in the latter step are publicly available (for 2-digit manufacturing sectors in 2009), the former are not and we do not know the weights of each item in the construction of $PPI_{s,t}$. A further complication is that the official PPI using the current methodology only dates back to 2005. Therefore, we first compute within-firm means of log price changes and then aggregate using sales of firms, a variable which we can obtain for many firms back to 1995, to obtain sector indices. The resulting chain-linked index is displayed in Figure D.1, panel (a).

**Results** Before the Great Recession, the VAR estimates a medium-run elasticity of GDP innovations and price responses of about 0.8. Therefore, given the 9% drop in GDP from peak to trough,

Figure D.1: VAR and conditional PPI forecast




(a) Full time series




(b) Conditional PPI forecast

*Notes*: Time series of the real GDP and chain-linked PPI, which is based on our own calculations using the PPI micro data, firm-level sales and industry weights provided by Statistics Denmark. Panel (b) plots the observed PPI index and a conditional forecast from a VAR(3) which, starting in 2008, assumes that its reduced form residuals exactly match the observed GDP path.

one would expect the price level to fall by around 7%. The blue solid line in panel (b) of Figure D.1 shows developments of actual prices, which grow by 5% during the first three quarters of 2008. As GDP starts falling in the second quarter of 2008, the implied growth of prices, shown in the red dotted line, would only have 3% inflation relative to the base period. Through the model's eyes, these positive inflation surprises are persistent, which is why the conditional forecast of prices only starts falling in early 2009. Therefore, we focus on medium-run shifts in the price level. By the time both actual prices and conditional forecasts grow in parallel trends, the gap between the two is around 9pp. The missing disinflation is still present once we control for the surprisingly inflationary period at the beginning of 2008: Between peak and trough, the VAR suggests prices should be 6% lower, but actual prices only fell by 2%. The results shown use $l = 3$ lags, but the extent of missing disinflation in the PPI is robust to different lag specifications.

Note that our VAR does not attempt to identify any structural shocks – the matrix $\Omega$ is entirely unrestricted. Therefore, the unusually small reaction of output prices to the Great Recession is neither a statement on the source of the shock (demand or supply) nor the slope of the Phillips curve. For example, Del Negro et al. (2020) document a lower pass-through from marginal cost to prices in the post-1990 period in the U.S. They use the excess bond premium by Gilchrist and Zakrajšek (2012) as a proxy for an aggregate demand shock depressing prices and identifying the slope of the Phillips curve. Following the evidence in this paper, this shock might still conflate movements in aggregate demand and supply and we document the inflationary effects in terms of firms' price-setting.

## D.2 Time series properties compared to United States

Table D.1: Time series comparison Denmark and U.S.

| | Denmark | | | United States | | |
|---|---|---|---|---|---|---|
| Period | ΔLoans 2003-2018 | ΔGDP 1991-2018 | ΔPPI 1995-2016 | ΔLoans 1984-2018 | ΔGDP 1984-2018 | ΔPPI 1986-2018 |
| Average growth | 1.98 | 2.13 | 1.89 | 5.59 | 2.55 | 1.83 |
| — 2005 | 15.68 | 6.64 | 1.44 | 13.19 | 3.08 | 5.45 |
| — 2006 | 22.35 | 4.08 | 4.05 | 13.40 | 2.56 | 1.52 |
| — 2007 | 18.51 | 2.68 | 3.74 | 17.51 | 1.95 | 6.24 |
| — 2008 | 11.00 | -2.20 | 4.98 | 12.02 | -2.79 | 2.16 |
| — 2009 | -13.38 | -5.80 | -2.30 | -20.05 | 0.18 | 0.02 |
| — 2010 | -6.42 | 1.86 | 3.26 | -8.05 | 2.54 | 4.63 |
| — 2011 | -10.94 | 3.05 | 3.55 | 8.40 | 1.60 | 6.48 |
| St. dev. | 13.31 | 4.02 | 2.75 | 10.37 | 2.27 | 6.53 |
| Corr($x$, ΔGDP) | 0.28 | | | 0.07 | | |
| Corr($x$, ΔPPI) | 0.23 | 0.11 | | 0.01 | 0.22 | |

*Notes*: Underlying series are annualized log differences of quarterly averages of loans, real GDP and manufacturing producer prices. Reported statistics cover time periods for which underlying series available for both countries. Sources: Loans from banks to non-financial corporations in Denmark, all currencies/maturities (series DNPUD in Statistikbanken); seas. adj. GDP in 2010-prices (NKH1); own PPI index based on micro data (see Section D.1). U.S. data: FRED mnemonics BUSLOANS (Commercial and industrial loans by commercial banks), GDPC1, PCUOMFGOMFG (Manufacturing PPI).