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Abstract

We study the interconnection between the productivity and pricing effects of financial shocks. Combining administrative records on firm-level output prices and quantities with quasi-experimental variation in credit supply, we show that a tightening of credit conditions has a persistent, yet delayed, negative effect on firms' long-run physical productivity growth (TFPQ) but also induces firms to change their pricing policies. Commonly used revenue-based productivity measures (TFPR)—which conflate price and productivity—offer biased predictions regarding the consequences of financial shocks for firms' productivity growth, underestimating the long-run elasticity of physical productivity to credit supply by half. We also show that the pricing adjustments themselves have productivity implications. Firms use low pricing as a source of internal financing, allowing them to avoid cutting expenditures on productivity-enhancing activities, thereby softening the impact of financial shocks. We incorporate these forces into a quantitative model of firm dynamics to quantify the importance of productivity and pricing dynamics (and their interplay) in driving the scarring effects of financial crises on aggregate productivity and welfare.

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Key words: productivity, pricing, financial constraints, innovation

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1 Introduction

Financial crises are frequently followed by persistent slowdowns in aggregate productivity growth (Cerra and Saxena, 2008; Reinhart and Rogoff, 2014; Hall, 2015). This has been recently documented for the US, Europe, and several developing countries in the wake of the Great Recession and subsequent sovereign debt crisis.[1] One explanation is that financial market conditions affect the ability of individual producers to sustain productivity growth (Midrigan and Xu, 2014; Cole, Greenwood, and Sanchez, 2016).

Despite the growing interest in this topic, studying micro-level productivity slowdowns and their drivers remains challenging. A key difficulty lies in their measurement: commonly used revenue productivity measures conflate output prices with physical productivity. Accordingly, observed productivity slowdowns could indicate an actual decline in physical productivity growth, declining output prices, or both.

In this paper, we construct a novel dataset that allows us to directly address this empirical challenge and systematically examine the separate physical productivity and output price responses to a contraction in credit supply, as well as their relationship. We provide rich reduced-form evidence and model-based quantitative results that demonstrate how accounting for the endogenous response of prices is crucial for measuring and understanding how firms respond to financial shocks and the associated implications for productivity growth.

Empirically, we find that a sudden tightening of financial conditions causes a delayed, but persistent and economically significant reduction in firm-level physical productivity growth (TFPQ). Revenue-based measures of productivity (TFPR), however, provide biased estimates of the effects on physical productivity as they also capture a change in pricing policies.[2] In the immediate aftermath of the credit crunch, firms cut output prices and, as a result, TFPR estimates suggest a short-run slowdown of firm-level productivity growth, despite TFPQ being unaffected. In the medium-to-long run, the TFPR and TFPQ responses are correlated, however the former substantially understates the decline in the latter because firms more affected by the shock eventually raise prices.

Furthermore, we show that firms that are able to respond to the shock in the short run by lowering output prices experience a significantly lower contraction in productivity growth in the long run. The reason is that financial shocks deprive firms of the liquidity needed to fund

[1] See, e.g., Jordà, Schularick, and Taylor (2013) and Queralto (2020).

[2] The TFPR-TFPQ terminology, now standard in the literature, was first introduced by the seminal contribution of Foster, Haltiwanger, and Syverson (2008). See Syverson (2011) for a discussion of the relationship between quantity- and revenue-based productivity measures.

investments in innovation and human capital that sustain productivity growth over time. By using low prices as a source of internal finance, firms can generate liquidity from the product market, allowing them to relieve the pressure to reduce expenditures in productivity-enhancing investments.

These findings offer a novel perspective and new insights regarding the contribution of financial factors to firm-level productivity growth. For one, they suggest that the consequences of financial shocks are sizable but take time to materialize, although movements in prices convey the (mistaken) impression that they impair firm-level productivity immediately. For another, they reveal that the price adjustments themselves have direct implications for productivity growth, as firms can use pricing adjustments as a source of internal finance. Embedding these insights into a quantitative model, we show how firm-level pricing and innovation decisions have important implications for aggregate productivity and welfare in the aftermath of financial shocks.

The paper proceeds as follows. In Section 2 we describe the data used in our empirical analysis and discuss the measurement of prices and productivity. We build a novel micro-level panel dataset that spans a decade of business and credit records for manufacturing firms in Belgium. Combining confidential administrative data from different sources, our dataset merges information on firm/product-specific output prices and quantities, a detailed account of firms' balance sheets and income statements, and comprehensive records of firm-bank credit relationships. The availability and granularity of our data enable us to build firm-level price indices that allow us to distinguish between TFPR and TFPQ.

Section 3 details the empirical design that allows us to identify firm-level credit supply shocks. The national business credit registry offers a detailed account of firms' overall access to bank finance, as well as disaggregated information on their credit suppliers and their individual positions with firms. By combining this information with the occurrence of an aggregate financial shock that differentially affected lending institutions in Belgium, we are able to isolate variation in firm-level credit driven by changes in credit supply, separately from changes in credit demand. Specifically, we use the burst of the 2010-2012 European sovereign debt crisis as a natural experiment to construct a set of firm-specific credit supply shifters, which allow us to identify the causal impact of credit supply shocks on firm-level productivity growth and pricing behavior.

Section 4 presents our main results on the separate effects of credit supply shocks on productivity and prices. Our estimates reveal that firms coping with a tightening of credit supply experience a significant contraction in technical productivity (TFPQ) growth that materializes three years after the credit shock and persists over time. Specifically, we estimate that a one standard deviation difference in exposure to the credit shock translates into a reduction of long-run productivity growth by 6.4 percent, which implies a long-run elasticity of firm-level productivity to credit supply of 0.4. The persistent productivity slowdown helps rationalize the slow economic recovery after financial crises documented by previous studies (Queralto, 2020).

A rather different picture emerges when we examine the effects of financial shocks on revenue-based productivity (TFPR) growth. The reason the effects are different is that this commonly used productivity measure captures not only the effects of financial shocks on physical productivity, but also changes in firm output prices, which we show are also directly affected by the shock. In the short run, the shock induces firms to reduce prices, with a one standard deviation difference in exposure to the shock leading to a 2 percent drop in prices, whereas TFPQ is unaffected. As a result, the TFPR estimates erroneously suggest that firms facing a financial shock experience an immediate slowdown of productivity growth. In the long run, firms eventually increase prices in response to the shock, with a one standard deviation in exposure generating an increase in prices of up to 4 percent in the years following the shock. Consequently, while revenue and physical productivity growth do co-vary over longer horizons, TFPR estimates significantly understate (by about half) the true impact of a tightening of financial conditions on physical productivity growth.

After decoupling the productivity and price effects of financial shocks, in Section 5, we provide evidence on the economic mechanisms underlying these responses. Our finding that TFPR provides biased estimates of both the magnitude and timing of the underlying TFPQ response is important for understanding which economic channels can plausibly explain the slowdown in firm-level productivity. We argue that the delayed, but persistent, drop in TFPQ is inconsistent with mechanisms in which financial shocks cause firms to inefficiently use resources. If this was the case, we would observe an immediate reduction in firm productivity. Instead, our results suggest that the effect of financial shocks take time to materialize, but have a lasting impact, for example by constricting investments in productivity growth.

To provide direct evidence for this, we first show that the sudden tightening of credit supply conditions has an immediate, contractionary effect on expenditures on productivity-enhancing activities, such as investments in innovation and worker's human capital. Using variation in these expenditures driven by firms' heterogeneous exposure to the credit shock, we then show that the contraction in investments in intangibles leads to a persistent, yet delayed, reduction in firm-level productivity growth. Specifically, we estimate that a one percent reduction in R&D and training expenses leads to decreases of productivity of over 2 percent and 0.4 percent, respectively.

Next, we study the mechanisms underlying the price response. First, we document that the credit supply shock led firms to seek alternative, more expensive, sources of external funding, leading to an increase in borrowing costs. Second, as discussed above, the shock reduced long-run productivity growth for firms. Together, higher financing costs and lower production efficiency lead to an increase in operating costs, which explains why prices of producers more exposed to the credit crunch increase in the long run, compared to less exposed producers.

A fundamentally different force explains the contraction of output prices in the immediate aftermath of the shock. The sudden tightening of credit supply conditions starves firms of liquidity and exposes them to the risk of financial distress. Since cutting costs or raising external finance from alternative sources takes time or might not be possible, firms use low pricing as a source of internal finance to counteract the reduction in external finance. A more aggressive pricing strategy, while sub-optimal in normal circumstances, allows firms to generate additional cash flows by selling off their inventories (Kim, 2020).

By decoupling the effects of financial shocks on firm productivity and pricing, our results not only enhance our understanding of the real and nominal effects of financial shocks, but also reveal an important inter-temporal relationship between them. In Section 5.3, we document a strong, negative correlation between a firm's short-term price response and long-run productivity growth. That is, firms that price more aggressively in reaction to the financial shock are the ones that experience a less pronounced long-run contraction in productivity growth. The explanation we propose is that liquidity is fungible, and firms that can leverage price reductions as a source of internal finance are able to avoid significant reductions in productivity-enhancing investments, thus softening the long-run impact on productivity.

To provide evidence for this hypothesis, we leverage cross-sectional variation in firm's latent ability to respond to the credit tightening by lowering prices. Previous work has shown that liquidity constrained firms shed inventories when hit by financial shocks (Gertler and Gilchrist, 1994; Kashyap, Lamont, and Stein, 1994) and that firms with larger inventory holdings are more likely to drop prices in the attempt to generate extra cash flows from the product market (Kim, 2020). Based on these insights—which find support in our data—we exploit heterogeneity in the (pre-shock) availability of firm-level inventories of both finished and unfinished goods as well as inventories of intermediate inputs used in production. We show that, consistent with an inventory channel, inventory levels are highly predictive of the observed price response. We then document that producers that can more readily adjust their pricing policies reduce their expenditures on productivity-enhancing activities less than other producers, and as a result they experience lower reductions in productivity growth in the long run.

In Section 6, we develop a dynamic stochastic general equilibrium model with heterogeneous firms and banks facing financial frictions that embeds the two mechanisms documented in our empirical analysis. First, following Kim (2020), stochastic demand introduces a motive for inventory management. Second, as in Comin and Gertler (2006), firm-level productivity is an endogenous variable determined by firms' investments in innovation. We use the model to illustrate and quantify the importance of these mechanisms (and their interplay) in driving aggregate productivity and welfare dynamics in the aftermath of a financial shock.

We simulate bank balance sheet shocks to generate credit market dynamics consistent with those observed in the micro-level data in the aftermath of the sovereign crisis. We then calibrate the parameters that govern productivity and pricing dynamics to match the estimated firm-level responses. The model captures the persistent fall in real economic activity and aggregate productivity as documented by the literature in the aftermath of financial crises (Queralto, 2020). Through the lens of our model, a persistent slowdown in firm-level productivity growth, caused by a contraction in innovation spending, is the key force driving these scarring effects. The model also features a meaningful role for pricing responses as firms affected by the financial shock liquidate inventories to counteract and alleviate the real effects of the shock. Accordingly, the model captures the wedge between the TFPQ and TFPR dynamics observed in the data.

We then use the model as a laboratory to conduct counterfactual exercises that quantify the importance of the endogenous productivity and inventory channels. In our first exercise, we prevent firms from using low pricing as a source of internal finance by not allowing them to sell off inventories in response to the credit tightening. In this counterfactual scenario, firms cut innovation expenses much more aggressively than in our benchmark economy, leading to significantly larger aggregate productivity and aggregate welfare losses in the long run, of 20 and 10 percent, respectively. In our second exercise, we focus on the importance of properly accounting for the endogenous nature of firm-level productivity in contributing to the aggregate productivity slowdown following a financial crisis. As discussed above, movements in commonly used revenue productivity measures underestimate the true long-run effect of financial shocks on technical productivity growth, and therefore may understate the importance of firm-level productivity in driving aggregate productivity slowdowns. To quantify this, we recalibrate the model parameters that control the sensitivity of firm-level productivity to innovation expenses to match the firm-level TFPR, as opposed to the TFPQ, responses. Indeed, the long-run aggregate productivity and welfare responses to the financial shock are found to be significantly smaller (25 and 13 percent, respectively).

Relation to the literature. This paper contributes to the literature studying the relationship between finance and productivity growth, and more specifically the influence of financial market conditions on producers' technical efficiency.[3] Using aggregate data from advanced economies and emerging market economies, Queralto (2020) documents a persistent productivity drop following financial crises, suggesting that financial tightening acts as a drag on business productivity. Bianchi, Kung, and Morales (2019) and Ottonello and Winberry (2024) develop quantitative models with endogenous productivity and R&D investments to explore the role of financial frictions for economic growth and business cycle fluctuations. Midrigan and Xu (2014) present a model of firm-level dynamics highlighting the role played by financial frictions in determining productivity growth and misallocation. More closely related to our study, Caggese (2019), Duval, Hong, and Timmer (2020), Levine and Warusawitharana (2021), and Manaresi and Pierri (2024) offer micro evidence on the negative relationship between financial frictions and firm-level revenue productivity growth.

To the best of our knowledge, our paper is the first to quantify the causal effects of financial shocks on firm-level productivity, disentangling changes in technical efficiency from simultaneous pricing effects. From a micro-perspective, we show that accounting for the distinction between revenue- and quantity-based productivity is key for understanding the mechanisms through which financial shocks affect firm-level productivity growth. From a macro-perspective, our analysis helps quantify the importance of properly accounting for both price and productivity effects in driving the scarring effects of financial crises on the real economy. We view our results as complementary to those of Benigno and Fornaro (2018) and Acharya et al. (2024). These papers propose theories of stagnation in which persistent—or even permanent—growth slumps arise either from weak aggregate demand, which dampens firms' incentives to invest in innovation, or from credit market frictions that distort banks' allocation of credit following a large aggregate shock.

Our paper also relates to a strand of studies documenting that revenue and physical productivity estimates may offer intrinsically different predictions in a variety of contexts. Foster, Haltiwanger, and Syverson (2008) explores the separate influence of physical productivity and demand on firm survival. Others emphasize the distinction between revenue and physical productivity when studying the implications of resource misallocation (Hsieh and Klenow, 2009; Haltiwanger, Kulick, and Syverson, 2018), foreign market participation (Katayama, Lu, and Tybout, 2009), trade liberalization (Eslava et al., 2013), learning-by-exporting (Garcia-Marin and Voigtländer, 2019), and firm dynamics (Eslava et al., 2024). We are the first to show that distinguishing between the two productivity measures is crucial to understanding the implications of financial shocks on firm productivity. Moreover, the bifurcation between the

[3] See Levine (2005) for a review of the finance and growth literature.

short-run TFPR and TFPQ effects is the result of a novel mechanism that is not ascribable to the demand– and supply–side explanations documented thus far in the literature. In contrast, it is driven by firms' responses to a sudden tightening of credit market conditions, which leads them to fundamentally change their behavior in the product market.

Finally, our paper bridges the finance-and-productivity literature with the previously unconnected literature studying how financial factors influence producers' pricing policies.[4] Within this literature, our paper is closest to Kim (2020), which documents a reduction of firms' output prices in response to a credit supply shock, emphasizing the role played by inventory management.[5] By studying both prices and productivity together, our paper demonstrates that the use of low pricing as a way to raise liquidity from the product market has not only nominal implications (pricing behavior), but also important real effects, as it mediates the impact of financial shocks on long-run productivity growth.

2 Data and measurement

The central objective of our analysis is to understand the consequences of financial shocks on productivity and pricing dynamics, as well as their relationship. To this end, we construct a novel product-firm-bank-matched dataset that allows us to observe information on product-level prices and quantities of the individual goods produced by manufacturing firms in Belgium, as well as detailed accounts of their production choices, assets and liabilities structure, and access to credit markets. Overcoming the limitations of previous empirical studies interested in the finance-productivity nexus, the granularity of these data allows us to compute firm-level technical efficiency measures.

2.1 Data

Our dataset combines confidential information from four administrative sources—PRODCOM, firms' annual accounts, corporate credit register records, and individual bank balance sheets—which we briefly describe below. Additional details on the sources, data construction, and variable definitions are provided in Appendix A.

[4] Chevalier (1995a) and Chevalier and Scharfstein (1995; 1996) provide empirical evidence that a firm's financial condition affects its pricing strategy. Borenstein and Rose (1995), Busse (2002), and Phillips and Sertsios (2013) document a contraction of firm output prices in response to financial shocks. Gilchrist et al. (2017) studies the role played by firms' liquidity constraints in the determination of inflation dynamics during the Great Recession.

[5] See also Hendel (1996) for a treatment of optimal price and inventory policy under demand uncertainty.

Product-level prices and quantities. We use the PRODCOM database to obtain detailed information on firms' real activity (value and quantity of production) for all manufacturing products for a large sample of firms. The PRODCOM survey, commissioned by Eurostat and administered in Belgium by the National Statistical Agency, is designed to cover at least 90% of production value within each NACE 4-digit manufacturing industry by surveying all firms operating in the country with (a) a minimum of 20 employees or (b) total revenue above 4.5 million euros (European Commission, 2014).[6] The surveyed firms are required to disclose product-specific revenues (in euros) and quantities (e.g., volume, kg, m^2, etc.) of all products sold on a monthly basis, disaggregated at the 8-digit product level (e.g., 15.93.11.93 for "Sparkling wine, alcohol by volume > 8.5%", 15.93.11.95 for "Sparkling wine, alcohol by volume ≤ 8.5%"). As detailed below, these data allow us to compute a firm-level price index, as well as a firm-level quantity-index used in the production function estimation.

Firm balance sheets and real investment activity. Data from the firms' annual accounts (AA) from the Belgian Central Balance sheet office provide us with detailed information on total firm revenues, production inputs (capital, labor, intermediate inputs), and the stock of inventories. These variables, combined with the price and quantity data from PRODCOM, allow us to estimate quantity-based production functions and recover firm-level technical efficiency. Moreover, the AA also contain information on firms' employment, capital investments, and investments in R&D and employee training. The latter are commonly regarded as productivity-enhancing expenses, which allow us to shed light on the channels through which credit tightening affects firms' production activity and productivity and how the ability to adjust prices can mediate these effects.

Credit data. A key feature of our data, used in the construction of the firm-specific credit supply shifters, is the ability to measure the amount of bank credit received by each firm from individual lenders. Unique firm identifiers allow us to merge our firm-product-level data with confidential firm-bank records from the Belgian Corporate Credit Registry (CCR). These data provide information on firms' credit relationships and monthly credit balances maintained with each financial institution operating under the supervision of the National Bank of Belgium.[7]

Bank balance sheets. As we explain in more detail in Section 3, the linchpin of our identification strategy is the burst of the European sovereign debt crisis—and subsequent

[6] The statistical classification of economic activities in the European Community, commonly referred to as NACE, is the standard industry classification system used in the European Union.

[7] To harmonize the frequency of the CCR records with that of the AA variables, we sum each firm's monthly credit balances (authorized credit) across its lenders and compute firm-level yearly debt balances averaging across months of each fiscal year.

contraction of bank credit—that followed the Greek bailout in 2010. We leverage information on firms' heterogeneous exposure to banks differentially impacted by the European sovereign crisis in order to isolate firm-specific variation in credit availability (i.e., movements in credit supply). To do so, we merge in bank balance sheet data from the National Bank of Belgium supervisory records, which provide us with quarterly accounting information on the balance sheets and income statements for each bank in the CCR. The key variable of interest is the bank-level stock of sovereign securities that experienced a significant loss in value after the burst of the European sovereign crisis.

Sample properties. We focus our analysis on an 11-year window centered around the Greek sovereign bailout (2006-2016), restricting our sample to firms with active lending relationships in the twelve months before the Greek bailout. Our final sample consists of $1,024$ firms and a total of $9,667$ firm-year observations between 2006 and 2016. As we discuss in Appendix A, we construct our sample starting from the PRODCOM database, focusing on firms whose main activity is within manufacturing, and merge in the data from the AA and the CCR. In this process, we drop observations with missing information on prices and on other variables used in the productivity estimation (inputs and outputs).[8] To minimize the impact of outliers, we trim the observations at the tails of the firm-level price growth distribution (top and bottom one percent) and winsorize variables measured in levels (growth rates) at the 1 percent (2.5 percent) level. Table 1 presents the summary statistics of the key variables used in the empirical analysis.

2.2 Productivity estimation

We estimate firm-level physical productivity (TFPQ) as the residual from a gross output production function:

$$\ln TFPQ_{jt} = q_{jt} - f(k_{jt}, l_{jt}, m_{jt}; \gamma), \tag{1}$$

where lowercase letters denote logs. The variable q_{jt} denotes firm-level output (quantity) produced by firm j in year t. The variables k_{jt}, l_{jt}, m_{jt} denote capital, labor, and intermediate

[8] In order to perform the production function estimation, we focus on industries (NACE Rev. 1.1 2-digit codes) with at least 50 firms and 200 firm-year observations. This leaves us with 16 industries, which covers over ninety percent of total manufacturing output in PRODCOM. Moreover, we require firms in our final sample to report information on firm-level inventories, which is mandatory only for larger firms filing the complete AA template. This filter, coupled with the PRODCOM inclusion criteria, implies that our sample is highly representative of the manufacturing sector but tends to under-sample smaller firms. A large body of research highlights how credit supply shocks tend to affect smaller firms more than larger firms (e.g., Gertler and Gilchrist, 1994 and Bottero et al., 2020). As a result, our reduced-form results on the real effects of financial shocks on productivity and prices may represent a lower bound of the effects observed across the entire firm size distribution.

Table 1: Summary statistics

Panel a: Firm characteristics

	Mean	pc25	pc50	pc75	SD	N
Total assets (million euros)	91.19	7.88	14.73	37.60	322.19	1024
Total revenues (million euros)	70.86	11.08	21.22	53.51	161.80	1024
Employees	177	42	79	166	317	1024
Bank debt / Total assets (Lev.)	0.21	0.04	0.15	0.34	0.19	1024
Long-term debt / Long-term liab.	0.80	0.70	1	1	0.35	1024
Inventories / Assets (Inv.)	0.19	0.09	0.17	0.27	0.13	1024
Z-score	2.06	1.35	2.04	2.67	1.12	1024
(Credit supply) Shock	0.14	0.11	0.15	0.17	0.05	1024

Panel b: Credit, productivity, and prices (growth rates)

	Short-term			Long-term		
	Mean	SD	N	Mean	SD	N
ΔCredit	-0.15	0.56	1024	-0.62	1.07	652
Δfc	0.00	0.12	700	0.00	0.16	386
$\Delta \ln TFPR$	0.03	0.11	1024	0.03	0.15	652
$\Delta \ln TFPQ$	0.04	0.16	1024	0.02	0.32	652
$\Delta \ln P$	0.01	0.14	1024	0.10	0.25	652

Panel c: Investment and employment variables (growth rates)

	Short-term			Long-term		
	Mean	SD	N	Mean	SD	N
Inv. rate R&D	0.10	0.35	775	2.97	9.11	484
Any R&D expense	0.16	0.37	775	0.20	0.40	484
Training expenses	0.48	1.70	701	1.29	2.77	459
Inv. rate M&E	0.12	0.17	1024	1.02	1.10	652
Employees	-0.02	0.13	1024	0.00	0.33	652

Notes: This table reports the summary statistics of the main variables used in the empirical analysis. Panel a presents descriptive statistics about the firms in our sample. All these variables are measured prior to the Greek bailout (end of fiscal year 2009). We also report the summary statistics of the credit supply shock (Shock, defined in Section 3). When running the regression models, this variable is standardized to have a mean of zero and a standard deviation of one. Panels b and c focus on outcome variables. Panel b presents short-term growth rates (2009–2010) and long-term cumulative growth rates (2009–2016) for credit balances, financing costs, and measures of productivity and prices. Panel c reports short-term (2009-2010) and long-term (2009–2016) cumulative investments in R&D and machinery and equipment (M&E), cumulative growth rates of training costs, and cumulative employment growth rates. The variable "Any R&D expense" is a dummy indicating whether the firm had any investment in R&D.

inputs, respectively. $f(\cdot)$ is the (log) production function, and γ is a vector of structural parameters to be estimated. TFPQ captures a firm's capability to turn inputs into physical output. As explained in Foster, Haltiwanger, and Syverson (2008), it is the appropriate measure of a firm's technical efficiency, essentially reflecting its average per unit cost of production.

We measure the firm-level quantity index, Q_{jt}, by dividing firm-level revenues (net of any changes in inventory value of finished goods) by a firm-level price index.[9] We measure the firm-level price index, P_{jt}, by aggregating and concatenating price changes across products of multi-product firms. Specifically, we first compute a Törnqvist index, a standard measure used by statistical agencies, to measure the average yearly growth rate of prices across 8-digit products within a firm:

$$P_{jt}/P_{jt-1} = \prod_{p \in \mathcal{P}_{jt}} (P_{jpt}/P_{jpt-1})^{\bar{s}_{jpt}},$$

where $\mathcal{P}_{jt}$ represents the set of 8-digit products manufactured by firm j, P_{jpt} is the unit value of product p in $\mathcal{P}_{jt}$, and $\bar{s}_{jpt}$ is a Törnqvist weight computed as the average of the sales shares of product p in $\mathcal{P}_{jt}$ between t and $t-1$.[10] We then build our firm-level price index (in levels), P_{jt}, by recursively concatenating the year-to-year Törnqvist index starting from a firm-specific base year: $P_{jt} = P_{jB} \prod_{\tau=B+1}^{t} P_{j\tau}/P_{j\tau-1}$. Following Eslava et al. (2024), we construct the base price index, P_{jB}, as a geometric average of the prices of all products of firm j in the base year B scaled by the average price for that product. This allows us to capture cross-sectional differences in prices across firms, which are important for the purposes of the productivity estimation.

On the input side, we measure labor services, L_{jt}, and intermediate inputs, M_{jt}, using the wage bill and expenses on materials and services used in production. To measure capital services, K_{jt}, we follow the perpetual inventory method using information on the flows of investments in fixed assets. We deflate labor, intermediate inputs, and capital by the corresponding industry-year price deflators.

We estimate the production function separately for each industry. The details of the estimation routine are provided in Appendix B.2 together with the corresponding elasticity estimates. Our approach is based on Gandhi, Navarro, and Rivers (2020) but augmented to allow for differences in market power in the product market (Blum et al., 2024) and to control for differences in output quality (De Loecker et al., 2016). This structural approach identifies

[9] To adjust our output measure for changes in inventories, we first adjust firm-level revenues by the change in firm-level inventory of final goods and then apply the firm-level price index to compute the adjusted quantity index.

[10] To ensure comparability of product-level prices across firms and over time, we define products as unique combinations of 8-digit PRODCOM product codes and units of quantity measurement (e.g., liters, kilograms, etc.). We then compute unit values for each product (i.e., prices) by dividing total value by total quantity for each firm-product-time observation.

the production function by addressing the simultaneity bias that arises from the correlation between input choices and unobserved productivity (Marschak and Andrews Jr., 1944), and it solves the identification problem that affects the estimates of the output elasticities of flexible inputs. Moreover, consistent with our empirical findings, we allow firm-level productivity to evolve according to a controlled Markov process in which firm investments in innovation (R&D and employee training) affect future productivity growth.[11] Since the European sovereign debt crisis (and preceding global financial crisis) may have generated frictions that caused firms to deviate from the unconstrained optimization, we perform the production function estimation using only data prior to 2008, and then apply the production function estimates to all years in order to compute productivity for the full sample.[12]

To underscore the importance of decoupling the effects of financial shocks on firms' productivity growth and pricing policies, we compute a common revenue productivity measure (TFPR), used in the literature as proxy for TFPQ when separate information on firm-level information on prices and quantities is not available. To construct this measure, we work under the standard assumptions in the literature and construct a productivity index that is the residual from a production function estimation where a firm's total revenues (net of changes in inventories) deflated by an industry-level price index is used as a proxy for the firm's physical output:

$$\ln TFPR_{jt} = r_{jt} - f(k_{jt}, l_{jt}, m_{jt}; \tilde{\gamma}), \tag{2}$$

where we denote the vector of parameters that determine revenue elasticities by $\tilde{\gamma}$ to distinguish it from the vector of structural parameters that characterize the curvature of the quantity production function in equation (1).[13]

3 Empirical design

The credit balances observed in the CCR data result from a combination of factors, some of which are attributable to the supply of credit, while others relate to firms' financial needs, investment opportunities, and consequently, credit demand. Since the same events that alter supply-side conditions may also trigger demand-side adjustments, we face a classic identification challenge

[11] As in Ericson and Pakes (1995) and Doraszelski and Jaumandreu (2013), the distribution of firm productivity in period t depends on both past expenditures on innovation and past productivity realizations.

[12] As a robustness check, we replicate our analysis using a productivity index derived from index-function methods–which does not rely on estimating the production function–as well as compute production function estimates using the full sample period. As shown in Appendix D, these results are similar to our main results.

[13] As pointed out by Klette and Griliches (1996), under general conditions, revenue elasticities are biased proxies of the elasticities estimated from quantity production functions.

in estimating how firm-level outcomes are affected by credit availability. We overcome this challenge by exploiting quasi-experimental variation in the credit supply conditions faced by individual producers. This variation is driven by their heterogeneous exposure to lenders holding different amounts of distressed sovereign securities in the wake of the 2010-2012 European sovereign debt crisis.

The key event in our study is the bailout request made by the Greek government in April 2010, which sparked tension in European sovereign markets and led to a reassessment of the risk profile of sovereign securities issued by peripheral European countries (Greece, Italy, Portugal, Spain, and Ireland, hereafter referred to as GIPSI).[14] The events in Greece triggered a sharp increase in the spread between the yield to maturity of GIPSI's bonds and German bonds, which were regarded as safe assets. The sudden change in the risk profile of these securities negatively impacted the balance sheets of financial intermediaries holding them, which, in turn, transmitted the shock to their borrowers in the form of credit tightening. This can be seen in the aggregate raw data, which reveals a divergence in aggregate bank lending after the Greek bailout between banks with high versus low exposure to distressed sovereigns (Figure A.1, Appendix C).

Belgian firms rely heavily on bank debt as their primary source of external finance. In our sample, only 1.35 percent of the firms are publicly listed and only 0.87 percent of them issue publicly traded bonds. The share of bank debt provided by banks reporting in the credit registry amounts, on average, to 21 percent of firms' total assets and debt vis-à-vis financial institutions represents, on average, 80 percent of firms' long-term liabilities (Table 1). Moreover, previous literature has shown that financial frictions prevent or limit a firm's ability to substitute toward alternative forms of external finance (Chodorow-Reich, 2014). Taken together, these observations suggest that a tightening of credit supply by a firm's legacy lender is likely to have significant effects on the firm's real activity.

3.1 Identification strategy

Following Bottero, Lenzu, and Mezzanotti (2020), we use the Greek bailout as a natural experiment to construct firm-specific credit supply shifters based on the presence and significance of firms' credit relationships with lenders differentially exposed to distressed sovereign securities. Specifically, we construct these shifters by measuring the weighted-average exposure of firm j's lenders to the sovereign shock:

$$\text{Shock}_j = \sum_{b \in \mathcal{B}_j} \omega_{jb} \cdot \text{GIPSI Sovereigns}_b,$$

[14]See Appendix C and Lane (2012) for a detailed description of the European sovereign crisis.

where $\mathcal{B}_j$ represents the set of financial institutions lending to firm j in 2010:Q1, the quarter prior to the Greek bailout request, ω_{jb} is the share of firm j's credit received from bank b in the same quarter, and the variable "GIPSI Sovereigns$_b$" measures bank b's holdings of sovereign securities issued by GIPSI countries in 2010:Q1, scaled by bank b's risk-weighted assets. By focusing on pre-bailout holdings we ensure that our measure is not affected by any endogenous portfolio adjustment that banks made in response to the sovereign crisis itself (Becker and Ivashina, 2018). At the onset of the sovereign crisis, the average firm in our sample was borrowing from a pool of banks that had invested a substantial portion of their risk-weighted assets (14 percent) in sovereign bonds issued by peripheral European countries. We also observe significant dispersion in firm exposure, as indicated by the standard deviation of Shock$_j$ (4.6 percent).

Leveraging the heterogeneous exposure of individual firms to the sovereign crisis, we estimate empirical impulse response functions for productivity and prices in response to the credit supply shock using local linear projections (Jordà, 2005). Specifically, we run a sequence of cross-sectional regressions over different time horizons, indexed by τ:

$$\Delta_\tau Y_j = \beta_\tau \cdot \text{Shock}_j + \Gamma^{'}_{K,\tau}\mathbf{K}_j + \Gamma^{'}_{X,\tau}\mathbf{X}_j + i_{ind,\tau} + i_{reg,\tau} + u_{j\tau}. \tag{3}$$

The left-hand-side variable $\Delta_\tau Y_j$ measures the cumulative growth rate of a firm-level outcome variable between the year prior to the crisis (2009) and the year $2009 + \tau$, where $\tau = \{1, ..., 7\}$. To facilitate the interpretation of the treatment effects, we de-mean and scale Shock$_j$ by its standard deviation. Therefore, the coefficients of interest, β_τ, capture the effect of a one standard deviation difference in exposure to the credit shock on the $\tau-$year cumulative growth rate of Y_j.[15]

We follow Bottero, Lenzu, and Mezzanotti (2020) by including bank-level controls ($\mathbf{K}_j$), all of which are measured before the Greek bailout in order to account for the fact that a bank's level of sovereign holdings is correlated with other bank characteristics (e.g., capitalization and exposure to stability of funding) that might affect a bank's propensity to adjust credit supply following the burst of the sovereign crisis.[16]

We also account for firms' heterogeneous scope and strength of credit market interactions by controlling for the average length and number of lending relationships of the borrower ($\mathbf{X}_j$), measured before the burst of the crisis.

We restrict the analysis to within-industry and within-region variation through the

[15] All of our baseline results are obtained from unweighted regressions. However, weighting observations by firm size (revenues at the end of 2009) leads to quantitatively very similar results.

[16] The bank-level controls in $\mathbf{K}_j$ include measures of lender size, funding structure, liquidity position, and lending portfolio quality. Similar to our measure of GIPSI sovereign exposure, each of these variables is constructed as a firm-level weighted average of the lender-specific variables, measured in the last quarter before the shock (2010:Q1), with weights based on the share of firm j's credit received from each bank (ω_{jb}). See Appendix A for further details on the sources and definitions of the control variables.

inclusion of detailed fixed effects, $i_{ind,\tau}$ and $i_{reg,\tau}$, to address the possibility that lenders with high sovereign holdings might specialize in industries or geographical regions experiencing a more severe contraction in economic activity (Paravisini et al., 2014).[17] This granular set of fixed effects ensures that the estimated productivity and price effects are not capturing firms' responses to a contraction in local, industry-level, or aggregate demand that might have resulted from the tensions in sovereign markets (Bocola, 2016). Moreover, by estimating the model in first-differences we control for any unobserved, time-invariant characteristics which might vary between more and less exposed firms.

Finally, we cluster standard errors at the main lender-level to account for the correlation of residuals across firms that share the same primary lender and are therefore exposed to similar treatment effects (Khwaja and Mian, 2008).[18]

3.2 Exposure to the sovereign shock and credit availability

We begin by demonstrating that the outbreak of the sovereign crisis impaired access to credit for firms borrowing from lenders highly exposed to distressed sovereigns. Figure 1, panel a, presents the dynamic effect of exposure to the sovereign shock on firms' cumulative growth rate of bank credit ($\Delta_\tau \text{Credit}_j$), estimated according to model (3). The full regression output is reported in Appendix C. A one standard deviation increase in lenders' exposure to GIPSI sovereigns corresponds to a (cumulative) reduction of about 18 percent of firms' total bank credit in the three years following the outbreak of the sovereign crisis.

The sovereign shock affected not only firms' access to external finance but also the cost of that finance. We do not have direct information on bank-specific lending rates. Therefore, we construct a proxy for firms' average financing costs using the ratio of financial charges to financial debt from the AA data ($\Delta_\tau fc_j$), and study how this measure of financing costs changes in the aftermath of the Greek bailout based on the firm's exposure to banks with varying holdings of distressed sovereigns.[19] While this is admittedly a noisy measure of the interest rates paid by firms, it is still potentially informative about the direction and timing of the change in financing costs facing firms. Figure 1, panel b, shows that a one standard deviation increase in lenders' exposure to GIPSI sovereigns eventually leads to an increase in the average cost of finance by

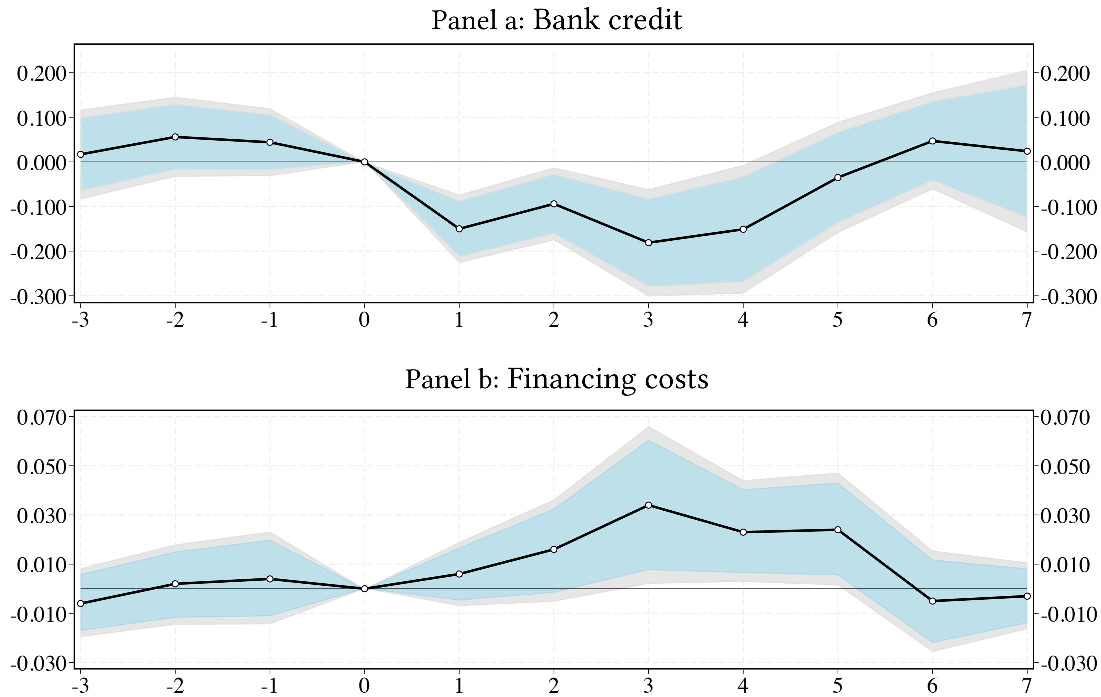
[17] Region fixed effects indicate in which of the three Belgian regions (the Flemish region, the Walloon region, and the Brussels-Capital region) the firm is headquartered. Industry fixed effects are measured using the industry code of the main product of the firm (measured in terms of production value in PRODCOM).

[18] As a robustness exercise, we also experimented with the Adao et al. (2019) procedure for computing standard errors and find that our results are robust, and if anything our clustered standard errors are more conservative.

[19] We measure average financing costs as $fc_{j,t} = \frac{\text{Financial Charges}_{j,t}}{\text{End of Year Financial Debt}_{j,t-1}}$ and compute their change relative to 2009 ($\Delta_\tau fc_j = fc_{j,2009+\tau} - fc_{j,2009}$).

about 3.5 percent in the years following the outbreak of the European sovereign crisis. Taken together, the movement of the quantity and cost of finance in *opposite* directions is consistent with a tightening of credit supply conditions, as a contraction in credit demand would have led to a reduction of both quantity and prices.

Figure 1: Exposure to the sovereign shock and credit market outcomes



Notes: This figure plots the coefficient estimates (solid lines) and associated confidence intervals capturing the relationship between firms' exposure to the sovereign shock and the cumulative growth rate of bank credit (panel a) and change in financing costs (panel b) estimated using model (3). The sky blue shaded areas depict 90 percent confidence intervals and the gray shaded areas depict 95 percent confidence intervals based on the estimated clustered standard errors.

To interpret this credit contraction as the causal effect of shocks to credit supply, it must be the case that, absent the sovereign debt crisis, firms borrowing from banks with high GIPSI exposure would not have experienced a differential change in their credit supply relative to firms borrowing from banks with low exposure. Two pieces of evidence lend support to this parallel trends assumption. First, Table A.1 in Appendix A shows that the sample of firms borrowing from more and less exposed lenders appears well-balanced on observable pre-shock characteristics, including size, bank leverage, productivity, and price level. Second, in direct support of the assumption, Figure 1 shows no differential trends in credit market outcomes between more and less affected firms prior to the sovereign shock.

In Appendix C, we present a series of additional empirical results and robustness tests. First, to provide further evidence that our results are driven by a sudden tightening of credit supply, rather than by demand-side factors, we leverage the availability of micro-data on individual firm-bank relationships and estimate a version of model (3) at the firm-bank relationship level, augmenting the regression model with firm-level fixed effects. This within-firm specification allows us to test whether banks with higher GIPSI holdings reduced their credit supply to the *same firm* relative to banks with lower GIPSI holdings, thereby controlling for unobservable changes in firm-specific factors, such as a contraction in credit demand or a worsening of firms' credit worthiness. The results indicate that more exposed banks indeed reduced lending relative to less exposed banks lending to the same firm. In addition, while the within-firm estimates are largely unaffected by whether we include firm-fixed effects, the R^2 of the regressions increase by a factor of seven to thirteen, depending on the time horizon, after inclusion of the fixed effects. In the spirit of Oster (2019), this observation suggests that while unobserved firm-specific factors (e.g., changes in credit demand) are important for explaining overall variation in bank lending to firms, this variation is not correlated with exposure to the sovereign shock.

Second, we study the impact of the shock on different types of credit: term loans and credit lines. Prior literature highlights how both products are used by firms to finance their production as well as their innovation activity (see, e.g., Hall and Lerner, 2010 and Manso, 2011). We find a significant contraction in the amounts borrowed across different credit types, suggesting that the credit tightening impacted various aspects of firms' financing.

Finally, as an additional validation exercise, we analyze the real effects of financial shocks on firms' input demands. Prior studies documented a contraction in investments and employment by firms experiencing a credit tightening.[20] Consistent with this evidence, we also find that firms more exposed to the sovereign shock display a persistent contraction in the cumulative investment rate in machinery and equipment and a reduction of employment growth relative to less exposed ones.

4 Decoupling the productivity and price effects of financial shocks

4.1 Productivity and pricing effects

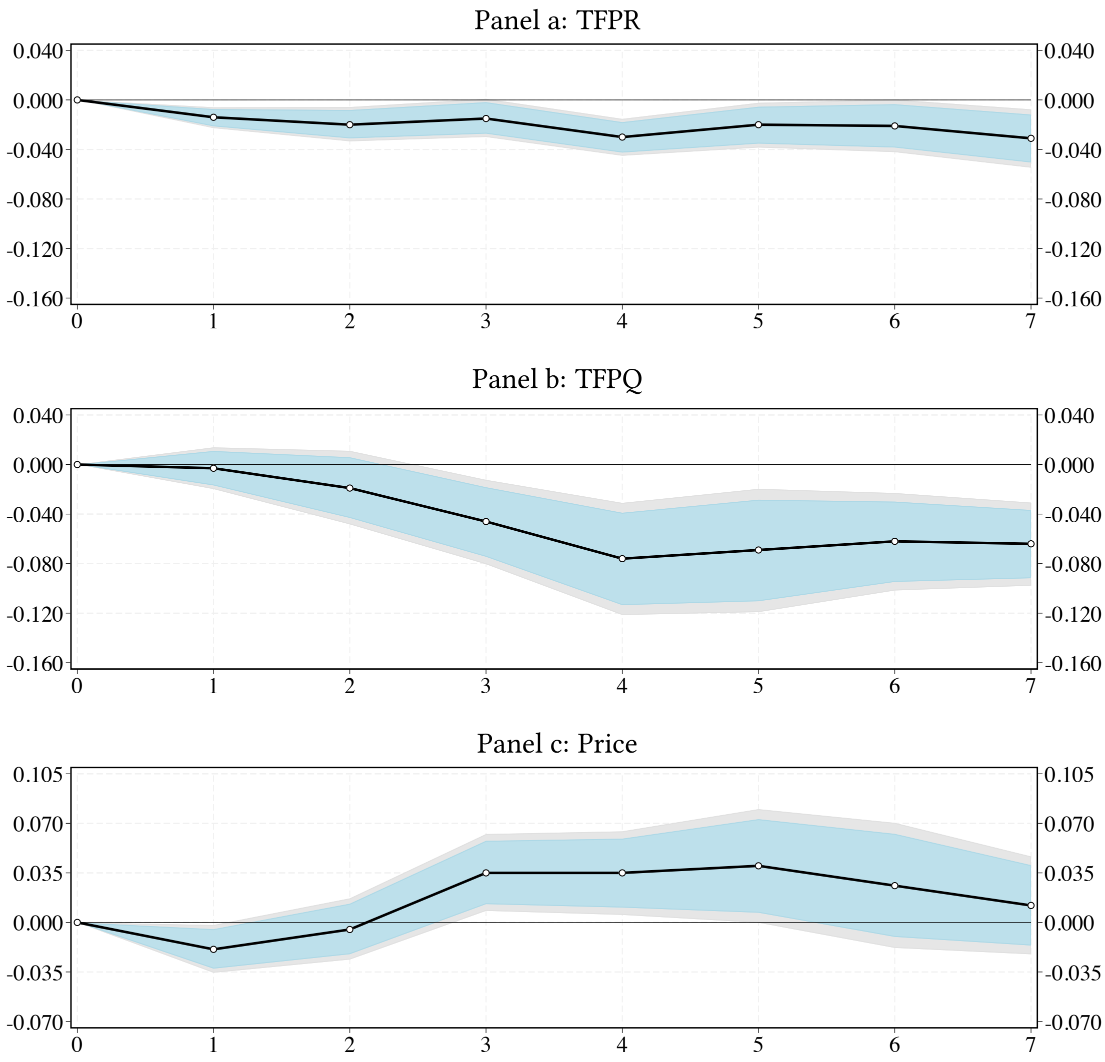
Having established the pass-through of lenders' balance sheet shocks to firms' credit supply, we now turn to quantifying the separate effects of the credit tightening on firm-level productivity

[20] See, e.g., Chodorow-Reich (2014) for employment, Cingano et al. (2016) for investments, and Bottero et al. (2020) for both employment and investments.

and prices. Figure 2 presents the estimated cumulative responses according to model (3). The full regression output is reported in Table A.6 in the Appendix.

Productivity effects. We begin by examining the response of revenue productivity (TFPR), a commonly used proxy for physical productivity in the literature when firm-level price data is unavailable. The estimates in panel a confirm that, in line with previous findings (see, e.g., Manaresi and Pierri, 2024), the exposure to a credit supply shock leads to a statistically and economically significant contraction of revenue productivity growth that materializes in the immediate aftermath of the shock and persists over time.

Figure 2: Response of productivity and prices to negative credit supply shocks



Notes: This figure plots the coefficient estimates (solid lines) and associated confidence intervals capturing the effect of the credit supply shock on firm-level revenue productivity (TFPR), technical productivity (TFPQ), and prices. The sky blue shaded areas depict 90 percent confidence intervals and the gray shaded areas depict 95 percent confidence intervals based on the estimated clustered standard errors.

The TFPQ response, however, paints a substantially different picture regarding both the timing and magnitude of the impact of credit tightening on firms' productivity growth (panel b of Figure 2). First, in stark contrast to the TFPR estimates, credit supply shocks have *no impact* on firms' technical productivity growth in the short run.

The estimated effect becomes economically sizable and statistically significant only three years after the shock. Second, revenue-based measures also offer a biased prediction regarding the long-run effects of the shock on physical productivity growth. While TFPR and TFPQ move in the same direction over the medium-to-long run, the estimated contraction in productivity growth is about twice as large as that suggested by the revenue-based estimates. A one standard deviation exposure to the shock translates into a contraction of 6.4 percent in firms' physical productivity growth by the end of our sample period. Combined with the effects of the shock on firm-level credit growth, these estimates imply a long-run elasticity of firm-level physical productivity to credit supply of approximately 0.4, which is *twice as large* as the elasticity implied by the revenue-based estimates.

Pricing effects. The bifurcation between the revenue-based and quantity-based productivity growth effects is driven by a statistically significant and economically meaningful adjustment of firms' output prices in response to the tightening of financial conditions. A one standard deviation increase in exposure to the credit shock leads, on average, to an immediate reduction of about 2 percent in firms' output prices (panel c of Figure 2). The short-term reduction of output prices is consistent with empirical findings in previous works documenting how firms adjust their short-term pricing policies in response to a deterioration of financing conditions (Borenstein and Rose, 1995; Busse, 2002; Phillips and Sertsios, 2013; Kim, 2020). However, the price contraction is short-lived as firms that were more exposed to the credit shock eventually increase their prices relative to less exposed firms. A one standard deviation increase in exposure to the credit shock implies a cumulative increase in output prices of up to 4 percent in the five years following the shock, before reverting back towards zero by the end of our sample period.

Taken together, the empirical evidence reveals that, in the short run, estimates based on TFPR are substantially *upward biased*, whereas over longer horizons, they are substantially *downward biased*. Importantly, while short-run adjustments in revenue-based productivity solely pick up the movements in output prices, in the same way, the subsequent rebound of output prices explains why inference based on revenue-based measures substantially underestimates the long-run slowdown of physical productivity growth. Previous studies have emphasized how supply side shocks—such as productivity innovations—are passed-through to output prices, generating a muted, or even opposite, response of TFPR relative to TFPQ (Foster, Haltiwanger, and

Syverson, 2008; Foster, Haltiwanger, and Syverson, 2016; Moreira, 2020). Our analysis indicates that similar forces can also explain long-run price dynamics (and thus the implied TFPR-TFPQ bifurcation) following episodes of financial market distress, emphasizing the important role played by the availability and cost of external finance for firms' production and pricing decisions.

4.2 Robustness analysis

In Appendix D, we present a series of robustness checks that validate the estimated productivity and pricing effects.

We first show that the estimated effects of financial shocks on productivity growth are robust to alternative ways of measuring productivity. We repeat the production function estimations assuming a less flexible, but more traditional, Cobb-Douglas functional form. Additionally, instead of estimating the production function parameters, we calibrate input elasticities based on the average revenue shares within each industry (index function approach). Finally, we developed an alternative production function estimation procedure that accounts for the possibility of working capital constraints distorting the first-order condition of intermediate inputs. In all cases, the estimates are comparable to the ones obtained by our baseline production function estimation approach.

As is typically the case, we cannot directly measure capacity utilization in the data. Therefore, our productivity estimates could be biased if firms adjust capacity utilization in response to the financial shock. To address this concern, we were able to merge supplementary survey data on firm-level capacity utilization for a subsample of firms in our sample. Examining the response of this variable to the shock, we find that the financial shock leads to a positive but economically and statistically small increase in capacity utilization. Since not accounting for an increase in capacity utilization would likely lead to an upward bias in the TFPQ estimates, these findings suggest that, if anything, we are underestimating the effects of the financial shock on firm-level TFPQ growth. That is, our baseline estimates might provide a lower bound of the effect of the shock on firm-level productivity.

We then assess the robustness of the pricing effects. As explained in Section 2, when constructing a firm-level price index, one needs to take a stance on how to aggregate the prices across the heterogeneous products produced by a firm. In our baseline specification, we use a conventional Törnqvist index. In Appendix D, we show that the estimated initial contraction, and subsequent rebound, of prices following the financial shock is also evident when one uses alternative price measures. Specifically, we demonstrate that our results remain robust when constructing the firm-level price index as the revenue-share weighted average of product-level prices or when using only the price of the firm's main product (highest revenue share).

As discussed above, in order to perform the production function estimation we constructed a firm-level measure of output produced, Q_{jt}, adjusting firm-level revenues by the change in inventories. To do so, we deflated the total change in inventories (in euros) by our price index, which might be a source of bias if firms reduce the prices of different products depending on their product-specific inventory stock. To address this concern, we re-estimated our baseline regressions on the subsample of single-product firms, finding estimates that are quantitatively similar, though less precisely estimated due to the smaller sample size.

Another concern is related to possible survival bias. About one-third of the firms in our regression sample in 2009–2010 are not in the regression sample by the end of our sample period. In Appendix A we discuss how this appears to be driven largely by the sampling scheme adopted by PRODCOM and survey attrition, rather than by selection induced by the financial shock. As an additional robustness test against survival bias, we show that the productivity and price estimates remain when re-estimating our baseline regressions on the subsample of permanent firms.

5 Transmission mechanisms

Having decoupled the effects of financial shocks on firm's productivity growth and pricing policies, we now provide evidence regarding the economic mechanisms underlying both responses. We show that in the immediate aftermath of the financial shock firms take actions to counteract the liquidity shortage that arose due to the drop in external financing. We document that producers reduce output prices in an attempt to increase cash flows from the product market by liquidating their existing stock of inventories. At the same time, firms exposed to the shock reduce operating costs by cutting expenditures on investments in innovation, which explains the persistent, but delayed, negative impact on long-run productivity growth. This productivity slowdown, combined with the increase in financing costs, explains the long-run increase in prices, as increases in the cost of production are passed-through to customers.

5.1 Transmission of financial shocks to productivity growth

Innovation in production processes, human capital accumulation, and organizational changes are the engine of firms' productivity growth (Syverson, 2011).[21] The availability of external

[21] Garcia-Macia (2017), Huber (2018), Anzoategui et al. (2019) highlight that reduced investments in intangible assets over time can lead to a slowdown of firms' productivity growth. Bloom et al. (2013) emphasizes the role of information technology investments and organizational capital in generating productivity increases at the firm level.

financing plays a central role in this process. Like any form of investment, innovation requires financing (Kerr and Nanda, 2015; Howell, 2017). Compared to other forms of investment, productivity-enhancing investments have delayed returns and tend to provide poor collateral to creditors (Shleifer and Vishny, 1992; Caggese, 2012). Therefore, they are among the first expenses cut by firms coping with a tightening of credit supply conditions (Almeida and Campello, 2007).

The data provide strong support in favor of the hypothesis that the transmission of financial shocks to firms' productivity growth operates through an innovation channel. We first show that firms reduced investments in innovation in response to the credit supply shock. We then provide evidence linking these reductions to sizable contractions in long-run productivity growth.

Table 2: Response of productivity-enhancing activities and TFPQ growth

Panel a: *Response of productivity-enhancing activity to the financial shock*

Dep. var. ↓	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$
Inv. rate R&D	-0.041***	-0.109***	-0.338***	-0.597***	-0.504	-0.335	-0.452
	(0.012)	(0.017)	(0.078)	(0.189)	(0.306)	(0.499)	(0.491)
Any R&D expense	-0.041***	-0.019	-0.072***	-0.041	-0.043	-0.0229	0.029
	(0.014)	(0.023)	(0.017)	(0.025)	(0.027)	(0.029)	(0.034)
Training expenses	-0.228***	-0.038	0.1386	0.112	0.127	0.230	0.326*
	(0.0698)	(0.064)	(0.084)	(0.108)	(0.128)	(0.169)	(0.166)

Panel b: *Response of productivity to contraction in productivity-enhancing activity*

	Dep. var: $\Delta_\tau \ln TFPQ$						
Endogenous var. ↓	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$
Inv. rate R&D	0.110	0.595	1.505***	2.183**	2.459**	1.544***	2.110**
	(0.236)	(0.411)	(0.543)	(0.938)	(1.124)	(0.565)	(0.865)
Any R&D expense	0.096	0.555	1.330**	1.611**	1.738*	1.236**	1.397***
	(0.208)	(0.435)	(0.546)	(0.711)	(0.849)	(0.512)	(0.451)
Training expenses	-0.039	0.0343	0.304	0.613*	0.397**	0.361*	0.434*
	(0.046)	(0.078)	(0.233)	(0.319)	(0.180)	(0.209)	(0.223)

Notes: Panel a reports the estimates of the cumulative effect of the credit supply shock on investments in productivity-enhancing activities (R&D and employee training expenses) estimated using the model in equation (3). Panel b reports the 2SLS estimates capturing the effect of variation in R&D and training expenses in the aftermath of the credit supply shock, instrumented with the credit supply shock, on cumulative TFPQ growth over different horizons, estimated using the model in equation (4). Standard errors are clustered at the main-lender level and reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Innovation response to financial shocks. We compute three indicators of firm expenditures on productivity-enhancing activities. First, for each year following the burst of the sovereign crisis, we compute the R&D investment rate (Inv. rate R&D$_\tau$, which is the ratio of cumulative expenses on R&D up to year 2009+τ ($\tau = \{1, ..., 7\}$) scaled by the stock of intangible assets in 2009. Our second indicator is a dummy variable that identifies firms investing any positive amount in R&D in a given year (Any R&D expense$_\tau$). This variable captures the extensive margin of innovation, accounting for the lumpy nature of R&D investments. Our third indicator recognizes that innovation spurs from R&D as long as a skilled and appropriately trained workforce is capable of integrating new technologies into the existing production processes (Hall and Lerner, 2010). To capture this aspect, we gather information on employee training expenditures (Training expenses$_\tau$). Specifically, we calculate cumulative average training expenditures per employee, scaled by expenditures per employee in 2009.[22]

Table 2, panel a, shows that firms more exposed to the credit supply shock reduce investments in innovation and training more than less exposed counterparts. For several years after the outbreak of the sovereign crisis, firms borrowing from lenders more exposed to distressed sovereigns display a widening innovation gap. We estimate that, on average, a one standard deviation increase in lenders' exposure to the distressed securities translates into a drop of about 4 percent in the R&D investment rate after one year, and a reduction of up to 60 percent in the cumulative R&D investment rate four years later. The effect of the credit contraction is also evident if one looks at the extensive margin of R&D investments, with a reduction of over 4 percentage points in the probability of devoting any resources to R&D in the year after the shock. Investments in human capital are also affected. Comparing two firms with a one standard deviation difference in lenders' exposure to the shock, we observe that the more exposed firm cuts expenditures on training by about 23 percent more per employee. The effect on training is more transitory relative to the estimated effects on R&D.[23]

Impact of innovation expenditures on productivity growth. We take our analysis one step further and provide direct evidence connecting the availability of external financing, productivity-enhancing activities, and productivity growth. Mirroring model (3), we run a

[22]Recall that Table A.5 shows that firms also decrease their investment in machinery and equipment in response to the shock. To the extent that these expenditures reflect firms upgrading to more productive vintages (as opposed to maintaining existing vintages), a reduction in these expenditures in response to the shock could also generate a reduction in TFPQ growth.

[23]These results are in line with those documented in recent papers (Manaresi and Pierri, 2024; Duval, Hong, and Timmer, 2020), suggesting that the contraction in credit supply reduces productivity growth because it forces firms to cut investments in productivity-enhancing activities. They are also consistent with Caggese (2019), which provides evidence linking financial frictions and productivity growth over a firm's life cycle through the impact that such frictions have on the ability to sustain more radical innovation.

sequence of IV-linear projections at different horizons:

$$\Delta_\tau \ln TFPQ_j = \alpha_\tau \cdot \Delta_1 Z_j + \Gamma'_{K,\tau}\mathbf{K}_j + \Gamma'_{X,\tau}\mathbf{X}_j + i_{ind,\tau} + i_{reg,\tau} + u_{j\tau}. \tag{4}$$

The left-hand-side variable measures the *cumulative* growth rate of TFPQ between the year 2009 and year 2009 + τ, $\tau = \{1, ..., 7\}$. The (endogenous) regressors of interest, $\Delta_1 Z_j$, measure changes in investments in innovation from 2009 to 2010 (R&D and training expenditures), which we have just shown are affected by the contraction in credit supply. These changes in investments are instrumented with our credit supply shock (Shock_j) in order to isolate variation in expenditures that is driven by firms' differential exposure to the credit tightening. This estimation approach allows us to tease out the credit supply driven connection between two endogenous variables (productivity and investments), whose covariation could otherwise be determined by factors other than the availability of external financing.

Table 2, panel b, reports the estimates over different horizons. The innovation gap materializes into lower productivity growth, as evidenced by the positive estimated coefficients. The timing of the effect is as relevant as its direction. A contraction of productivity-enhancing investments, driven by the lack of financing possibilities, is not felt immediately but rather materializes into a productivity slowdown in the medium-long run. For example, we estimate that a one percent reduction in the R&D investment rate in 2010 translates into a reduction of productivity growth of over 2 percent six years later. Similarly, a reduction in training expenses per employee by one percent translates into 0.4 percent lower productivity growth six years later. These results offer direct evidence of the link between productivity growth and firms' decisions to innovate. More specifically, the delayed and persistent productivity response documented by our analysis helps rationalize the slow economic recovery observed after financial crises.[24]

Other transmission mechanisms. We note that the connection between financial shocks and firm-level productivity dynamics could also operate through other channels besides the investment channel. While we do not directly test these alternative theories, our earlier results from Figure 2 offer insights regarding their empirical relevance. In light of the negative long-run response of productivity growth, we can rule out economic channels predicting that a tightening of external financing conditions might spur productivity growth because, for example, it causes firms to be more selective in their investment projects (Jensen, 1986) or to innovate more in an effort to survive (Field, 2003). The timing of the TFPQ response further narrows the set of channels that produce predictions consistent with the data. Specifically, our findings are inconsistent with the hypothesis that financial shocks affect firms' technical efficiency because they force firms to

[24]See, among others, the evidence in Cerra and Saxena (2008), Jordà, Schularick, and Taylor (2013), Reinhart and Rogoff (2014), Hall (2015), and De Ridder (2019).

inefficiently use their resources, for example because a lack of working capital impedes certain input purchases, or because the shock shifts managers' attention towards seeking alternative sources of financing and away from maximizing efficiency. In fact, in both cases, one would expect to see an immediate productivity effect that gradually fades as firms regain access to credit markets, which is the opposite of what our TFPQ estimates indicate.

5.2 Transmission of financial shocks to pricing policies

We now examine the economic forces that lead firms to adjust their pricing behavior in response to tightening credit supply conditions and why these responses differ depending on the time horizon.

Long-run price adjustment. Consider first the long-run price dynamics. The estimates in Figure 2 indicate a gradual increase in output prices and subsequent mean reversion. One natural explanation for this is that the shock eventually led to an increase in production costs, and firms passed this through to consumers. The empirical analysis presented so far provides two pieces of evidence to support this idea.

First, as shown in Section 3, firms were eventually able to compensate for the contraction in credit, but only by relying on more expensive sources of financing. This finding is consistent with the ones in Barth III and Ramey (2001) and Christiano et al. (2015), whereby higher financing costs leads to a rise in the cost of working capital, which increases firms' production costs. Secondly, financial shocks set firms on a lower (long-run) productivity growth path. To the extent that firms pass through efficiency gains to consumers in the form of lower prices, ceteris paribus, firms more affected by the credit shock will price at a higher level relative to similar, less affected competitors.

Short-run price adjustment. In contrast to the long-run increase in prices, in the short run we find that firms more affected by the credit crunch reduce their prices relative to less affected ones. We show that this adjustment can be explained by firms using low pricing as a source of internal finance in an effort to counterbalance the drop in external financing.

Recognizing the increased value of liquidity, firms have the option to liquidate assets or reduce operating costs in order to increase cash flows. As discussed in Section 3.2 and 5.1, we do find evidence that firms exposed to the credit crunch reduce investments in machinery and equipment, employment growth, and investments in intangibles. However, firms may be limited in their ability or willingness to leverage these options as these actions might impact current revenues by reducing output produced, or, as we have shown in Section 5.1, have severe long-term consequences for firm productivity and thus firm value.[25]

An alternative option is to raise liquidity from the product market, by selling their inventories at discounted prices. While this behavior would be sub-optimal in normal circumstances, selling off inventories can help firms generate additional cash flows when the financial shock makes liquidity particularly valuable. As a first piece of evidence for this hypothesis, we show that producers that were more likely to be impacted by the credit crunch are those that display sharper adjustments of their pricing policies.

Table 3 shows how the short-term price response to the credit shock varies depending on the importance of the bank-credit shock for firms' financing. Column (1) shows that firms that entered the crisis with higher leverage (the ratio of bank debt to total assets at the end of fiscal year 2009) reduced prices more aggressively when coping with the credit crunch. Column (2) shows that the price reduction is increasing in the likelihood of financial distress (measured by the Z-score at the end of fiscal year 2009), as firms in precarious financial conditions are more affected by debt rollover risk.[26] In fact, the data indicates that the credit shock had practically no impact on the pricing behavior of firms that entered the sovereign crisis with strong balance sheets.

Next, we present empirical evidence linking pricing and inventory adjustments. As documented by Kim (2020), firms with higher levels of existing inventories should be better able to exploit low pricing as a form of liquidity management, as liquidating existing inventories does not involve incurring additional production costs.[27] We find strong support for this prediction in the data. First, in columns (4) and (5) we show that borrowers more exposed to the credit supply shock did indeed liquidate some of the inventories in the immediate aftermath of sovereign shock relative to less exposed firms. This response is primarily driven by firms that entered the crisis with larger inventory holdings.[28]

[25]In principle, reducing wages is another potential option to cut operating costs without impacting a firm's production capacity. We find no evidence that firms reduce wages in response to the shock. Unlike other countries with more flexible labor markets (see e.g., Chan et al., 2023 in the context of Denmark), collective bargaining plays a dominant role in shaping employment compensations in Belgium, which prevents firms from unilaterally downward-adjusting wages (Alvarez et al., 2006).

[26]The Z-score (Altman, 1968) is a credit-strength test that gauges a company's likelihood of bankruptcy. A score below 1.8 indicates a likelihood of bankruptcy, while a score above 2.9 signals a very low likelihood of financial distress. See Appendix A for additional details on the construction of the Z-score.

[27]Previous work has shown that liquidity constrained firms also shed inventories in response to demand and monetary policy shocks. See, e.g., Gertler and Gilchrist (1994) and Kashyap, Lamont, and Stein (1994).

[28]Our firm-level inventory measure includes finished goods, semi-finished goods, and raw materials, all measured at the end of 2009. In unreported results, we show that our results are driven by inventories of semi-finished goods and raw materials. This is consistent with the idea that many of the finished goods in inventory at the end of 2009 were sold by the time the credit supply shock arrives (April 2010), and that firms use inventories of semi-finished

Table 3: Heterogeneous pricing effects and the inventory channel

	Heterogeneous short-term price response			*Inventory channel*						
	Short-run effect			Short-run effect			Short-run effect			Long-run effect
	$\Delta \ln P$			$\Delta \ln Inv$		$\Delta \ln P$	Inv. rate R&D	Any R&D expense	Training expenses	$\Delta \ln TFPQ$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Shock	-0.013	-0.033***	-0.022***	-0.041***	-0.020	-0.012	-0.068***	-0.093***	-0.299***	-0.112***
	(0.008)	(0.010)	(0.008)	(0.008)	(0.012)	(0.007)	(0.011)	(0.016)	(0.065)	(0.031)
Shock × Bank leverage	-0.034***									
	(0.015)									
Shock × Z-score		0.007***								
		(0.003)								
Shock × Safe			0.016*							
			(0.009)							
Shock × Firm inv.					-0.115**	-0.035**	0.145**	0.249***	0.354***	0.245**
					(0.055)	(0.016)	(0.052)	(0.078)	(0.118)	(0.118)
Low inv. holdings					-0.030***	-0.015*	-0.055***	-0.072***	-0.267***	-0.090***
					(0.009)	(0.007)	(0.011)	(0.014)	(0.064)	(0.023)
High inv. holdings					-0.051***	-0.021***	-0.030*	-0.027	-0.204***	-0.047**
					(0.011)	(0.008)	(0.015)	(0.019)	(0.066)	(0.017)
Low-High inv. holdings					0.021**	0.006**	-0.026**	-0.044***	-0.063**	-0.044**
					(0.010)	(0.003)	(0.009)	(0.014)	(0.021)	(0.021)
R-squared	0.070	0.065	0.062	0.039	0.062	0.062	0.054	0.092	0.034	0.101
Observations	1024	1024	1024	1024	1024	1024	775	775	701	648

Notes: This table reports estimates of the heterogeneous effect of the credit supply shock on short-term ($\tau = 1$) prices, inventories, and expenditures on productivity-enhancing activities, and long-term ($\tau = 7$) TFPQ growth, estimated using model (3). The baseline model is augmented to include interactions between the shock and various firm-level variables. In the first 3 columns, the interacted regressors are bank leverage (bank debt over assets) and measures of the likelihood of financial distress (the Z-score and a dummy identifying firms with very low likelihood of distress, i.e., a Z-score higher than 2.9). In the remaining columns, the interacted regressor is firm-level inventory stocks. The interacted regressors themselves are also included in the regression model. The middle panel reports the estimated effects evaluated at different points of the distribution of firm-level inventory holdings (Low and High inventory holdings, corresponding to the 25th and 75th percentiles, respectively) and their difference. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Importantly, firms that can count on larger inventory stocks to liquidate more likely use low pricing as a source of internal finance, cutting output prices more aggressively in response to the credit shock (column (6)). A one-standard deviation increase in exposure to the shock leads to a relative contraction in output prices of over 2 percent for a firm with 27 cents worth of inventories per euro of assets (75th percentile), while a firm with 9 cents worth of inventories per euro of assets (25th percentile) reduced output prices by 1.5 percent. Underscoring the external validity of the analysis, we note that our estimates are consistent in both direction and magnitude with those reported in Kim (2020), estimated using consumer price data for a sample of US firms whose lenders were differentially exposed to the Lehman Brothers' default.

5.3 Linking the productivity and price effects of financial shocks

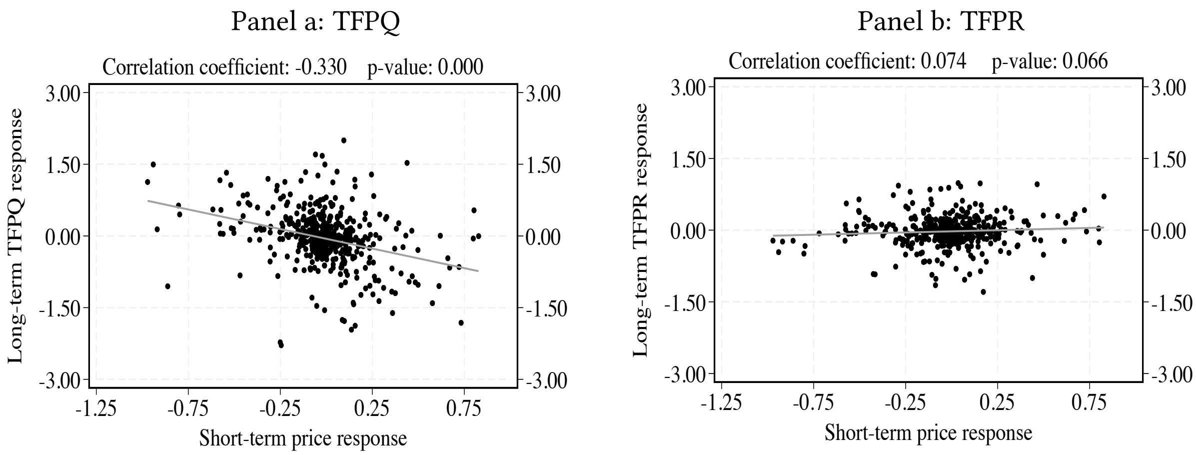
In this section we provide evidence showing that the price and productivity effects of financial shocks are in fact linked. We begin by documenting a statistical relationship between the causal effect of financial shocks on short-run pricing policies and long-run productivity growth. We compute the contribution of each firm to the average short-term price effect ($\hat{\beta}_1$) and the average long-run TFPQ growth effect ($\hat{\beta}_7$) presented in the impulse responses in Figure 2, (panels b and c).[29] We then group firms into percentiles based on their contribution to the short-term pricing response. The binned scatter plot in Figure 3, panel a shows the average contribution to the long-term TFPQ response (y-axis) within each group of firms, sorted by their contribution to the short-term pricing response (x-axis). We find a strong negative correlation between firms' short-term price response and long-term productivity growth response, with a correlation coefficient of -0.33 (significant at the one percent level). This exercise reveals that firms that endogenously respond to the financial shock by pricing more aggressively are the ones that experience, in the long-run, a less pronounced contraction of physical productivity growth.

It is important to note that the revenue productivity estimates are unable to detect the inter-temporal relationship between the price and productivity responses to the financial shock, casting further doubt on inferences based on TFPR movements (panel b). Since firms affected by the shock eventually increase prices, the revenue productivity estimates suggest either no relationship or even a positive relationship between short-term price adjustments and long-run

goods and raw materials (some of which have likely already been converted to final goods when the shock arrives) to respond to the shock.

[29]The contribution of each firm to the average short- and long-run treatment effects ($\hat{\beta}_\tau$, $\tau = 1, 7$) of productivity and prices are obtained using the influence function method (Cook and Weisberg, 1982). We rescale the influence functions so that the average contribution across observations (firms) equals the estimated treatment effects at each horizon.

Figure 3: Linking the short-term price and long-term productivity response



Notes: These binned scatter plots show the correlation between firms' short-term price and long-term productivity response to the financial shock. In each plot, a dot represents the average contribution to the productivity response (y-axis) and the average contribution to the price response (x-axis) of observations that belong to a given percentile of the distribution of the price and productivity responses. The gray line is the best linear predictor of the long-run productivity effect given the short-term price effect.

productivity.

We now provide evidence showing how the inventory management and innovation channels interact to generate the link between short-term price and long-term productivity effects. Increasing cash flows through inventory sales and reducing innovation expenses are substitutable for the purpose of freeing up liquidity. Therefore, ceteris paribus, we expect that firms that are able to expand sales by selling inventories at discounted prices should be able to reduce their investments in innovation less, thereby mitigating the long-run impact of the credit shock on productivity growth.

To test this hypothesis, we examine how the effect of the shock on investments in productivity enhancing activities (R&D and training) varies with a firm's inventories. The results reported in columns (7)–(9) of Table 3 show that firms that can rely on a larger stock of inventories to liquidate are the ones that display a smaller contraction of both innovation expenses and investments in workers' human capital. Comparing firms at the 25th and 75th percentile of inventories, we find that firms that were better able to reduce prices in response to the shock (i.e., those with higher inventory levels) reduce their investments in innovation by between 23 and 62 percent less, depending on the measure of innovation expenditure.

Finally, we show that firms' ability to reduce prices more, and therefore reduce investments in intangibles less, translates into significantly smaller contractions in long-run productivity. In column (10), we examine the heterogeneous response of long-term productivity growth as a function of firms' inventories. Consistent with the evidence provided by the non-parametric exercise in Figure 3, the estimates indicate that firms with greater ability to adjust prices in response to a financial shock systematically experience a lower contraction of long-run productivity growth in response to the shock. To put our estimates into perspective, firms that differ in their ability to respond by pricing more aggressively thanks to their possibility to tap into larger inventory stocks (25th vs 75th percentile of the distribution of inventories) experience a contraction in productivity growth that is almost 50 percent smaller.

6 Quantitative analysis

In this section we build a quantitative framework to study the importance of the pricing and productivity effects in generating the persistent slowdown in aggregate productivity and welfare observed after financial crises. We develop a general equilibrium model of firm dynamics under financial frictions and endogenous productivity that features the economic channels analyzed in the empirical analysis. After calibrating the model parameters to match the empirical impulse responses presented above, we use the model as a laboratory to study the aggregate implications of a large credit supply shock (i.e., a financial crisis) and simulate counterfactual economies that quantify the role of the different transmission mechanisms documented in the data.

6.1 Agents and economic environment

Below, we describe the main features of the model. We provide the characterization of the complete model in Appendix E.

Households. A representative household chooses consumption (C_t^h), labor supply (N_t^h), and savings in the form of bank deposits (D_t^h) to inter-temporally maximize its utility $U^h(C_t^h, (1-N_t^h))$ subject to the real flow-of-funds constraint $C_t^h + D_t^h = w_t N_t^h + \mathcal{R}_{t-1} D_{t-1}^h$. The consumption basket C_t^h is a CES composite of differentiated goods produced by firms. We denote by P_t the price of the consumption basket (the aggregate price index of the economy), and normalize it to one. Total deposits are the sum of deposits across multiple banks, $D_t^h = \sum_{j=1}^{J} D_{jt}^h$, paying a deposit rate $\mathcal{R}_t$ determined when deposits are made.

Firms. The economy is populated by a finite set of heterogeneous firms, indexed by $j = \{1, ..., J\}$. Firms use capital and labor to produce differentiated goods (Y_{jt}^e), which are used as both consumption goods and investment. Each firm is run by an entrepreneur that inter-temporally maximizes its utility from consumption $U^e(C_{jt}^e)$ subject to the budget constraint:

$$C_{jt}^e + w_t(L_{jt}^e + O_{1jt}^e + O_{2jt}^e) + \iota_{jt}^e + \mathcal{A}C_{jt}^e \leq (B_{jt}^e - R_{jt} B_{jt-1}^e) + P_{jt}^e Y_{jt}^e.$$

Uses of funds—The variables on the left-hand-side of the equation represent the entrepreneur's real consumption (C^e_{jt}) and expenditures. L^e_{jt} denotes the amount of labor employed in production, while O^e_{1jt} and O^e_{2jt} represent the firm's demand for workers involved in innovation and adoption activities, all of whom are hired at the real wage w_t. The variable ι^e_{jt} represents the amount of investment in physical capital, which evolves according to the accumulation equation $K^e_{jt+1} = (1-\delta_K)K^e_{jt} + \iota^e_{jt}$, subject to real adjustment costs $\mathcal{AC}^e_{jt}$.

Sources of funds—The variables on the right-hand-side of the budget constraint represent the entrepreneur's sources of finance: internal finance (real sales, $P^e_{jt}Y^e_{jt}$) and bank debt (net real borrowing, $B^e_{jt} - R_{jt}B^e_{jt-1}$), where R_{jt} is the gross interest rate on debt. Consistent with our empirical findings, bank borrowing is subject to financial frictions in the form of a borrowing constraint:[30]

$$B^e_{jt} \leq \gamma^e_{jt}\mathbb{E}_t\left[\frac{K^e_{jt+1}}{R_{jt+1}}\right] - \nu(L^e_{jt} + O^e_{1jt} + O^e_{2jt})w_t.$$

The first term on the right-hand-side captures a collateral constraint. As in Kiyotaki and Moore (1997), the amount entrepreneurs can borrow is bounded by a multiple of their assets. The parameter $\gamma^e_{jt} \in [0,1]$ governs the strength of financial frictions faced by entrepreneur j. As we discuss in the Appendix, we assume the tightness of the borrowing constraint, γ^e_{jt}, is affected by the strength of bank's balance sheet. The second term on the right-hand-side of the equation represents the firm's need for working capital. As in Neumeyer and Perri (2005), it captures the idea that a fraction $\nu \in [0,1]$ of the firms' wage bill must be paid in advance.

Production and inventory management—Firms produce a continuum of parts $Y^e_{jt}(i)$, which are assembled by the entrepreneur to produce the final good Y^e_{jt} using the technology $Y^e_{jt} \equiv \left(\int_0^1 \theta_{jt}(i)\left(Y^e_{jt}(i)\right)^\rho di\right)^{1/\rho}$. At the beginning of each period t, the firm employs capital and production labor to produce parts using a Cobb-Douglas technology:

$$\int_0^1 Q^e_{jt}(i)\,di \leq A^e_{jt}(L^e_{jt})^{\alpha_L}(K^e_{jt})^{\alpha_K},$$

where $Q^e_{jt}(i)$ denotes quantity produced and A^e_{jt} the firm's technical efficiency (TFPQ). Following Wen (2011) and Kim (2020), firms face idiosyncratic demand shocks for parts, $\theta_{jt}(i)$, that are realized after the entrepreneur's input production decisions have been made, but before choosing how much to produce of the final good. This creates a scope for inventory management as firms hold inventories to help insure against stocking out of parts with particularly high demand

[30]The formulation of entrepreneurs' preferences rules out the possibility of equity issuances (i.e., negative consumption). This is a simplifying assumption which, however, is consistent with the rare injection of equity capital observed among the firms in our dataset, which use bank debt and internal finance as their primary financing sources.

realizations.[31]

Depending on the realization of the taste shock $\theta_{jt}(i)$, the firm decides how much of $Q^e_{jt}(i)$ to use for sales $Y^e_{jt}(i)$ and how much to store as inventory $I^e_{jt}(i)$, where $Y^e_{jt}(i) \leq (1-\delta_I)I^e_{jt-1}(i) - I^e_{jt}(i) + Q^e_{jt}(i)$, with δ_I being the depreciation rate of the inventory stock. Aggregating across parts, we define firm-level inventories as $I^e_{jt} \equiv \int I^e_{jt}(i)di$.

Innovation and productivity—As in Comin and Gertler (2006), entrepreneurs invest to develop new technologies that replace obsolete ones. To do so, they hire researchers who work on the development of ideas that ultimately generate intangible assets (knowledge) according to the law of motion:

$$Z^e_{jt+1} = \phi_A Z^e_{jt} + \Xi^e_{1jt},$$

where ϕ_A denotes the depreciation rate of firm's productive technologies, $\Xi^e_{1jt} \equiv \Xi^e(O^e_{1jt})$ represents the investment in knowledge, which is an increasing and concave function of the amount of researchers employed by the firm, O^e_{1jt}.

Knowledge generates productivity, as a firm's technical efficiency depends on the stock of non-depreciating technologies already adopted ($\phi_A A^e_{jt}$) as well as on the flow of newly adopted ones:

$$A^e_{jt+1} = \left(\phi_A A^e_{jt} + \phi_A (Z^e_{jt} - A^e_{jt})\Xi^e_{2jt}\right) \cdot e^{a^e_{jt}},$$

where $\phi_A(Z^e_{jt} - A^e_{jt})$ denotes the stock of unadopted technologies. The adoption rate of technology, $\Xi^e_{2jt} \equiv \Xi^e(O^e_{2jt})$, in an increasing and concave function of the workers employed in the technology adoption process, O^e_{2jt}. a^e_{jt} captures an idiosyncratic productivity shock, independent of the firm's innovation choices. Together, the laws of motion for knowledge and productivity capture the endogenous nature of firm-level productivity, its dependence on investments on innovation, as well as the slow-moving pace of its evolution, as documented in the data.

Banks. Banks intermediate funds between households (savers) and entrepreneurs (borrowers), earning a spread between the deposit rate offered to households, $\mathcal{R}_{t-1}$, and the loan rate charged to firms, R_{jt}. They also invest in securities that serve as collateral, as explained below. For tractability, we assume each bank matches with one firm (both indexed by j). The banker maximizes its inter-temporal utility from consumption, subject to the flow-of-funds constraint $C^b_{jt} + \mathcal{R}_{t-1}D^b_{jt-1} + B^b_{jt} = D^b_{jt} + R_{jt}B^b_{jt-1} - (S^b_j - S^b_{jt})$, where $(S^b_j - S^b_{jt})$ denotes loss provisions or profits due to changes in the market value of securities.

[31] To fix ideas, consider the production of smartphones which are comprised of various parts including batteries, displays, memory, processors, etc. Consumer tastes may change from one year to the next. Suppose that demand for longer battery life increases. If the firm stocks out of the longer-lasting batteries, it could *compensate* customers, for example, by offering more memory, but at the expense of a higher production cost for the firm.

Following Iacoviello (2015), we assume bankers are constrained in their ability to issue deposits by their amount of net worth, which cannot exceed a fraction $\gamma^b \in (0,1)$ of their assets:[32]

$$D^b_{jt} \leq \gamma^b (B^b_{jt} + S^b_{jt}).$$

Shocks to the value of securities erode banks' net worth, forcing them to deleverage. This leads to a credit crunch (higher interest rates and lower lending amounts) that propagates to the real economy.

6.2 General equilibrium

Market clearing for the goods, labor, deposits, and credit markets follows from Walras's law, aggregating all agents' budget constraints. Given the realization of the stochastic variables $\{\boldsymbol{\theta}_t, \boldsymbol{S}^b_t, \boldsymbol{a}^e_t\}$ and predetermined states $\{\boldsymbol{K}^e_t, \boldsymbol{Z}^e_t, \boldsymbol{A}^e_t, \boldsymbol{D}^b_{t-1}, \boldsymbol{B}^b_{t-1}\}$, the stochastic general equilibrium of the model is represented by a vector of prices and $\{P_t, w_t, \mathcal{R}_t, \boldsymbol{R}_t, \boldsymbol{P}^e_t\}$, and quantities, $\{C^h_t, \boldsymbol{C}^b_t, \boldsymbol{C}^e_t, \boldsymbol{K}^e_{t+1}, \boldsymbol{L}^e_t, \boldsymbol{I}^e_t, \boldsymbol{O}^e_{1t}, \boldsymbol{O}^e_{2t}, \boldsymbol{D}^b_t, \boldsymbol{B}^b_t\}$, such that agents optimize and markets clear.

6.3 The pass-though of bank balance sheet shocks to firms' real activity

The optimality conditions of the firm's problem capture the core economic forces that rationalize the dynamics documented in the micro data. Financial frictions affect firm policies by increasing both the direct cost (R_{jt+1}) and shadow cost (χ^e_{jt}, the Lagrange multiplier attached to the borrowing constraint) of finance, thereby lowering firms' input demand, output, and entrepreneurs' consumption. Moreover, it also forces firms to reduce innovation expenses (O^e_{1jt} and O^e_{2jt}) and—given the endogenous nature of firms' technical efficiency—sets them on a lower productivity trajectory (the innovation channel). The intuition is that financial shocks raise the cost of funds and increase the value of liquidity in the current period relative to the future, thus distorting the trade-off between short-term and long-term decisions. A similar mechanism is present, for example, in Eisfeldt and Rampini (2007) and Caggese et al. (2019).

The possibility to use low pricing as a source of internal financing (through the liquidation of inventories) helps firms mitigate this effect by freeing up resources that would otherwise be obtained through a more severe contraction of innovation activity. Specifically, in the model firms price at a markup over marginal costs. The markup consists of both a fixed component

[32] This constraint is motivated by standard limited commitment problems or by regulatory concerns (e.g., the capital to assets ratio imposed by the Basel Committee on Banking Supervision).

(determined by the elasticity of substitution, ϵ) and a variable component:

$$\mathcal{M}^e_{jt} = \left(\frac{\epsilon}{\epsilon - 1}\right) \Lambda^e{}_{jt}.$$

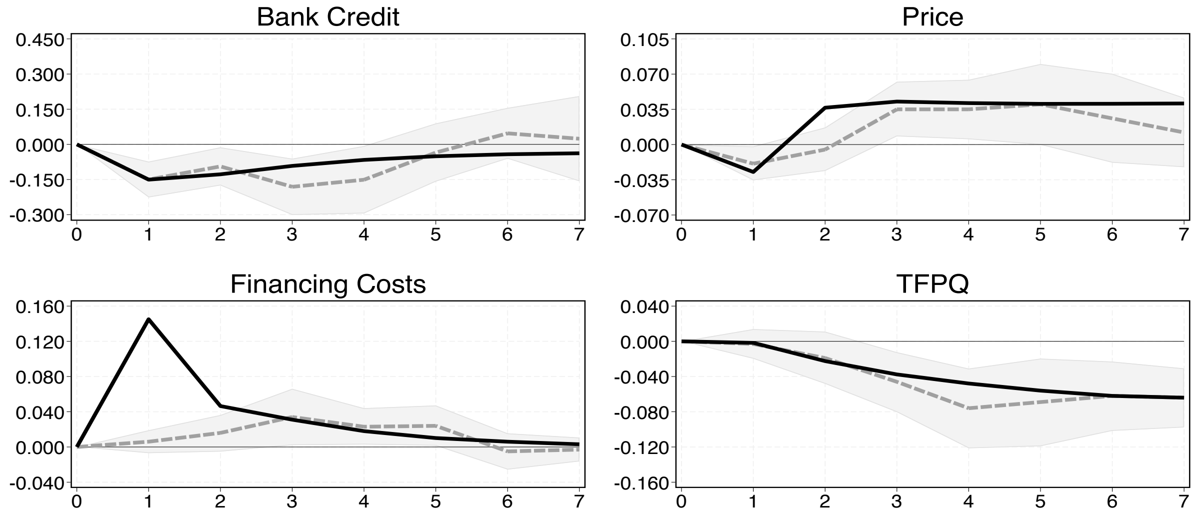
As we explain in Appendix E.2, the variable component, $\Lambda^e{}_{jt}$, arises from firms' ability to use inventories to adjust output sold after production decisions have been made. Although firms do not hold inventories in anticipation of financial shocks, an unexpected tightening of credit supply conditions increases the value of liquidity, leading firms to sell off inventories. To do so, they reduce their short-term profit margin and lower their prices relative to those of their competitors ($\Lambda^e{}_{jt}$ and therefore $\mathcal{M}^e_{jt}$ fall) in order to move along their demand curve and expand sales (the inventory management channel). Although the decision to liquidate inventories at low prices would be sub-optimal in normal circumstances, it allows a firm squeezed by a credit crunch to generate additional liquidity from the product market, thereby alleviating the effects of the shock on consumption, factor demands, and innovation expenses. The inventory management channel, however, can only provide temporary relief against the credit supply shock. In the long run, more affected firms face higher borrowing costs and reduced productivity, which they pass through in the form of higher final goods prices, as in the data.

6.4 Calibration and model-based IRFs

We solve for the agents' policy functions and compute the model's transitional dynamics by feeding a sequence of idiosyncratic productivity shocks and shocks to the market value of securities held by banks. To model the latter, we define $S^b_{jt} \equiv e_{jt} S^b_j$. As discussed above, S^b_j denotes the book value of securities (i.e., their value absent shocks) and e_{jt} is a stochastic variable with $\mathbb{E}[e_{jt}] = 1$, which evolves as an autoregressive process. These shocks generate a tightening of credit supply conditions that mimic what we observe empirically in the wake of the sovereign debt crisis. A low realization of e_{jt} simultaneously increases the cost, and decreases the quantity, of credit available to firm j.

In Appendix E we describe the calibration procedure for the model parameters, and we briefly summarize it here. We partition the model's parameters into two sets. The first set of parameters is externally calibrated to standard values used in the literature. We subsequently calibrate the set of parameters that control firms' pricing and productivity dynamics to match our reduced-form estimates obtained in the micro-data. Specifically, given a sequence of shocks, the firms' policy functions, and a value of the parameters, we simulate a firm-level panel dataset that allows us to estimate model-based counterparts to those estimated in the micro data. We then calibrate the remaining parameters to simultaneously minimize the distance between the

Figure 4: Empirical and model-based impulse response functions



Notes: These graphs compare the model-based impulse response functions (black solid lines) to the empirical impulse response functions (gray dashed lines and 95 percent confidence intervals in shades) presented above in Figures 1 and 2.

empirical and model-based impulse responses of credit balances, borrowing costs, productivity, and prices reported previously in Figures 1 and 2.

Figure 4 overlays the empirical IRFs and their model-based counterparts obtained at the calibrated parameter values. The model closely matches the estimated reduced-form estimates, qualitatively and quantitatively, in both the short and long run. Specifically, it reproduces both the V-shaped pricing response and the delayed but persistent contraction in firm-level productivity growth. It also produces an average inventory to sales ratio of 0.13 prior to the credit shock, which is very close to the value observed in the data (0.15). One discrepancy is the higher sensitivity of financing costs in the short run, which is higher in the model than in the data. This arises because debt contracts are renegotiated on a yearly basis in the model but have longer maturity in the data.

6.5 Simulating financial crisis under factual and counterfactual scenarios

We use the model to evaluate the aggregate effects of a financial crisis in the baseline model and in counterfactual economies. To generate the financial crisis, we simulate heterogeneous shocks to the value of securities held by individual banks that in the aggregate leads to a large contraction in bank lending: a 20% drop in aggregate credit over two years that gradually recovers. We then measure the effects of the financial shock on aggregate variables by calculating their

Table 4: Aggregate effects of a financial crisis

	Panel a: Baseline economy					
	$\Delta \ln TFP$	$\Delta \ln C$	$\Delta \ln Q$	$\Delta \ln I$	$\Delta \ln O$	Δ Welfare
Short run	-0.005	0.002	-0.032	-0.330	-0.177	-0.062
Medium run	-0.019	-0.087	0.017	-0.222	-0.011	-0.043
Long run	-0.016	-0.042	-0.016	-0.077	0.013	-0.018
	Panel b: Counterfactual economy – No inventory channel					
	$\Delta \ln TFP$	$\Delta \ln C$	$\Delta \ln Q$	$\Delta \ln I$	$\Delta \ln O$	ΔWelfare
Short run	-0.003	-0.072	0.031	0.000	-0.271	-0.095
Medium run	-0.037	-0.083	-0.016	0.000	0.069	-0.042
Long run	-0.019	-0.046	-0.024	0.000	0.021	-0.020

Notes: Panel a presents the aggregate dynamics of the baseline model. We calculate the log deviations of aggregate TFP, aggregate consumption, aggregate production, aggregate inventories, aggregate employment of knowledge labor, and per-period welfare in different time periods ($\tau = 1, 4, 7$, short, medium, and long run, respectively) relative to an economy that receives the same idiosyncratic firm-level productivity shocks, but without the bank balance sheet shock to securities. Aggregate productivity (TFP) is defined as $Q_t/(L_t^{\alpha_L} K_t^{\alpha_K})$, aggregate consumption as $C_t = C_t^h + \sum_{j=1}^N C_{jt}^e + \sum_{j=1}^N C_{jt}^b$, aggregate production as $Q_t = \sum_{j=1}^N Q_{jt}^e$, aggregate inventories as $I_t = \sum_{j=1}^N I_{jt}^e$, and aggregate employment of knowledge labor as $O_t = \sum_{j=1}^N (O_{1jt}^e + O_{2jt}^e)$. We define aggregate welfare as the average utility of consumers, entrepreneurs, and bankers. Panel b presents the same aggregate statistics computed in a counterfactual economy where we prevent firms from adjusting their inventory holdings from their steady state levels.

log deviations, over different horizons, relative to an economy that receives the same path of idiosyncratic firm-level productivity shocks, but does not experience shocks to the value of securities.

Aggregate effects of the financial crisis in the baseline economy. Panel a of Table 4 reports the effects of the credit crunch in the baseline economy over the short, medium, and long run (1, 4, and 7 years from the shock). That is, the economy where the parameters are calibrated to match the micro-level IRFs, as explained above. The crisis generates long-lasting effects on real economic activity. Through the lens of our model, the persistent slowdown in aggregate productivity growth is a key channel for these scarring effects. Consistent with the innovation channel, the shock leads to a meaningful contraction of firms' innovation expenses (O_{1t}^e and O_{2t}^e), which gradually leads to a reduction in aggregate productivity through a decrease in firm-level productivity growth. Our quantitative exercise also highlights the role the inventory channel plays in driving the aggregate responses. In the aftermath of the shock, aggregate production (Q_t) drops as firms contract their economic activity. However, aggregate consumption (C_t) remains relatively stable due to the inventory sell-off (I_t). This result echoes the one in Khan and Thomas (2007) on the procyclicality of inventories, which act as a smoothing force, moderating the fall in final sales in downturns.

The role of low pricing as a source of internal financing. In our first counterfactual exercise we study the role of the endogenous response of firm prices in mitigating the effect of a financial shock. To quantify the importance of this mechanism in determining the aggregate outcomes, we simulate a counterfactual economy where we prevent firms from liquidating inventories. To perform this exercise, we keep all parameters at their calibrated values and feed the model the same sequence of idiosyncratic productivity shocks and bank balance sheet shocks that hit our baseline economy. We then simulate the transitional dynamics as in the baseline economy, but preventing firms from adjusting their inventory holdings in response to the credit shock, by forcing firms to keep inventories at their pre-shock level. In doing so, we prevent firms from using low pricing as a source of internal finance.

The results of this exercise are reported in Table 4, panel b. In the counterfactual economy, since firms cannot use inventories to mitigate the effect of the credit shock, consumption immediately declines. Preventing firms from liquidating their inventories also substantially amplifies the medium-run and long-run effects through the innovation channel. Firms are forced to cut innovation expenses much more aggressively than in the baseline economy. As a result, firm-level productivity, and therefore aggregate productivity, losses are larger and longer-lasting in the counterfactual economy.

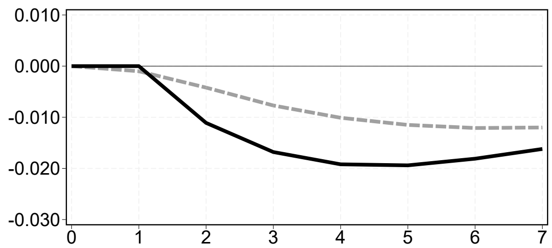
Aggregating the utilities of the different agents in the model, we can compute the welfare losses in this counterfactual economy and compare to the losses in our baseline economy. When we prevent firms from using low pricing as a source of internal finance, we find that per-period welfare losses are over 50 percent higher in the immediate aftermath of the shock and remain 10 percent higher in the long run. The behavior of aggregate consumption, which can be viewed as an alternative welfare metric, conveys a similar message.

The role of endogenous firm-level productivity. In our empirical analysis in Section 4, we documented how movements in revenue-based productivity measures underestimate the true long-run effect of financial shocks on firm-level productivity growth. In our second counterfactual exercise, we quantify the importance of properly accounting for micro-level productivity dynamics in determining the scarring effects on aggregate productivity and welfare.

We recalibrate the model parameters that control the sensitivity of firm-level productivity to investments in innovation to allow the model-based IRFs of productivity to match the empirical IRFs of TFPR, as opposed to those of TFPQ. In Figure 5 we compare the log change in aggregate productivity and per-period welfare due to the financial shock in the baseline model and in the (recalibrated) counterfactual economy.

Through the lens of our model, this exercise suggests that underestimating the effect

Figure 5: Aggregate productivity effects: The role of endogenous firm-level productivity



Notes: This graph compares the response of aggregate productivity under our baseline model (black solid line) and under a counterfactual scenario in which the parameters that control the sensitivity of firm-level productivity to innovation expenses are recalibrated to match the empirical IRFs of TFPR, as opposed to TFPQ (gray dashed line).

of financial shocks on firm-level productivity results in a severe underestimate of the impact on aggregate productivity by 50 percent in the medium run and more than 25 percent in the long run. The incorrect parametrization of the productivity process also leads to a significant understatement of the long-run aggregate welfare costs of the financial shock, which are 13 percent smaller in the counterfactual economy.

7 Concluding remarks

This paper sheds new light on the nexus between financing frictions and firm-level productivity growth. Using detailed administrative records of firm-level output prices and quantities, combined with quasi-experimental variation in credit availability, we systematically explore the relationship between a tightening of financing conditions and firm productivity growth, emphasizing the crucial role of firm price adjustments in quantifying and understanding this relationship.

By disentangling the effects of pricing and productivity, we document that financial shocks have no immediate impact, but instead cause a substantial, delayed, and persistent long-term reduction in firm-level technical productivity growth. We show that this occurs because a tightening of external finance conditions leads to a contraction in investments in intangible assets, such as R&D and worker training, setting firms on a lower productivity growth path. Importantly, because firms adjust their pricing policies to cope with the shock, we also document that revenue-based productivity measures provide biased estimates and potentially misleading predictions regarding the implications of financial shocks on firm productivity in both the short and long run.

Our study emphasizes that understanding and accounting for the endogenous price response to financial shocks has important welfare implications that extend beyond measurement considerations. Financial shocks jeopardize a firm's capacity to sustain productivity growth through investments in innovation and human capital. We are the first to document how the ability to generate additional cash flows via low pricing in the product market enables firms to mitigate this effect, thereby softening the long-term impact of the shock on productivity. Embedding our empirical results into a quantitative model of firm dynamics, we show that a slow-down in firm-level productivity growth, caused by a drop in credit supply, generates substantial scarring effects on aggregate productivity and welfare. Counterfactual analysis demonstrates that firms' ability to price more aggressively leads to a significant mitigation of these aggregate effects.

These mechanisms highlight that the nominal and real impacts of financial shocks are more interconnected than previously recognized. The connection between the behavior of firms in product markets and productivity growth is an active area of research. For example, research shows that product market conditions shape aggregate productivity through misallocation effects and firm selection (see, e.g., Restuccia and Rogerson, 2017 and Syverson, 2004). This paper offers new insights that further connect the two though the interplay of firms' innovation and inventory decisions.

Finally, due to data availability, our study focuses on manufacturing firms. As economies transition toward service-oriented structures, it would be relevant to extend our analysis to the services sector. Due to its higher demand cyclicality and limited collateralizable assets, financial crises could result in even more severe financial frictions in services compared to manufacturing. In that case, we would expect to find even larger contractions in innovation and productivity growth than the ones presented in this paper. Moreover, while in this study we exploit data from Belgium, we believe our findings are more broadly applicable to other countries, particularly other EU countries that share similar market institutions and dependence on bank finance and to some extent to the UK and the US. We leave these as topics for future research.

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Financial Shocks, Productivity, and Prices

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Online Appendix

A Data appendix

In this appendix, we provide additional details on the source and definition of the variables used in the empirical analysis.

Firm-level variables. We denote by $\text{Credit}_{j,t}$ the firm-level outstanding bank credit balance (sum of term loans, credit lines, credit backed by receivables) from the CCR, which is constructed by summing across all lenders b of firm j in year t ($b \in \mathcal{B}_{j,t}$), $\text{Credit}_{j,t} = \sum_{b\in\mathcal{B}_{j,t}} \text{Credit}_{jb,t}$. As in Chodorow-Reich (2014), we measure the τ-year cumulative growth in total bank credit of each firm as $\Delta_\tau \text{Credit}_j = \frac{\text{Credit}_{j,2009+\tau} - \text{Credit}_{j,2009}}{0.5(\text{Credit}_{j,2009+\tau} + \text{Credit}_{j,2009})}$, where $\text{Credit}_{j,2009}$ measures the average outstanding bank credit of firm j in the year prior to the burst of the sovereign crisis, and $\text{Credit}_{j,2009+\tau}$ measures the average outstanding credit τ-years afterwards. We measure average financing costs incurred during a year using information on financial charges and outstanding principal of financial debt from the firms' income statements and balance sheets as reported in the AA: $fc_{j,t} = \frac{\text{Financial Charges}_{j,t}}{\text{End of Year Financial Debt}_{j,t-1}}$. We then compute the change in the average financing costs relative to 2009, $\Delta_\tau fc_j = fc_{j,2009+\tau} - fc_{j,2009}$.

From the AA, we gather the following set of firm-level variables from firms' balance sheets and income statements: firm size (natural logarithm of total assets), bank leverage (bank debt outstanding over total assets), and stock of inventories (sum of final goods and intermediate goods over total assets), all measured at the end of the fiscal year 2009. For each firm in our sample, we construct the Z-score at the end of fiscal year 2009 by adapting the Altman (1968) formula to private firms: Z-score = 3.107 × (EBIT / Total Assets) + 0.998 × (Sales / Total Assets) + 0.420 × (Capital / Total Liabilities) + 0.717 × (Working Capital / Total Assets) + 0.847 × (Retained Earnings / Total Assets).

Using the information reported in the AA, we compute three indicators of firm expenditures on productivity-enhancing activities, investments in machinery and equipment, employment, and average labor compensations. First, for each year following the burst of the sovereign crisis, we compute the R&D investment rate (Inv. rate $\text{R\&D}_\tau$), which is the ratio of cumulative expenses on R&D up to year 2009+τ scaled by the stock of intangible assets in 2009: Inv. rate $\text{R\&D}_\tau$

$= \sum_{t=1}^{\tau}$ R&D expenditures$_{2009+t}$/Intangible assets$_{2009}$. Our second indicator is a dummy variable that flags firms investing any positive amount in R&D in a given year (Any R&D expense$_{\tau}$). This variable captures the extensive margin of innovation, accounting for the lumpy nature of R&D investments. Our third indicator recognizes that innovation spurs from R&D as long as a skilled and appropriately trained workforce is capable of integrating new technologies into the existing production processes. To capture this aspect, we gather information on employee training expenditures (Training expenses$_{\tau}$). Specifically, we calculate cumulative average training expenditures per employee scaled by expenditures per employee in year 2009: Training expenses$_{\tau}$ $= \left(\sum_{t=1}^{\tau} \text{Training expenditures}_{2009+t}\right) / \text{Training expenditures}_{2009} - 1$.

Similarly, we compute the cumulative growth rate in investments in machinery and equipment (M&E) as the ratio of cumulative expenses in machinery and equipment up to year 2009+τ scaled by the stock of these assets in 2009: Inv. rate M&E$_{\tau}$ = $\sum_{t=1}^{\tau}$ M&E expenditures$_{2009+t}$/Stock of M&E$_{2009}$. We then use information from the firm's social balance sheet—a subsection of the annual accounts—to compute the growth rate of total employees, part-time employees, and full-time employees $\left(\Delta_{\tau}\text{X}_j = \frac{\text{X}_{j,2009+\tau} - \text{X}_{j,2009}}{0.5(\text{X}_{j,2009+\tau} + \text{X}_{j,2009})}\right)$. Finally, we compute the growth rate of Average labor compensations, defined as the ratio of total wage bill to total employment.

Section 2.2 and Appendix B describe how we construct our measures of price and productivity growth.

Bank-level variables. We collect bank-level variables from confidential supervisory records of the National Bank of Belgium. The key variable of interest is the banks' exposure to the sovereign crisis via their holdings of GIPSI sovereign securities—GIPSI Sovereigns$_b$ = GIPSI Sovereign Holdings$_b$/Risk-weighted Assets$_b$ in 2010:Q1—which is used to construct our firm-level credit supply shifter, as described in Section 3. We also gather information on a battery of bank-level characteristics which are included as controls in all econometric specifications. The set of bank-level variables includes bank size (natural logarithm of bank assets), variables capturing banks' funding structure (Tier 1 ratio, deposits over risk-weighted assets, net interbank liabilities scaled by risk-weighted assets), liquidity position (liquidity over risk-weighted assets), and quality of lending portfolio (non-performing loans over risk-weighted assets), measured before the shock (2010:Q1). Similar to our measure of GIPSI sovereign exposure, we aggregate these lender-specific variables to the firm-level by computing a weighted average across lenders using the share of firm j's credit received from each bank in the pre-shock period as weights.

Firm-bank-level variables. Exploiting the panel dimension of the CCR, we calculate the length of the lending relationship (in quarters) between borrower j and bank b,

Table A.1: Characteristics of high and low exposure firms

	Low exposure	High exposure	Difference (1)-(2)
	(1)	(2)	(3)
Total assets (million euros)	108.584	76.659	31.925
	(15.463)	(13.313)	(20.399)
Bank leverage	0.217	0.201	0.015
	(0.009)	(0.009)	(0.013)
$\ln TFPR$	8.715	8.731	-0.017
	(0.008)	(0.010)	(0.012)
$\ln TFPQ$	15.379	15.399	-0.021
	(0.033)	(0.035)	(0.048)
$\ln P$	1.788	1.734	0.054
	(0.183)	(0.121)	(0.219)
Inventories	0.188	0.191	-0.004
	(0.006)	(0.006)	(0.008)
Z-score	2.028	2.073	-0.045
	(0.048)	(0.050)	(0.070)

Notes: This table compares firm characteristics, measured at the end of fiscal year 2009, across firms borrowing from banks with low holdings (below median) and high holdings (above median) of distressed sovereign bonds. Columns (1) and (2) report means and their standard errors (in parentheses). Column (3) reports the difference and standard errors (in parentheses) of a two-tailed test of equality of the means of the two groups. *** denotes that the mean difference is significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Length of relationships$_{jb}$, measured as the number of consecutive quarters the relationship has been in place between 2006:Q1 and 2010:Q1. We subsequently aggregate across lenders and calculate the firm-level weighted average length of lending relationships as Length of relationships$_j = \sum_{b \in \mathcal{B}_j} \omega_{jb} \times$ Length of relationships$_{jb}$, where ω_{jb} is the share of debt provided by each lender in 2010:Q1. We also compute the number of active lending relationships of each firm in the last quarter before the crisis (Number of relationships$_j$).

Sample construction. The construction of our dataset begins with the PRODCOM database, as it contains the crucial data on prices and quantities for our analysis. We start with a sample of 3,169 manufacturing firms operating in 16 manufacturing industries that report a "normal" legal and economic standing (i.e., no liquidation, no default, no ongoing mergers or acquisitions), strictly positive total assets and total PRODCOM revenues, and a well-defined location (region) in 2009 (the year prior to the burst of the sovereign crisis). We then exclude a small number firms for which we are unable to construct our Törnqvist price index (due to a lack of continuing products in consecutive years), resulting in a sample of 3,127 firms.

Next, we merge this sample with the annual accounts, excluding observations with missing revenues or missing information on production inputs (wage bill, intermediate input expenses, and stock of tangible capital needed to initialize the perpetual inventory method). We also exclude observations with missing information on inventories.[33] These variables are required to obtain the firm-level TFPQ estimates used in our empirical analysis and to demonstrate the role of the inventory channel in explaining firms' price dynamics. After imposing these filters, we are left with a sample of $1,265$ firms and $12,633$ firm-year observations in the time-frame $2006 - 2016$.

Finally, we merge this firm-level sample with the combined CCR-bank supervisory records database (after collapsing it at the firm level) to obtain information on firms' credit balances and to construct our firm-level credit supply shock. In doing so, we keep firm-year observations for which we observe a positive credit balance in 2009 in the CCR vis-à-vis at least one of the domestic banks submitting financial statements. This process results in a final sample of $1,024$ firms and $9,667$ firm-year observations between 2009 and 2016. The total PRODCOM sales in 2009 for the firms in our final sample account for approximately 65 percent of total PRODCOM sales in 2009.

Comparison of firm characteristics and sample attrition. Table A.1 compares characteristics for the group of firms borrowing from banks with low GIPSI holdings (below the median of Shock_j) and the group of firms with high GIPSI holdings (above the median of Shock_j), measured at the end of fiscal year 2009, before the burst of the sovereign debt crisis. Columns (1) and (2) report means and their standard errors (in parentheses). Column (3) reports the difference and standard errors (in parentheses) of a two-tailed test of equality of the means of the two groups. All firm variables are measured at the end of fiscal year 2009, the last quarter before the burst of the sovereign crisis.

We observe a significant degree of sample attrition between 2009 and 2016, with the number of firms dropping from $1,024$ to 652 between the beginning and the end of our sample. This appears to be driven largely by the sampling scheme adopted by PRODCOM and survey attrition in the response rate, rather than by selection induced by the financial shock. As we note in the paper, while the PRODCOM survey is designed to cover at least 90% of domestic production value within each NACE 4-digit manufacturing industry, firms might not be surveyed in all years. Since the construction of the price index requires the concatenation of the yearly price changes, a firm that is not surveyed in a given year permanently exits our regression sample, even if the firm later re-enters the PRODCOM sample. To confirm that attrition due to the PRODCOM sampling scheme is the main driver of the attrition in our regression sample, we matched our sample to the Crossroads Bank for Enterprises (the Belgian census of enterprises) and found that 86% of the firms that exit at some point our regression sample still appear in the Crossroads as firms in

[33] Reporting this information is mandatory for firms filing a complete annual account template but is optional for firms filing simplified versions of the annual accounts.

"normal legal standing" in 2016 (the last year in our sample).

B Price measurement and productivity estimation

B.1 Price measurement

To build our baseline price measure (in levels), we follow a standard approach by concatenating yearly price changes starting from a base year. We first aggregate price changes across products of multi-product firms using a Törnqvist index, a standard measure used by statistical agencies, to measure the yearly growth rate of prices across 8-digit products within a firm:

$$P_{jt}/P_{jt-1} = \prod_{p \in \mathcal{P}_{jt}} \left(P_{jpt}/P_{jpt-1}\right)^{\bar{s}_{jpt}},$$

where $\mathcal{P}_{jt}$ represents the set of 8-digit products manufactured by firm j, P_{jpt} is the unit value of product p in $\mathcal{P}_{jt}$, and $\bar{s}_{jpt}$ is a Törnqvist weight computed as the average of the sale shares of product p in $\mathcal{P}_{jt}$ between t and $t-1$. We then build our firm-time price measure, P_{jt}, by recursively concatenating the year-to-year Törnqvist index starting from a firm-specific base year:

$$P_{jt} = P_{jB} \prod_{\tau=B+1}^{t} P_{j\tau}/P_{j\tau-1}.$$

The construction of the firm-specific base year price, P_{jB}, follows Eslava et al. (2024):

$$P_{jB} = P_{base,B} \prod_{\mathcal{P}_{jB}} \left(\frac{P_{jpB}}{\bar{P}_{pB}}\right)^{s_{jpB}}, \quad \bar{P}_{pB} = \prod_{j} \left(P_{jpB}\right)^{\tilde{s}_{jpB}},$$

where B is the first year in which firm j is in the sample, $\mathcal{P}_{jB}$ is the set of products produced by firm j in year B, and $\bar{P}_{pB}$ is the geometric average of prices for product p in the base year, with weights $\tilde{s}_{jpB}$ denoting the revenue share of firm j in total revenues for product p in year B. $P_{base,B}$ is an overall base price such that:

$$P_{base,B} = \begin{cases} 1 & \text{if } B \text{ is the first year of the sample} \\ \prod \left(P_{jB-1}\right)^{\tilde{s}_{jB-1}} & \text{if } B > \text{first year of the sample} \end{cases}$$

We also construct two alternative price measures which deliver similar results. The first is a simple revenue-share weighted-average of the product-level prices. The second avoids taking a stance on aggregation across different products, and uses just the price of the firm's main product.

B.2 Productivity estimation

Our main production function estimation strategy follows the two-stage estimation routine in Gandhi, Navarro, and Rivers (2020) (GNR, henceforth), augmented to control for differences in output quality (De Loecker et al., 2016), and extended by allowing productivity to evolve according to a controlled Markov process in which firm investments in innovation (R&D and employee training) affect future productivity growth. We also modify the procedure to control for differences in market power in the product market following an approach similar to that used in Blum et al. (2024). We outline here the basic steps of the procedure, as well as our modifications, and refer the reader to GNR for additional details regarding the standard GNR approach.

B.2.1 Quantity production function estimation and TFPQ

We first discuss the quantity production function (in logs) that relates observed output measured in quantities to inputs:

$$q_{jt} = f(k_{jt}, l_{jt}, m_{jt}; \gamma) + \underbrace{\omega_{jt} + \epsilon_{jt}}_{\ln TFPQ_{jt}} \tag{A.1}$$

where k, l, m, are capital, labor, and intermediate inputs (materials, third-party services, and energy consumption) used by the firm to produce (log) quantities q. ω_{jt} is a persistent productivity shock that is observable by the firm when it makes production decisions, and unobserved by the econometrician. ϵ_{jt} represents non-persistent shocks that are not observable (or predictable) by firms before making their input decisions at t. Physical productivity, TFPQ, is defined as the sum of these two shocks and therefore can be formed as:

$$\ln TFPQ_{jt} = q_{jt} - f(k_{jt}, l_{jt}, m_{jt}; \gamma).$$

Estimation routine. We assume that productivity evolves following a controlled first-order Markov process. Specifically, as in Ericson and Pakes (1995) and Doraszelski and Jaumandreu (2013), the distribution of productivity in period t is allowed to depend on past expenditures on innovation as well as past realizations of productivity:

$$P_\omega(\omega_{jt} \mid \mathcal{I}_{jt-1}) = P_\omega(\omega_{jt} \mid \omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}),$$

where $\mathcal{I}_{jt}$ denotes the firm's information set in period t and the vector $\boldsymbol{Z}_j$ includes firm j's investment rate in R&D, a dummy indicating any R&D expense, and training expenses per employee.[34] This implies that we can write $\omega_{jt} = h(\omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}) + \xi_{jt}$, where $h(\omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}) = \mathbb{E}\left[\omega_{jt} \mid \omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}\right]$ and ξ_{jt} is an unanticipated productivity "innovation" such that $\mathbb{E}\left[\xi_{jt} \mid \mathcal{I}_{jt-1}\right] = 0$. ϵ_{jt} is an unanticipated shock to output that is assumed to be independent of the firm's information set in period t. Capital and labor are assumed to pre-determined, i.e., k_{jt} and l_{jt} are assumed to be in the firm's information set in period t. Intermediate inputs are flexibly chosen in period t.

The estimation routine for TFPQ consists of two steps. The first step of the estimation strategy in GNR is based on a transformation of the firm's first-order condition for intermediate inputs, which relates observed input shares for intermediate inputs to the elasticity of output for intermediate inputs. The baseline specification in GNR assumes firms are perfectly competitive in the product market. In order to allow for imperfect competition, we modify the first stage of GNR following the approach in Blum et al. (2024). The first step of GNR shows that under perfect competition the output elasticity of intermediate inputs, $\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})$, can be recovered by regressing the shares of intermediate inputs on input levels:

$$s_{jt} = \ln\left(\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})\right) - \epsilon_{jt} \tag{A.2}$$

where $s_{jt} \equiv \frac{P_t^M M_{jt}}{R_{jt}}$ are the intermediate input shares, and P_t^M is the price of intermediates.[35]

Blum et al. (2024) show that under imperfect competition, this generalizes to

$$s_{jt} = \ln\left(\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})\right) - \ln \mu_{jt} - \epsilon_{jt}, \tag{A.3}$$

where μ_{jt} is the markup charged by firm j in period t. They further show that one can express the equilibrium markup as a function of the elasticity of demand at the optimum. Here we assume that the quantity demanded can be written as a function of price P_{jt}, demand shifters z_{jt}, and a multiplicative demand shock χ_{jt}^e: $Q_{jt} = Q(P_{jt}, z_{jt})\chi_{jt}^e$. As a result, the demand elasticity $\left(\frac{\partial Q_{jt}}{\partial P_{jt}} \frac{P_{jt}}{Q_{jt}}\right)$ will generically be a function of (P_{jt}, z_{jt}). Thus equation (A.3) can be re-written as:

$$s_{jt} = \ln\left(\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})\right) - \ln \mu(P_{jt}, z_{jt}) - \epsilon_{jt}. \tag{A.4}$$

To estimate this equation, we regress the intermediate input shares, s_{jt}, on a polynomial of $(k_{jt}, l_{jt}, m_{jt}, P_{jt}, z_{jt})$. The residual of this regression is $-\epsilon_{jt}$, which is used in the second stage

[34] Since an important result in our paper is that firm investments in innovation drive productivity growth, we allow the process for productivity to depend on these investments for internal consistency. However, productivity estimates derived from assuming an exogenous Markov process, in which these investment do not enter, yield similar quantitative results.

[35] GNR also includes in equation (A.2) a constant term $\ln(\mathcal{E}) = \ln(E[e^{\epsilon_{jt}}])$. For simplicity and since Gandhi, Navarro, and Rivers (2020) notes that this term is close to zero in practice, we abstract away from this.

of the estimation procedure.

The second step of the estimation procedure recovers the production function and productivity. In contrast to the standard GNR procedure, since the output elasticity of intermediate inputs is no longer recovered in the first stage, it is recovered in the second stage, along with the rest of the production function.

Define output net of the ex-post shock ϵ_{jt} as

$$\mathcal{Q}_{jt} \equiv q_{jt} - \epsilon_{jt} = f(k_{jt}, l_{jt}, m_{jt}) + \omega_{jt} \tag{A.5}$$

where $\mathcal{Q}_{jt}$ is an "observable term" that can be recovered from the estimates in step 1.

Exploiting the Markovian property of ω_{jt}, equation (A.5) can be re-written as:

$$\mathcal{Q}_{jt} = \underbrace{h\left(\mathcal{Q}_{jt-1} - f(k_{jt-1}, l_{jt-1}, m_{jt-1})\right)}_{h(\omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2})} + f(k_{jt}, l_{jt}, m_{jt}) + \xi_{jt}.$$

We model $f(k_{jt}, l_{jt}, m_{jt})$ and $h(\omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2})$ as:

$$\begin{aligned} f(k_{jt}, l_{jt}, m_{jt}) = \quad & \gamma_k k_{jt} + \gamma_l l_{jt} + \gamma_k k_{jt} + \gamma_{kk} k_{jt}^2 + \gamma_{ll} l_{jt}^2 + \gamma_{mm} m_{jt}^2 \\ & + \gamma_{kl} k_{jt} l_{jt} + \gamma_{km} k_{jt} m_{jt} + \gamma_{lm} l_{jt} m_{jt}, \end{aligned} \tag{A.6}$$

$$h(\omega_{jt-1}) = \sum_{0<a\leq 3} \psi_a \omega_{jt-1}^a + \varphi_{b_1} \boldsymbol{Z}_{jt-1} + \varphi_{b_2} \boldsymbol{Z}_{jt-2}. \tag{A.7}$$

Combining equations (A.6) and (A.7), we construct the following recursive estimation equation:

$$\begin{aligned} \mathcal{Q}_{jt} \quad = \quad & f(k_{jt}, l_{jt}, m_{jt}; \gamma) + \sum_{0<a\leq 3} \psi_a \left(\mathcal{Q}_{jt-1}(\psi, \gamma) - f(k_{jt-1}, l_{jt-1}, m_{jt-1}; \gamma)\right)^a \\ & + \varphi_{b_1} \boldsymbol{Z}_{jt-1} + \varphi_{b_2} \boldsymbol{Z}_{jt-2} + \xi_{jt} \end{aligned} \tag{A.8}$$

and identify the vector of coefficients (ψ, φ, γ). Because $(k_{jt}, l_{jt}, \mathcal{Q}_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}) \in \mathcal{I}_{jt-1}$, and are thus orthogonal to ξ_{jt}, they can be used as instruments for themselves. However, since m_{jt} is chosen in period t it is correlated with ξ_{jt}. Therefore we use m_{jt-1} as an instrument and use the following moment conditions:

$$\begin{aligned} \mathbb{E}[\xi_{jt} \cdot k_{jt}^{\tau_k} l_{jt}^{\tau_l} m_{jt-1}^{\tau_m}] = 0 \qquad & \mathbb{E}[\xi_{jt} \cdot \mathcal{Q}_{jt-1}^a] = 0 \\ \mathbb{E}[\xi_{jt} \cdot \boldsymbol{Z}_{jt-1}] = 0 \qquad & \mathbb{E}[\xi_{jt} \cdot \boldsymbol{Z}_{jt-2}] = 0 \end{aligned}$$

where $0 < \tau_k + \tau_l + \tau_m \leq 2$, and $\tau_k, \tau_l, \tau_m \geq 0$.

Controlling for input price bias in quantity production functions. In a typical production function estimation, data on physical quantities of output and inputs are often not available and instead are measured as values (revenues for output and expenditures for inputs) that are deflated by common aggregate (often industry-level) deflators. Previous work has shown that this can lead to biased estimates of the production function and productivity (Katayama, Lu, and Tybout, 2009).

Table A.2: Production function estimates

Industry Code (NACE Rev. 1.1)	Output elasticities: Quantity-based Labor	Int. Inputs	Capital	Revenue-based Labor	Int. Inputs	Capital
15	0.178	0.779	0.058	0.233	0.736	0.043
17	0.255	0.694	0.052	0.310	0.685	0.022
18	0.280	0.674	0.047	0.355	0.642	0.040
20	0.213	0.731	0.054	0.257	0.698	0.042
21	0.203	0.719	0.081	0.259	0.693	0.052
22	0.207	0.761	0.022	0.269	0.709	0.015
24	0.188	0.747	0.076	0.255	0.714	0.043
25	0.195	0.756	0.054	0.263	0.694	0.052
26	0.204	0.725	0.077	0.269	0.681	0.053
27	0.241	0.738	0.083	0.236	0.724	0.041
28	0.269	0.662	0.071	0.328	0.627	0.042
29	0.273	0.684	0.049	0.330	0.640	0.033
31	0.281	0.684	0.052	0.329	0.640	0.045
32	0.170	0.757	0.094	0.399	0.625	0.073
33	0.242	0.701	0.035	0.328	0.630	0.031
36	0.236	0.716	0.053	0.307	0.665	0.033

Notes: This table reports the within industry average production function elasticities estimated using the approach described above. The first three columns report the estimates obtained from the quantity production function estimation. The last three columns report the estimates obtained from the revenue production function estimation.

Under some conditions, these biases cancel out (see De Loecker and Goldberg, 2014). However, when output is measured in quantities, and inputs are measured as expenditures (as in our data), the biases no longer cancel out. To deal with this, we follow the approach in De Loecker et al. (2016), which suggests using a control function of (output) prices and market shares to correct for the bias.

In practice, for the quantity-based production function estimation, we augment the production function with a control function in prices and market shares. That is, we replace $f(k_{jt}, l_{jt}, m_{jt})$ with $f(k_{jt}, l_{jt}, m_{jt}) - cf(P_{jt}, ms_{jt})$ in equation (A.8):

$$\begin{aligned} Q_{jt} = \; & f(k_{jt}, l_{jt}, m_{jt}; \gamma) - cf(P_{jt}, ms_{jt}; \phi) \\ & + \textstyle\sum_{0<a\leq 3} \psi_a \left(Q_{jt-1} - f(k_{jt-1}, l_{jt-1}, m_{jt-1}; \gamma) + cf(P_{jt-1}, ms_{jt-1}; \phi)\right)^a \\ & + \varphi_{b_1} \boldsymbol{Z}_{jt-1} + \varphi_{b_2} \boldsymbol{Z}_{jt-2} + \xi_{jt} \end{aligned} \tag{A.9}$$

where we also approximate $cf(\cdot)$ with a polynomial in price and market shares. Accordingly, we add moments interacting ξ_{jt} and the terms of the polynomial approximation to estimate the parameters (ϕ) of $cf(\cdot)$. The remaining steps of the estimation procedure are unchanged.

B.2.2 Revenue production function estimation and TFPR

As discussed in the main text, we construct a standard revenue productivity measure, computed as the residual of a revenue production function relating output, measured in revenues, to inputs:

$$r_{jt} = f(k_{jt}, l_{jt}, m_{jt}; \tilde{\gamma}) + \underbrace{\tilde{\omega}_{jt} + \tilde{\epsilon}_{jt}}_{\ln TFPR_{jt}}, \tag{A.10}$$

where we use $\tilde{\gamma}$, $\tilde{\omega}$, and $\tilde{\epsilon}$ to distinguish these objects from those of the quantity-based production function.

To recover TFPR, in order to make our results comparable to the literature, we follow a more standard approach of estimating the production function using Gandhi, Navarro, and Rivers (2020), augmented to allow for $\tilde{\omega}$ to follow a controlled Markov process following equation (A.7) above.

B.3 Estimation results

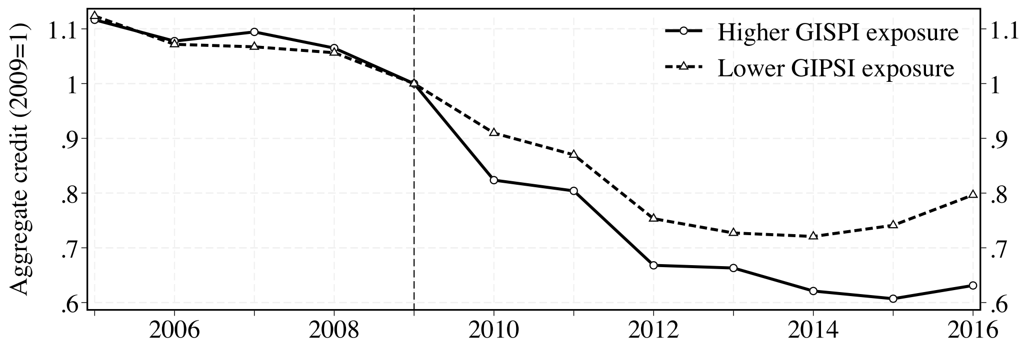
We perform the production function estimation separately for each 2-digit industry for both the quantity-based and revenue-based specifications (equations (A.1) and (A.10)). In Table A.2, we report the average elasticity estimates for each industry. For both the quantity and revenue versions, the elasticity estimates are sensible, highlighting roughly constant returns to scale, on average, across industries.

C The pass-through of the sovereign shock to credit supply

C.1 The burst of the European sovereign debt crisis

After the parliamentary elections held in Greece in October 2009, the newly elected government acknowledged significant budget misreporting in previous years and a larger-than-expected fiscal deficit, which forced the Greek government to request, on April 23, 2010, an EU/IMF bailout package to cover its financial needs for the remainder of the year. In response to these events, international rating agencies downgraded Greece's sovereign debt rating to "junk bond" and the yields on Greek government bonds rose sharply, effectively barring the country's access to capital markets (Lane, 2012).

Figure A.1: Aggregate credit



Notes: This figure displays the time-series evolution of the aggregate credit provided by banks with above versus below median exposure to the sovereign crisis in the last quarter before the Greek bailout request (2010:Q1). Exposure to the sovereign crisis is based on residual holdings of GIPSI sovereigns. Both series are normalized by their 2009 level.

Shortly after the events in Greece, investors became concerned with the solvency and liquidity of the public debt issued by other peripheral European countries, starting with Ireland and Portugal, and soon after Spain and Italy (Angelini, Grande, and Panetta, 2014). The yield spread with Germany, which had been low and relatively stable for most Euro-zone countries since the introduction of the euro, significantly increased following news from Greece and the subsequent bailout at the end of the first quarter of 2010.

Investigating the channels of transmission of the financial shock to bank lending activity, Bottero, Lenzu, and Mezzanotti (2020) documents that the sovereign shock affected banks' lending because it unexpectedly increased the riskiness of bank assets, forcing financial intermediaries with low capital buffers to adjust the riskiness of their assets, and also impaired the ability to pledge these securities as collateral in interbank transactions, which is a crucial funding source for many banks.

The balance sheet shock had important credit supply implications. Figure A.1 plots the aggregate credit supplied to the firms in our dataset by financial intermediaries with above versus below median exposure to the sovereign crisis.[36] It shows that, right after the burst of the crisis, the amount of credit provided by the two groups of banks started diverging relative to the pre-shock period.

[36]To produce the figure, we first sorted banks into a "Higher GIPSI exposure" group and a "Lower GIPSI exposure" group based on whether their pre-shock holdings of GIPSI sovereigns (residualized by bank characteristics) were above or below the median. Then, we aggregated the total corporate loans granted by "Higher GIPSI exposure" and those granted by "Lower GIPSI exposure" banks, and plotted the two series over time, normalizing them by their 2009 level.

Table A.3: Exposure to the sovereign shock and credit market outcomes

	Δ_τCredit (1)			$\Delta_\tau fc$ (2)		Δ_τTerm loans (3)		Δ_τCredit lines (4)	
	Pre		Post	Pre	Post	Pre	Post	Pre	Post
$\hat{\beta}_{-3}$	0.016	$\hat{\beta}_1$	-0.150***	-0.006	0.006	-0.022	-0.116**	-0.215*	-0.204*
	(0.047)		(0.036)	(0.007)	(0.006)	(0.052)	(0.053)	(0.124)	(0.112)
$\hat{\beta}_{-2}$	0.056	$\hat{\beta}_2$	-0.094**	0.002	0.016	-0.007	-0.180*	-0.490***	-0.412***
	(0.043)		(0.039)	(0.008)	(0.010)	(0.038)	(0.092)	(0.108)	(0.105)
$\hat{\beta}_{-1}$	0.044	$\hat{\beta}_3$	-0.18***	0.004	0.034**	-0.012	-0.159**	-0.239***	-0.439***
	(0.036)		(0.057)	(0.009)	(0.015)	(0.035)	(0.074)	(0.099)	(0.104)
		$\hat{\beta}_4$	-0.151**		0.023**		-0.159*		-0.378***
			(0.068)		(0.010)		(0.079)		(0.124)
		$\hat{\beta}_5$	-0.035		0.024**		-0.050		-0.366***
			(0.059)		(0.011)		(0.099)		(0.104)
		$\hat{\beta}_6$	0.047		-0.005		-0.013		-0.098
			(0.051)		(0.010)		(0.096)		(0.166)
		$\hat{\beta}_7$	0.024		-0.003		-0.062		-0.007
			(0.085)		(0.006)		(0.118)		(0.158)

Notes: This table accompanies Figure 1. It reports the estimates of the effect of the credit supply shock on the cumulative growth rate of firm-level credit (column (1)) and the change in the average financing costs (column (2)) using model (3). Columns (3) and (4) study the individual effect of the credit shock on the two main categories of bank credit, term loans and revolving credit lines, respectively. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

C.2 The effect of banks' sovereign holdings on firm-level credit supply

Table A.3 reports the estimated cumulative effect of the bank balance sheet shock on the firm-level growth rate of bank credit (column (1)) and the firm-level change in financing costs (column (2)). Figure 1 in the paper graphs the coefficients and associated confidence intervals. In addition to the pre-trend check discussed in the main body of the paper, we perform a series of robustness analyses to test the validity of our identification strategy, which we discuss below.

Credit types. Columns (3) and (4) look at the components of bank credit, studying the individual effect of the shock on the growth rate of term loans and revolving credit lines. Both types of credit are used by firms to finance their production activity as well as their innovation expenses. We find that both types of credit are affected by the credit shock, although the effect of a one-standard deviation exposure to the shock is both larger (approximately 3 times as large) and more persistent for credit lines. To put these numbers in perspective, it is important to consider that, on average, a much larger amount of bank debt is held in term form of term loans (approximately 2.5 as larger, or 70 percent of firm's credit balance). Thus, the contribution of the contraction of the two types of credit on the total credit tightening is quantitatively similar, on average. Note also that the negative coefficients on credit lines in the pre-period indicate that, if anything, the firms most affected by the shock in the post-period were growing faster (higher credit demand/supply) before the credit crunch.

Within-firm estimator. We present additional analysis that supports the identification assumption that the drop in credit observed in the data is explained by a sudden tightening of credit *supply* rather than driven by demand-side factors. In particular, we address the potential concern that the coefficients are picking up a shift in firms' credit demand or a change in borrower's credit worthiness that takes place at the same time as the credit shock. To do so, we leverage the micro-data containing information on individual firm-bank relationships. Because the vast majority of the firms engage in multiple lending relationships at the same time, we can augment model (3) with firm fixed effects (i_j) and test whether banks with larger GIPSI holdings reduced their credit supply to the *same firm* relative to banks with lower holdings. By exploiting variation across lenders to the same firm, this within-firm estimator allows us to control for changes in unobservable firm-specific factors, such as a simultaneous contraction of credit demand or a worsening of firms' credit worthiness. Specifically, we estimate the following model at different horizons indexed by τ:

$$\Delta_\tau \text{Credit}_{jb} = \beta_\tau \cdot \text{GIPSI Sovereigns}_{jb} + \Gamma'_{K,\tau}\mathbf{K}_{jb} + \Gamma'_{X,\tau}\mathbf{X}_{jb} + i_{j,\tau} + u_{jb\tau}, \tag{A.11}$$

where now the left-hand-side is the cumulative growth rate of credit to firm j that is provided by bank b, as opposed to the total credit summed across all banks.[37] In this case, the right-hand-side variable of interest is the interaction between bank b's holdings of sovereign securities issued by GIPSI countries scaled by bank b's risk-weighted assets before the Greek bailout (GIPSI Sovereigns$_{jb}$). As we did in our main firm-level specification in Section 3 (model (3)), we condition on a set of bank-level controls ($\mathbf{K}_{jb}$), which are now measured at the individual bank level, as well as two relationship-level controls ($\mathbf{X}_{jb}$)—the length of the lending relationship between firm j and lender b and the share of credit provided by lender b in firm j total credit—all measured before the burst of the crisis. Finally, note that the industry and region fixed effects in model (3) are subsumed here by the firm fixed effects. As in our firm-level specification, we de-mean and scale the variable of interest (GIPSI Sovereigns$_{jb}$) by its standard deviation so that the coefficients β_τ in (A.11) capture the effect of a one standard deviation difference in exposure to the credit shock on the $\tau-$year cumulative growth rate of credit to firm j from lender b.

[37]In the construction of credit growth rates at the relationship level, we account for bank M&A by adopting the standard correction that identifies bank acquisitions over pairs of consecutive years and treats the acquired and acquiring bank as a single entity over that span (Bernanke, Lown, and Friedman, 1991).

Table A.4: Response of growth rate of credit to credit supply shocks: Within-firm estimation

	Total growth ($\Delta_\tau \text{Credit}_{jb}$)		Extensive margin ($\text{Cut}_{jb\tau}$)		Intensive margin ($\Delta_\tau \ln\text{Credit}_{jb}$)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_1$	-0.259***	-0.284***	0.090***	0.087***	-0.100***	-0.115***
	(0.035)	(0.047)	(0.025)	(0.014)	(0.022)	(0.036)
	0.489	*0.083*	*0.456*	*0.056*	*0.449*	*0.050*
$\hat{\beta}_2$	-0.206***	-0.213***	0.054*	0.049	-0.180***	-0.168***
	(0.047)	(0.074)	(0.029)	(0.029)	(0.050)	(0.028)
	0.487	*0.049*	*0.491*	*0.055*	*0.473*	*0.034*
$\hat{\beta}_3$	-0.177*	-0.182**	-0.004	0.015	-0.411***	-0.319***
	(0.085)	(0.078)	(0.031)	(0.032)	(0.115)	(0.059)
	0.525	*0.024*	*0.487*	*0.044*	*0.555*	*0.037*
$\hat{\beta}_4$	-0.147*	-0.215***	-0.005	0.005	-0.507***	-0.566***
	(0.083)	(0.069)	(0.032)	(0.044)	(0.081)	(0.070)
	0.528	*0.030*	*0.544*	*0.049*	*0.554*	*0.045*
$\hat{\beta}_5$	-0.198*	-0.249***	0.017	0.046	-0.563***	-0.562***
	(0.105)	(0.069)	(0.046)	(0.045)	(0.149)	(0.095)
	0.529	*0.035*	*0.534*	*0.064*	*0.606*	*0.048*
$\hat{\beta}_6$	-0.264*	-0.310***	0.034	0.042	-0.657***	-0.749***
	(0.125)	(0.090)	(0.051)	(0.050)	(0.152)	(0.086)
	0.519	*0.040*	*0.530*	*0.077*	*0.576*	*0.050*
$\hat{\beta}_7$	-0.337***	-0.396***	0.036	0.075*	-0.794***	-0.943***
	(0.110)	(0.074)	(0.042)	(0.036)	(0.126)	(0.064)
	0.523	*0.051*	*0.524*	*0.080*	*0.564*	*0.071*
Firm FE	Y	N	Y	N	Y	N

Notes: This table reports estimates of the effect of the credit supply shock on credit growth at the firm-bank relationship-level using model (A.11). We report estimates for overall credit growth as well as the extensive and intensive margin separately, both with and without firm fixed effects. Standard errors are clustered at the lender-level and are reported in parentheses. R^2 are reported in italics. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table A.4, column (1), presents the estimation results. The estimates show that among banks lending to the *same* firm, those that were more exposed to the shock (i.e., had larger holdings of GIPSI sovereigns) decreased their lending to that firm relative to less exposed banks, providing strong evidence that the credit contraction was supply-driven. In column (2), we repeat the relationship-level regression, but omitting the firm fixed effects. Importantly, while the estimated coefficients are largely unaffected by whether we include firm-fixed effects, the R^2 of the regressions increase significantly (by about an order of magnitude) when fixed effects are included. In the spirit of Oster (2019), this observation demonstrates that while unobserved firm-specific factors (e.g., changes in credit demand) are important for explaining the overall variation in bank lending to firms, that variation is not correlated with exposure to the shock.

Table A.4 also highlights that the contraction in credit supply is evident along both the intensive and extensive margins. For the extensive margin, we define the variable $\text{Cut}_{jb\tau}$ as an indicator variable for whether a lending relationship that existed between firm j and bank b before the sovereign crisis is still in place τ-years after the shock, with a 1 indicating the relationship is no longer in place. We also calculate the percentage change in credit balances between firm j and bank b for relationships that are in place both before the shock and τ-years after the shock ($\Delta_\tau \text{lnCredit}_{jb}$). Columns (3) and (4) show that banks more exposed to the shock are more likely to break existing lending relationships. Columns (5) and (6) show that banks also reduce their credit supply in surviving relationships. As was the case for the overall credit results, including firm fixed effects increases the R^2 but has little effect on the coefficients.

Finally, we note that the contraction in credit at the firm-bank level persists throughout our sample period, whereas the contraction in credit at the firm level (Figure 1 and Table A.3) was transitory. Together, these results suggest that over time firms were gradually able to compensate for the contraction in credit supply by their most exposed pre-shock lenders by establishing new lending relationships with other financial intermediaries.

Response of investments and employment. We analyze the real effects of financial shocks on firms' input demands. Prior studies have documented a contraction in investments and employment following a credit tightening (e.g., Chodorow-Reich, 2014, Cingano et al., 2016, and Bottero et al., 2020). Table A.5 shows that this is also the case in our setting. Column (1) shows the effect of the financial shock on the (cumulative) investment rate of machinery and equipment. Consistent with the presence of capital adjustment costs, we find a persistent contraction in investment.

Column (2) shows the effect of the financial shock on the cumulative growth rate of employment. A one-standard deviation exposure to the shock leads to a contraction of 3.1 percent contraction in employment in the immediate aftermath of the shock, relative to a less exposed firm. Columns (3) and (4) further break down the employment response into two categories of workers: full-time and part-time employees. While both categories are impacted by the shock, we find that part-time employed workers experience a much larger (about 2.5 times larger, on impact) and persistent contraction relative to full-time workers. We interpret these results as consistent with the idea that full-time workers are 'more essential'—having longer tenure and more firm-specific human capital—and thus are less affected by the credit shock than part-time workers. Finally, in column (5), we find no evidence that firms reduced wages in response to the shock. If anything, we observe that the impact of the shock has a small positive effect on average labor compensations in the medium-to-long run. We speculate that this is driven by a change in

Table A.5: Response of investment and employment

	Inv. rate M&E (1)	Employees (Total) (2)	Employees (Full-time) (3)	Employees (Part-time) (4)	Average labor compensation (5)
$\hat{\beta}_1$	-0.026***	-0.031***	-0.028***	-0.067**	0.002
	(0.007)	(0.007)	(0.005)	(0.028)	(0.007)
$\hat{\beta}_2$	-0.041***	-0.018	-0.011	-0.124***	0.010
	(0.014)	(0.013)	(0.010)	(0.039)	(0.009)
$\hat{\beta}_3$	-0.059***	-0.013	-0.003	-0.056	0.011
	(0.014)	(0.012)	(0.011)	(0.042)	(0.006)
$\hat{\beta}_4$	-0.073***	-0.017	-0.0078	-0.096*	0.019**
	(0.015)	(0.019)	(0.020)	(0.0467)	(0.007)
$\hat{\beta}_5$	-0.048**	-0.0112	-0.004	-0.144***	0.016**
	(0.022)	(0.012)	(0.012)	(0.0543)	(0.007)
$\hat{\beta}_6$	-0.016	0.007	0.024	-0.0850*	0.021**
	(0.032)	(0.015)	(0.015)	(0.039)	(0.008)
$\hat{\beta}_7$	-0.010	0.018	0.032**	-0.052	0.006
	(0.037)	(0.016)	(0.015)	(0.045)	(0.009)

Notes: This table reports the estimates of the effect of the credit supply shock on investments in machinery and equipment (M&E) and different measures of employment and labor compensation using the model in (3). In column (1), the dependent variable is the cumulative investment rate on machinery and equipment between the end of fiscal year 2009 and the end of fiscal year 2009 + τ ($\tau = \{1, ..., 7\}$), scaled by the book value of these assets in 2009. In columns (2)–(4), the dependent variable is the growth rate of total employment, full-time workers' employment, and part-time workers' employment, respectively. In column (5), the dependent variable is the growth rate of the average compensations (measured as the total wage bill over total employment). Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

the composition of the workforce, e.g., as firms lay off part-time workers, who tend to be paid lower wages and lower benefits.

D Effect of the shock on productivity and prices

Baseline productivity and price estimates. Table A.6 reports the estimated cumulative effect of the credit supply shock on firm-level productivity and prices that are presented in the main body in Figure 2. Table A.7 presents a series of robustness checks, which we discuss below.

Table A.6: Response of productivity and prices to negative credit supply shocks

	$\Delta_\tau \ln TFPR$	$\Delta_\tau \ln TFPQ$	$\Delta_\tau \ln P$
	(1)	(2)	(3)
$\hat{\beta}_1$	-0.014***	-0.003	-0.019**
	(0.004)	(0.008)	(0.008)
$\hat{\beta}_2$	-0.020***	-0.019	-0.005
	(0.007)	(0.014)	(0.010)
$\hat{\beta}_3$	-0.015*	-0.046***	0.035***
	(0.007)	(0.016)	(0.013)
$\hat{\beta}_4$	-0.030***	-0.076***	0.035**
	(0.007)	(0.021)	(0.014)
$\hat{\beta}_5$	-0.020**	-0.069***	0.040*
	(0.009)	(0.023)	(0.019)
$\hat{\beta}_6$	-0.021*	-0.062***	0.026
	(0.010)	(0.019)	(0.021)
$\hat{\beta}_7$	-0.031***	-0.064***	0.012
	(0.011)	(0.016)	(0.016)

Notes: This table reports the estimates of the effect of the credit supply shock on the cumulative growth rate of TFPR, TFPQ, and prices estimated using model (3). Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

D.1 Robustness analysis

Alternative productivity measures. In the baseline regressions reported in the paper, we estimate the measures of firm-level productivity as residuals from revenue or quantity production functions, modeling firms' production technologies using a Translog functional form (see Section 2.2 in the paper and Appendix B.2). We test the robustness of our results regarding the effect of financial shocks on productivity to alternative measures of productivity. In column (1) of Table A.7, we repeat the quantity production function estimation assuming a less flexible but more traditional Cobb-Douglas functional form. In column (2), instead of estimating the production function parameters, we calibrate input elasticities to the average revenue shares within each industry (index function approach).

In the presence of borrowing constraints (e.g., if the firm faces some working-capital constraints) the firm's first-order condition for intermediate inputs might not hold with equality, possibly leading to biased estimates in the first stage of our production function estimation procedure (equation (A.4)). As a first pass to address this concern, we performed the production function estimation prior to 2008 (thus excluding both the global financial crisis and the sovereign debt crisis from the estimation sample). To further tackle this concern, we develop an alternative production function estimation procedure that allows for the possibility that working capital constraints might distort the first-order condition of intermediate inputs. Specifically, in the spirit of the exercise in Manaresi and Pierri (2024), we augmented the first stage of the estimation to include a firm-specific credit supply shifter to capture wedges generated by financial frictions. The firm-specific credit supply shifter is a Bartik-style shifter computed following the method in Amiti and Weinstein (2018), which is designed to measure the impact of changes in bank credit supply on firms that is independent of the borrowers' characteristics and overall credit demand. We use these alternative estimates to construct an alternative productivity index and re-estimate our baseline regression. The results are presented in column (3). Reassuringly, the estimated coefficients are essentially unchanged in terms of both point estimates and statistical precision.

Capacity utilization. We study whether firms adjust their capacity utilization in response to the financial shock. To do so, we collect data on capacity utilization from a supplementary data source, the Business Survey administered by the National Bank of Belgium. The survey covers a subset of firms in our sample, asking them to report the percentage of their production capacity utilized.

After matching the Business Survey to our final regression sample, we are able to gather information on capacity utilization for 348 firms. In this sub-sample, firms operate (on average) with a seventy-two percent production capacity utilization before the crisis (year 2009). This figure increases to seventy-seven percent by the end of our sample (year 2016). We explore in this subsample how adjustments in capacity utilization might affect the interpretation of our baseline productivity results.

We estimate our local linear projection looking at the effect of the shock on the (cumulative) percentage change in capacity utilization. The results are reported in columns (4) of Table A.7. We find no significant effect on capacity utilization in the short run: the coefficient estimates are economically small and, at best, marginally significant. In the medium-to-long run we find larger point estimates, although mostly insignificant. These results suggest that if anything the financial shock leads to a small increase in capacity utilization.

Alternative price measures. As explained in the paper, when constructing a firm-level price index, one needs to take a stance on how to aggregate the prices across the heterogeneous products produced by a firm. We did so building a conventional Törnqvist index, which computes a sales-weighted geometric average of the price changes across continuing products in a firm's portfolio. Here we show that the estimated contraction and subsequent rebound of output prices following a negative credit supply shock is also evident when one uses alternative measures of firm-level prices. First, we construct a price index that averages across 8-digit product price levels,

Table A.7: Response of productivity and prices to negative credit supply shocks: Robustness

	$\Delta_\tau \ln TFPQ$ Cobb-Douglas	$\Delta_\tau \ln TFPQ$ Index func.	$\Delta_\tau \ln TFPQ$ Fin. frictions	Capacity utilization	$\Delta_\tau \ln P$ Main	$\Delta_\tau \ln P$ Revenue	$\Delta_\tau \ln TFPQ$ Single product	$\Delta_\tau \ln P$	$\Delta_\tau \ln TFPQ$ Balanced sample	$\Delta_\tau \ln P$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\hat{\beta}_1$	0.003	0.003	-0.003	-0.010	-0.030***	-0.024**	0.004	-0.018	-0.002	-0.019*
	(0.009)	(0.008)	(0.008)	(0.018)	(0.009)	(0.011)	(0.015)	(0.036)	(0.010)	(0.009)
$\hat{\beta}_2$	-0.014	-0.012	-0.019	-0.015	-0.018	0.008	-0.038	0.010	-0.005	-0.014
	(0.014)	(0.014)	(0.014)	(0.021)	(0.021)	(0.016)	(0.030)	(0.012)	(0.013)	(0.009)
$\hat{\beta}_3$	-0.049***	-0.050***	-0.046***	0.036	0.043*	0.050***	-0.048	0.026	-0.037***	0.010
	(0.016)	(0.017)	(0.016)	(0.029)	(0.022)	(0.016)	(0.034)	(0.020)	(0.013)	(0.009)
$\hat{\beta}_4$	-0.075***	-0.075***	-0.076***	0.051*	0.048*	0.047***	-0.054	0.0410	-0.046***	0.012
	(0.020)	(0.020)	(0.021)	(0.029)	(0.0243)	(0.015)	(0.031)	(0.024)	(0.014)	(0.011)
$\hat{\beta}_5$	-0.060***	-0.057***	-0.067***	0.043	0.072***	0.039*	-0.049	0.060	-0.055***	0.023
	(0.022)	(0.022)	(0.023)	(0.025)	(0.022)	(0.021)	(0.032)	(0.039)	(0.016)	(0.017)
$\hat{\beta}_6$	-0.048***	-0.045***	-0.057***	0.072**	0.046	0.040	-0.059	0.0442	-0.046***	0.015
	(0.017)	(0.017)	(0.018)	(0.028)	(0.031)	(0.026)	(0.037)	(0.0443)	(0.016)	(0.019)
$\hat{\beta}_7$	-0.052***	-0.053***	-0.058***	0.058*	0.097***	0.055***	-0.043	0.016	-0.056***	0.006
	(0.015)	(0.015)	(0.016)	(0.027)	(0.016)	(0.017)	(0.028)	(0.024)	(0.016)	(0.016)

Notes: This table reports the estimates of the effect of the credit supply shock on alternative measures of TFPQ and prices as well as a measure of capacity utilization. All regressions are estimated using model (3). Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

weighting them by their revenue-share. We then compute the price change in the firm-level price as the delta-log: $\Delta_\tau \ln P_j^{Rev} = \ln(\sum_{p \in \mathcal{P}_{j\tau}} s_{jp\tau} P_{jp\tau}) - \ln(\sum_{p \in \mathcal{P}_{j2009}} s_{jp2009} P_{jp2009})$. As before, $P_{jp\tau}$ is the unit value of product p in $\mathcal{P}_{j\tau}$, and $s_{jp\tau}$ is the sales share of product p in $\mathcal{P}_{j\tau}$. Second, we study the change in the price of the main product of the firm (defined as the product with the highest revenue share), without taking a stance on aggregation across different products. The estimation results, reported in columns (5) and (6) of Table A.7, are largely in line with the estimates obtained using the Törnqvist price index.

Inventory adjustment and balanced sample. As discussed above, in order to perform the production function estimation we constructed a firm-level measure of output produced, Q_{jt}, adjusting firm-level revenues by the change in inventories. To do so, we deflated the total change in inventories (in euros) by our price index. To the extent that firms differentially reduce prices of different products depending on the product-specific inventory stock, this might generate biased results. To address this concern, we re-estimated our baseline regressions in the subsample of single-product firms (columns (7) and (8) of Table A.7), finding estimates that are quantitatively similar, although less precisely estimated due to the smaller sample size.[38]

Another concern is related to possible survival bias. About one-third of the firms in our regression sample in 2009–2010 are not in the regression sample by the end of our sample period. In Appendix A we discuss how this appears to be driven almost entirely by the sampling scheme adopted by PRODCOM and survey attrition in the response rate, rather than being the result of selection induced by the financial shock. As an additional robustness test against survival bias, columns (9) and (10) of Table A.7 show that the productivity and price estimates are essentially unchanged if we re-estimate our baseline regressions in the subsample of permanent firms.

E Model appendix

This section presents our quantitative model discussed in Section 6 in detail. We begin by discussing the problems of the agents in the model (households, firms, and banks) and the market clearing conditions that characterize the equilibrium of the model. We then provide additional details on the calibration of the parameters of interest.

[38] Approximately 40 percent (408 out of 1024) of the firms in our sample are classified as single-product firms, which is consistent with other studies showing the prevalence of multi-product firms in manufacturing.

E.1 Households

The economy is populated by a unit mass of households. The representative household chooses consumption (C_t^h), labor supply (N_t^h), and savings in the form of bank deposits (D_t^h) to maximize its inter-temporal utility:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} (\beta^h)^t [\ln(C_t^h) + \ln(1 - N_t^h)]$$

subject to the real flow-of-funds constraint, $C_t^h + D_t^h = w_t N_t^h + \mathcal{R}_{t-1} D_{t-1}^h$.

The consumption basket is a CES composite of differentiated goods produced by firms, $C_t^h = \left(\sum_{k=1}^{J} C_{kt}^{h\,\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}$, with elasticity of substitution equal to ϵ. We normalize the cost of the consumption basket (the price index of the economy) $P_t \equiv \left(\sum_{k=1}^{J} P_{kt}^{e\,(1-\epsilon)}\right)^{\frac{1}{(1-\epsilon)}} = 1$. Total deposits are the sum of deposits across multiple banks, $D_t^h = \sum_{j=1}^{J} D_{jt}^h$, paying a deposit rate $\mathcal{R}_t$ that is determined when deposits are made.

The household problem is characterized by standard optimality conditions. Defining the household's stochastic discount factor between period t and $t+1$ as $M_{t,t+1}^h := \beta^h \mathbb{E}_t \left(\frac{C_t^h}{C_{t+1}^h}\right)$, the household's problem is characterized by a standard Euler equation and labor supply condition:

$$\frac{1}{\mathcal{R}_t} = M_{t,t+1}^h; \qquad w_t \quad = \left(\frac{C_t^h}{1-N_t^h}\right).$$

Note that the first equation implies that, in steady state, the household risk-neutral discount rate pins down the deposit rate: $\mathcal{R} = \frac{1}{\beta^h}$. The total amount of deposits for the household, D_t^h, is pinned down by the household's budget constraint.

E.2 Firms

Firms are run by entrepreneurs that obtain loans from banks and produce heterogeneous goods that are used as investment goods by firms and as consumption goods by all consumers in the economy. Each entrepreneur maximizes its inter-temporal utility from consumption:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} (\beta^e)^t \ln(C_{jt}^e)$$

subject to the budget constraint:

$$C_{jt}^e + w_t(L_{jt}^e + O_{1jt}^e + O_{2jt}^e) + \iota_{jt}^e + \mathcal{AC}_{jt}^e \leq (B_{jt}^e - R_{jt} B_{jt-1}^e) + P_{jt}^e Y_{jt}^e.$$

The variables on the left-hand-side represent the entrepreneur's *uses of funds*. Consumption, C_{jt}^e, is a CES aggregator, as described above for households. The wage bill, $w_t(L_{jt}^e + O_{1jt}^e + O_{2jt}^e)$, captures the cost of hiring workers involved in production, L_{jt}^e, and in productivity-enhancing activities (research and adoption), O_{1jt}^e and O_{2jt}^e. The term $\iota_{jt}^e + \mathcal{AC}_{jt}^e$ captures capital expenditures in tangible assets (investments), inclusive of adjustment costs $\mathcal{AC}_{jt} := \frac{\Psi}{2}\left(\frac{K^e_{jt+1}}{K^e_{jt}} - 1\right)^2 K^e_{jt}$. The evolution of firm's tangible assets are subject to the the law of motion, $K^e_{jt+1} = (1-\delta_K)K^e_{jt} + \iota^e_{jt}$, where δ_K is the depreciation rate of capital.

The variables on the right-hand-side of the budget constraint represent the entrepreneur's *sources of finance*. These include sales, $P^e_{jt}Y^e_{jt}$, and net bank borrowing, $B^e_{jt} - R_{jt}B^e_{jt-1}$.

Production and inventory management. Given the CES preferences of consumers, each firm faces a residual demand curve $Y^e_{jt} = (P^e_{jt}/P_t)^{-\epsilon}Y_t$, where Y^e_{jt} denotes output sold and Y_t is aggregate demand. On the production side, we assume that output sold is composed of a continuum of parts $i \in [0,1]$, which are produced and assembled by the entrepreneur using the following technology:

$$Y^e_{jt} \equiv \left(\int_0^1 \theta_{jt}(i)\left(Y^e_{jt}(i)\right)^{\rho} di\right)^{1/\rho}.$$

Following Wen (2011) and Kim (2020), the variables $\theta_{jt}(i)$ denote part-specific idiosyncratic demand shocks, which are realized after the entrepreneur's input demand decisions have been made but before setting its price. We assume that the demand shocks $\theta(i)$ are i.i.d. draws from a Pareto distribution, with unitary scale parameter and shape parameter ξ.

At the beginning of each period t, after observing the realization of its productivity, the firm employs capital and labor to produce parts using a Cobb-Douglas technology:

$$\int_0^1 Q^e_{jt}(i)\, di \leq A^e_{jt}(L^e_{jt})^{\alpha_L}(K^e_{jt})^{\alpha_K},$$

where $Q^e_{jt}(i)$ denotes quantity produced and A^e_{jt} the firm's technical efficiency (TFPQ). Depending on the realization of the taste shock $\theta_{jt}(i)$, the firm decides how much of $Q^e_{jt}(i)$ to use for sales, $Y^e_{jt}(i)$, and how much to store as inventory, $I^e_{jt}(i)$. Thus the following equation links sales, production, and inventory dynamics for each part i:

$$Y^e_{jt}(i) \leq (1-\delta_I)I^e_{jt-1}(i) - I^e_{jt}(i) + Q^e_{jt}(i),$$

with $\delta_I \in [0,1)$ denoting the depreciation rate of the inventory stock.

Innovation and productivity. As in Comin and Gertler (2006), entrepreneurs invest to develop new technologies that replace obsolete ones. There is a continuum of divisions $z \in [0,1]$ within the firm. Each division hires researchers, O^e_{1jt}, who work on the development of intangible assets (knowledge), Z^e_{jt}, that evolve according to the following law of motion:

$$Z^e_{jt+1}(z) = \phi_A Z^e_{jt}(z) + \eta_1\left(O^e_{1jt}(z)\right)^{\kappa_1} \cdot \mathcal{Z}^e_{jt}, \tag{A.12}$$

where ϕ_A denotes the depreciation rate of the firm's knowledge and $\eta_1 \left(O_{1jt}(z)\right)^{\kappa_1}$ represents the investment in research and development for a given idea z, with parameters $\eta_1 > 0$ and $\kappa_1 \in (0,1)$. The term $\mathcal{Z}^e_{jt}$ captures knowledge spillovers within the firm. These spillovers affect the returns to investments in innovation and capture through, for example, learning-by-doing and knowledge sharing among high-skill workers involved in the development and adoption of new technologies. We adopt the following generalized logistic functional form $\mathcal{Z}^e_{jt} := \tau \left(1 + (\tau - 1) e^{-\tau\left(\frac{A^e_{jt+1}}{A^e_{jt}} - 1\right)}\right)^{-1}$, with $\tau > 1$ determining both the strength and asymmetry (positive versus negative) of the spillovers. Note that this functional form implies that spillovers are zero ($\mathcal{Z}^e_{jt} = 1$) in the deterministic steady state of the model.

The knowledge that firms produce generates changes in productivity. The technical efficiency of the firm depends on the stock of non-depreciated technologies already adopted by each division, as well as on the flow of newly adopted ones:

$$A^e_{jt+1}(z) = \left(\phi_A A^e_{jt}(z) + \phi_A \left(Z^e_{jt}(z) - A^e_{jt}(z)\right) \cdot \eta_2 \left(O^e_{2jt}(z)\right)^{\kappa_2} \mathcal{Z}^e_{jt}\right) e^{a^e_{jt}}, \tag{A.13}$$

where $\phi_A(Z^e_{jt}(z) - A^e_{jt}(z)) > 0$ denotes the stock of unadopted technologies of division z. The adoption rate of technology, $\eta_2 \left(O^e_{2jt}(z)\right)^{\kappa_2}$, depends positively on the human resources invested by the firm, $O^e_{2jt}(z)$, is controlled by parameters $\eta_2 > 0$ and $\kappa_2 \in (0,1)$, and influenced by the spillovers. The variable a^e_{jt} captures an idiosyncratic firm-level productivity shock, unrelated to innovation choices. We assume $a^e_{jt} \sim N\left(\frac{-\sigma_a^2}{2}, \sigma_a^2\right)$, such that $\mathbb{E}\left(e^{a^e_{jt}}\right) = 1$, and is *i.i.d.* across firms and time. Given the symmetry across divisions z, equations (A.12) and (A.13) can be aggregated to the firm level as:

$$\begin{aligned} Z^e_{jt+1} &= \phi_A Z^e_{jt} + \eta_1 \left(O^e_{1jt}\right)^{\kappa_1} \cdot \mathcal{Z}^e_{jt} \\ A^e_{jt+1} &= \left(\phi_A A^e_{jt} + \phi_A \left(Z^e_{jt} - A^e_{jt}\right) \cdot \eta_2 \left(O^e_{2jt}\right)^{\kappa_2} \mathcal{Z}^e_{jt}\right) e^{a^e_{jt}} \end{aligned}$$

where we define the following firm-level aggregates: $O^e_{1jt} \equiv \int_0^1 O^e_{1jt}(z)\,dz$, $O^e_{2jt} \equiv \int_0^1 O^e_{2jt}(z)\,dz$, $Z^e_{jt} \equiv \int_0^1 Z^e_{jt}(z)\,dz$, and $A^e_{jt} \equiv \int_0^1 A^e_{jt}(z)\,dz$.

External financing. Financial frictions constrain firms' access to bank capital. As in Kiyotaki and Moore (1997), the amount entrepreneurs can borrow is bounded by a multiple of their assets. Moreover, as in Neumeyer and Perri (2005), labor contracts are such that a fraction $\nu \in [0,1]$ of the firms' wage bill must be paid in advance (i.e., before production takes place), which generates a demand of $\nu(L^e_{jt} + O^e_{1jt} + O^e_{2jt})w_t$ in the form of working capital. This gives rise to the following borrowing constraint:

$$B^e_{jt} \leq \gamma^e_{jt} \mathbb{E}_t \left[\frac{K^e_{jt+1}}{R_{jt+1}}\right] - \nu(L^e_{jt} + O^e_{1jt} + O^e_{2jt})w_t, \tag{A.14}$$

where the parameter $\gamma^e_{jt} \in [0,1]$ governs the strength of financial frictions faced by firm j.

The firm problem. We denote by χ^e_{jt} and the λ's the multipliers associated with the various constraints and by $\Xi^e_{1jt} \equiv \eta_1 \left(O^e_{1jt}\right)^{\kappa_1} \mathcal{Z}^e_{jt}$ and $\Xi^e_{2jt} \equiv \eta_2 \cdot \left(O^e_{2jt}\right)^{\kappa_2} \mathcal{Z}^e_{jt}$ the investment in research and development and the adoption rate of technology. The Lagrangian of the firm problem is:

$$\begin{aligned}
\mathcal{L}_{jt} = \mathbb{E}_0 \textstyle\sum_{t=0}^{\infty} (\beta^e)^t \ln C^e_{jt} \\
&+\chi^e_{jt}\left(\gamma^e_{jt}\cdot \mathbb{E}_t\left[\frac{K^e_{jt+1}}{R_{jt+1}}\right] - \nu\left(L^e_{jt} + O^e_{1jt} + O^e_{2jt}\right) w_t - B^e_{jt}\right) \\
&+\lambda_{1,jt}\left(P^e_{jt}Y^e_{jt} + B^e_{jt} - R_{jt}B^e_{jt-1} - C^e_{jt} - w_t\left(L^e_{jt} + O^e_{1jt} + O^e_{2jt}\right) - \left(K^e_{jt+1} - (1-\delta_K)K^e_{jt}\right) - \mathcal{AC}_{jt}\right) \\
&+\lambda_{2,jt}\left(A^e_{jt}\left(L^e_{jt}\right)^{\alpha_L}\left(K^e_{jt}\right)^{\alpha_K} - \textstyle\int_0^1 Q^e_{jt}(i)\,di\right) \\
&+\lambda_{3,jt}\left(\left(\phi_A A^e_{jt} + \phi_A\left(Z^e_{jt} - A^e_{jt}\right)\Xi^e_{2jt}\right)e^{a^e_{jt}} - A^e_{jt+1}\right) \\
&+\lambda_{4,jt}\left(\phi_A Z^e_{jt} + \Xi^e_{1jt} - Z^e_{jt+1}\right) \\
&+\textstyle\int_0^1 \lambda_{5,jt}(i)\left[(1-\delta_I)\,I^e_{jt-1}(i) + Q^e_{jt}(i) - I^e_{jt}(i) - Y^e_{jt}(i)\right]\,di \\
&+\lambda_{6,jt}\left[\left(\textstyle\int_0^1 \theta_{jt}(i)\left(Y^e_{jt}(i)^{\rho}\right)di\right)^{1/\rho} - Y^e_{jt}\right] \\
&+\textstyle\int_0^1 \lambda_{7,jt}(i) I^e_{jt}(i)\,di
\end{aligned}$$

In writing the Lagrangian, we use the normalization of the price index $P_t = P_{t+1} = 1$ and omit the index (z) for the knowledge and productivity equations taking advantage of the symmetry of the development and adoption decisions across the continuum of the firm's divisions. The first-order conditions characterizing the entrepreneur's problem are:

$$\begin{aligned}
&\left[C^e_{jt}\right]:\ \lambda_{1,jt} = \left(C^e_{jt}\right)^{-1} \\
&\left[B^e_{jt}\right]:\ \lambda_{1,jt} = \chi^e_{jt} + \beta^e\mathbb{E}_t\left[R_{jt+1}\lambda_{1,jt+1}\right] \\
&\left[K^e_{jt+1}\right]:\ \lambda_{1,jt}\left[1 + \Psi\left(\frac{K^e_{jt+1}}{K^e_{jt}} - 1\right)\right] - \chi^e_{jt}\cdot\gamma^e_{jt}\mathbb{E}_t\left[\frac{1}{R_{jt+1}}\right] \\
&\qquad = \beta^e\mathbb{E}_t\left[\lambda_{2,jt+1}\alpha_K\frac{Q^e_{jt+1}}{K^e_{jt+1}} + \lambda_{1,jt+1}\left[(1-\delta_K) + \Psi\left(\frac{K^e_{jt+2}}{K^e_{jt+1}} - 1\right)\left(\frac{K^e_{jt+2}}{K^e_{jt+1}}\right) - \frac{\Psi}{2}\left(\frac{K^e_{jt+2}}{K^e_{jt+1}} - 1\right)^2\right]\right] \\
&\left[L^e_{jt}\right]:\ \left(\lambda_{1,jt} + \chi^e_{jt}\nu\right)w_t = \lambda_{2,jt}\alpha_L\frac{Q^e_{jt}}{L^e_{jt}} \\
&\left[O^e_{1jt}\right]:\ \left(\lambda_{1,jt} + \chi^e_{jt}\nu\right)w_t = \lambda_{4,jt}\kappa_1\left(\frac{\Xi^e_{1jt}}{O^e_{1jt}}\right) \\
&\left[O^e_{2jt}\right]:\ \left(\lambda_{1,jt} + \chi^e_{jt}\nu\right)w_t = \lambda_{3,jt}\cdot\kappa_2\left(\frac{\Xi^e_{2jt}}{O^e_{2jt}}\right)\phi_A(Z^e_{jt} - A^e_{jt})\cdot exp\left(a^e_{jt}\right) \\
&\left[Y^e_{jt}\right]:\ \frac{\varepsilon-1}{\varepsilon}\cdot\lambda_{1,jt}P^e_{jt} = \lambda_{6,jt} \\
&\left[A_{jt+1}\right]:\ \lambda_{3,jt} = \beta^e\mathbb{E}_t\left[\lambda_{2,jt+1}\left(L^e_{jt+1}\right)^{\alpha_L}\left(K^e_{jt+1}\right)^{\alpha_K} + \lambda_{3,jt+1}\phi_A\left(1 - \Xi^e_{2jt+1}\right)\right] \\
&\left[Z_{jt+1}\right]:\ \lambda_{4,jt} = \beta^e\mathbb{E}_t\left[\lambda_{3,jt+1}\phi_A\left(\Xi^e_{2jt+1}\right) + \lambda_{4,jt+1}\phi_A\right] \\
&\left[I^e_{jt}(i)\right]:\ \lambda_{5,jt}(i) = \lambda_{7,jt}(i) + \beta^e\left(1-\delta_I\right)\mathbb{E}^i_t\left[\lambda_{5,jt+1}(i)\right]
\end{aligned}$$

$$\left[Q^e_{jt}(i)\right] : \lambda_{2,jt} = \mathbb{E}^i_t\left[\lambda_{5,jt}(i)\right]$$
$$\left[Y^e_{jt}(i)\right] : \lambda_{5,jt}(i) = \lambda_{6,jt}\theta_{jt}(i)\left(\frac{Y^e_{jt}(i)}{Y^e_{jt}}\right)^{\rho-1}$$

Consumption and input demands. The optimality conditions of the firm's problem capture the core economic forces that rationalize the dynamics documented in the micro data. Financial frictions affect firm policies by increasing both the direct cost (R_{jt+1}) and shadow cost of finance (χ^e_{jt}, the Lagrange multiplier associated with the firm's borrowing constraint). This leads to a reduction in consumption through the Euler equation:

$$\left(C^e_{jt}\right)^{-1} = \chi^e_{jt} + \beta^e\mathbb{E}_t\left[R_{jt+1}\left(C^e_{jt+1}\right)^{-1}\right], \tag{A.15}$$

as well as a reduction of input demands, as shown by the wedges in the first-order conditions of capital and labor above.

Innovation and productivity dynamics. The credit shock also has real effects on firms' long-run operations through the innovation channel. A severe credit tightening forces firms to reduce innovation expenses, which sets firms on a lower productivity trajectory. Manipulating the first-order conditions of labor employed in development and adoption of new technologies, the following conditions characterize the firm's labor demand for workers employed in the development and adoption of new technologies:

$$w_t = \frac{\lambda_{4,jt}}{\lambda_{1,jt}(1+\nu\chi^e_{jt})}\left[\kappa_1\frac{\Xi^e_{2jt}}{O^e_{1jt}}\right]$$
$$w_t = \frac{\lambda_{3,jt}}{\lambda_{1,jt}(1+\nu\chi^e_{jt})}\phi_A\left(Z_{jt}-A_{jt}\right)\left[\kappa_2\frac{\Xi^e_{2jt}}{O^e_{2jt}}\right].$$

The expressions in square brackets represent the marginal return to investments in research and adoption. Financial frictions generate the wedges $\frac{\lambda_{3,jt}}{\lambda_{1,jt}(1+\nu\chi^e_{jt})}$ and $\frac{\lambda_{4,jt}}{\lambda_{1,jt}(1+\nu\chi^e_{jt})}$, which are decreasing in the shadow cost χ^e_{jt}. Because marginal returns to investments are decreasing functions ($\kappa_1, \kappa_2 \in (0,1)$), a tightening of credit supply conditions reduces the amount of resources firms devote to innovation, which harms productivity in the medium-long run. The possibility to use low pricing as a source of internal financing (through the liquidation of inventories) helps firms mitigate this effect by freeing up resources that would otherwise be obtained through a more severe contraction of innovation activity.

Inventory management. As shown by Kim (2020), the optimal inventory management policy is characterized by a threshold rule. That is, there exists a cut-off point θ^*_{jt} (firm-time specific but common across all parts i) such that, for realizations of $\theta(i) > \theta^*_{jt}$, the entrepreneur faces a product stockout: $\lambda_{7,jt}(i) > 0$, $I^e_{jt}(i) = 0$, and $Y^e_{jt}(i) = (1-\delta_I)\, I^e_{jt-1}(i) + Q^e_{jt}(i)$; while for realizations of $\theta(i) < \theta^*_{jt}$, the entrepreneur holds a positive inventory of that part: $\lambda_{7,jt}(i) = 0$, $I^e_{jt}(i) > 0$, and $Y^e_{jt}(i) < (1-\delta_I)\, I^e_{jt-1}(i) + Q^e_{jt}(i)$, with $\partial I^e_{jt}(i)/\partial\theta^*_{jt} < 0$. Defining $I^e_{jt} \equiv \int I^e_{jt}(i)di$, we have that firm-level inventories are an increasing function of the cut-off value.

More specifically, it can be shown that the rate of returns to liquidity (returns to inventory investment) is given by:[39]

$$R^I\left(\theta^*_t\right) = F(\theta^*_t) + \int_{\theta(i)>\theta^*_t} \frac{\theta(i)}{\theta^*_t} dF(\theta) = 1 + \left(\frac{\xi}{\xi-1} - 1\right)\left(\frac{1}{\theta^*_t}\right)^{\xi} > 1,$$

with $\frac{dR^I(\theta^*_t)}{d\theta^*_t} < 0$, where recall that ξ is the shape parameter governing the Pareto distribution of the $\theta(i)$'s. Define the aggregate $\tilde{Y}^e_{jt} \equiv \int_0^1 Y^e_{jt}(i)\, di$ and the quantities:

$$G\left(\theta^*_{jt}\right) := \frac{\xi}{\frac{1}{1-\rho}-\xi}\left(\left(\theta^*_{jt}\right)^{\frac{1}{1-\rho}-\xi} - 1\right) + \frac{\xi}{\xi-1}\left(\theta^*_{jt}\right)^{\frac{1}{1-\rho}-\xi}$$

$$D\left(\theta^*_{jt}\right) := \left[1 + \frac{\xi}{\frac{1}{1-\rho}-\xi}\right]\left[\left(\theta^*_{jt}\right)^{\frac{1}{1-\rho}-\xi}\right] - \frac{\xi}{\frac{1}{1-\rho}-\xi}$$

$$H\left(\theta^*_{jt}\right) := \left(\theta^*_{jt}\right)^{\frac{1}{1-\rho}}\left(1 - \left(\theta^*_{jt}\right)^{-\xi}\right) - \frac{\xi}{\frac{1}{1-\rho}-\xi}\left(\left(\theta^*_{jt}\right)^{\frac{1}{1-\rho}-\xi} - 1\right).$$

The following equations summarize the optimal firm-level inventory dynamics:

$$Y^e_{jt} = \frac{\left(G(\theta^*_{jt})\right)^{\frac{1}{\rho}}}{D(\theta^*_{jt})}\tilde{Y}^e_{jt}$$

$$I^e_{jt} = \tilde{Y}^e_{jt}\left[\frac{H(\theta^*_{jt})}{D(\theta^*_{jt})}\right]$$

$$Q^e_{jt} + (1-\delta_I)I^e_{jt-1} = \tilde{Y}^e_{jt}\left[\frac{D(\theta^*_{jt})+H(\theta^*_{jt})}{D(\theta^*_{jt})}\right] = \tilde{Y}^e_{jt} + I^e_{jt}$$

$$\left(C^e_{jt}\right)^{-1}\left(G(\theta^*_{jt})\right)^{\frac{1-\rho}{\rho}} P^e_{jt} = \beta^e(1-\delta_I)\mathbb{E}_t\left\{R^I(\theta^*_{jt+1})\left(C^e_{jt+1}\right)^{-1}\left(G(\theta^*_{jt+1})\right)^{\frac{1-\rho}{\rho}} P^e_{jt+1}\right\},$$

where the last equation characterizes the firm's optimal inventory demand.

Pricing. Firms price at a markup over marginal costs, $P^e_{jt} = \mathcal{M}^e_{jt} MC^e_{jt}$. The optimal markup, set by the firm after all uncertainty and shocks are realized, is given by:

$$\mathcal{M}^e_{jt} := \left(\frac{\epsilon}{\epsilon-1}\right)\Lambda^e{}_{jt}.$$

As discussed in the main text, the first term in the markup is a standard monopolistic competition markup. The second term is a variable component, $\Lambda^e{}_{jt} := \frac{G_j(\theta^*_t)}{R^I_j(\theta^*_t)\cdot D_j(\theta^*_t)}$, due to firms' ability to use inventories in order to adjust output sold after production decisions have been made.

Although firms do not hold inventories in anticipation of financial shocks, an increase in the cost of credit or a tightening of the credit constraint generates a liquidity need that shifts θ^*_{jt} to the left ($\partial\theta^*_{jt}/\partial R_{jt} < 0$ and $\partial\theta^*_{jt}/\partial\chi^e_{jt} < 0$). The variable component of firms' markups, Λ_{jt}, is

[39] We refer to the online appendix of Kim (2020) for details on the derivation of the expressions below.

an increasing function of the threshold value θ^*_{jt} and, therefore, a decreasing function of the cost and shadow cost of external finance. For a plausible parametrization, when firms can tap into a sufficient stock of inventories, the drop in the markup dominates the change in marginal cost due to the shock. This allows the firms coping with a credit tightening to reduce their (relative) price and move along their demand curve to increase the amount of internal finance coming from sales.

E.3 Banks

Banks intermediate funds between households (savers) and entrepreneurs (borrowers), earning a spread between the deposit rate offered to households, $\mathcal{R}_{t-1}$, and the loan rate charged to firms, R_{jt}. For tractability, we assume each firm j matches with one bank (also indexed by j).

On the asset side, banks hold loans to firms, B^b_{jt}, and securities whose market value, S^b_{jt}, can fluctuate above or below their book value, S^b_j. On the liability side, banks hold deposits issued to households, D^b_{jt}. The difference between a bank's market value of assets and its deposits represents the bank's net worth ($\mathcal{A}^b_{jt} := B^b_{jt} + S^b_{jt} - D^b_{jt}$).

Each banker maximizes its inter-temporal utility from consumption:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} (\beta^b)^t \ln(C^b_{jt})$$

where $\beta^b < \beta^h$, subject to the flow-of-funds constraint:

$$C^b_{jt} + \mathcal{R}_{t-1} D^b_{jt-1} + B^b_{jt} = D^b_{jt} + R_{jt} B^b_{jt-1} - (S^b_j - S^b_{jt}).$$

Here $(S^b_j - S^b_{jt})$ denotes loss provisions or profits due to changes in the market value of securities. Following Iacoviello (2015), we assume bankers are constrained in their ability to issue deposits by their amount of net worth, which cannot exceed a fraction $\gamma^b \in (0, 1)$ of their assets:

$$D^b_{jt} \leq \gamma^b (B^b_{jt} + S^b_{jt}). \tag{A.16}$$

This constraint is motivated by standard limited commitment problems or by regulatory constraints (e.g., the capital to assets ratio required under modern banking supervisory frameworks).

The Lagrangian of the bank's problem is given by:

$$\begin{aligned}\mathcal{L}^b_j = {} & \mathbb{E}_0 \textstyle\sum_{t=0}^{\infty} (\beta^e)^t \ln C^b_{jt} \\ & + \lambda^b_{jt} \left[D^b_{jt} + R_{jt} B^b_{jt-1} - (S^b_j - S^b_{jt}) - C^b_{jt} - \mathcal{R}_{t-1} D^b_{jt-1} - B^b_{jt} \right] \\ & + \chi^b_{jt} \left[\gamma^b (B^b_{jt} + S^b_{jt}) - D^b_{jt} \right]\end{aligned}$$

We denote by $M^b_{jt,t+1} := \beta^b \mathbb{E}_t \left(\frac{C^b_{jt}}{C^b_{jt+1}}\right)$ the banker's stochastic discount factor between period t and $t+1$ and by χ^b_{jt} the multiplier associated with the leverage constraint. Thus, the banker's Euler equation and the optimality conditions for deposits and loans are given by:

$$\begin{aligned}
\left[C^b_{jt}\right] &: \quad \left(C^b_{jt}\right)^{-\sigma} = \lambda^b_{jt} \\
\left[D^b_{jt}\right] &: \quad 1 - \chi^b_{jt} = \mathbb{E}_t[M^b_{jt,t+1}\mathcal{R}_t] \\
\left[B^b_{jt}\right] &: \quad 1 - \gamma^b \chi^b_{jt} = \mathbb{E}_t[M^b_{jt,t+1}R_{jt+1}]
\end{aligned}$$

The last two conditions illustrate that banks price loans to entrepreneurs at a spread relative to the deposit rate charged to households (since $\gamma^b > 0$). This spread—and therefore firms' cost of external finance—is increasing in the tightness of the regulatory constraint (lower γ^b) and, crucially, is affected by shocks to the value of sovereign securities. Combining the two equations we obtain:

$$\mathbb{E}_t[M^b_{jt,t+1}(R_{jt+1} - \mathcal{R}_t)] = (1 - \gamma^b)\chi^b_{jt}.$$

A reduction of S^b_{jt} erodes the bank's net worth and the leverage constraint in (A.16) becomes tighter. This increases the shadow cost of the bank's capital, χ^b_{jt}, which increases the spread. At the same time, the bank needs to contract its lending, in order for the bank to restore its leverage ratio. In principle, the banker could avoid contracting lending by reducing its consumption. However, this choice would be sub-optimal given the banker's impatience and given that the loss in the value of securities also tightens the banker's budget constraint.

E.4 Market clearing

Market clearing is implied by Walras's law by aggregating all the budget constraints. Four markets need to clear: labor, deposits, credit, and goods.

$$\begin{aligned}
N^h_t &= \textstyle\sum_{j=1}^N \left(L^e_{jt} + O^e_{1jt} + O^e_{2jt}\right) \\
D^h_t &= \textstyle\sum_{j=1}^N D^b_{jt} \\
B^b_{jt} &= B^e_{jt} \quad \forall j \\
Y_t &= C^h_t + \textstyle\sum_{j=1}^N C^b_{jt} + \sum_{j=1}^N C^e_{jt} + \sum_{j=1}^N \left[\left(K^e_{jt+1} - (1-\delta_K)K^e_{jt}\right) + \mathcal{AC}_{jt}\right] + \sum_{j=1}^N \left(S^b_j - S^b_{jt}\right)
\end{aligned}$$

In addition, the price of goods from firm j should satisfy the demand function $Y^e_{jt} = \left(\frac{P^e_{jt}}{P_t}\right)^{-\epsilon} Y_t$.

E.5 Calibration

We solve for the agents' policy functions and compute the model's transitional dynamics. To do so, we feed a sequence of idiosyncratic productivity shocks and shocks to the market value of securities held by banks and solve a linearized version of the system of equations describing the equilibrium of the model, under the assumption that the bank and firm leverage constraints in equations (A.14) and (A.16) are always binding.[40]

We assume that entrepreneurs discount the future more heavily than households and bankers, calibrating the discount factors $\beta^h = 0.96$, $\beta^b = 0.94$, and $\beta^e = 0.92$. This calibration ensures that both the entrepreneurs' borrowing constraints and the bankers' leverage constraints bind in equilibrium in a neighborhood of the steady state.[41] To match the data, we set the tightness of the bank's leverage constraint to $\gamma^b = 0.8$ and the book value of securities, S_j^b, such that, in the stochastic steady state, securities account for 20% of bank assets (IMF 2011).

Moving to the firm side, we partition the model's parameters into three sets. The first set of parameters is externally calibrated to standard values used in the literature. We calibrate the elasticity of substitution across goods to $\epsilon = 3.5$ and the depreciation rate of capital to $\delta_K = 0.045$. To ensure a sufficient degree of real rigidity in physical capital adjustment, we assume $\mathcal{AC}_{jt} := \frac{\Psi}{2}\left(\frac{K^e_{jt+1}}{K^e_{jt}} - 1\right)^2 K^e_{jt}$ and set the adjustment cost parameter to $\Psi = 20$. Consistent with the empirical results, we assume constant returns to scale in production and set the capital and labor elasticities such that $\alpha_L = (1 - \alpha_K) = 2/3$.

The second set of parameters controls the evolution of the bank balance sheet shock and its transmission to firms' borrowing conditions. To model the shocks to the value of bank securities, we define the market value of securities $S^b_{jt} \equiv e_{jt} S^b_j$. As discussed above, S^b_j denotes the book value of securities (i.e., their value absent shocks) and e_{jt} is a stochastic variable with $\mathbb{E}[e_{jt}] = 1$, which evolves as an autoregressive process of order two: $e_{jt} = (1 - b_1 - b_2) + b_1 e_{jt-1} + b_2 e_{jt-2} - \varsigma_{jt}$, where ς_{jt} is a one-period shock. At time $t = 1$ (the period in which the model economy is hit by the bank balance sheet shocks), ς_{jt} takes a positive value, heterogeneous across banks. In all other periods it takes value zero. These shocks mimic the effects of a credit supply tightening, as a low realization of e_{jt} simultaneously increases the cost, and decreases the quantity, of credit available to firm j. To reproduce the credit dynamics observed in the data, we allow the strength of banks' balance sheets to affect the tightness of the borrowing constraints. We adopt the following reduced-form expression for the parameter governing the collateral constraint: $\gamma^e_{jt} = \bar{\gamma}\left(1 + m(e_{jt} - 1)\right)$, where

[40] We have verified that given the size of the productivity and securities shocks, the multipliers associated with the leverage constraints, χ^e_{jt} and χ^b_{jt}, are always positive. We also estimated a version of the model allowing the firm's borrowing constraint to be occasionally binding (e.g., because banks demand for credit might fall in response to a slowdown of economic activity) and found that the quantitative implications of our analysis are essentially unchanged.

[41] Formally, we set the discount factors of households and bankers to satisfy $\beta^e < \left(\gamma^b \frac{1}{\beta^h} + (1 - \gamma^b)\frac{1}{\beta^b}\right)^{-1}$, ensuring that the entrepreneurial discount rate is higher than a weighted average of the discount rates of households and bankers.

$m = 0.3$. We set $\bar{\gamma} = 0.7$ and $\nu = 0.2$, such that absent shocks to the value of securities ($e_{jt} = 1$), firm debt-to-capital ratios are in line with the ones observed in the data.

The final set of parameters controls firms' pricing and productivity dynamics. Given the response of credit supply (borrowing rates and credit limit), we calibrate this last set of parameters to match our reduced-form estimates obtained in the micro-data. Specifically, given a sequence of shocks, the firms' policy functions, and the calibrated parameter values, we simulate a firm-level panel dataset that allows us to estimate model-based counterparts to the Jorda projections estimated in the data. We then calibrate the parameters $\{\xi, \rho, \delta_I, \eta_1, \kappa_1, \eta_2, \kappa_2, \tau, \phi_A, \sigma_a\} = \{3, 0.75, 0.1, 1, 0.23, 0.07, 0.18, 5, 0.87, 0.01\}$ and discipline $\{e_{jt}\}$ by setting $\{b_1, b_2\} = \{0.8, -0.12\}$ and feeding the model a cross-section of shocks $\{\varsigma_{j1}\}$ to simultaneously minimize the distance between the empirical and model-based impulse responses of credit balances, borrowing costs, productivity, and prices reported in Figures 1 and 2. Specifically, to obtain the model-based counterparts, we estimate the following Jorda projection regressions: $\Delta_\tau Y_j = \beta_\tau \cdot \text{Shock}_j + u_{j\tau}$, where Shock_j is equal to ς_{jt}, and is standardized to have mean zero and standard deviation one, as in the empirical regressions in the data.