Credit supply shocks and prices: Evidence from Danish firms

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Online Appendix

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A. Supplementary Figures and Tables

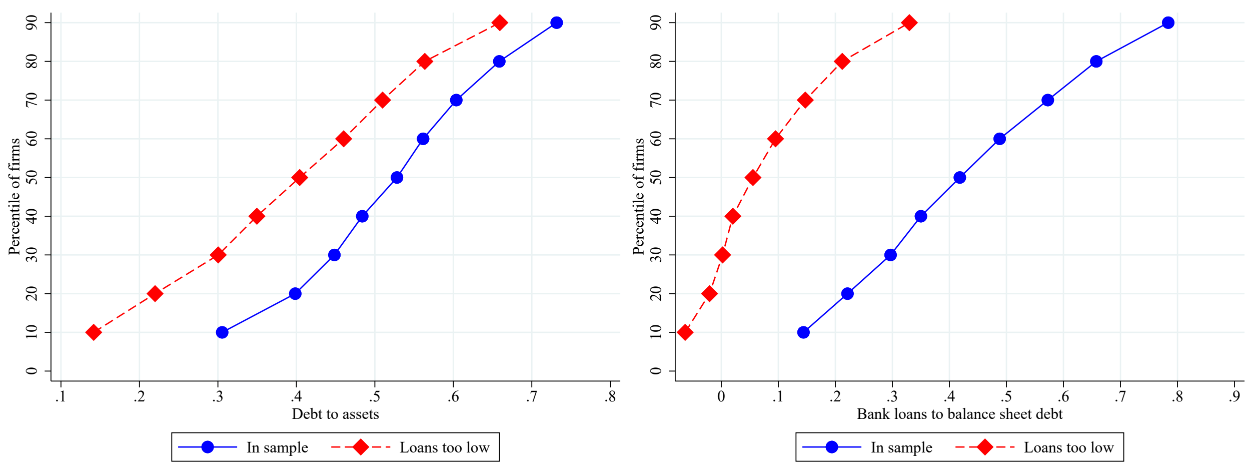
A.1. Sample

Table A.1: Sample construction

Restriction	All firms		PPI match		Export unit values match	
	Firms	Employ-ment[a]	Firms	Employ-ment[b]	Firms	Employ ment[b]
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. 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.
[a] Share of initial firm sample with full-time equivalent employment of 366,000, according to our micro data
[b] Share of matched sample relative to column 2

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



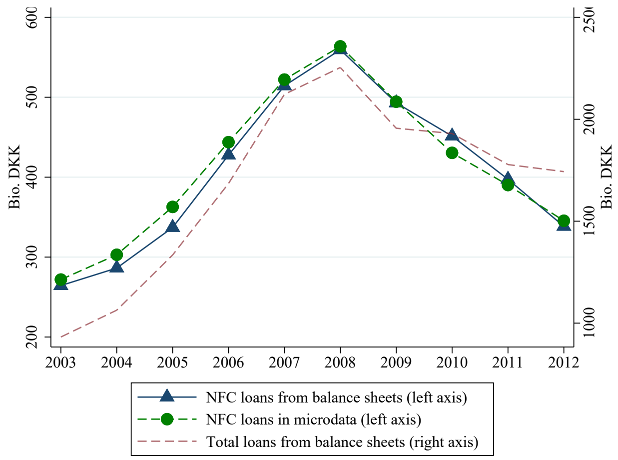
(a) Debt to assets

(b) Bank loans to debt

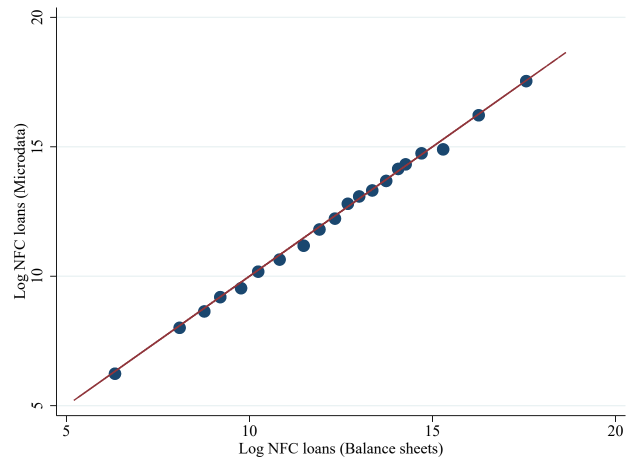
Notes: Our sample excludes firms with below 0.01 2007 loan-to-sales ratios and firms with loans below 100,000 DKK in 2006 or 2007 (see section D). The figure compares the distributions of debt and bank loans between firms excluded from the sample on this ground and firms in the sample. Firms excluded 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



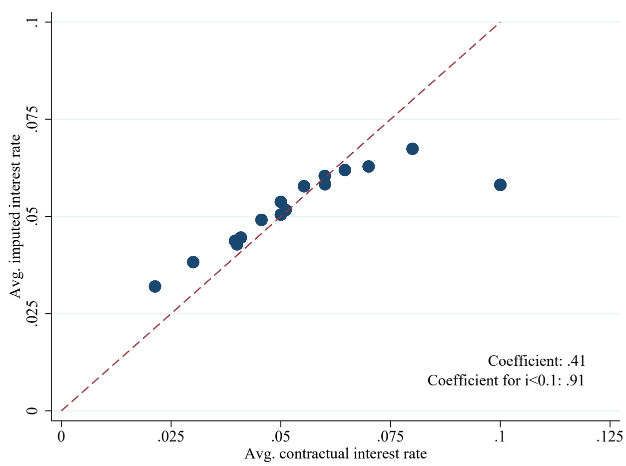
(a) Aggregate lending over time



(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.

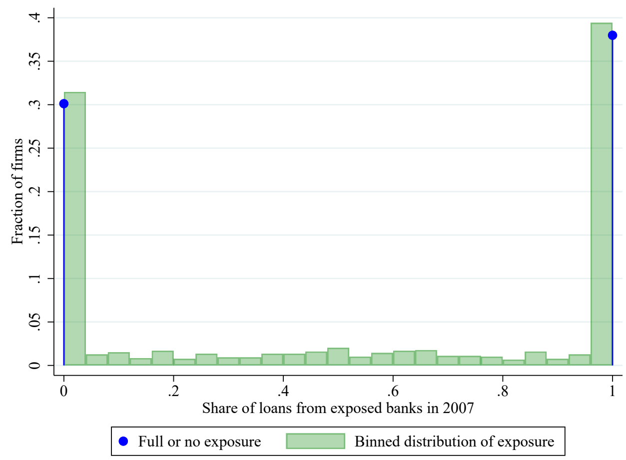
Figure A.3: Calculated average and reported contractual interest rate



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.

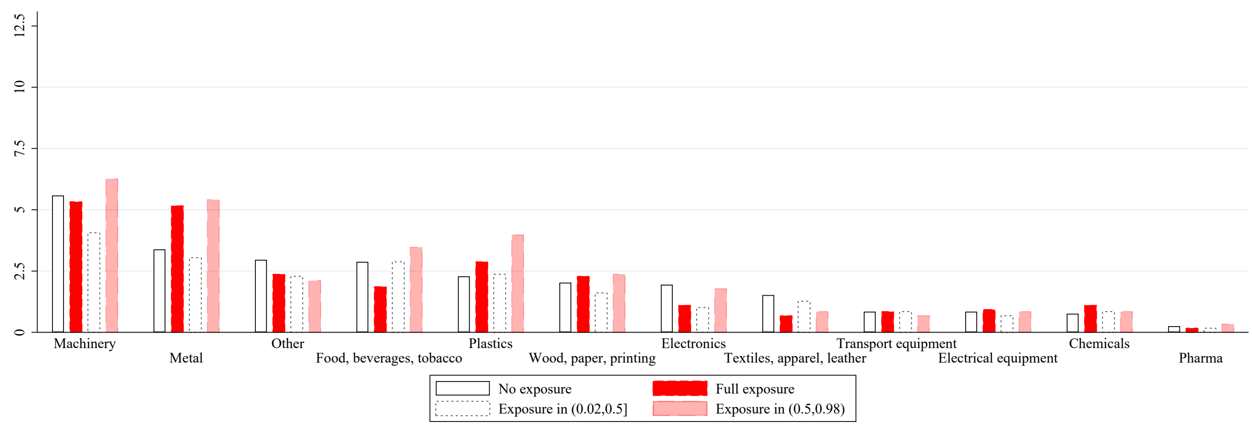
Table A.2: Sample characteristics by exposure to wholesale-funded banks

	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	24.2	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	2.4	3.9	2.5	0.83	2.9	2.2	3.3	2.4	0.78
— (export unit values)	4.0	2.4	3.6	2.4	0.66	3.4	2.4	3.5	2.5	0.19
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) and they 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 elasticity of demand estimated for categories of goods by Broda and Weinstein (2006), which we use in Section B.
*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 fulfil 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 relative to 2007	IHS	Log	Growth relative 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**	-0.16	-0.19*	-0.10**
	(0.15)	(0.14)	(0.05)	(0.13)	(0.10)	(0.04)
2010	-0.36**	-0.37**	-0.06	-0.20	-0.22*	-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	6,811	6,888	10,350	10,199	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	-0.20	-0.24
	(0.14)	(0.26)	(0.15)	(0.15)	(0.15)
2010	-0.34*	-0.62*	-0.20	-0.34*	-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	-0.17	-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 fixed effects. "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)	(2)	(3)	(4)	(5)
	Baseline	Trend	No controls	PDSLASSO	All controls
2008	0.25	0.33	0.27*	0.25	0.27*
	(0.16)	(0.25)	(0.16)	(0.16)	(0.16)
2009	0.42**	0.57	0.29	0.42**	0.44**
	(0.21)	(0.40)	(0.22)	(0.21)	(0.20)
2010	0.51	0.72	0.12	0.51	0.57*
	(0.32)	(0.59)	(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)	(7)	(8)	(9)	(10)
	Baseline	Trend	No controls	PDSLASSO	All controls
2008	0.26**	0.39**	0.24*	0.26**	0.28**
	(0.12)	(0.20)	(0.13)	(0.12)	(0.12)
2009	0.39**	0.62**	0.23	0.38**	0.38**
	(0.16)	(0.31)	(0.17)	(0.16)	(0.16)
2010	0.56**	0.90**	0.23	0.55**	0.58**
	(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) Baseline	(2) Incl. trend	(3) Incl. CN FE	(4) No controls	(5) PDS-LASSO	(6) All 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	17,286
Firms	1,089	1,089	1,089	1,089	1,089	1,089

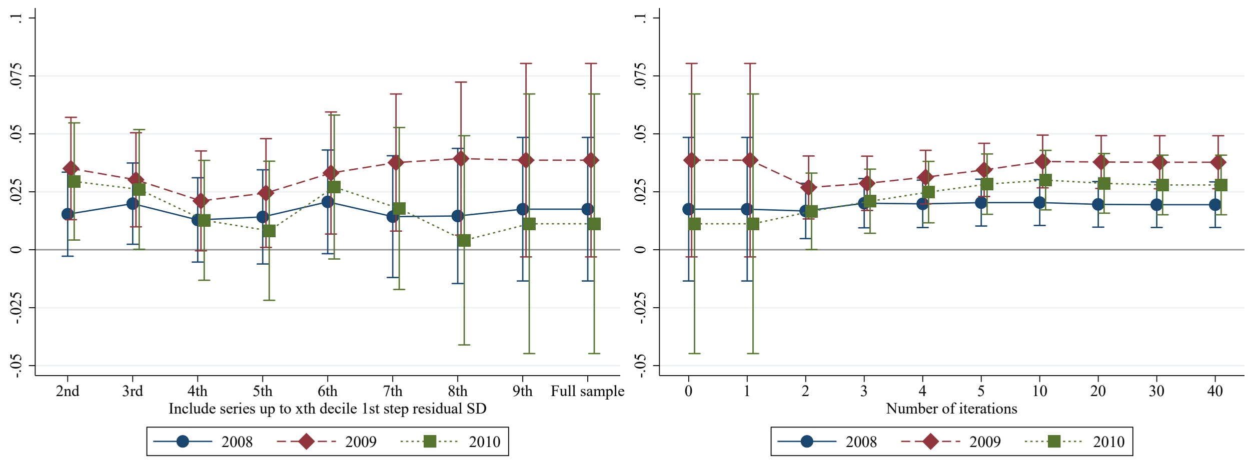
Notes: Evolution of export unit values (relative to 2007) conditional on the firms' lending portfolio exposure. Estimation based on Equation (4). All regressions include firm×product and 4-digit NACE×year fixed effects as well as controls for 2007 firm characteristics. Column (2) additionally controls 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 β_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.

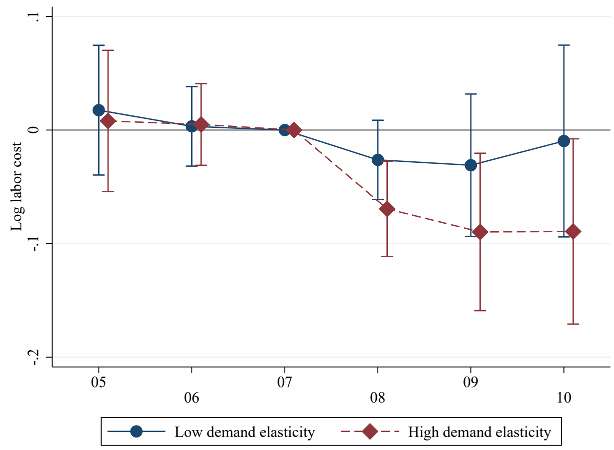
A.6. Additional firm outcomes

Table A.10: Other firm outcomes

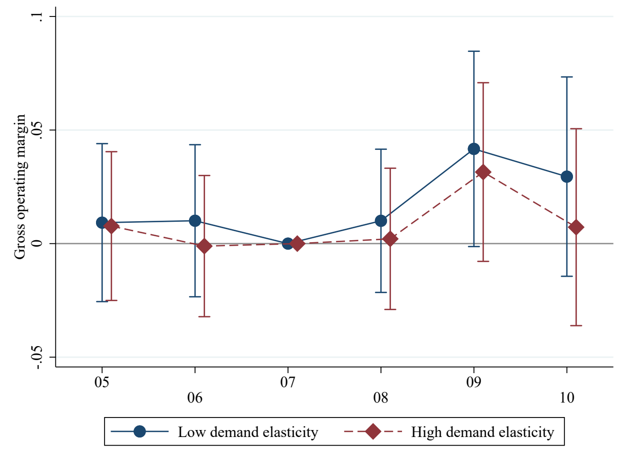
	(1) Sales per worker	(2) Gross op. margin	(3) —, excl. int. paym.	(4) Sales	(5) Domestic sales	(6) Exports
2008	0.037**	0.006	0.006	-0.014	0.009	-0.017
	(0.016)	(0.011)	(0.012)	(0.017)	(0.036)	(0.037)
2009	0.077***	0.035**	0.036**	0.009	-0.017	-0.028
	(0.023)	(0.015)	(0.015)	(0.030)	(0.049)	(0.051)
2010	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***	0.007	-0.016	-0.194	-0.284
	(0.014)	(0.013)	(0.006)	(0.028)	(0.297)	(0.323)
2009	-0.060**	-0.068***	0.017**	-0.002	0.086	0.154
	(0.024)	(0.023)	(0.008)	(0.047)	(0.388)	(0.455)
2010	-0.050*	-0.052*	0.002	-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 level, 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, 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.

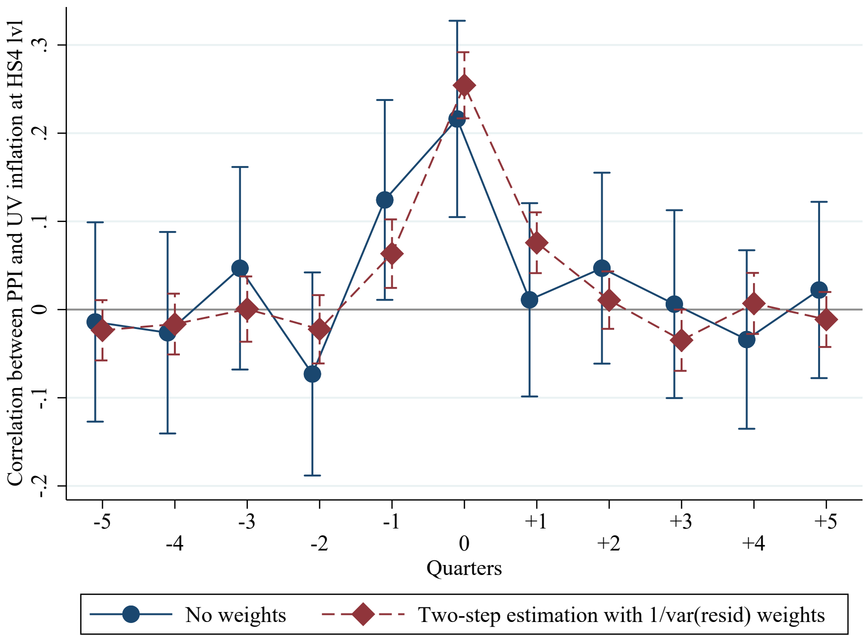
We then calculate changes in log unit values for firm f, year y and mapping m

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

We ensure that all quantities in I and J are measured in the same unit. When this is not the case, we use the 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 B. 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[21] 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[22]. 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.

[21] http://www.columbia.edu/ dew35/TradeElasticities/TradeElasticities.html

[22] We use conversion tables provided in UN Statistics Division (2022).

C.2. Consumer packaged goods

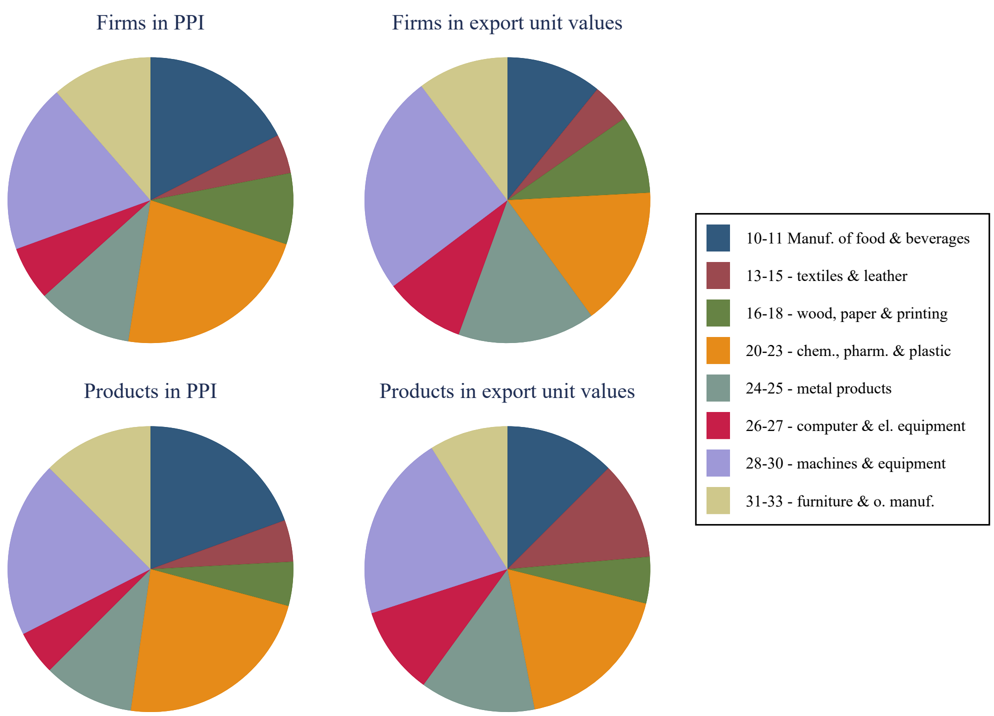
We argue that this difference in the sample of products is important to understanding the difference between our results consisting on a sample of firms in all manufacturing sectors and those of Kim (2020), who looks at consumer packages goods. This includes foods and beverages but also clothing and 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 (2020)? 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[23]. 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.

[23] https://www.oecd.org/sdd/prices-ppp/43905313.pdf

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 (Eurostat, 2021). 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, Itskhoki and Konings, 2014).[24] 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, Kristoffersen and Züllig, 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 $\Gamma/(1+\Gamma)$. 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 $\Gamma_i/(1+\Gamma_i)$ for each 2-digit product category in our data, we use the 1995-2007 vintages of the customs data on Danish exporters (**?**). The

[24] 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).

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 $P_{i,p,d,t} = \text{Export value}_{i,p,d,t}/\text{Export quantity}_{i,p,d,t}$, 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 year. We estimate

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

$\Delta e_{d,t}$ 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 γ_{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[25] in the vector $\mathbf{X}_{d,t}$. 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 β^{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

[25] We take this data from the OECD (2021) national accounts database.

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, Itskhoki and Konings (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 β^{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 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 B.

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)	(0.048)	(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	1,333	1,331
Firms	10,846	9,324	14,505	10,898	10,845
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.

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).

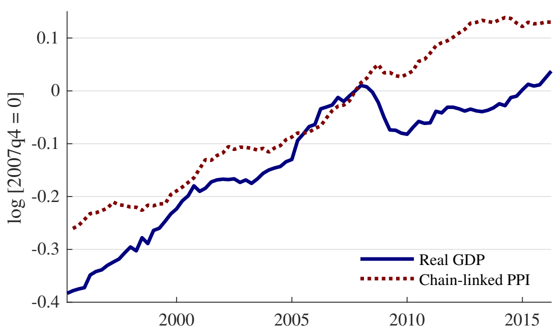
VAR specification We estimate a 2-variable reduced-form vector autoregression:

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

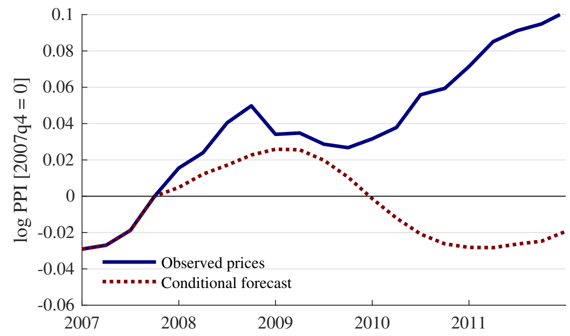
y is the log of real GDP and p the log price level. c are variable-specific constants, A_j matrices of dynamic coefficients as a function of l lags, and u the vector of reduced-form residuals with variance-covariance matrix Ω. The estimation sample includes data up to 2007. For subsequent periods, we 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 ($PPI_t = \sum_s \omega_{s,0}(PPI_{s,t})/(PPI_{s,0})$). 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

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.

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, 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 Ω 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		
	ΔLoans	ΔGDP	ΔPPI	ΔLoans	ΔGDP	ΔPPI
Period	2003-2018	1991-2018	1995-2016	1984-2018	1984-2018	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: Commercial and industrial loans by commercial banks are obtained from Board of Governors of the Federal Reserve System (2021), GDP from U.S. Bureau of Economic Analysis (2021), and the Manufacturing PPI from U.S. Bureau of Labor Statistics (2021).

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