Financial Shocks and Productivity:
Pricing response and the TFPR-TFPQ bifurcation

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September 30, 2019

Abstract

We measure the causal effect of negative credit supply shocks on firms’ productivity growth, systematically exploring the distinction between the effect on technical productivity growth (TFPQ, quantity of physical units produced per unit of inputs) and revenue productivity growth (TFPR, the product of TFPQ and output prices). We show that this distinction matters, and document when it matters and why. We match administrative records on product-level prices and quantities of goods produced by a large sample of manufacturing firms in Belgium and exploit quasi-experimental variation in the availability of credit faced by individual firms to separately estimate the causal effect of negative credit supply shocks on TFPR, TFPQ, and output prices. Confirming the results of previous empirical studies, we find that, on average, TFPR growth declines in response to credit tightening. Unlike previous empirical work, however, we document that the short-run effect on TFPR is entirely driven by firms’ output price adjustments, whereas TFPQ growth is unaffected. Over the long-run, credit supply shocks have a negative impact on TFPQ growth, which is driven by a persistent contraction of firms’ investments in innovation and technology adoption.

Keywords: Financial Constraints, Financial Crisis, Productivity, Pricing, Innovation.
JEL: D24, E31, E44, G31, G33, O47, P42

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1 Introduction

There is increasing recognition that financial crises are followed by a persistent slowdown in aggregate productivity growth (Queralto 2019). This has been the case for the U.S., Europe, and a number of developing countries in the wake of the Great Recession and subsequent sovereign debt crisis. Investigating the channels through which credit supply contractions affect aggregate productivity, a number of research papers have focused on the impact that a sudden credit tightening has on firm-level productivity growth, finding a negative relationship between the two variables that materializes in the wake of a credit supply shock and endures over time.\footnote{Christiano et al. (2015) offers a taxonomy of possible explanations for the slow recovery after a financial crisis. Hall (2015), Reifschneider et al. (2015), and Anzoategui et al. (2019) and Queralto (2019) argue that the drop in productivity may be the result of a decline in productivity-enhancing investments, and thus an endogenous response to the recession. Schmookler (1966) and Shleifer (1986) emphasize the role of aggregate demand on the timing of innovation and technology adoption. Duval et al. (2017), Dörr et al. (2018), and Manaresi and Pierri (2018), explore the relationship between firm-level productivity and credit supply tightening.}

The empirical evidence available so far, however, fails to account for the potentially differential response of firms’ output prices to financial shocks. The inability to observe firm-level output quantities separately from output prices has forced researchers to examine the relationship between financial shocks and a composite of technical productivity (defined as quantity of physical units produced per unit of inputs) and output prices, rather than focusing on the relationship with technical productivity alone. This implies that the observed variation in the analyzed productivity measure – commonly referred to as “revenue productivity” or TFPR (Foster et al. 2008) – reflects unobserved variation in both output prices and technical productivity (TFPQ).

Does this limitation matter for conclusions regarding the impact of credit frictions on productivity growth? There are reasons to believe it may. It is not clear how one can rationalize a TFPQ slowdown that materializes in the immediate aftermath of a negative credit shock. The reason is that firm-level technical productivity is a slow-moving variable, which only gradually responds to innovation in production processes, human capital accumulation, and organizational changes (Syverson 2011). This suggests that the estimated TFPR response might be partially or entirely driven by changes in output prices. In fact, previous research has shown that financing conditions affect firms’ pricing strategies. The literature, however, has reached somewhat opposite conclusions regarding the direction of the price response (see e.g., Gilchrist et al. (2013) and Kim (2018)), which implies that the TFPR effect might either understate or overstate the true impact of credit shocks on TFPQ.

In this paper, we explore the TFPR-TFPQ bifurcation systematically. The longitudinal
nature of our data and its granularity in several dimensions allow us to study the causal impact of credit supply shocks over different horizons (short-term versus long-term) and shed light on the forces that drive them. We are able to observe both producers’ physical outputs and prices, which allows us to measure firm-level revenue productivity, technical productivity, and prices. In order to generate idiosyncratic, exogenous variation in credit supply, we take advantage of quasi-experimental variation in the availability of credit faced by individual firms coming from the differential exposure of their lenders to distressed sovereign securities during the recent European sovereign debt crisis (Bottero et al. 2019).

Our research highlights that financing, pricing decisions, and productivity dynamics are intrinsically related. We present two main sets of empirical findings that shed light on these links. First, in the short-run, we document a strong relationship between financial shocks and firms’ pricing decisions, but no relationship between financial shocks and technical productivity. Confirming the findings of previous empirical studies, TFPR declines in the immediate aftermath of a credit supply contraction. Over a one-year horizon, a 10 percent decrease in bank credit, driven by a contraction of credit supply, leads to a 1.2 percent average drop in firm-level revenue productivity. However, we show that this short-term response is entirely driven by a reduction of output prices, while we observe essentially no change in TFPQ over the same horizon. Importantly, we document that the direction and strength of the price adjustment is highly heterogeneous across firms. On the one hand, a downward price adjustment is observed for firms with a large stock of inventories, consistent with a fire sale of their inventory stock to raise liquidity (Kim 2018). On the other hand, an upward price adjustment is observed for firms with high liquidity needs (high share of liabilities due within one year) but low inventory holdings, leading firms to increase prices to raise liquidity (Gilchrist et al. 2013).

Our second set of findings highlight the link between financing shocks and long-run productivity dynamics. We find that credit supply shocks have a short-lived effect on prices but a significant impact on long-run productivity growth. Both TFPR and TFPQ persistently decline over time for firms more exposed to a credit tightening. Exploring the channels leading to the long-term decline in productivity growth, we emphasize the role played by investments in innovation (R&D investments) and technology adoption (patent adoption expenditures). A credit supply contraction translates into a persistent contraction of investments in innovation over the five years following the burst of the sovereign crisis, which, in turn, negatively affects the cumulative TFPQ growth over the same period.

The implications of our findings are straightforward: over the short-run, we should not expect any TFPQ response to credit supply shocks, and inference based on TFPR provides biased results. Notably, the direction of the bias is a priori difficult to assess as it depends
on how pricing policies respond to the shock, which, in turn, depends on the both the assets and liabilities composition of the firms affected by the credit contraction. Credit supply shocks, however, do affect productivity growth in the long-run, as firms decrease productivity enhancing investments when access to credit becomes more difficult and/or more expensive.

Our paper is directly related to the literature studying the implications of adverse financial shocks on firm-level productivity. Duval et al. (2017), Dörr et al. (2018), and Manaresi and Pierri (2018), find empirical support for a negative relationship between revenue productivity and credit supply tightening. We depart from these papers in the unusual opportunity to observe output prices, which allow us to estimate the separate causal effect of negative credit shocks on revenue-based productivity measures and on measures of physical efficiency, both in the short- and long-run, and show the economic mechanisms behind these effects. Since the lack of data on firm-level prices makes revenue-based measures ubiquitous, we hope our findings provide guidance regarding the conditions under which researchers can confidently draw inference on TFPQ based on TFPR, which appear to hold only over the long-run.\footnote{We note that the focus of this paper is on the effect of credit supply contractions on productivity growth. It may be the case that firms respond differently to credit supply expansions, which is an important area of ongoing research (Mian et al. 2019).}

More broadly, this paper shares a common thread with the growing body of work interested in determining the relationship between financing conditions, productivity growth, and economic growth. Queralto (2019) documents that financial crisis that impair the functioning of credit markets are associated with a particularly strong contraction in innovation activity and, in turn, a more pronounced slowdown in aggregate productivity growth. Aghion et al. (2010) shows theoretically that credit constraints can lead firms to cut R&D spending—and long-term illiquid investments more broadly—during recessions. Aghion et al. (2012), Garcia-Macia (2017), Huber (2018) and Anzoategui et al. (2019) provides supportive empirical evidence of this channel highlighting the link between firm-level productivity growth and innovation activity. While the focus on this paper is on firm-level productivity, our analysis complements the findings of separate strand of the literature focusing on the possibly large misallocative effects that credit market disruptions and exacerbation of financial frictions might bring about (Hsieh and Klenow 2009; Midrigan and Xu 2014; Lenzu and Manaresi 2018; Schivardi et al. 2017).

We are not the first to use micro-data on prices and quantities to quantify the importance of the distinction between firms’ technical productivity and revenue productivity. For example, the seminal work of Foster et al. (2008), whose theme perhaps mostly closely matches that of this paper, explores the separate influence of idiosyncratic productivity and demand on firm survival. The distinction between TFPQ and TFPR has also been emphasized in a number of other settings including misallocation (Hsieh and Klenow 2009; Haltiwanger et al.}
foreign market participation (Katayama et al. 2009), trade liberalization (Eslava et al. 2013), learning-by-exporting (Garcia-Marín and Voigtländer 2018), firm dynamics (Eslava and Haltiwanger 2018), among others. To the best of our knowledge, however, we are the first to systematically examine the TFPR-TPQ bifurcation when studying the causal relationship between firms’ productivity and financing conditions, which we are able to estimate using quasi-experimental variation in banks’ credit supply to individual firms. Our identification strategy allows us to shed light on a particular factor affecting firm-level productivity – the access to stable sources of funding – effectively addressing the endogeneity of firms’ financing choices.

Finally, our paper also serves to bridge the finance/productivity literature with an entirely separate literature studying the relationship between finance and pricing policies. This literature has found contrasting empirical evidence on the response of pricing to financial shocks. Borenstein and Rose (1995), Zingales (1998), Busse (2002), Phillips and Sertsios (2013), and Kim (2018) find a negative relationship between firms’ financial conditions and price adjustments. Another set of influential empirical studies finds instead that firms increase prices in response to an exacerbation of financial frictions or higher likelihood of financial distress (Chevalier, 1995a; Chevalier, 1995b; Chevalier and Scharfstein, 1995; Chevalier et al., 1996; Gilchrist et al., 2017). This result is also found in a number of industry-level studies focusing on business cycle fluctuations (Phillips, 1995; Campello, 2003). Our results confirm that it is difficult a priori to sign the effect of negative financial shocks on firms’ pricing policies. We help reconcile the contrasting effects found in the literature. The ability to “fire sale” inventory to boost sales, we show, can explain the average, negative response of prices to the credit supply shocks (Kim, 2018). When the inventory channel is not available, however, the strength of the firm’s balance sheet determines the direction of the price response to the shock, as firms with pressing liquidity needs and low inventories respond by increasing prices.

The paper proceeds as follows. The next section provides a theoretical motivation for the paper by highlighting the potentially differential impact of credit shocks on revenue and technical productivity. Section 2 details the relationship between TFPR and TFPQ. Section 3 describes the data. Section 4 discusses issues related to the measurement of productivity and illustrates the empirical design that allows us to identify credit supply shocks from bank balance sheet shocks. The central results on the effects of negative credit supply shocks on productivity and prices are presented in Section 5. Section 6 concludes.

3Complementing our results on credit supply contractions, Mian et al. (2019) point out that credit supply expansions can also affect prices. They show that credit supply expansions boost non-tradable sector employment and the price of non-tradable goods by stimulating household credit demand.

4The seminal works of Kashyap et al. (1994) and Gertler and Gilchrist (1994) provide evidence of the importance of inventory management for the response to negative financial shocks.
2 Financial shocks, productivity, and pricing behavior

2.1 Empirical motivation

The large impact of several recent financial crises have sparked an interest in examining the effects of financial shocks on firm-level outcomes, including employment and investment. More recently, the attention has turned to the effects on firm-level productivity growth (Dörr et al., 2018; Duval et al., 2017; Manaresi and Pierri, 2018). When information on prices is not available, researchers proxy technical productivity (TFPQ), the variable of interest, with a revenue productivity (TFPR), typically scaling sales by some industry-level deflator. This simplification can be motivated by the fact that technical and revenue productivity are generally positively correlated with each other (see Foster et al. 2008 and the analysis in section 4.1):

\[
\ln(TFPR_{jt}) = \ln(TFPQ_{jt}) + \ln(P_{jt}).
\] (1)

Equation (1) implies that we can decompose the growth rate of TFPR (approximated by the log-change) as the sum of the growth rate of TFPQ and the growth rate of output prices:

\[
\Delta \ln(TFPR_j) = \Delta \ln(TFPQ_j) + \Delta \ln(P_j).
\] (2)

Let \( g(Credit(Z)_{jt}) \) denote the growth rate of firm-level bank credit, driven by a negative credit supply shock \( (Z) \). Consider the following empirical models:

\[
\Delta \ln(TFPQ_j) = \alpha_0 + \alpha_1 g(Credit(Z)_{jt}) + u_j
\] (3)

\[
\Delta \ln(TFPR_j) = \beta_0 + \beta_1 g(Credit(Z)_{jt}) + \eta_j,
\] (4)

\[
\Delta \ln(P_j) = \gamma_0 + \gamma_1 g(Credit(Z)_{jt}) + \nu_j
\] (5)

The exact decomposition in (2) implies that the elasticity of TFPR to changes in credit supply \( (\beta_1) \) is the sum of two separate elasticities: the effect of credit supply shocks on technical productivity \( (\alpha_1) \) and the effect on pricing \( (\gamma_1) \). To the extent that the change in prices is uncorrelated with the change in the credit supply, \( \beta_1 \) provides an unbiased estimate of the coefficient of interest \( \alpha_1 \). However, when credit supply also affects the prices that firms charge, then this is no longer the case. The sign of \( \gamma_1 \) is theoretically ambiguous (Gilchrist et al. 2017; Kim 2018), and thus so is the sign of the bias. Therefore it is an empirical question as to how the use of TFPR as a proxy for TFPQ affects estimates of the finance-productivity

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See, for example, Chodorow-Reich (2014); Cingano et al. (2016); Amiti et al. (2018) and Bottero et al. (2019).
We present a simple model that ties together credit shocks, pricing behavior, and productivity dynamics. The model highlights that the price response to a financial shock can drive the short-term movements of TFPR, even if TFPQ is unaffected. It also highlights that a credit tightening can affect long-run technical productivity because it curbs firms’ investments in innovation.

2.2 Theoretical model

Building on the work of Hendel (1996), we present a model that helps explore the relationship between credit availability and firms’ optimal pricing and productivity growth. We first focus on the pricing response, treating productivity as exogenous. Then we introduce productivity enhancing investments in innovation.

A model with exogenous productivity growth

Consider a profit-maximizing firm facing downward sloping demand $D(P)$ for his product. Each period, the firm decides production and pricing in sequential stages as more uncertainty is resolved. Figure 1 presents the timeline of the model.

In stage 1, the firm carries over a given stock of inventories $I \geq 0$ from the previous period and it decides how many units of input $L$ to acquire in order to produce $Q$ units of output using the following technology:

$$Q = TPFQ \cdot f(L)$$

$L$ is inelastically supplied at a unit-cost of one, which is paid by the firm at the end of
the period, after production takes place and the uncertainty is resolved. The production decision takes place under uncertainty. Firms know that a debt payment $F$ is due at the end of the period, but they do not know what fraction $\lambda \leq 1$ will not be rolled-over by lenders. At the same time, firms face an unforeseen mean-zero revenue shock $\epsilon$, which makes the level of future liquidity from sales uncertain.

In stage 2, financing uncertainty is resolved – i.e., $\lambda F$ is realized – and firms choose their pricing strategy ($P$). While production $Q$ is already pinned down, firms can choose to deplete their inventories in order to lower prices and increase sales. Note that we assume that inventories can only be used for operational purposes – i.e., they can be used to satisfy demand selling them in the market – but they cannot be used to directly cancel financial obligations or as collateral for additional credit.

At stage 3, the liquidity shock $\epsilon$ is realized and sales are collected. Firms pay inputs and repay the share of debt that cannot be be rolled-over. The end-of-period cash flows are given by:

$$V_3 = P \cdot \min\{I + Q, D(P)\} - \lambda F - L + \epsilon$$

Given $P$ and conditional on the realization of the revenue shock, the firm survives if the firm has enough resources to repay all stakeholders ($V_3 \geq 0$), otherwise it enters a default state. If the firm survives it collects the continuation period value $\pi > 0$. Otherwise the firm collects the default value $\bar{\pi} < \pi$. Continuation values capture future profits of the firm and they introduce a dynamic considerations in firms’ optimal behavior. The difference in continuation values $(\pi - \bar{\pi})$ provides firms with incentives to survive and avoid the costs of financial distress (e.g., costly bankruptcy litigation or asset fire-sales). Finally, we assume that at the end of the period, firms recover $\delta$ for each unit of unsold output $(I + Q - D(P))$, where $\delta \in [0, 1]$ captures the level of sunkness of inventories or, alternatively, the opportunity cost of using inventories today versus using them in the future.

We first derive the optimal pricing behavior by solving the model backward, conditional on a given level of inputs, production, and inventory. Then, we solve the production stage taking into consideration the subsequent optimal pricing behavior.

**Pricing Stage** – Given $L$ and $Q$, at stage 2 the firm sets its price to maximize profits after observing the realized financial obligations $\lambda F$:

$$\max_P V_2 = P \cdot D(P) - \lambda F - L + \delta(L + I - D(P)) + (\pi - \bar{\pi})\Phi(P \cdot D(P) - \lambda F - L) + \bar{\pi}$$

subject to

$$D(P) \leq Q + I$$
where $\Phi(\cdot)$ denotes the cumulative distribution function of the liquidity shock, assumed to be a standard normal without loss of generality, and it captures the probability of financial distress. The solution to problem (6) is characterized by the following first-order condition:

$$[P - (\delta + \zeta)] D'_P(P) + D(P) + (\pi - \bar{\pi})\phi(P \cdot D(P) - \lambda F - L) (P \cdot D'_P(P) + D(P)) = 0 \quad (7)$$

where $\phi(\cdot)$ is the probability density function of $\epsilon$. $\zeta \geq 0$ represents the shadow value of inventories, which is zero when the firm’s pricing policies are not constrained by the production capacity ($D(P^*) < Q+I$). The first term in (7) is the standard optimality condition of a firm facing downward sloping demand in the absence of liquidity considerations, with the marginal cost of production (which is a sunk cost at stage 2) replaced by the cost of depleting inventories. The second term captures the liquidity effect. It represents the increase in the probability of surviving due to one more dollar of revenues $- \phi(P \cdot D(P) - \lambda F - L) -$ times the marginal revenue $- (P \cdot D'_P(P) + D(P)) -$ times the future benefit of not defaulting $(\pi - \bar{\pi})$.

**Production Stage** – In stage 0, the firm commits to a given production capacity, knowing its level of inventories and facing uncertainty in financing conditions and revenues. We can heuristically characterize the firm’s optimal input demand noting that $I$ and $L$ are substitutes and that if a firm was choosing $L$ while perfectly informed about $\lambda$, the optimal input demand would be a non-increasing function of $\lambda$. Therefore, a firm with high $I$ and high $F$ chooses lower $L$ since every unit of inputs reduces the probability of surviving (through higher input cost obligations), and hence compromises long-run profits.

The model yields testable implications about the relationship between the exogenous credit supply shock ($\lambda$) and the endogenous, optimal response of prices. The first observation is that the cost of financial distress is captured by the difference in the continuation value $(\pi - \bar{\pi})$. When there is no difference in the continuation value, firms act as static profit maximizers. Imposing $\pi - \bar{\pi} = 0$ in equation (7), the second term drops and we have that $P^* = \frac{\eta}{(1+\eta)}(\delta + \zeta)$, which is a standard static monopoly pricing condition: price equals marginal cost times a markup that depends on the elasticity of demand $\eta = D'_P(P) \cdot \frac{\frac{P}{P}}{P} < -1$. When $\pi - \bar{\pi} > 0$, the second term in (7), evaluated at the price that maximizes static profits, is negative, which implies that $P^*$ is lower than static profit maximizing price. The intuition for this result is simple. When the the cost of financial distress is substantial, optimal behavior involves maximizing a combination of current and future profits. By pricing below the one-period profit-maximizing price, firms can increase revenues, which in turn decreases the probability of default and increases the chance to collect future profits.

We further explore the comparative static predictions of the model to draw connections between financial shocks and firm pricing policies distinguishing between firms with strong
and weak balance sheets, which we identify by looking at the amount of liabilities due \( F \) times the realized credit supply shock \( \lambda \). We consider first firms with strong balance sheets that, ceteris paribus, have a moderate probability of default.

**Proposition 1.** For a moderate probability of default, prices decrease with the severity of the credit supply shock \((\lambda)\).

A formal proof this proposition is in Appendix A. Given the uncertainty regarding future revenues, the realization of the credit supply shock \((\lambda)\) provides new information regarding the likelihood of survival. In particular, a negative credit supply shock decreases the probability of survival. Firms respond to this by lowering prices in order to increase revenues, and thus increase the probability of survival.

The model also delivers interesting comparative statics regarding the heterogeneous effects of the shock depending on the stock of inventories and strength of the firm’s balance sheets.

**Proposition 2.** For a moderate probability of default, holding constant the magnitude of the credit shock \((\lambda)\), the price drop is stronger for firms with large inventories \((I)\). For a large probability of default, holding constant the magnitude of the credit shock \((\lambda)\), the price drop is smaller for firms with weak balance sheets \((high F)\).

Consider the first part of the proposition. Because production has been committed to, inventory depletion is used to increase the likelihood of survival, as it allows firms to sell more quantity by lowering price. At the extreme, firms with no inventories are have no additional room to expand sales by lowering price.

The intuition behind the second part of the Proposition 2 is that firms gain more from generating revenues when these revenues can have a significant impact on the probability of survival. When a firm hit by a credit supply shock \((\lambda > 0)\) is almost certain to end up in the default region due to a high amount of liabilities due \((F)\), it is not worth to give up current profits to increase revenues/liquidity, since the marginal effects of revenues on the probability of survival is small. See Appendix A for a formal proof.

Taken together, Propositions 1 and 2 present a pricing behavior asymmetry between firms facing a negative credit supply shock and those firms that do not. This asymmetry drives a wedge between revenue and technical productivity, which is summarized by the following proposition:

**Proposition 3.** The price response drives a bifurcation between the effect of a credit supply shock on TFPQ and TFPR. On impact, TFPQ is unaffected by the credit shock, while TFPR moves one-for-one with prices. Relative to a firm that did not experience a credit supply shock \((\lambda = 0)\), TFPR drops for firms with a moderate probability of default and increases for firms with a high risk of default.
A model with endogenous productivity growth

We now allow for productivity enhancing investments $N$, which we refer to as intangible assets or innovation. Investments in intangibles are chosen after observing the realization of the productivity shock and simultaneously to pricing decisions. In the current period, the cost per unit of intangible investment is one, which is paid out of current profits at the end of the period. Innovation increases a firm’s continuation value, since it affects the firm’s future technical productivity. That is: $\pi'_{N}, \pi''_{N} > 0$, and we assume $\pi''_{N}, \pi'''_{N} < 0$, where $\pi_{N}$ denotes the partial derivative of the continuation value with respect to intangible investments. Furthermore, we assume that the increase in the continuation value stemming from investments in innovation is smaller if the firm is in financial distress ($\pi'_{N} > \pi'_{N}$). This assumption is justified by empirical evidence showing that firms in financial distress are often forced to liquidate their most valuable intangible assets (Ma et al. 2019). The problem of the firm in stage 1 is now:

$$\max_{P,N} V_2 = P \cdot D(P) - \lambda F - L + \delta(L + I - D(P)) + (\pi(N) - \pi'(N))\Phi(P \cdot D(P) - \lambda F - L - N) + \pi(N)$$

s.t. $D(P) \leq Q + I$

The first-order condition characterized by the firm’s pricing policies is similar to (7). The only difference being that $N$ also enters the argument of $\phi(\cdot)$, thereby negatively affecting the chances of survival, and all previous propositions still hold. The first-order condition characterizing optimal investment behavior is the following:

$$[(\pi - \pi')\Phi(P \cdot D(P) - \lambda F - L - N) + (\pi''_{N} - \pi'''_{N})\Phi(P \cdot D(P) - \lambda F - L - N)] + \pi''_{N} = 1$$

**Proposition 4.** Investments in intangible assets decrease with the severity of the credit supply shock ($\lambda$). Holding constant the severity of the shock, the investment response is larger for high-leverage firms ($F$). In the long-run, the reduction in investments in innovation has negative effects on $TFPQ$, but no effect in the short-run.

The first part of proposition 4 is intuitive. Investments reduce current profits and capital-ize them into future profits. Firms react to a credit supply shock by reducing investments in innovation, sacrificing an increase in future profits in order to avoiding the costs of financial distress. The second result is also intuitive: for firms with a moderate probability of default, a large $F$ triggers a larger reduction of investments in innovation to reduce the negative effects of the credit shock on the probability of default; moreover, for any level of $\lambda$, firms with high $F$ are more likely to end up in default regardless of their mitigation efforts: these
firms choose not to invest at all since they act like profit maximizers. The third result follows from the positive relationship between innovation and productivity.

In testing the empirical predictions outlined above, there are two main challenges. One challenge is related to the measurement of both firm-level prices and productivity. Since prices are measured at the product level, one needs to decide how to aggregate these prices to construct a measure of prices at the firm level. Regarding firm-level productivity, it is unobserved and therefore needs to be estimated. The second main challenge is an econometric one. Firms choose their demand for credit – possibly facing financing constraints – together with input utilization and investments, in order to maximize the present discounted value of their future profits. Therefore, identifying the causal impact of financing constraints on productivity and prices require exogenous variation in the supply of financing.

Our empirical analysis proceeds in three main stages. First, the next section describes the dataset we use. Second, section 4 addresses the measurement and econometric issues, highlighting the identification strategy that allows us to estimate firm-specific credit supply shocks. Third, in section 5 we quantify the response of firm-level productivity to credit supply shocks and investigate the role played by changes in pricing policies.

3 Data

In order to perform our empirical analysis, we require detailed firm-level data on a number of different variables. In particular, we require separate data on the product-level prices and quantities of the goods produced by each firm, as well as detailed information on their liability structure. To construct the main dataset for our analysis, we merge several highly-detailed administrative datasets covering manufacturing firms in Belgium. Specifically we combine (a) firms’ annual accounts (AA) and value added fiscal (VAT) declarations from the Belgian central balance sheet office and the tax authorities, respectively; (b) the PRODCOM survey from the Belgian statistical agency, (c) the corporate credit register (CCR) of the National Bank of Belgium, and (d) individual bank balance sheets (BBS) from the National Bank of Belgium supervisory records. Below, we briefly elaborate on relevant aspects of our data and sample selection, providing additional details in Appendix B.

3.1 Data sources

**Firm-level information** – Belgian corporations featuring limited liability are obliged to file their annual accounts (AA) – balance sheets and income statements – electronically to the National Bank of Belgium. We use firms’ AA to measure intermediate inputs use,
capital expenditures and book value of assets (investments in and stock of fixed tangible and intangible assets), labor utilization, and inventory stock. We also collect a battery of firm-level balance sheet and income statement items – total assets, firm age, bank leverage (bank debt over assets), share of total liabilities due (liabilities due within the year over total liabilities), liquidity (cash over assets), ROA, inventories stock (inventories over sales), and the number of products produced by the firm. We use these variables as controls in our regression models and to explore the heterogeneous effects of the credit shock. In order to shed light on the channels through which credit tightening might affect firm-level productivity, we also gather information on firms’ investments in intangible assets: R&D expenditures, expenditures related to the purchase and utilization of third-party patents, and the overall investments in intangibles assets (sum of R&D and patents expenditures). For each of these measures, we construct investment rates scaling expenditures by the stock of intangibles in 2009. Using unique firm identifiers, we merge the AA with firms’ value-added tax declarations (VAT) to gather detailed information on firm operating revenues.⁶

Product-level sales and quantities – We collect information on product-level quantities and sales by linking the merged AA-VAT database to the PRODCOM database. The PRODCOM database collects accurate information on firms’ real activity (value and quantity of production). The survey, administered by the Belgian Statistical Agency, is designed to cover at least 90% of production value within each NACE 4-digit manufacturing industry by surveying all Belgian firms with (a) a minimum of 10 employees or (b) total revenue above 2.5 million euros (European Commission 2014).⁷ The surveyed firms are required to disclose, on a monthly basis, product-specific revenues (in euros) and quantities (e.g., volume, kg., m², etc.) of all products sold, disaggregated at the 8-digit product level (e.g., 10.92.10.30 for “Dog food”, 10.92.10.31 for “Cat food”).⁸ The availability of product-level prices allows us to analyze different measures of prices and price indexes that help us testing the robustness our findings. We return to this point below and in section 4.1.

Firm-bank matched credit relationships – Unique firm-identifiers allow us to merge the firm-product-level data with the firm-bank records of the Belgian Corporate Credit Registry (CCR). The CCR, administered by the National Bank of Belgium, provides us with

⁶As detailed in Appendix B, small firms are not obliged to report sales in their AA, so we complement the AA with the confidential sales measure taken from VAT declarations. For large firms, we cross-check sales reported in (a) total sales declared to the VAT authority and (b) annual accounts. Across these data sources, firm-level sales are broadly mutually consistent.

⁷The statistical classification of economic activities in the European Community, commonly referred to as NACE, is the industry standard classification system used in the European Union.

⁸The following turnover components are not included; (i) turnover/consumer taxes, (ii) discounts and (iii) separately charged freight costs.
detailed, confidential information on the credit relationships maintained by the firms in our database with all banks operating under the supervision of the National Bank of Belgium.

We collect data on the outstanding stock of bank debt of each borrower vis-a-vis each financial institution between January 2006 and December 2014. Debt amounts from the CCR are recorded at a monthly frequency. To harmonize the CCR records with firms’ annual balance sheets, we calculate the average credit exposure of a firm across all lenders in each fiscal year. In particular, we observe the amount of credit granted by each institution (Credit\(_{jbt}\)) and aggregate these amounts at the firm-level summing across lending relationships (Credit\(_{jt}\)).\(^9\) We define the variable Number of relationships\(_{jt}\) that counts the number of active credit relations between a firm and its lending institutions during year \(t\). Exploiting the panel dimension of the CCR, we also measure the (weighted) average length of the lending relationships between a borrower and each of its lenders, counting the number of quarters of continuous credit interactions between borrower and lenders (i.e., months with outstanding debt in the CCR). We denote this variable by Length of relationships\(_{jt}\), which we calculate as the weighted average across different relationships using the share of debt provided by each lender as weight.\(^10\)

**Bank balance sheets** — The National Bank of Belgium supervisory records provide us with quarterly accounting information on balance sheets and income statements and with a detailed account of sovereign-bond holdings for each bank operating in Belgium. As we describe in section 4, the variable of interest is the stock of sovereign securities that experienced significant loss in value after the burst of the European sovereign crisis: Greece, Ireland, Portugal, Spain, and Italy (GIPSI). We measure the stock of GIPSI government bonds held by bank \(b\) in at the end of 2010:Q1 scaled by risk-weighted assets (Sov\(_b\)). We treat this variable a bank-specific measure of financial institutions’ exposure to the sovereign shock. We construct a firm-specific measure of exposure to the sovereign crisis as a weighted average of the exposure of its lenders, using as weights the share of each bank in the firm’s total credit measured in the quarter prior to the Greek bailout event (2010:Q1). Our empirical models also include the following set of bank-level variables as controls: bank size, capitalization, retail funding, interbank funding, liquidity, and quality of lending portfolio, all measured in the pre-bailout period (2010:Q1). We return to the importance of this set of controls in the discussion of our identification strategy.

\(^9\)Our measure of bank debt is the balance across four different types of bank debt (term loans, loans backed by account receivables, and revolving credit lines, and guarantees).

\(^10\)Specifically, we have Length of relationships\(_{jt}\) = \(\sum_{b \in N^B_{jt}}\) Share of credit\(_{jbt}\) × Length of relationships\(_{jbt}\), where Share of credit\(_{jbt}\) = Credit\(_{jbt}\)/\(\sum_{b \in N^B_{jt}}\) Credit\(_{jt}\) and \(N^B_{jt}\) is the set of lenders of firm \(j\) in year \(t\).
Sample selection and properties of the sample – The key event in our study is the Greek bailout in the second quarter of 2010, which triggered the 2010-2012 European sovereign debt crisis. We restrict our analysis to a nine-year window around the Greek bailout event (2006-2014) and apply the following selection rules to our sample. First, we restrict our attention to firms that appear in the credit registry in the last quarter before the Greek bailout (2010:Q1). We do so because, as we describe in the following section, the identification of firm-specific credit supply shocks requires information on firms’ relationships with financial intermediaries before the event that triggered the sovereign crisis. Second, we keep only firms that report information on both the value of sales and quantity of their products in PRODCOM: this restriction is necessary in order to be able to compute output prices. Third, we drop firms that, during our time window, do not report information on total assets, investments, the wage bill, sales, intermediate inputs, or inventories. Applying these rules yields a pooled sample of 4,650 firm-year observations, 1,002 firms, and 3,064 firm-bank credit relationships over the five-year window that begins with the year prior to the Greek bailout. Table 1 presents summary statistics that describe the characteristics our sample. Panel a describes the cross-section of firms in our dataset. Panel b focuses on growth rates of the TFP measures and prices. Panel c looks at lenders’ characteristics. All variables in levels refer to the end of fiscal year 2009, the year prior to the credit supply shock. Growth rates are calculated over a one-year (2009–2010) or five-years horizon (2009–2014). Lender’s variables are firm-level weighted averages of bank-level characteristics, which we describe in the following section.

A number of noteworthy features distinguish our data from those used in previous studies in the productivity and finance literature. First, the availability of product-level measures of prices allows us to separately measure TFPQ from TFPR. Second, the information on inventories management allows us to construct TFP estimates that are based on output produced, rather than output sold, and it allows us to test the impact of the inventory channel as a driver of price adjustments. Third, we construct firm-specific credit supply shifters leveraging the detailed bank balance sheet data and firm-bank links. These credit supply shifters allow us to go beyond the endogenous correlations between financial conditions, productivity, and price behavior – which are jointly determined by credit demand and credit supply forces – and shed light on the causal relationship between financing shocks and the firm-outcomes of interest.
### Table 1: Summary Statistics

#### Panel a: Firm characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total assets, $j$</td>
<td>93,834.909</td>
<td>309,750.667</td>
</tr>
<tr>
<td>Employees, $j$</td>
<td>218.24</td>
<td>1130.784</td>
</tr>
<tr>
<td>Age, $j$</td>
<td>32.421</td>
<td>19.142</td>
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<tr>
<td>Bank leverage, $j$</td>
<td>.211</td>
<td>.205</td>
</tr>
<tr>
<td>Share liabilities due, $j$</td>
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<td>.235</td>
</tr>
<tr>
<td>Cash, $j$</td>
<td>.064</td>
<td>.085</td>
</tr>
<tr>
<td>ROA, $j$</td>
<td>.021</td>
<td>.109</td>
</tr>
<tr>
<td>Number of products, $j$</td>
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<td>2.225</td>
</tr>
<tr>
<td>Inventory, $j$</td>
<td>.144</td>
<td>.111</td>
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<tr>
<td>Multiple relationships, $j$</td>
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<td>.481</td>
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<tr>
<td>Number of relationships, $j$</td>
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<td>.104</td>
</tr>
<tr>
<td>Length of relationships</td>
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<td>11.285</td>
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<tr>
<td>Investments in R&amp;D, $j$</td>
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</tr>
<tr>
<td>Investments in patents, $j$</td>
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<tr>
<td>Investments in intangibles, $j$</td>
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<tr>
<td>$g$(Credit)</td>
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<td>.584</td>
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</table>

#### Panel b: Prices and TFP growth

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
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<tbody>
<tr>
<td>$\Delta \ln(P_j)$</td>
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<td>.157</td>
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<tr>
<td>$\Delta_5 \ln(P_j)$</td>
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<td>.449</td>
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<tr>
<td>$\Delta \ln(TFPR_j)$</td>
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<td>.163</td>
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<tr>
<td>$\Delta \ln(TFPQ^R_j)$</td>
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<td>.189</td>
</tr>
<tr>
<td>$\Delta_5 \ln(TFPQ^R_j)$</td>
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<td>.455</td>
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<tr>
<td>$\Delta \ln(TFPQ^Q_j)$</td>
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#### Panel c: Lenders characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
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</thead>
<tbody>
<tr>
<td>Sov, $j$</td>
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<td>.046</td>
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<tr>
<td>Bank Size, $j$</td>
<td>19.067</td>
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<td>Tier1 ratio, $j$</td>
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<td>.01</td>
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<tr>
<td>Net interbank liabilities ratio, $j$</td>
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<td>.083</td>
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<tr>
<td>Liquidity ratio, $j$</td>
<td>.226</td>
<td>.092</td>
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<tr>
<td>Deposits ratio, $j$</td>
<td>.421</td>
<td>.074</td>
</tr>
<tr>
<td>Bad loans ratio, $j$</td>
<td>.001</td>
<td>.002</td>
</tr>
</tbody>
</table>

**Notes:** In **Panel a**, all variables are measured at the end of 2009 and vary at the firm-level. Total Assets is firm’s total assets (expressed in thousand of Euros); Employees is the number of full time employees (average of the fiscal year); Age is firm age; Bank leverage is bank debt over total assets; Share liabilities due is (liabilities due within one year - cash)/total assets; Cash is cash/total assets; ROA is return on assets; Number of products is the number of products produced by the firm, where a product is defined as a combination of 5-digit industry and unit of measurement; Inventory is inventory of final goods and intermediates over sales; Multiple relationships is a dummy variable that flags firms with multiple active lending relationships; Number of relationships is the number of active lending relationships between firm and financial intermediaries; Length of relationships is the average length of lending relationships (measured in quarters); The variables Investments in R&D, Investments in patents and Investments in intangibles are expenditures in R&D, patents, and intangible assets, scaled by the stock of intangible assets in 2009, respectively; $g$(Credit) is the growth rate of bank debt between 2009 and 2010. In **Panel b**, all variables are growth rates between 2009 and 2010 and vary at the firm-level. $\Delta \ln(P)$ and $\Delta_5 \ln(P)$ are the one-year and five-year growth rates of the firm-level price index; $\Delta \ln(TFPR)$ and $\Delta_5 \ln(TFPR)$ are the growth rates of revenue productivity; $\Delta \ln(TFPQ^R)$ and $\Delta_5 \ln(TFPQ^R)$ are the growth rates of technical productivity calculated as the difference between TFPR and prices; $\Delta \ln(TFPQ^Q)$ and $\Delta_5 \ln(TFPQ^Q)$ are the growth rates of technical productivity estimated directly from quantities. All growth rates are relative to the levels in 2009. The production function estimation is performed assuming a non-parametric functional. In **Panel c**, all variables are firm-level averages of bank balance sheet variables and are measured in 2010:Q1. Sov is the stock of sovereigns issued by GIPSI countries scaled by total assets; Bank Size is the log of total assets measured in millions of Euros; Tier1 ratio is Tier1 capital over risk-weighted assets; Net interbank liabilities ratio is (interbank liabilities - interbank assets)/total assets; Liquidity ratio is liquid assets over total assets; Deposits ratio is callable deposits over total assets; Bad loans ratio is bad loans over total assets.
4 Prices and productivity measurement and identification of credit supply shocks

4.1 Prices and productivity measures

Price measures — The main objective of our analysis is to show how credit shocks affect firm performance, disentangling the separate effects on prices and technical productivity. Since our analysis is conducted primarily at the firm-level, it seems natural to construct a firm-level price index aggregating the product-level prices. However, one potential concern with aggregating across different products, is that these products may have different price levels, and thus changes in product mix over time may end up being conflated with changes in prices. The PRODCOM database, which contains the value and quantity sold of each product produced by each firm, allows construct three different price measures that help us address this concern: two at the level of the firm’s main product and one firm-level price that incorporates all of the firm’s products.

Our first measure is the price of main product of the firm \( P_{\text{Main},jt} \). To construct this measure we first sum the value and quantity of sales of all the 8-digit product codes within each of the firm’s 6-digit product codes. The 6-to-8-digit aggregation is necessary to obtain a consistent product classification across years because the PRODCOM product classification system was re-organized in 2008.\(^{11}\) Furthermore, we define a product as unique combinations of 6-digit product codes and units of quantity measurement (e.g., volume, kg, etc.) to ensure unit prices are comparable. We then compute a unit price for each product, \( P_{pjt} \), dividing total value by total quantity. We select the price of the firm’s main product, and use that as our price measure.\(^{12}\)

While focusing on the firm’s main 6-digit product avoids much of the potential issues with aggregating across products, there is still some aggregation involved in moving from the 8-digit to the 6-digit level. Our second price measure tries to address this. For this measure, we compute the average price (across all firms) for each 8-digit product code and scale the firm-level quantities by this average price relative to a numeraire price (the average price of the 8-digit product with the highest sale). We refer to these prices as \( P_{p-\text{adj},jt} \). This has the effect of putting the quantities of each 8-digit product in common units of the numeraire product. As with the first price measure, we use the price of the firm’s main 6-digit product, which we label \( P_{\text{Main-adj},jt} \).

Our third measure aggregates prices to the firm-level. Our firm-level price index, \( P_{jt} \), is

\(^{11}\)See Van Beveren (2012) for a discussion of the re-classification in the context of Belgian firm data.

\(^{12}\)For each firm, the main product is defined as the 6-digit product code/units of measurement combination with the highest share of revenues in the year before the Sovereign debt crisis, 2009.
constructed as a revenue-share weighted average of the prices of each 6-digit product produced by the firm in each year.\textsuperscript{13} In order to minimize any issues of related to aggregation, we use the adjusted prices, $P_{p-adj,jt}$\textsuperscript{14}.

**Productivity measures** — Following the standard practice in the literature, we estimate firm-level TFPR as a residual from a gross output production function:

$$\ln(TFPR_{jt}) = y_{jt} - f(k_{it}, l_{it}, m_{it}; \Theta)$$

where $y_{jt}$ denotes the logarithm of firm revenues adjusted by the change in inventory and deflated with an industry output deflator. $l_{jt}, k_{jt}, m_{jt}$ denote the logarithm labor, capital, and intermediate inputs, respectively. $f(\cdot)$ is the log-production function, and $\Theta$ is a vector of structural parameters to be estimated.

We measure labor services using the deflated wage bill and construct a measure of capital stock from investments in fixed assets (both tangibles and intangibles) following the perpetual inventory method (Becker and Haltiwanger 2006).\textsuperscript{15} Intermediate inputs are measured as the total value of materials and services used in production during a year. We deflate labor, capital, and intermediate inputs by the corresponding industry-year price deflators. Because we use expenditures to compute input use, idiosyncratic firm-level variation in input prices will be captured here as high measured inputs and, in turn, low measured productivity. In our context this does not pose a significant threat as long as the growth rate of input prices is uncorrelated with our measure of idiosyncratic credit supply shocks.

We estimate $\Theta$ separately for each 2-digit industry following the structural approach developed in Gandhi et al. (2017). In particular, we perform a estimation assuming a non-parametric functional form for production technologies $f(\cdot)$. This approach does not impose any restrictions on the elasticity of substitution between different inputs and allows us to estimate firm-time-specific elasticities that are a non-linear function of industry-specific structural parameters and of the input-mix utilized by each firm: $\theta_{jt}^X = \theta^X(l_{jt}, k_{jt}, m_{jt}; \gamma), \ X = \{L, K, M\}$.\textsuperscript{16} The elasticity estimates, presented in Table A.1 in the Appendix, highlight

\begin{footnotesize}
\textsuperscript{13} Amiti et al. (2019), De Loecker et al. (2014), and Dhyne et al. (2017) employ a similar approach, also using Belgian data.

\textsuperscript{14} In the robustness analysis of Section 5 we show that our results are very similar if we use quantity shares as weights to aggregate product-level prices into a firm-level price.

\textsuperscript{15} The perpetual inventory method provides us with a better proxy for capital services than the book value of fixed assets. Using the total wage bill as a measure of labor services accounts for differences in the quality of firms’ workforce. However, measuring labor using the number of employees delivers estimates very similar to the ones obtained using the wage bill.

\textsuperscript{16} The structural approach in Gandhi et al. (2017) identifies the production function addressing the simultaneity bias that derives from the correlation between input choices and unobserved (to the econometrician) productivity (Marschak and Andrews 1944), and it solves the identification problem that affects the estimates
\end{footnotesize}
roughly constant returns to scale, on average, across industries and, at the same time, substantial heterogeneity in firms’ production technologies.\textsuperscript{17} The empirical results of our study are remarkably robust when we use alternative approaches to estimate of TFPR, such as performing the production function estimation assuming a Cobb-Douglas functional form or using a standard index-function approach that uses industry-revenue shares as estimates of gross-output elasticities.\textsuperscript{18}

We construct two different measures of TFPQ. Our first measure, $TFPQ^R$, uses estimates of TFPR and different measures of prices to construct a corresponding measure of physical productivity as the log-difference between the two (equation (1)). The strength of $TFPQ^R$ is that it satisfies the convenient identity that the growth rate in TFPR equals the sum of the growth rate of TFPQ and the growth rate of prices. Thus, one can interpret the analysis below as exactly decomposing the effect of a credit shock on TFPR into the effect of the shock on its components: physical efficiency and prices. The weakness of this measure is that, in principle, it might induce a mechanical, negative correlation between technical productivity and prices. Our second measure, $TFPQ^Q$, address this concern as it is constructed directly from quantities as a residual from the production function (De Loecker et al. (2016); Blum et al. (2019)):

$$\ln(TFPQ^Q_{jt}) = q_{jt} - f(k_{it}, l_{it}, m_{it}; \Theta)$$

where $q_{jt}$ is a firm-level quantity index. While $TFPQ^Q$ is invariant with respect to how prices are measured, it has the disadvantage of using revenue elasticities in the construction of a technical measure of productivity. Moreover, one might also expect $TFPQ^Q$ to be a more noisy proxy of technical productivity since it relies on the definition of an appropriate firm-level quantity index, which poses aggregation measurement issues similar to the ones highlighted above for prices.

**Correlation between productivity and prices** – Table 1, panel b, reports the mean and standard deviation of the growth rates of prices and productivity measures. Table 2 of the output elasticities of flexible inputs. We provide the details of the estimation routine in Appendix C and refer to Gandhi et al. (2017) for a more detailed exposition and discussion of its underlying assumptions.

\textsuperscript{17}In 4 of the 20 industries we were not able to obtain estimates of the production function due to the lack of observations (firms) for these industries. Since these industries are very small, our subsequent results are unaffected by whether or not we include them, something we can verify using instead an index number approach to measuring productivity, as discussed below.

\textsuperscript{18}For each 2-digit industry, we compute the average labor and intermediate input revenue shares to form our estimates of $\theta^L$ and $\theta^M$. We then back out the capital elasticity $\theta^K$ under constant returns to scale as $\theta^K = 1 - \theta^L - \theta^M$. Despite its simplicity and widespread utilization in the literature, the revenue share approach to measuring of TFPR involves some potentially strong assumptions (e.g., constant returns to scale, inputs are flexibly chosen, no within-industry heterogeneity in input elasticities). Nevertheless, we are able to replicate all our empirical findings using this measure.
shows their pairwise correlations, both in levels and growth rates (elasticities). A number of remarks are in order. First, the two TFPQ measures are highly correlated with each other. This fact, together with the almost numerically equivalent response of $TFPQ_R$ and $TFPQ_Q$ to the credit supply shock (section 5), represent an important validity check on our price-index measure. Second, there is a strong, negative correlation between prices and TFPQ, which is consistent with the notion that TFPQ differences are cost differences (Foster et al. 2008): Higher TFPQ implies lower marginal costs, and these costs are then passed through in the form of lower prices. Third, the cost pass-through is imperfect, as the correlation between prices and TFPQ is less than minus one, especially when TFPQ is measured directly from quantities ($TFPQ_Q$). The imperfect pass-through drives a positive correlation between TFPR and TFPQ. This positive correlation motivates the use of TFPR as a proxy of TFPQ in the absence of information about prices.\footnote{These positive correlations, which have been found by other researchers using price and quantity to compute TFPR and TFPQ (e.g., Eslava et al. 2013; Eslava and Haltiwanger 2018), suggest that the commonly adopted dispersion of TFPR is not a valid metric to measure the costs of misallocation (Haltiwanger et al. 2018).} The imperfect pass-through, however, also implies a positive correlation between TFPR and prices, which confounds the co-movement of TFPR and TPFQ and, in particular, their response to financial shocks.

The question we would like to answer is to what extent the inability to observe price variation matters when drawing conclusions regarding the impact of financial frictions on productivity growth. Based on the relative magnitude of the correlation coefficients in the first column of Table 2, it is tempting to conclude that this data limitation is of second-order importance, and, therefore, the elasticity of TFPR to credit shocks is a “sufficient statistic” for the TFPQ elasticity. This observation, of course, fails to account for the fact that the relation between TFPQ, TFPR, and the profit maximizing price hinges on both demand- and supply-side components. Therefore, how relevant is the distinction between the TFPQ and TFPR elasticities to financial conditions is determined by the sign and magnitude of the price elasticity, both in the short- and long-run. Identification of this price elasticity requires variation in financing conditions that is orthogonal to other factors that simultaneously determine firms’ credit demand. We describe our identification strategy next.

### 4.2 Credit supply shocks

#### 4.2.1 Identification strategy

In order to estimate the causal relationship between the availability of credit and firm-level productivity and prices, we need to isolate exogenous variation in the firm’s credit supply. It would be hard to interpret OLS estimates in a causal fashion, since changes in banks’ credit
### Table 2: Correlation between TFPR, TFPQ, Prices, and Credit

#### Panel a: Correlations in levels – raw data

<table>
<thead>
<tr>
<th></th>
<th>ln(TFPR)</th>
<th>ln(P)</th>
<th>ln(TFPQ_R)</th>
<th>ln(TFPQ_Q)</th>
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</thead>
<tbody>
<tr>
<td>ln(TFPR)</td>
<td>1.000</td>
<td>(-)</td>
<td>0.615***</td>
<td>0.605***</td>
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<tr>
<td>ln(P)</td>
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<td>-0.766***</td>
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<td>ln(TFPQ_Q)</td>
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<td>(0.000)</td>
<td>(-)</td>
<td>1.000</td>
</tr>
</tbody>
</table>

#### Panel b: Correlations in levels – residual variation

<table>
<thead>
<tr>
<th></th>
<th>ln(TFPR)</th>
<th>ln(P)</th>
<th>ln(TFPQ_R)</th>
<th>ln(TFPQ_Q)</th>
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<tr>
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<td>0.034***</td>
<td>0.316***</td>
</tr>
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<tr>
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<td>(0.000)</td>
<td>(-)</td>
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#### Panel c: Correlations of short-term growth rates

<table>
<thead>
<tr>
<th></th>
<th>Δ ln(TFPR)</th>
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<th>Δ ln(TFPQ_R)</th>
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<tr>
<td>Δ ln(TFPR)</td>
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<td>(-)</td>
<td>1.000</td>
<td>0.655***</td>
</tr>
<tr>
<td>Δ ln(TFPQ_Q)</td>
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#### Panel d: Correlations of long-term growth rates

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<tbody>
<tr>
<td>Δ ln(TFPR)</td>
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<tr>
<td>Δ ln(TFPQ_R)</td>
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<td>(-)</td>
<td>1.000</td>
<td>0.670***</td>
</tr>
<tr>
<td>Δ ln(TFPQ_Q)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(-)</td>
<td>1.000</td>
</tr>
</tbody>
</table>

**Notes:** Each panel shows the pairwise correlation between the variables in the rows and the variables in the columns. In panel a we present the raw pairwise correlations between the variables in (log) levels. Panel b presents pairwise correlations between the variables in (log) levels, netting out the variation explained by industry, time, and time-invariant firm-level components. Panel c presents pairwise correlations between the one-year growth rates, netting out the variation explained by industry and time. Panel d presents pairwise correlations between the five-years growth rates, netting out the variation explained by industry and time. P-values are reported in parentheses.
supply are typically correlated with unobservable changes in firms’ credit demand or credit worthiness. To address this identification challenge, we exploit quasi-experimental variation in the supply of credit faced by individual firms that is driven by the exposure of their lenders to distressed sovereign securities during the recent European sovereign debt crisis.

**Measuring idiosyncratic credit supply shocks** — The key event in our study is the burst of the European sovereign debt crisis triggered by the bailout request advanced by the Greek government in April 2010. The announcement generated concerns about the health of the Greek economy and the solvency of its sovereign debt. Shortly after the events in Greece, investors began to be concerned with the solvency and liquidity of the public debt issued by other peripheral European countries, starting with Ireland and Portugal and spreading soon thereafter to Spain and Italy (Angelini et al. 2014). Figure 2, panel a, displays the spread between the yield to maturity of 10 year bonds issued by GIPSI countries (Greece, Ireland, Portugal, Spain, and Italy) and the yield of maturity of the German 10 year bonds. This spread, which had been low and relatively stable since the introduction of the Euro, significantly increased following news from Greece and the subsequent bailout at the end of

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20 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. The announcement generated concerns about the health of the Greek economy and the solvency of its sovereign debt. This ultimately 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, Standard & Poor’s 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. See Lane (2012) for a detailed description of the European sovereign crisis.
the first quarter of 2010.\textsuperscript{21} The sudden change in the risk profile of government securities issued by GIPSI countries had a direct negative effect on the balance sheets of banks holding these assets because it decreased the market value of their assets and reduced the ability of financial intermediaries to use these distress sovereign securities as collateral in interbank transactions. As shown by Bottero et al. (2019) and Acharya et al. (2018), banks passed the shock through to their borrowers in the form of a credit tightening.

Following Bottero et al. (2019), we construct a firm-level credit supply shifter exploiting variation in the presence and importance of firms’ credit relationships with lenders heavily exposed to distressed sovereigns. Formally, let $B_j$ be the set of all lenders to firm $j$ in the pre-bailout period (2010:Q1). We construct the firm-level credit supply shock measuring firm $j$’s exposure to the sovereign shock as:

$$
Sov_j = \sum_{b \in B_j} \omega_{jb} \cdot Sov_b
$$

where $Sov_b$ is bank $b$’s holdings of sovereign securities issued by GIPSI countries scaled by bank $b$’s risk-weighted assets, both measured in the quarter before the Greek bailout request (2010:Q1). The variable $\omega_{jb}$ is the share of firm $j$’s credit received from bank $b$ in 2010:Q1.\textsuperscript{22} Table 1, panel c, shows that in 2010:Q1, the average exposure of Belgian firms to the GIPSI sovereigns was 14 percent, with a standard deviation of about 4.5 percent. As we discuss later, alternative definitions of exposure to the sovereign debt crisis provide a comparable picture.

**Empirical model** – We study how the change in different firm-level outcomes ($Y_j$) are affected by their exposure to the credit shock:

$$
Y_j = \beta \cdot Sov_j + \Gamma_1'X_j + \Gamma_2'K_j + \Gamma_3'Z_j + i_{ind} + i_{reg} + u_j \tag{9}
$$

The control variables and fixed effects in (9) are important in this setting. Our identification strategy relies on the orthogonality between banks’ exposure to sovereign securities and changes in firms’ credit demand and/or investment opportunities. One might be wor-

\textsuperscript{21}The turmoil spread to the Belgian sovereign market as well, although to a smaller extent compared to the sovereign bond market of Southern European countries (see Figure A.1 in the Appendix).

\textsuperscript{22}The strength of our credit supply shocks relies on the stickiness of firm-bank relationships. If firms can compensate a reduction of credit supply from ongoing lending relationships with more exposed lenders either by borrowing more from other ongoing relationships with less exposed lenders or by establishing new relationships, then $Sov_j$ would not explain changes in lending patterns. Table 3 shows that the credit supply shock has strong predictive power on lending, indicating that lenders’ substitution is limited and, in line with a large body of empirical work (Degryse et al. 2009; Lenzu and Manaresi 2018), lending relationships are indeed persistent: in 2010, 88 percent of the firm-bank relationships observed in 2009 are still in place, 71 percent in 2012, and 59 percent in 2014.
ried that banks with high sovereign exposure systematically lend to firms experiencing a negative demand shock. If this is the case, our estimates of $\beta$ would be biased downward. This negative sorting between firms and banks may arise because of geographical or industry segmentation in credit markets, and it could falsely lead us to attribute demand-driven drops in credit to movements in credit supply.\(^\text{23}\) This is potentially important in our setting given the large contraction of economic activity experienced in Europe in the aftermath of the sovereign debt crisis (Bocola 2016). We address this concern in several ways. First, by taking first-differences of the left-hand side variable in (9), we soak up any variation driven by unobserved, time-invariant characteristics of the firms. This includes, for example, any persistent mismeasurement of firm-level prices or productivity. Second, we include in the regression a set of firm-level controls measured in 2010:Q1, before the Greek bailout ($X_j$): log assets, log age, leverage (bank debt over assets), liquidity (cash over assets), ROA, inventories stock (inventories over sales), and the number of products produced by the firm. The firm-level controls absorb variation in the LHS not directly imputable to firms’ exposure to the sovereign shock, and, to the extent that they correlate with firms’ unobservable changes in investment opportunities and credit demand, they help mitigate the above-mentioned concern. Third, we control for a set of narrowly-defined industry fixed effects ($i_{ind}$, NACE 4-digit codes) and region fixed effects ($i_{reg}$).\(^\text{24}\) By restricting the analysis to within industry and within region variation, we can better address the concern that lenders with high sovereign holdings might specialize in industries or geographical regions experiencing a more severe contraction of economic activity. Fourth, we include in the regression two variables measuring the strength of firms’ credit relationships and the overall intensity of firms’ credit market participation ($K_j$): average length of credit relationships and the number of lending relationships, both measured in 2010:Q1. The former allows us to control for the fact that the pass-through of banks’ balance sheet shocks to credit supply might differ depending on the strength of the relationships. The latter captures firms’ ability to respond to the shock, as firms with multiple established lending relationships are in a better position to substitute borrowing from affected banks with credit from other lenders.

A limitation of using firms’ exposure to banks with large sovereign holdings as a proxy of credit shocks is that sovereign holdings are not randomly assigned across banks (Gennaioli et al. 2014a). Instead, they correlated with bank characteristics (e.g., capitalization and exposure to stability of funding), which, in turn, might affect banks’ propensity to lend after

\(^{23}\)For example, consider the case of poor areas within a country. In these areas banks may end up holding more sovereign assets on average because of lower investment opportunities. At the same time, they will lend to local firms, which may be weaker and therefore more sensitive to sovereign shocks. A similar argument can be developed for banks specialized in specific industries.

\(^{24}\)The country of Belgium is divided into three regions: the Flemish region, the Walloon region, and the Brussels-Capital Region.
the burst of the sovereign crisis.\textsuperscript{25} For this reason, we follow Bottero et al. (2019) and exploit only residual variation in banks’ sovereign exposure by controlling for a set of (weighted-average) bank controls ($Z_j$), measured in 2010:Q1: size (log assets), funding structure (tier1 ratio, deposits over risk-weighted assets, and net interbank liabilities scaled by risk-weighted assets), liquidity position (liquidity over risk-weighted assets), quality of lending portfolio (non-performing loans over risk-weighted assets).\textsuperscript{26}

\subsection*{4.2.2 Exposure to the sovereign debt crisis and credit availability}

We begin by providing evidence of the lending channel triggered by the sovereign shock. We show that firms exposed to lenders with high holdings of distressed sovereigns experienced a contraction of credit supply after the burst of the sovereign crisis.

We start by showing the relationship between credit and banks’ holdings of distressed securities at the aggregate level. We sort banks into a “High Sovereign” group or “Low Sovereign” group based on whether their pre-shock (conditional) holdings of GIPSI sovereigns place them above or below the median. For consistency with the rest of the analysis, we residualize the measure of bank credit against our set of bank characteristics. Then, we aggregate these residuals in two groups: those granted by “High Sovereign” and those granted by “Low Sovereign” banks, and plot them over time (Figure 3, panel a).\textsuperscript{27} Overall, we find that, before the sovereign shock, aggregate credit provided by the institutions with high and low holdings displays a very similar dynamic. However, after 2009 the two groups start diverging. More exposed intermediaries cut lending more extensively, while the credit supply of less exposed banks does not react. These patterns present the first evidence in favor of the parallel trend assumption. Next, we move to the micro data to quantify the effect of the bank balance sheet on credit supply, by taking model (9) to the data. The dependent variable is the firm-level growth rate of bank debt between 2009 and 2010, which we construct following Davis et al. (1996) to account for changes in credit along both the intensive and extensive margin:

\begin{align*}
g(Credit_j) &= \frac{Credit_{j,Post} - Credit_{j,Pre}}{0.5(Credit_{j,Post} + Credit_{j,Pre})},
\end{align*}

where $Credit_{j,Post}$ and $Credit_{j,Pre}$ are the average quarterly credit granted to firm $j$ from 2010:Q2 to 2011:Q2 and from 2009:Q1 to 2010:Q1, respectively. The growth rate, $g(Credit_j)$,

\textsuperscript{25}See Bottero et al. (2019) for more discussion on the relationship between sovereign holdings, bank characteristics, and credit supply.

\textsuperscript{26}Each variable in $Z_j$ varies at the firm-level and it is constructed as a weighted average of the lender-specific variables using as weights the share of firm $j$’s credit received from the bank $b$ in 2010:Q1 ($\omega_{jb}$).

\textsuperscript{27}The two time series are normalized such that aggregate lending is zero in 2009 for each group. Appendix D provides a detailed description of the procedure followed to conduct Figure 3, panel a.
is a second-order approximation of the log difference growth rate around 0. It is bounded in the range [-2,2], which limits the influence of outliers. This measure also accounts for changes in credit along both the intensive and extensive margins.\footnote{For example, if a firm has positive credit in the $Pre$ period and zero credit in the $Post$ period, then $g(\text{Credit}_j)$ takes value -2, thus capturing the extensive margin as well as bounding the influence of outliers in the intensive margin.}

Table 3 presents the estimation results. The coefficients on the bank-level variables are reported as z-scores (de-meaning and scaling observations by the standard deviation). Standard errors are clustered at the main lender-level to address the fact that our credit supply shock measure is correlated across firms that are borrowing from the same set of lenders. Column 1 shows that firms more exposed to lenders with larger holdings of distressed sovereigns experienced a drop in credit availability. This effect is both statistically and economically significant. On average, a one standard deviation increase in banks’ holdings of GIPSI sovereign securities corresponds to a reduction of 16 percent in bank credit in the year following the burst of the sovereign crisis. Figure 3, panel b, presents a binned-scatter plot showing that the negative relationship between exposure to the sovereign crisis and the growth rate of firm credit is monotone and holds throughout the entire distribution of sovereign exposure, and is not driven by outliers. We note that the exposure to lenders with high sovereign holdings had a stronger effect on credit for firms that rely more on bank credit (column 2) and for firms with a large amount of liabilities coming due within the end of the next fiscal year. We will return to this point in section 5.

In Appendix D, we provide additional regression analysis demonstrating that credit supply factors, rather than a contraction of credit demand or a worsening of firms’ credit worthiness, are driving the observed drop in bank credit. We focus on firm-bank relationship, which allows us to estimate a variant of model (9) that includes firm-fixed effects in order to control for differences in firm-level credit demand. We find similar results as those presented above in Table 3, which supports idea that the contraction in credit was due to supply shocks.

Finally, columns 2–4 show that the credit shock did not affect firms’ growth rates of credit equally. We interact the GIPSI exposure with firms’ leverage and with the share of firms’ net liabilities outstanding in 2009 (liabilities due within one year minus cash). The negative interaction terms highlights that firms that entered the crisis with a high leverage and, in particular, with large share of liabilities coming due experienced the greater contraction of bank credit. These results suggest that the credit shock affected firms’ real activity not only preventing them from expanding their balance sheet but also, and mostly, forcing them to shrink it. We will return to this point in Section 5 when we study how firm policies responded to the negative credit shock.

A causal interpretation of the estimates in Table 3 relies on the validity of the parallel
Figure 3: Credit growth and exposure to the sovereign crisis

Panel a: Aggregate credit

Panel b: Credit growth and exposure to the sovereign crisis

Panel c: Firm-level and relationship-level credit growth

Notes: Panel a displays the aggregate amount of credit received by firms exposed to lenders with high holdings of sovereigns issued by GIPSI countries and lenders with low sovereign holdings. See Appendix D.1 for a detailed description of the procedure use to construct this figure. Panel b displays a binned-scatter plot showing the growth rate of credit, grouping firms according to their lenders’ exposure to GIPSI securities. Panel c displays the relationship between firms’ exposure to the sovereign crisis ($\text{Sov}^{\text{GIPSI}}_j$, measured in 2010-Q1) and the growth rate of credit over different time horizons (2006-2013), relative to the period of the Greek bailout.
Table 3: **Effect of sovereign shock on bank credit**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sov$_j$</td>
<td>-.166***</td>
<td>-.123***</td>
<td>-.077**</td>
<td>-.074**</td>
</tr>
<tr>
<td></td>
<td>(.046)</td>
<td>(.037)</td>
<td>(.045)</td>
<td>(.038)</td>
</tr>
<tr>
<td>Sov$_j$ x Bank Leverage$_j$</td>
<td>-.258**</td>
<td>-.202*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.109)</td>
<td>(.097)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sov$_j$ x Share liabilities due$_j$</td>
<td>-.255***</td>
<td>-.176**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.097)</td>
<td>(.068)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>.223</td>
<td>.233</td>
<td>.232</td>
<td>.237</td>
</tr>
<tr>
<td>Observations</td>
<td>1,002</td>
<td>1,002</td>
<td>1,002</td>
<td>1,002</td>
</tr>
<tr>
<td>Industry FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Geography FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Firm FE</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
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</table>

**Notes:** In columns (1)–(4), the dependent variable is the firm-level growth rate of credit $g(Credit_j)$. Each regression includes firm-, bank-, relationship-level controls and industry and region fixed effects. All coefficients of bank-level variables are expressed in z-scores. Standard errors (in parentheses), are clustered at the main-bank level.

trend assumption. While this assumption is fundamentally untestable, we can provide indirect evidence consistent with its validity. At an aggregate level, Figure 3 panel a, shows that the stock of credit for the firms exposed to banks with high and low GIPSI’s sovereign holdings moved similarly prior to the sovereign debt crisis. The micro-level data confirm these patterns. We estimate the panel version of model (9):

$$g_t(Credit_j) = \sum_{\tau=1}^{5} \beta_{\tau} \cdot Sov_j \times 1(\tau = 1) + \Gamma_1'X_{j\tau} + \Gamma_2'K_{j\tau} + \Gamma_3'Z_{j\tau} + i_{ind} + i_{reg} + i_{\tau} + u_j$$ (10)

where the left-hand-side variable $g_t(Credit_{j\theta})$ now measures the cumulative growth rate of bank credit of firm $j$ between year 2009 $-$ $\tau$ and 2009. The Boolean variable $1(\tau = 1)$ takes value one $\tau$–years from the shock and zero otherwise, $i_{\tau}$ are year fixed effects. The vectors $X_{j\tau}, K_{j\tau}, Z_{j\tau}$ are vectors of firm–, relationship–, and bank–level controls, fully interacted with the time-fixed effects. Figure 3, panel c reports the estimates of the coefficients of interest ($\beta_\tau$) showing no relationship between credit growth and our measure of exposure to the sovereign shock prior to the Greek bailout. In Appendix D, we present additional empirical tests that provide further support of these assumptions and of the robustness of our findings.
5 The effect of negative financial shocks on productivity and prices

We now move to the primary focus of our analysis, the connection between credit supply shocks and productivity growth, taking advantage of quasi-experimental variation in credit supply driven by firms’ heterogeneous exposure to the sovereign shock. As emphasized in Section 2, this implies that any inference relating revenue productivity and negative credit shocks may be misleading, since TFPR growth might reflect movements in prices rather than any change in TFPQ growth. We organize our investigation into two parts. We start by studying the short-term effects of a credit supply shock and then extend our time-frame to study the long-term effects.

5.1 Short-run effects

Following previous empirical studies in the finance-productivity literature, we begin our analysis estimating the reduced-form relationship between the credit shock and productivity and price growth (model (9)). Results are presented in Table 4, panel a, column 1. In line with previous findings, we find a statistically significant and economically relevant negative relation between negative credit supply shocks and revenue productivity growth (Dörr et al., 2018; Duval et al., 2017; Manaresi and Pierri, 2018). Comparing two similar firms that operate in the same industry and region, a one-standard deviation difference in the exposure to the sovereign crisis translates into a reduction of 2 percent in firm-level revenue productivity for the more exposed firm.

Next we turn to the main focus of our analysis: the decomposition of the contribution of the TFPR effect into TFPQ growth and price adjustments. The estimates suggest a statistically and economically significant negative effect on firm-level prices. The price-adjustment is economically meaningful: Over a one-year window, a one-standard deviation difference in exposure to the credit shock is associated with a 1.2 percent drop in prices (column 2). The estimates of the impact of a credit supply shock on TFPQ paint a clear picture: There is no evidence of an effect of the credit shock on technical productivity over the short-run, as the estimated effects are both economically negligible and statistically insignificant (columns 3 and 4). This result is remarkably robust across the two measures, $TFPQ^R$ and $TFPQ^Q$. These findings are in line with the theoretical predictions in section 2.2 that highlight how, on average, in the presence of financial frictions the optimal response to a negative credit supply shock is a reduction of output prices (Proposition 1). This drives a reduction in revenue productivity, while technical productivity is unchanged (Proposition 3).
As discussed in section 4, the presence of multi-product firms poses an empirical challenge when it comes to the construction of an appropriate firm-level price index. The similarity between the coefficients of the shock on $TFPQ^R$ and $TFPQ^Q$ suggests our price-index measure is not driving the empirical results. Table 4, panel b, provides additional evidence in this direction. We replicate our analysis on prices and TFPQ, focusing on the price of the main product ($P_{Main,j}$) and the adjusted price of the main product ($P_{Main-adj,j}$), obtaining price and technical productivity responses that are very similar to the ones obtained at firm-level in our baseline specification.

In order to put these estimates into perspective, and gauge the economic magnitude of the implications of credit supply movements on productivity and pricing, we instrument the growth rate of credit ($g(Credit_j)$) with our credit supply shock variable and estimate the elasticity of productivity and price growth to credit supply movements (Table 4, panel c). We find that a 10 percent decrease in the growth rate of bank credit, driven by a contraction of credit supply, leads to a 1.1 percent drop in revenue productivity over a one-year horizon. This drop is explained by a reduction of output prices (1.3 percent), whereas the response of technical productivity is essentially zero, regardless of how prices and TFPQ are measured.

**Economic channels: Inventory management and balance sheet strength** – What economic mechanisms drive these short-term effects? The answer to this question we start with the recognition that the average price response to the credit shock may mask important heterogeneity across firms. To investigate this, we estimate a discretized version of model (9) that estimates the average price change comparing firms with the highest exposure to the credit supply shock (third tercile of Sov$_j$) to those with the lowest exposure (first tercile of Sov$_j$). On average, firms in the high exposure group reduce prices by 5 percent relative to firms in the low exposure group. Then, we focus on the high-exposure firms and calculate the marginal contribution of each observation to the average response of $\Delta \ln(P_j)$.

Figure 4 plots the cumulative distribution of these contributions. Two observations are in order. First, we observe significant heterogeneity in the price adjustment, among firms that respond to the credit shock by reducing their prices. Second, we find that around a third of the observations respond to the shock by increasing prices, although the price increases are smaller in magnitude than the price decreases of those firms that reduce prices. The large

---

29We estimate the marginal contribution of each observation to the average effect via an influence function: $\beta_j = (\tilde{S}_{ovj} - \tilde{\mu}_{sov}) \times [(\Delta \ln(P_j) - \tilde{\mu}_{\Delta \ln(P_j)}) - \beta (\tilde{S}_{ovj} - \tilde{\mu}_{sov})]$, where $\tilde{S}_{ovj}$ and $\Delta \ln(P_j)$ are residuals of a regression of firm-, relationship-, bank-level variables and fixed effects on $S_{ovj}$ and $\Delta \ln(P_j)$, respectively. $\tilde{\mu}$ and $\tilde{\sigma}^2$ are the average and standard deviation of the residuals in the subset of firms with high sovereign exposure. By construction, the sum of each contribution is equal to zero ($\sum_j \beta_j = 0$). We add back the estimated average effect ($\beta = -0.05$) when we plot the distribution of $\beta_j$ in Figure 4.
Table 4: Short-term effect of credit supply shocks on productivity and prices

<table>
<thead>
<tr>
<th>Panel b: Reduced form regression</th>
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<tbody>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>Δ ln(TFPR&lt;sub&gt;i&lt;/sub&gt;)</td>
</tr>
<tr>
<td>Sov&lt;sub&gt;j&lt;/sub&gt;</td>
</tr>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
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<table>
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<th>Panel b: Price of the main product</th>
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<tbody>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>Δ ln(P&lt;sub&gt;Main,i&lt;/sub&gt;)</td>
</tr>
<tr>
<td>Sov&lt;sub&gt;j&lt;/sub&gt;</td>
</tr>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
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<table>
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<th>Panel c: 2SLS Regression</th>
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<tr>
<td>(1)</td>
</tr>
<tr>
<td>Δ ln(TFPR&lt;sub&gt;i&lt;/sub&gt;)</td>
</tr>
<tr>
<td>g(Credit&lt;sub&gt;i&lt;/sub&gt;)</td>
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<tr>
<td></td>
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<tr>
<td>Firm Controls</td>
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<tr>
<td>Relationship Controls</td>
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<td>Bank Controls</td>
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<tr>
<td>Geography FE</td>
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<td>Observations</td>
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Notes: This table estimates the effect of a credit supply tightening on the one-year growth rate of revenue productivity (Δ ln(TFPR<sub>i</sub>)), technical productivity (Δ ln(TFPQ<sub>R</sub>)), and prices (Δ ln(P<sub>i</sub>)). In panel a, we estimate the reduced-form coefficient measuring the effect of exposure to the credit shock (Sov<sub>j</sub>, de-meaned and scaled by its standard deviation) on the one-year growth rate of TFP and prices at the firm-level. In column (1) the dependent variable is the firm-level growth rate of revenue productivity (Δ ln(TFPR<sub>i</sub>)). In columns (2) and (3) the dependent variables are the growth rate of the firm-level price index (P<sub>i</sub>) and the growth rate of TFPQ measured as the log difference of that price and TFPR (Δ ln(TFPQ<sub>R</sub>)). In column (4) the dependent variable is the growth rate of TFPQ measured directly from quantities (Δ ln(TFPQ<sub>Q</sub>)). In panel b, we look at the prices of the main product and the corresponding TFPQ measures. In columns (1) and (2) the dependent variables are the growth rate of the price of the main product (P<sub>Main,i</sub>) and the growth rate of TFPQ measured as the log difference of that price and TFPR (Δ ln(TFPQ<sub>R</sub>)<sub>Main,i</sub>). In columns (3) and (4) the dependent variables are the growth rate of the adjusted price of the main product (P<sub>Main-adj,i</sub>) and the growth rate of TFPQ measured as the log difference of that price and TFPR (Δ ln(TFPQ<sub>R</sub>)<sub>Main-adj,i</sub>). In panel c, we report the 2SLS estimates, where we regress the growth rate of credit (g(Credit)) on the growth rate of TFPR, prices, and TFPQ, instrumenting g(Credit) with the credit supply shifter Sov<sub>j</sub>. All regressions include a battery of firm-specific, relationship-specific, and bank-specific controls, as well as industry and region fixed effects. Standard errors (in parentheses), are clustered at the main-bank level.
heterogeneity in the response of pricing policies to financial shocks is not surprising. In fact, previous studies have provided contrasting empirical evidence on this matter. Borenstein and Rose (1995), Zingales (1998), Busse (2002), Phillips and Sertsios (2013), and Kim (2018) – the closest to our study – find a negative relationship between firms’ financial conditions and price adjustments. Another set of influential studies finds instead that firms increase prices in response to an increase of financial frictions and higher likelihood of financial distress (Chevalier, 1995a; Chevalier, 1995b; Chevalier and Scharfstein, 1995; Chevalier et al., 1996; Gilchrist et al., 2017).

A natural questions arises: What firm characteristics can explain the heterogeneous response of firms’ pricing policies? Our theoretical model highlights that inventory management allows firms to respond to negative financial shocks, as companies might find it optimal to “fire sale” their inventory to cope with a credit tightening.

We test the “inventory fire sale” channel, summarized by the first part of Proposition 2: Firms have an incentive to liquidate inventories and sell their products at a lower price in order to generate the extra cash flows needed to repay debt that cannot be rolled-over or to finance current costs or business expansions. We should expect a stronger price response comparing the pricing response of firms that are equally exposed to the credit shock but have higher stocks of inventory when the shock hits. The data provides strong support for this theoretical prediction. Table 5, column (1), shows that prices of firms with high inventory holdings drop by 2 percentage points more than firms with low inventory holdings that are equally exposed to the credit shock, helping explain the large heterogeneity in the negative
These findings are in line with the ones in seminal work of Kashyap et al. (1994) and Gertler and Gilchrist (1994) and the more recent study by Kim (2018), all of which provide empirical evidence in support of the inventory channel for firms in the U.S.

A second theoretical prediction is that, ceteris paribus, a firm at high risk of financial distress responds to a credit tightening by increasing prices relative to a firm not exposed to the shock and, a fortiori, relative to firms equally exposed to the shock but with low risk of default (second part of Proposition 2). Intuitively, if the likelihood of default is high, it is not optimal to lower prices and give up current profits in order to increase revenues, since the marginal effects of more revenues on the probability of survival is tiny. We use the share of liabilities due within one year, measured in 2009 before the credit shock, as an indicator of which firms are more likely to be in distress. The idea is that a credit tightening impairs debt rollover and therefore disproportionately exposes firms with a large amount of liabilities due in the short-term to bankruptcy risk. The analysis in section 4.2 (Table 3, column 2) highlights that indeed firms entering the crisis with a large share of liabilities coming due did experience a sharper contraction in credit in the wake of the crisis. In Table 5, we interact the share of liabilities due with our measure of credit shock (columns 2 and 3). In line with the prediction of the model, we find that firms facing high rollover risk do not respond to the credit shock by lower prices as much as firms with lower default risk do. We highlight that the effect of Share liabilities due\textsubscript{j} is non-linear, since only firms with a substantial share of liabilities coming due are the ones at high risk of financial distress. Column 4 shows that this is the case, isolating the effect of the shock on the subset of firms with Share liabilities due\textsubscript{j} in the top quintile of the distribution (dummy High Default Risk\textsubscript{j}).

Next, we can show that high default risk firms, not only decrease prices less, but they actually increase them relative to firms not exposed to the shock. To see this, we need to distinguish between firms that can exploit the inventory channel and those that cannot. In columns 5 and 6, we study the price response for firms with high and low default risk, as a function of their inventories. We find that among those firms with high liabilities due, firms with low inventory holdings seem respond by increasing their output prices relative to firms at the top and bottom decile of the distribution of inventories over sales (0.30 and 0.03, respectively). In unreported analysis, we also experimented with a quadratic interaction with inventory holding and found that the a linear model better fits data. Moreover, we did detect any heterogeneity in the response of the firm-level growth rate of credit to the credit shock – the first-stage regression – as a function of the inventories level of firms.

\textsuperscript{30}These calculations reflect the comparison of the effect of the shock on prices for firms at the top and bottom decile of the distribution of inventories over sales (0.30 and 0.03, respectively). In unreported analysis, we also experimented with a quadratic interaction with inventory holding and found that the a linear model better fits data. Moreover, we did detect any heterogeneity in the response of the firm-level growth rate of credit to the credit shock – the first-stage regression – as a function of the inventories level of firms.

\textsuperscript{31}Firms with High Default Risk\textsubscript{j} = 1 have over 30 percent of their 2009 liabilities due within the end of the following fiscal year. In unreported regressions we run an horse-race regression between bank-leverage and the share of liabilities that are due within one year. While both high leverage and high share of liabilities due predict a stronger first-stage coefficient (Table 3, column 3 and 4), we find that the former cannot explain the heterogenous prices response while the latter retains its explanatory power.
a similar firm which is less exposed to the shock.\textsuperscript{32} These results are also consistent with the idea that firms with higher liquidity needs (measured by the share of liabilities due) have more incentive to lower prices by liquidating inventory. Taken together, the results in Table 5 reveal that a joint consideration of firms’ asset (inventory “fire sale” channel) and liabilities is crucial to understand the real effects of credit supply shocks, which is a literal application of the celebrated Modigliani and Miller (1958) result.

To summarize: In the short-run, the response of TFPR growth to credit shocks is, on average, driven by price adjustments. The strength and sign of the price adjustment is highly heterogeneous across firms. Firms with high levels of inventories decrease prices substantially as these firms fire sale their inventory stock to raise liquidity. However, firms with both low inventories and weak balance sheets increase their prices in response to the credit tightening. The fact that, in the short-run, technical productivity does respond to a negative credit shock is a sensible result. Productivity is a slow-moving variable, which gradually evolves as a result of innovation in production processes, higher human capital accumulation, or organizational changes. The same reasoning suggests that, in the long-run, productivity growth might be affected by a negative, persistent credit tightening, which is what we analyze next.

5.2 Long-run effects

In order to study the long-term implications of credit supply on productivity we estimate a panel version of the model in (10) using as dependent variables the cumulative growth rate of TFP (and prices) calculated over different horizons.\textsuperscript{33} Table 6 presents the estimates of $\hat{\beta}_r$, and captures much of the paper’s primary findings: the negative supply shock has a short-lived effect on prices and a long-lived effect on technical productivity.\textsuperscript{34} Revenue productivity persistently declines over time for firms more exposed to the credit tightening. The slowdown in TFPQ is the driver of the long-run decrease in TFPR.

\textsuperscript{32}The price increase is consistent with the finding in Gilchrist et al. (2017). The authors showing that financially weak firms raise prices, while their financially stronger counterparts lowered prices in periods characterized by credit market distress. The rationalize their findings using a model in which firms face financial frictions while setting prices in customer markets. The decision to increase prices in response to a financial shock reflects the firms’ decisions to preserve internal liquidity and avoid accessing expensive external finance. Although this force is not a direct prediction of our stylized model, it is consistent with the our findings.

\textsuperscript{33}All reported standard errors are clustered at the main lender level and and firm level to account for the fact that different firms are exposed to a similar or equal treatment effect and for the autocorrelation of firm-level residuals. In addition to the empirical model with firm, time, and region fixed effects, we experimented with a fully interacted model with industry-by-year and region-by-year fixed effects. The basic results are unchanged by these alterations in the specification.

\textsuperscript{34}We find that, over the long-run, the prices of the firms most affected by the shock recover, or even increase, relative to less affected firms, although the long-run price increase is not statistically significant at conventional levels.
Table 5: Short-term effect of credit supply shocks on prices: Channels

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<tr>
<td>( \Delta \ln(P_j) )</td>
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<tr>
<td>Sov(_j)</td>
<td>-.014</td>
<td>-.032**</td>
<td>-.027***</td>
<td>-.028***</td>
<td>-.024***</td>
<td>-.024**</td>
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<tr>
<td></td>
<td>(.008)</td>
<td>(.009)</td>
<td>(.008)</td>
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<td>(.009)</td>
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<tr>
<td>Sov(_j) \times \text{Inventory}_j</td>
<td>[A]</td>
<td>-0.074***</td>
<td>.015</td>
<td>-.037</td>
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<tr>
<td></td>
<td>(.018)</td>
<td>(.018)</td>
<td>(.044)</td>
<td>(.028)</td>
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<td></td>
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<tr>
<td>Sov(_j) \times \text{Share liabilities due}_j</td>
<td>[B]</td>
<td>.029</td>
<td>-.007</td>
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<tr>
<td></td>
<td>(.017)</td>
<td>(.016)</td>
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<tr>
<td>Sov(_j) \times \text{Share liabilities due}_j^2</td>
<td>[C]</td>
<td>.050**</td>
<td></td>
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<td>(.021)</td>
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<tr>
<td>Sov(_j) \times \text{High Default Risk}_j</td>
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<td></td>
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<td>.043***</td>
<td>.050**</td>
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<td>(.009)</td>
<td>(.012)</td>
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<tr>
<td>Sov(_j) \times \text{Inventory}_j \times \text{Share liabilities due}_j</td>
<td>[B]</td>
<td></td>
<td>-.209**</td>
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<td></td>
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<td>(.108)</td>
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<tr>
<td>Sov(_j) \times \text{Inventory}_j \times \text{High Default Risk}_j</td>
<td>[C]</td>
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<tr>
<td>[A] + [B]</td>
<td></td>
<td></td>
<td>-0.194**</td>
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<td></td>
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<td>(.069)</td>
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<tr>
<td>[A] + [C]</td>
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<td>-0.181**</td>
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<td>Geography FE</td>
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<td>1,002</td>
<td>1,002</td>
<td>1,002</td>
<td>1,002</td>
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</table>

Notes: This table explores the heterogeneity in the pricing effect of a credit supply shock. In all columns, the left-hand side variable is the one-year growth rate of the firm-level price index (\( \Delta \ln(P_j) \)). We estimate model (9), interacting firms’ exposure to the sovereign shock (Sov\(_j\), de-meaned and scaled by its standard deviation) with measures of inventories stock (Inventory\(_j\)) and share of liabilities due (Share Liabilities Due\(_j\)). The variable High Default Risk\(_j\) takes value one if Share Liabilities Due\(_j\) is in the top quintile of its distribution. All regressions include a battery of firm-specific, relationship-specific, and bank-specific controls, as well as industry and region fixed effects. Standard errors (in parentheses), are clustered at the main-bank level.
Table 6: **Long-term effect of credit supply shocks on productivity and prices**

<table>
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<th>(1)</th>
<th>(2)</th>
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<tbody>
<tr>
<td>$\text{Sov}^{\text{GIPSI}} \times 1(\tau = 1)$</td>
<td>-0.025***</td>
<td>-0.042**</td>
<td>0.017</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.021)</td>
<td>(0.019)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>$\text{Sov}^{\text{GIPSI}} \times 1(\tau = 2)$</td>
<td>-0.025***</td>
<td>-0.037*</td>
<td>0.011</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.021)</td>
<td>(0.020)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>$\text{Sov}^{\text{GIPSI}} \times 1(\tau = 3)$</td>
<td>-0.031***</td>
<td>-0.006</td>
<td>-0.024</td>
<td>-0.002</td>
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<tr>
<td></td>
<td>(0.005)</td>
<td>(0.022)</td>
<td>(0.021)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>$\text{Sov}^{\text{GIPSI}} \times 1(\tau = 4)$</td>
<td>-0.042***</td>
<td>0.049*</td>
<td>-0.091***</td>
<td>-0.098***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.024)</td>
<td>(0.025)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>$\text{Sov}^{\text{GIPSI}} \times 1(\tau = 5)$</td>
<td>-0.044***</td>
<td>0.058</td>
<td>-1.01***</td>
<td>-1.01**</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.035)</td>
<td>(0.037)</td>
<td>(0.048)</td>
</tr>
</tbody>
</table>

Firm Controls | Y | Y | Y | Y |
Relationship Controls | Y | Y | Y | Y |
Bank Controls | Y | Y | Y | Y |
Year FE | Y | Y | Y | Y |
Industry FE | Y | Y | Y | Y |
Geography FE | Y | Y | Y | Y |
$R^2$ | .276 | .172 | .169 | .133 |
Observations | 4,329 | 4,329 | 4,329 | 4,329 |

Notes: This table presents the estimates of the effect of a credit supply tightening on the cumulative growth rate of TFP and prices over different time-horizons. The dependent variable is firms’ exposure to the sovereign shock ($\text{Sov}_{j}$, de-meaned and scaled by its standard deviation). In columns (1) and (2) we focus on the growth rate of firm-level revenue productivity ($\text{TFPR}_{j}$) and firm-level price index ($P_{j}$), respectively. In columns (3) and (4) we focus on the growth rate of technical productivity, constructed as the difference between the log-change in TFPR and the log-change in the firm-level price ($\text{TFPQ}_{j}^{Q}$) and estimated directly from quantities ($\text{TFPQ}_{j}^{Q}$). Growth rates are calculated relative to the levels in 2009. All regressions include a battery of firm-specific, relationship-specific, and bank-specific controls, as well as year, industry, and region fixed effects. Standard errors (in parentheses), are double clustered at the main-bank level and the firm level.

Starting from three years after the credit shock, the growth rate of technical productivity for firms facing a credit tightening is significantly below the growth rate of otherwise similar firms that are less affected by the shock. The results in columns 3 and 4 in Table 6 highlight that the estimated long-run effect of the credit shock is almost numerically equivalent for our two measures of technical productivity, $\text{TFPQ}_{j}^{Q}$ and $\text{TFPQ}_{j}^{Q}$. 

**Economic channels: Investments in innovation and technology adoption** – Why do firms facing a credit tightening experience a long-run TFPQ slowdown? Our model delivers a similar prediction (Proposition 4).\textsuperscript{35} We take it to the data by estimating model (10) using as dependent variables different measures of investments in innovation activities.

Figure 5, panels a and b, shows the estimated effect of the credit supply shock on the (cumulative) investments in intangible assets, distinguishing between R&D investments and expenditures on patent adoption, over the five years following the burst of the sovereign crisis.

\textsuperscript{35}Queralto (2019) presents a quantitative macroeconomic model featuring endogenous growth in TFP through innovation, in which financial frictions affect firms ability to innovate. See also Aghion et al. (2012); Garcia-Macia (2017), Huber (2018), and Anzoategui et al. (2019).
A one-standard deviation increase in the exposure to the sovereign crisis translates into a persistent reduction of 2.5 percentage points in firm-level direct investments in innovation and technology adoption (-0.5 and -3 percentage points for R&D and patents, respectively).

The gradual but persistent slow-down in innovation can explain why we find no impact of credit shocks on productivity in the short-run but sizable negative effects at longer horizons. To directly link the long-term slowdown in TFPQ with under-investment in innovation, we project variation in TFP growth onto the cumulative investment in intangibles. Figure 5, panel d, presents the results of this “naive” 2SLS estimator. The positive relation between the variation in innovation activity explained by the credit shifter and long-run productivity growth suggests that one way for firms to respond to the credit shocks and raise liquidity in the short-run is to reduce expenditures on long-term investments such as investments in innovation. Due to the slow-moving nature of productivity, the effects of this contraction may not be felt immediately, but a persistent reduction of firms’ innovation activity leads to lower productivity growth in the long-run.

5.3 Robustness

We conclude our empirical investigation with a discussion of the robustness of the estimated effects of credit shocks and prices and productivity, which we present in Appendix E. First, we show that the pricing response also holds for single-product firms. Second, we find that the economic magnitude and statistical significance of the price effect for multi-product firms is very similar to the one reported in Table 4 if we calculate the firm-level price index weighting the adjusted product-level prices by quantity shares rather than revenue shares. Third, we conduct a number of robustness exercises to assess whether the TFPR and TFPQ results are affected by the details of the production function estimation. Overall, our results are confirmed if one performs the production function estimation assuming a Cobb-Douglas production function or using an index-function approach that assumes constant returns to scale and approximates input elasticities with industry-level input revenue shares.

6 Conclusion

This paper explores the relationship between credit supply shocks and productivity growth, emphasizing the distinction between technical productivity and revenue productivity. Much of the recent empirical literature exploring the finance-productivity nexus has focused on the latter effect overlooking the pricing response to negative financial shocks. Unlike previous research, we leverage on administrative data on product-level prices to separately measure
Figure 5: Long-run effects of credit shock on investments in innovation

Panel a: R&D expenditures

Panel b: Patents expenditures

Panel c: Overall innovation expenditures

Panel d: Innovation and TFP growth

Notes: Panel a and panel b show the effect of the credit shock on the two components of investments in intangibles: cumulative investment rate on R&D and technology adoption (expenditures on patents acquisition and utilization). Panel c shows the effect of the credit shock on the overall cumulative investments in intangible assets (R&D plus patent expenditures). Panel d shows the correlation between the variation in investments in innovation explained by the exposure to the credit supply shock and long-run TFPQ growth. Cumulative investment rates are calculated by scaling cumulative expenditures by the stock of intangible assets in 2009. The confidence bands represent ±1.645 times the standard errors of each point estimate. Standard errors are double clustered at the main-bank level and at the firm-level.
revenue productivity and technical efficiency. This, together with quasi-experimental variation in credit supply, allows us to empirically decouple the effect of negative credit supply shocks on TFPR, TFPQ, and pricing.

We find that, consistent with the previous literature, short-term revenue productivity growth is negatively affected by a credit tightening. This effect, however, is entirely driven by a significant decrease in output prices, rather than a slowdown of technical productivity growth. We investigate what variables help characterize the firm-level pricing response. We find that inventory management strategies and the strength of the firm’s balance sheet play a crucial role in explaining the different pricing responses during episodes of credit contraction. These findings allow us to link the previously disconnected literatures on the productivity and pricing responses to financing constraints and, at the same time, they reconcile the contrasting pricing effects previously documented by the literature.

While technical productivity does not respond in the short-run, we do find that the credit shock has a significant impact on long-run productivity growth. Both TFPR and TFPQ decline over time for firms more exposed to a credit tightening. Exploring the channels leading to the long-term decline in productivity, we highlight the role played by investments in innovation.

We believe our findings provide important implications for the existing literature interested in understanding the contribution of financial frictions to the slowdown in aggregate productivity growth following episodes of financial distress. On the one hand, the short-term sensitivity of prices to changes in credit availability makes it important to decompose revenue productivity measures into its price and physical productivity components, something that unfortunately cannot be done easily with common micro-data. On the other hand, the ability to observe other commonly-available balance sheet variables (such as stock of inventory, strength of balance sheet, and measures of product differentiation) can provide some guidance on the sign and magnitude of the TFPR-TPQ bifurcation even when pricing information is not available.
References


