Credit Supply and Productivity Growth

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Abstract

We study the impact of bank credit supply on firm output and productivity. Exploiting a matched firm-bank database, covering all credit relationships of Italian corporations over more than a decade, we measure idiosyncratic supply-side shocks to firm credit availability. We use this to estimate a production model augmented with financial frictions, and show that an expansion of credit supply leads firms to increase both their inputs and value added and revenues for a given level of inputs. Our estimates imply that a credit crunch will be followed by a productivity slowdown, as experienced by most OECD countries after the great recession. Quantitatively, the credit contraction between 2007-2009 can account for about a quarter of the observed decline in Italian total factor productivity growth. Results are robust to an alternative measure of credit supply shock that uses the 2007-2008 interbank market freeze as a natural experiment to control for assortative matching between borrowers and lenders. Finally, we investigate the possible channels: access to credit fosters IT-adoption, innovation, exporting, and the adoption of superior management practices.

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1 Introduction

Does lenders’ credit supply affect borrower firms’ productivity, and if so, how?

Most of OECD economies have been experiencing a decline in aggregate productivity growth over the last decade, as illustrated by figure 1. While financial crises are found to induce strong and persistent recessions,\(^1\) it is still an open question whether credit supply (or lack thereof) played a major role in generating (and/or sustaining) this productivity slowdown.\(^2\)

In this paper, we estimate the effect of idiosyncratic changes in the credit supply faced by Italian firms on their total factor productivity growth. We focus on Italy because of the availability of detailed loan- and firm-level data on credit, inputs, and output. Khwaja & Mian (2008), Chodorow-Reich (2013), and Amiti & Weinstein (2017) exploit lenders-borrowers connections to provide evidence that negative bank shocks diminish credit supplied to borrowing firms and constrain their investment and employment.\(^3\) This paper extends on the previous literature by looking at the impact of credit on productivity.

The sign of the causal relation between availability of external finance and productivity is theoretically and empirically ambiguous. Standard models of financial frictions assume that agents are endowed with an exogenous productivity, implying that credit constraints affect output only via reductions in the amount of capital used in production. Richer models can generate either a positive or a negative relationship. On one hand, being forced to operate with fewer resources might spur innovation (Field, 2003),\(^4\) while abundance might induce managers to exert low effort (Jensen, 1986). If firms can choose between several business opportunities, they are more likely to invest first in the most profitable ones. As credit constraints become slacker, the marginal project may be of worse quality. Additionally, credit booms are sometimes followed by sharp declines in output, see

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\(^1\)Several authors found that financial crises, and the great recession in particular, are different than other recessions. See, for instance, Cerra & Saxena (2008), Reinhart & Rogoff (2009), Reinhart & Rogoff (2014), Jordà et al. (2013), and Oulton & Sebastiá-Barriel (2013). A contrasting view is expressed by Stock & Watson (2012).

\(^2\)Fernald et al. (2017) document that the disappointing recovery of output post great recession in the US is mainly due to low TFP dynamics, although they find implausible that this is generated by financial shocks. Alternative explanations for the productivity slowdown are low business dynamism (e.g. Decker et al. (2014) and Davis & Haltiwanger (2014)), mismeasurement of digital goods (e.g. Mokyr (2014), Feldstein (2015), Byrne et al. (2016)), slowdown of technological progress (e.g. Gordon (2016), Gordon et al. (2015), Bloom et al. (2016), Cette et al. (2016)), and weak demand conditions (Anzoategui et al., 2016). Additionally, Gopinath et al. (2017) and Cette et al. (2016) argue that low interest rates have triggered unfavorable resource reallocations in southern Europe. Adler et al. (2017) argue for the interaction of several factors, from raised uncertainty to aging workforce. Focusing on Italy, Hall et al. (2008) underline the lack of product innovation as a pre-crisis productivity problem.

\(^3\)See also Bentolila et al. (2013), Greenstone et al. (2014), Cingano et al. (2016), and Bottero et al. (2015).

\(^4\)He documents that the years after the great depression represent the most technologically progressive decade of modern American history. In particular, he states: “In other sectors, for example railroads, the disruptions of financial intermediation and very low levels of capital formation associated with the downturn fostered a search for organizational innovations that enabled firms to get more out of what they had.”
Total Factor Productivity in the OECD

Figure 1: TFP provided by OECD (https://data.oecd.org/lprdty/multifactor-productivity.htm). Values in 1985 are normalized to 100 for each Country, with the (unweighted) average plotted. All countries with data since 1985 are included: AUS, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, KOR, NLD, PRT, SWE and USA. The vertical line indicates year=2008.

Schularick & Taylor (2012), Gorton & Ordoñez (2016), and Brunnermeier et al. (2017).

On the other hand, external funds might be necessary to support productivity improvements, generating a positive relationship. Hall & Lerner (2010) survey some evidence about the difficulties to finance innovation. Firms facing tighter credit constraints might invest less in R&D because of liquidity risk (Aghion et al. , 2010), acquire fewer intangible assets because it is more difficult to use them as collateral (Garcia-Macia, 2015), and undertake less radical innovation (Caggese, 2016). Fixed costs might also play a significant role (Midrigan & Xu, 2014). Additionally, negative credit shocks might hurt small firms by forcing managers/entrepreneurs to divert time and effort away from productivity improvements to create relationships with new lenders (“managerial inattention”).

We contribute to the relevant literature on four dimensions. Firstly, we combine the credit register, which contains loan-level data on credit granted by all financial intermediaries to all Italian incorporated firms over the period 1997-2013, with detailed balance-sheet information for a large sample of around 70 thousands firms. The final dataset provides a complete picture of firm access to bank credit together with high quality data on inputs acquisition and output production for both
large and small firms. Importantly, it allows us to credibly study firm-level financial constraints without limiting our analysis to syndicated loans or public companies.

Secondly, we identify idiosyncratic credit supply shocks by exploiting bank-firm relationships and a natural experiment. In contrast to previous empirical studies of finance and productivity, we do not rely on self-reported measures of credit constraints, (potentially endogenous) proxies of financial strength, or local and industry-specific shocks (which might correlate with demand/technology dynamics). In our main analysis, we decompose the growth rate of credit of each bank-firm pair in firm-year component and bank-year component. The bank-year component reveals how different banks change the quantity of credit granted to the same firm, and it captures shocks to bank supply. This additive decomposition, similar to the one developed by Amiti & Weinstein (2017), rests on assumptions related to the matching between banks and firms, and the structure of substitution/complementarity between lenders. We provide novel tests for these hypotheses. To aggregate bank-specific credit supply shocks at the firm level, we exploit the stickiness of bank-firm relations. Because of relationship lending, expansions or contractions of credit from one lender affects disproportionately more its existing borrowers. As a result, two firms serving the same market might experience different shocks to their ability to finance their operation because they have pre-existing credit relations with different lenders. Thus, we average bank shocks at the firm level, using lagged credit shares as weights, to obtain a firm-specific credit supply shock. These shocks allow us to study the effect of credit on firm output and productivity both in “normal times” and during recessions.

Quantitatively, we find that a 1% increase in credit granted raises value added TFP growth by around 0.1%, and revenue TFP growth by 0.02-0.03%. During the financial crisis of 2007-2009, credit growth shrank by around 12%; our estimates imply that a similar supply-driven credit crunch would have induced between 12.5% and 30% of the average drop in firm TFP experienced by Italian firms during the same period. The effect of credit on TFP growth lasts up to two years and does not revert afterwards, so that the impact on TFP levels is persistent over time. Large firms and firms with more lending relations, which are probably more able to substitute away from contracting lenders, are largely unaffected by credit supply. Effects are stronger in sectors where bank credit is

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5The relevance of this phenomenon has been documented in several countries, such as USA (Chodorow-Reich, 2013), Italy (Sette & Gobbi, 2015), Spain (Jiménez & Ongena, 2012) and Pakistan (Khwaja & Mian, 2008).

6Since we do not observe firm-level output prices, productivity is the amount of revenues or value added (not the quantity of goods) generated for a given amount of inputs. In section 3.2.1 we clarify our terminology in relation with previous literature. We also argue that, although investigating the effect of credit supply on physical productivity would be an interesting addition, this limitation does not significantly impair the relevance of our results. Appendix C.1 contains a more formal treatment of the topic. Measures of productivity based on revenues and quantities are usually found to be highly correlated.
more important, that is manufacturing and industries characterized by higher leverage. Our results imply that a credit crunch can generate a productivity slowdown by depressing firm-level TFP. This effect may persist for several years.

To rule out that results are driven by either assortative matching between firms and banks, or other confounding factors, or some forms of reverse causality, we exploit the freeze of the interbank market in 2007-2008 as a natural experiment. This shock affected differently (and unexpectedly) Italian banks according to their pre-crisis reliance on this source of funding. We show that firms hit harder by the credit crunch, through their lenders, experienced lower growth rate of productivity afterwards. Firm exposure is found to be uncorrelated with pre-crisis growth potential and sensitivity to business cycle. This alternative empirical strategy confirms the causal link between credit supply and productivity. Its estimated magnitude is significantly larger, suggesting that the productivity effects are stronger during financial turmoils.

Thirdly, we argue that the standard production function estimation methods would not allow to identify the causal effect of credit supply on productivity. See De Loecker (2013) for a conceptually analogous case regarding the effect of exporting on efficiency. Therefore, we enrich the production function estimation by allowing for the presence of heterogeneous credit constraints affecting both input acquisition and productivity dynamics.

Fourthly, we enrich our dataset with additional administrative and survey-based data sources in order to show that several productivity-enhancing activities, such as R&D, patenting, export, innovation, IT-adoption, and adoption of superior management practices, are stimulated by credit availability. These strategies increase productivity both in the short- (e.g. IT-adoption) and in the long- run (e.g. R&D). Therefore, their sensitivity to credit can both explain the immediate effect of credit supply shock on TFP and it also suggests that there are additional effects over longer horizon. Finally, we discuss some indirect evidence consistent with the “managerial inattention” hypothesis.

Our results imply that disrupting access to external funds depresses output above and beyond the observable contraction of investments. This contributes to the theoretical literature on the aggregate effects of financial frictions and to the empirical investigation of frictions and investment decisions.

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7 Cingano et al. (2016) show that firms that in 2006 were borrowing from banks more reliant to the interbank market experienced a stronger credit crunch, and this in turn reduced investments.


(see Fazzari et al. (1988) and Rauh (2006)).

Our findings are an important complement to the literature on misallocation of production factors. After the seminal paper by Hsieh & Klenow (2009), this strand of research has been thriving in recent years. These papers study how frictions, in particular financial ones, affect overall productivity by shaping the allocation of capital and other inputs between firms for a given distribution of idiosyncratic productivity. We show how financial frictions alter the location of such productivity distribution. Therefore, any empirical investigation of a change in financial conditions on productivity should take into account jointly the impact on allocative efficiency of inputs and the direct effect on firms’ efficiency of production. Furthermore, our results imply that part of the vast heterogeneity in firms’ productivity, that have been consistently found by several empirical works (Syverson, 2011), may be traced back to unequal access to external funds.

We show that the relation between credit supply and productivity is positive and concave. Negative shocks have larger effects than positive ones, and credit supply is particularly important during a financial crisis. These empirical results underline that it is not only the quantity of credit that matters for productivity, but also its stability. Consequently, a credit crunch is likely to have a larger effect on TFP growth than a credit expansion of the same magnitude. Volatility of the banking sector’s supply is detrimental to firm productivity.

A large literature is interested in the link between finance and productivity. For instance, see Schiantarelli & Sembenelli (1997), Gatti & Love (2008), Butler & Cornaggia (2011), Ferrando & Ruggieri (2015), Levine & Warusawitharana (2014), and recent papers by Duval et al. (2017), Dörre et al. (2017), and Mian et al. (2017).

Furthermore, few papers investigate the effect of access to credit on specific productivity-enhancing strategies, such as R&D (Bond et al. (2005), Aghion et al. (2012), and Peters et al. (2017a)), innovation (Benfratello et al. (2008) and Caggese (2016)) intangible investments (Garcia-Macia (2015) and de Ridder (2016)), and exporting (Paravisini et al. (2014) and Buono & Formai (2013)). Access to other sources of external funds can also affect productive investments: for instance, Bernstein (2015) documents how IPOs change innovation strategies in the USA.

The paper proceeds as follows. Section 2 presents the data sources, discusses sample selection and provides descriptive statistics of main variables. Section 3.1 describes the estimation of idiosyn-
ocratic credit supply shocks. Section 3.2 presents a partial-equilibrium model of firm production with heterogeneous credit constraints, which is used to back out firm-level productivity. Section 4 shows that credit supply affects firm input acquisition and output production. Section 5 contains the main results, and deals with their robustness, heterogeneity, and persistence. Section 6 presents additional evidence from the 2007-2008 collapse of the interbank market. Section 7 investigates the mechanisms driving the effect of credit supply on productivity. Section 8 concludes.

2 Data

To perform our empirical analysis, we combine detailed balance-sheet data with loan-level data from Italian credit register and survey-based information on productivity-enhancing activities.

2.1 Firm balance-sheets: the CADS dataset

The Company Accounts Data System (CADS) is a proprietary database administered by CERVED-Group Ltd. for credit risk evaluation. It collects detailed balance-sheet and income statement information on non-financial corporations since 1982. It is the largest sample of Italian firms for which data on actual investments flows are observed; net revenues of CADS firms account for about 70% of total revenues of private non-financial sectors. It is used by banks for credit decisions and, hence, the data are carefully controlled.

We estimate production functions for firms sampled in CADS from 1998 to 2013. Firm-level capital series are computed applying the perpetual-inventory method (PIM) on book-value of capital, investments, divestments, and sector-level deflators and depreciation rates. Operating value added and intermediate expenditures are recorded in nominal values in profit-and-loss statements: we convert them in real terms using sector-level deflators from National Accounts. The baseline measure of labor is measured by the wage bill, deflated using the consumer price index (CPI). Expenditure on intermediate inputs are deflated using a combination of sector-level deflator and regional level CPI. Through the paper, we use a Nace Rev.2 2-digit definition of industry. In addition, in a robustness exercise, (section 5.1) we show that the main results of the paper are very similar if one uses a finer 4-digit definition.

11 See Lenzu & Manaresi (2017) for details on PIM. We thank Francesca Lotti for providing capital series for an early version of this paper.

12 Namely, we assume the price of intermediate inputs is the arithmetic mean between national price and national price deflated by local CPI. This is done because some inputs might be bought on national rather than local markets.
From CADS, we also collect information on firm characteristics such as age, cash-flow, liquidity, assets, and leverage (total debt over asset). Their lagged values are used throughout the analysis of section 5 as firm-level time-varying controls.

### 2.2 Firm-bank matched data: the Italian Credit Register

The Italian Credit Register (CR), owned by the Bank of Italy, collects individual data on borrowers with total exposures (both debt and collateral) above €30,000\textsuperscript{13} towards any intermediary operating in the country (banks, other financial intermediaries providing credit, and special purpose vehicles).\textsuperscript{14} The CR contains data on the outstanding bank debt of each borrower, distinguished into loans backed by account receivables, term loans, and revolving credit lines. CR data can be matched to CADS using the firm unique tax identifier.

For all credit relationship any Italian incorporated firm and any intermediary between 1998 to 2013, we measure net credit flows as the yearly growth rate (delta-log) of total outstanding debt. We do not differentiate between different kinds of credit (for instance credit line versus loans), because the choice of which type of credit to increase/decrease is ultimately the result of strategic bargaining between banks and firms. We also focus on credit granted rather than on credit used, as the latter is more strongly affected by credit demand.

### 2.3 Additional data sources

While the baseline estimate of the effect of credit supply on productivity exploits CADS and CR, further enquiries into the channels that drive this effect and several robustness checks of our analyses rely on several additional data sources.

To test whether estimates of credit supply shocks are robust to assortative matching between firms and banks (see section 3.1), we control for past interest rates charged by banks to firms. This information is available from the TAXIA database, administered by the Bank of Italy, for a large sample of Italian banks (encompassing over 70% of all credit granted to the Italian economy). Interest rates are computed as the ratio between interest expenditures and the quantity of credit used.

Information on banks assets, ROA, liquidity, capital ratio, as well as their interbank liabilities and

\textsuperscript{13}For instance, a borrowing firm with debt of €20,000 towards a bank appears in the CR if it also provides guarantees worth at least €10,000 to any another bank. The threshold was €75,000 before 2009.

\textsuperscript{14}We follow previous literature (Amiti & Weinstein, 2017) and include all financial intermediaries in the main analysis. We use the generic term of “bank” for all of them. In a robustness exercise, available upon request, we show that the results of the paper are unchanged if we exclude firms which rely heavily on credit from non-bank intermediaries (≈0.33% of total observations).
assets are obtained from the Supervisory reports: they are used in our study of the consequences of the 2007-2008 interbank market collapse as an exogenous change in credit supply (section 6). In Section 7, we study the relevance of specific productivity-enhancing activities that are fostered by credit supply. These include IT adoption, R&D expenditures, patenting, and export. These information are difficult to identify using balance-sheets data, because of reporting by firms is generally non-compulsory. For this reason, we complement CADS with two sources of data. Data on IT adoption, R&D, and export come from the INVIND Survey, administered by the Bank of Italy. INVIND is a panel of around 3,000 firms, representative of Italian firms above 20 employees active in manufacturing and private services. For patent applications to the European Patent Office we use the PatStat database. In particular, we exploit a release prepared by the Italian Association of Chambers of Commerce (UnionCamere), which matches all patent application made during the period 2000-2013 with the tax identifiers of all Italian firms. Furthermore, we obtain data on management practices for more than 100 manufacturing companies from the World Management Survey, see section 7.

2.4 Sample selection and descriptive statistics

Our main analysis is based on two samples. A relationship-level dataset, in which an observation corresponds to a bank-firm-year triplet, is used for the identification of credit supply shocks. A firm-level dataset, in which observations correspond to firm-year pairs and credit supply shocks are aggregated across banks, for production function estimates.

The relationship-level dataset is based on the CR data. It consists of all relationships between incorporated firms and financial intermediaries over the period 1997-2013. The resulting dataset consists of 13,895,537 observations, and is composed of 852,196 unique firms, and one 1,008 banks per year.

For production function estimation, we consider all firms in CADS that report positive revenues, capital, labor cost, and intermediate expenditures, so that a revenue production function can be estimated. As a result, we exclude around a fifth of the original CADS dataset: the final sample consists of 76,542 firms, corresponding to 656,960 firm-year observations. This dataset is used to estimate all the baseline regressions. Table 1 reports the main variables from the firm-level dataset for both the whole sample and manufacturers only. To provide preliminary descriptive evidence that bank credit is a relevant source of finance for Italian firms, we study the credit intensity of firms’ activity. We define credit intensity of firm $i$ at time $t$ as the ratio between total credit granted at the end of year $t - 1$ and the net revenues of year $t$. On average, manufacturers are granted 43 cents
for each euro of revenues generated, while this figure is only 34 cents non-manufacturer. Appendix figure A.1 shows that credit intense companies are larger in non-manufacturing sectors, but not in manufacturing. Appendix figure A.2 shows that industries with higher capital labor ratio are more credit intensive.

3 Theoretical Framework

We investigate the relation between credit supply and productivity. As a first step to this goal, we consider an empirical model to disentangle idiosyncratic shocks to credit supply from shocks to credit demand and shocks to the general economic context (section 3.1). Then, we build a model of production with heterogeneous credit constraints to recover firm TFP (section 3.2).

3.1 Credit Supply Shocks

We define credit supply shocks as any change in bank-specific factors affecting its ability and willingness to provide credit to firms. Banks are heterogeneous in their exposure to different macroeconomic risks (Begenau et al., 2015). This heterogeneity can arise because of differences in liabilities, assets or capital.15

Total credit granted to firm $i$ at the end of year $t$ equals the sum of credit granted by all existing intermediaries $b$: $C_{i,t} = \sum_b C_{i,b,t}$. We define firm $i$ and bank $b$ to have a pre-existing lending relation in period $t$ if and only if $C_{i,b,t-1} > 0$. Credit granted $C_{i,b,t}$ is an equilibrium quantity which depends on both supply and demand factors, as well as aggregate shocks. We collect all the observable and unobservable factors that determine the idiosyncratic supply of credit to corporations from bank $b$ in year $t$ into the vector $S_{b,t}$. For instance, bank-specific cost of funds, capital, and lending strategies may all be components of $S_{b,t}$. Similarly, let $D_{i,t}$ be the vector of observables and unobservables shaping firm $i$’s demand for credit and its desirability as a borrower, such as productivity, size and leverage. In addition, credit may be affected by firm-bank specific factors, such as the length of the pre-existing lending relationship, or the quantity of credit previously provided by the bank to the firm (affecting the incentive to evergreen). We collect these match-specific covariates in the vector $X_{i,b,t}$. Finally, aggregate factors affecting all intermediaries and borrowers, such as aggregate demand, or

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15For instance, Khwaja & Mian (2008) show that the Pakistani banks who relied more on dollar deposits experienced stronger liquidity shocks after the unexpected nuclear tests in 1998. Chodorow-Reich (2013) uses US banks’ connections to Lehman brother and their exposure to mortgage-backed securities as an instrument for their financial health. In section 6 we exploit heterogeneity in reliance on Interbank market as sources of exogenous variation during the credit crunch in Italy.
the monetary and fiscal stance are collected in $J_t$.

**Assumption 1**

∃ some smooth, unknown, function $C(\cdot)$ such that:

$$\frac{C_{i,b,t}}{C_{i,b,t-1}} = \frac{C(J_t, D_{i,t}, S_{b,t}, X_{i,b,t})}{C(J_{t-1}, D_{i,t-1}, S_{b,t-1}, X_{i,b,t-1})} \tag{1}$$

While this assumption is very general, it nonetheless limits the substitution patterns between different lenders. Indeed, it rules out the impact of other banks’ idiosyncratic shocks $S'_{b,t}$ on credit granted by $b$ to $i$. In appendix A.1 we show that the exclusion of other banks’ supply from equation (1) does not significantly affect our estimate of idiosyncratic credit supply shocks.

Log-linearizing equation (1) yields:

$$\Delta c_{i,b,t} = j_t + \Delta d'_{i,t} c_1 + \Delta s'_{b,t} c_2 + \Delta x'_{i,b,t} c_3 + \text{approx}_{i,b,t} \tag{2}$$

We define the credit supply shock of bank $b$ in period $t$ to be $\Delta s'_{b,t} c_2$. The idiosyncratic credit supply shock experienced by firm $i$ in period $t$ is a function of $\Delta s'_{b,t} c_2$ for all the previously connected banks.

Decomposition (2) can be written as:

$$\Delta c_{i,b,t} = j_t + d_{i,t} + \phi_{b,t} + \epsilon_{i,b,t} \tag{3}$$

where: $j_t$ is the mean growth rate of credit in the economy, $\phi_{b,t}$ is the change in credit granted explained by bank $b$’s supply factors, $d_{i,t}$ is the change in credit granted explained firm $i$ factors, and $\epsilon_{i,b,t}$ is the sum of a matching specific shock $\Delta x'_{i,b,t} c_3$, and the approximation error $\text{approx}_{i,b,t}$.

**Assumption 2**

$$\epsilon_{i,b,t} \perp D_{i}, S_{b}$$

where $D$ and $S$ are sets of dummy variables indicating the identity of the borrower and of the lender. Furthermore, without loss of generality, we normalize $E[d_{i,t}] = E[\phi_{b,t}] = 0$. Then, under assumption 2 we can obtain $\phi_{b,t}$ from equation (3) using OLS, and consider them unbiased estimate of $\Delta s_{b,t}$.

We focus on corporations having multiple relations, so to estimate bank-idiosyncratic shocks by exploiting within-firm-and-time variability. This allows us to condition for time-varying observable and unobservable at borrower level.\(^\text{16}\)

\(^{16}\)Because we are using a delta-log approximation, the expected values are to be intended as conditional on credit given from bank $b$ to firm $i$ being positive in both $t$ and $t - 1$. In a robustness exercise, available upon request, we
Amiti & Weinstein (2017) (AW hereafter) study the identification of model (3). They show that assumption 2 holds without loss of generality, as long as one is willing to conveniently “relabel” the firm and bank fixed effects. That is, one can write the idiosyncratic component $\Delta x_{i,b,t}$ as $\Delta x_{i,b,t} = a_{i,t} + b_{b,t} + e_{i,b,t}$ where $a$ and $b$ are the linear projection of $\Delta x_{i,b,t}$ on dummies for bank and firm identity and $e_{i,b,t}$ is uncorrelated with these dummies by construction. Therefore, bank fixed effects in (3) correspond to $\phi_{b,t}^{AW} = \phi_{b,t} + c^3 \cdot b_{b,t}$, which correspond to the parameters of interest in the empirical analysis of AW. In fact, they show that the idiosyncratic match-specific terms do not affect the bank aggregate lending. In our study, however, we are interested in identifying the role of pure supply-side factors $\Delta s_{b,t}$, so that the orthogonality assumption 2 does not come without loss of generality. In particular, it limits the interaction between demand and supply shocks (which enter the approximation error) and it restricts the correlation between match-level covariates and bank or firm factors. We argue in appendix A.1 that this assumption is testable: we focus on two potential source of omitted variables in $\epsilon_{i,b,t}$ which may bias our estimate of supply-side shocks: substitution (or complementarity) patterns (such as those discussed in Assumption 1) and relation characteristics. We show that our results on the impact of credit supply shocks on productivity are unaffected by the inclusion of these controls in the estimation of credit supply shocks. We, thus, rely on the simpler specification in equation (3) for our main analysis.

In this paper, we study how borrowers’ inputs acquisition and output production is affected by lenders’ supply. Consequently, the cornerstone of the empirical strategy is a firm-level measure of credit supply shocks. To move from the bank-level measure of equation (3) to its firm-level counterpart, we rely on the intuition of the “lending channel” (Khwaja & Mian, 2008): borrower-lender relationships are valuable because they help mitigate asymmetric information, limited commitment or other problems which might generate credit rationing. Consequently, they are sticky: changes in credit supplied by a bank affect disproportionally more the firms with whom it has already an established credit relations.\footnote{Further causes of stickiness may encompass personal or political connections between firms’ and banks’ managers. Stickiness may be considered a credit market friction, because it may prevent credit to flow to the firms with best investment opportunities. Our analysis abstracts from any welfare consequences of relationship lending, and focus on one of its empirical implications.} Obviously, a firm connected to a bank whose supply contracts can always apply to another bank for credit (see below). Yet, as long as credit from an unconnected bank is less likely or more costly, substitution between lenders will be imperfect. The empirical relevance of this phenomenon has been shown in several previous studies. We exploit this well-established fact compute the model by measuring growth rates as suggested by Davis et al. (1996) $\left(\Delta c_{i,b,t} = 2 \cdot \frac{C_{i,b,t} - C_{i,b,t-1}}{C_{i,b,t} + C_{i,b,t-1}} \right)$, which we can compute as long as credit is positive in either $t$, or $t - 1$, or both.
to identify firm-specific credit supply shocks.

As a simple benchmark, we assume that the strength of a firm-bank relationship is proportional to the amount of credit granted. Therefore, we measure the shock to credit supply faced by firm $i$ in period $t$ as

$$
\phi_{i,t} = \sum_b \phi_{b,t} \cdot \frac{C_{b,i,t-1}}{\sum_b C'_{b',i,t-1}}
$$

(4)

An histogram of $\phi_{i,t}$ is provided in figure 3. Although the estimation of $\phi_{b,t}$ is performed considering only firms with multiple banking relations, the variable $\phi_{i,t}$ is defined for all firms which have some credit granted in year $t - 1$.

Two empirical findings validate this measure of credit supply shocks. Firstly, we expect a positive supply shock to decrease the number of loan applications with new lenders, while we expect a positive demand shock to increase these applications. Appendix A.2 shows that an increase of our measures of credit supply shock is indeed associated with fewer loan applications both on the intensive and on the extensive margin. Secondly, appendix D shows that our measure responds negatively to the freeze of the interbank market, which was the very trigger of the credit crunch in Italy (see section 6 for details).

3.2 Production with heterogeneous financial frictions

We propose an empirical model to estimate firm production function and recover firm-idiosyncratic productivity. Firm $i$, operating in industry $s$, in year $t$, has an idiosyncratic Hick-neutral productivity $\omega_{i,t}$. It combines capital, labor and materials to generate sales, according to an industry-specific production function $f(\cdot)$, known up to a set of parameters $\beta$:

$$
y_{i,t} = \omega_{i,t} + f(l_{i,t}, k_{i,t}, m_{i,t}, \beta_s)
$$

We augment the classical production function estimation framework with control function (Ackerberg et al., 2007) by adding two elements: a set of credit constraints and a modified law of motion for productivity dynamics. Credit supply can affect both. Thus, the main identification assumption is:

$$
E [\omega_{i,t}|I_{t-1}] = E [\omega_{i,t}|\omega_{i,t-1}, \phi_{i,t-1}]
$$

(5)
where $I_{t-1}$ is the firm information set at $t - 1$. Credit constraints take the form:

$$X_{i,t} \leq K_{i,t-1} \cdot \Gamma^X (B_{i,t-1}, \phi_{i,t}, \omega_{i,t})$$

where $X_{i,t}$ is either the total debt of firm $i$ at the end of period $t$ or any input (capital, labor or materials). $B_{i,t-1}$ is the amount borrowed in $t - 1$. Similar constraints are standard in the literature on financial frictions, such as Moll (2014), Buera & Moll (2015) or Gopinath et al. (2017), and they can be micro-founded by several market failures. We innovate by allowing them to depend on firm TFP and credit supply shocks. The results of the paper hold if we exclude credit rationing and, alternatively, we assume that firms face heterogeneous costs of external funds which are determined by the credit supply of connected lenders. The model and the estimation of the parameter of interest ($\beta_s$) are described in appendix B.1.\(^\text{18}\)

Observing the credit supply shocks is essential to consistently estimate the production function for two different reasons. Firstly, input acquisition might be constrained and, therefore, using unconstrained FOC to estimate the model might be misleading. Secondly, movements in credit supply are correlated over time and they may affect both input accumulation and productivity (what we aim to study). Therefore, the exclusion of credit shocks from the law of motion of productivity leads to invalid moment conditions. Consequently, it is not correct to estimate productivity without including financial frictions in the estimation procedure\(^\text{19}\) and, then, regress the productivity residual on financial variables. An analogous problem is highlighted by De Loecker (2013) discussing the measurement of productivity gains from exporting.

Gandhi et al. (2011) show that most of the estimation procedures based on control function approach fail to identify the elasticity of output with respect to the flexible inputs (e.g. intermediate inputs). De Loecker & Scott (2016) argue that a researcher can overcome this non-identification result under the assumption that firms face heterogeneous and autocorrelated input prices. They rely on firm-level wages to estimate their model. However, heterogeneity in wages might reflect heterogeneous worker quality or productivity. We, instead, allow local price shocks to affect input real prices. In this way, we can recover all the production function parameters.

\(^{18}\)Table A.2 presents some descriptive statistics of the estimated parameters $\beta_s$. Once the parameter $\beta_s$ are estimated, we back up the revenue productivity as residuals from $\omega_{i,t} = y_{i,t} - f(k_{i,t}, l_{i,t}, m_{i,t}, \beta_s)$. In the value added case $\omega_{i,t} = va_{i,t} - f(k_{i,t}, l_{i,t}, \beta_s)$.\(^{\text{19}}\)For instance, by using "off-the-shelf" methods such as cost share, see Asker et al. (2014), or the direct application of the control function approach (e.g. Ackerberg et al. (2015)) not allowing for heterogeneous credit shocks.
3.2.1 TFP, TFPR and TFPQ

As detailed in section 2, we observe balance sheet and income statements but do not observe firm-level output prices. Therefore, this paper is about the ability of firms to transform inputs into sales and value added and not (only) about their technical efficiency. Our measure of productivity is referred to as “productivity” in several empirical studies, such as Olley & Pakes (1996), and as $tfpr^{rr}$ (or “regression-based total factor revenue productivity”) in Foster et al. (2017). Furthermore, our measure of productivity is proportional to the empirical estimate of (log) $TFPQ$ (or “total factor quantity productivity”) used in Hsieh & Klenow (2009), although we do not assume [constant returns to scale] a constant degree of proportionality between the two. Our choice on this regard is somehow constrained, as no firm-level data on product-level prices is available to economists for a sufficiently large number of Italian firms.

Empirical investigation based on data on revenues rather than quantities presents both challenges and opportunities. The main challenge is to provide evidence that the results are not driven by correlation between output demand (or other local competitive conditions) and credit supply factors: evidence provided in section 5.1 are reassuring on this regard. At the same time, we have the opportunity to take into account other sources of productivity increase, besides technical efficiency. These encompass improvements in quality of the product offered and access to new markets or new niches that may result in an increase in markups. Measures of pure technical efficiency may ignore changes in product quality, which are found to explain the vast majority of the heterogeneity in firms’ size (Hottman et al., 2016). Moreover, notice that it is difficult to properly define quantity productivity in service industries, where products are intrinsically non-homogeneous. How to measure, for instance, the “quantity” produced by a law firm?

Many business-enhancing activities we study in section 7 can be related to both quantity and revenue productivity. For instance, innovative effort can increase both firm products’ quality and its technical efficiency (Hall, 2011). Appendix C.1 provides a more detailed treatment of the topic.

4 Credit Supply Shocks and Firm Production

Is firm production affected by its lenders’ credit supply? If credit frictions are not important, the amount of credit received by each companies should be unaffected by the supply shocks of their lenders. In a frictionless world, firm policy function might be affected by aggregate financial conditions but should not be shaped by the idiosyncratic shocks hitting any specific lender. Therefore, we
estimate:

\[ \Delta x_{i,t} = \psi_i + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t} \]  \quad (6)

where \( x_{i,t} \) is either the log of total credit granted to firm \( i \), or a measure of output (log value added or net revenues) produced by firm \( i \) during year \( t \), or a measure of (log) input. The \( \psi \) terms are firm and year times \times industry \times province fixed effects. The former control for firm-specific unobserved heterogeneity which might affect both financial conditions and production. The latter capture local\(^{20}\) and sectoral demand and technology shocks, which might create spurious correlation between credit supply and firms dynamics. Results are presented in Table 2. Firms connected with banks expanding their supply of credit show higher growth of both credit received, inputs acquired, and output produced with respect to other firms operating in the same market. The elasticity of credit granted with respect to the firm-level credit supply shock is approximately equal to one. This allows for simple interpretation of the magnitude of all the main specification of this paper: one percentage point increase in \( \phi_{i,t} \) is the changes of credit supply necessary to increase the average credit granted of one percent.

The effect of an expansion of credit supply is stronger for value added than for capital accumulation. Net revenues respond almost as much as capital. Labor and intermediate inputs are found to be much less sensitive to credit supply shocks than output and capital, both from economic and statistical points of view. Capital investments are likely to be fully paid upfront, while expenditure for materials or labor can sometimes be delayed after some cash flow has been generated from the production. For instance, wages are usually paid at the end of the month. Therefore, it is not surprising that these inputs are less sensitive to changes in firm ability to access external finance. To understand whether the effect on inputs is sufficiently large to rationalize the impact on output or, conversely, also productivity is responding to credit shocks, we need to rely on the elasticities of output to inputs estimated in section 3.2.

\(^{20}\) A province is a local administrative unit, which is approximately of the size of a US county. CADS reports the province in which each firm is headquartered.
5 The Effect of Credit Supply on Firm Productivity Growth

Is firm productivity growth affected by the credit supply of its lenders? After identifying firm-level measures of credit supply shocks (section 3.1) and measuring TFP (section 3.2), we now tackle the main research question by estimating the model:

$$\Delta \omega_{i,t} = \psi_i + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$$ (7)

where: $\Delta \omega_{i,t}$ is the growth (delta log) of the Hicks-neutral productivity for firm $i$ between years $t - 1$ and $t$, and $\phi_{i,t}$ is the weighted average of credit supply shocks of $i$'s previous period lenders. The $\psi$ terms are firm and year $\times$ industry $\times$ province fixed effects. The former control for firm-specific unobserved heterogeneity which might affect both financial conditions and production. The latter capture local and sectoral demand and technology shocks, which might create spurious correlation between credit supply and firm dynamics. Results are shown in Table 3. One observation is one firm per year in CADS for 1998-2013, subject to selection criteria detailed in section 2.4. In each column, we consider productivity growth as obtained from a different production function estimation. The two columns on the left use value added as a measure of output, while productivity in columns 3 and 4 is based on net deflated revenues. Columns 1 and 3 are based on Cobb-Douglas production function, while 2 and 4 on Trans-Log. The top panel presents results for the whole economy, while the bottom panel focus on manufacturers. All specifications clearly show that an increase in credit supply boosts productivity growth. A credit supply shock of 1 percentage point induces an increase in the growth rate or value added productivity of approximately a tenth of a percentage point for the whole economy and 0.13 points for manufacturing.

The difference between the size of the effect of credit supply on value added productivity growth and on revenue productivity growth can be partially explained by the fact that the standard deviation of the former is more than 3 times larger than the latter in our sample.

The magnitude of the effects is economically large. For instance, the drop in the total growth rate of credit granted between 2007 and 2009 is around 12% in our sample. Over the same period,

\[\text{For instance, Malacrino (2016) shows that firms founded by wealthier owners have different dynamics of profitability and growth over their life-cycle.}\]

\[\text{As shown in Table 2, 1% increase in supply shock is the changes in supply which cause an increase of the credit granted by 1%.}\]
(mean) value added productivity growth declined by a bit more than 8% and revenue productivity growth declined by 1%. Therefore, if the drop in credit was fully driven by supply, it would explain between 12% and 30% of the productivity drop over the same period. These figures are likely to be conservative estimates: below we show that the productivity effects of credit shock are persistent and that credit supply is particularly valuable during financial turmoil.

Appendix figure A.8 reports the bootstrapped distribution of the estimated effect of credit supply shock on productivity. Production function is re-estimated for each bootstrap sample. All coefficients are above zero. This finding indicates that the sampling error in estimating productivity dynamics does not distort statistical inference based on Table 3.

5.1 Robustness

This paper argues for a causal interpretation of the estimated relations between credit supply and firm productivity growth. We provide a broad set of robustness exercises to support this claim. Table 4 contains the relative results for the Cobb-Douglas Revenue productivity case. Column (1) reports baseline estimate (as in Table 3). Column (2) adds a set of lagged controls: a polynomial in assets size and the ratios of value added, cash flow, liquidity and bank debt over assets. The inclusion of such controls have negligible impact on the estimated coefficients.

Estimates of equation (7) face both measurement and identification-related threats. This section deals with the latter and with potential problems related to the estimation of the productivity dynamics. Measurement error issues are discussed in appendix C.3. Analogously to the “peer effect” literature (Bramoullé et al., 2009), three main threats may hamper our identification strategy of credit supply shocks based on firm-bank connections: reverse causality, correlated unobservables and assortative matching. That is, \( \phi_{i,t} \) can be correlated with the error term in equation (7) either because connected agents are subject to correlated shocks, or because lenders might decrease credit supply when expecting their borrowers to experience lower productivity growth, or because banks which are expanding their supply of credit are more likely to establish lending relations with firms that are increasing their productivity. The productivity shocks received by sizable borrowers might be the very reason why their lenders contract the supply of credit. That is, if banks have information about the future profitability of some particularly significant borrowers, they might preemptively

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23 Results for value added productivity are for revenue translog productivity are in Tables A.9 and A.10. They all show remarkable stability across specifications.

24 For instance, Bonaccorsi di Patti & Kashyap (2017) document that the banks which recover earlier from distress are the ones which cut faster their credit to risky borrowers. Notice that the additive growth rate model allows for assortative matching in levels.
decrease the supply of credit to all borrowers. We define an “important” borrower any firm which, at any point in time between 1997 and 2013 represents more than 1% of the credit granted by any of its lenders. Then, we estimate model (7) excluding such firms. Results are reported in column (3) of Table 4, which shows that the estimated effect of credit supply shocks on productivity growth are unaffected by the exclusion of the borrowers that are most likely to lead to reverse causality, mitigating this concern.

A further concern is that connected borrowers and lenders might be affected by correlated unobservable shocks. In particular, the output market of the borrower might overlap with the lender’s collection or lending market. For instance, a drop in local house prices might contemporaneously lower consumption and also affect the value of collateral backing lender’s loans. Since we measure revenue-based productivity, any demand shock might increase markups and be picked up as a change in productivity. To investigate the relevance of correlated unobservables for our results, we compare specifications with two different fixed effects structures:

\[
\Delta \omega_{i,t} = \psi_i + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t}
\]

\[
\Delta \omega_{i,t} = \psi_i + \psi_{p} + \psi_s + \psi_t + \gamma \cdot \phi_{i,t} + \eta_{i,t}
\]

The first specification includes industry×province×year fixed effects, which aim to control for demand and technology shocks. The second includes only industry and province and year fixed effects, therefore it allows only for nation-wide economic fluctuations. Results are reported in columns (1) and (5) of Table 4. The magnitude of the coefficient is remarkably stable across the two specifications, despite the inclusion of the finer grid of fixed effects more than double the $R^2$. This finding reveals that, if any unobservable is affecting both credit supply shocks and productivity, then it must be orthogonal with respect to location or industry. Since credit activity is indeed concentrated at local (and/or industry) level, this is extremely unlikely to happen. Consequently, we can reasonably conclude that correlated unobservables are not driving our results. A formal econometric treatment of this intuitive argument is provided by Altonji et al. (2005) and Oster (2016). In appendix C.2, we provide bounding sets for the coefficient of interest, following Oster (2016), and we show that they do not contain zero. Therefore, our results are “robust” to the presence of unobservable shocks. Furthermore, column (4) of Table 4 shows that firm fixed effects, while useful to control for firm-level unobservable characteristics, are not essential to our results.

Columns (6) of Table 4 employs an alternative measure of credit supply shocks, which controls for
match-level characteristics, see appendix A.1 for details. The estimated effect of credit supply on productivity growth is similar than in the baseline specification of column (1), providing no evidence that assortative matching is explaining our results. Finally, section 6 exploits a natural experiment to confirm that credit supply affect productivity; this, together with relative placebo tests, eliminates residual concerns.

The bank-level credit supply shocks are computed using information on all its borrowers. Therefore, if firm \( i \) has a lending relation with bank \( b \), then its credit supply is estimated from a linear regression including observations relative to the amount of credit granted by \( b \) to \( i \), see section 3.1. This could generate problems in small samples. Therefore, we estimate an alternative set of bank-level credit supply shocks using a “split sample” procedure. Column (7) presents estimate of the baseline specification using the “split sample” credit supply shock as an instrument. The similarity between estimates in columns (1) and (7) confirm that, since we rely on the universe of credit relations, this (potential) finite sample bias is not a concern.

Estimation of production function parameters is a difficult exercise involving several (strong) assumptions, such as absence of measurement error on inputs and Markovian structure for the productivity dynamics. We perform several exercises to show that the specific modeling choices of section 3.2 do not affect the estimated effect of credit supply on productivity growth neither qualitatively nor in terms of its magnitude. Firstly, we re-estimate both production function and equation (7) using a finer 4 digits industry classification (baseline is 2 digits). Results are reported in column (8) of Table 4, which mitigates the concern that heterogeneity in the shape of the production function is a main driver of the baseline specification. Secondly, we re-estimate production function by controlling for endogenous exit as in Olley & Pakes (1996). Column (9) of Table 4 shows that the magnitude of the relations between credit supply shocks and productivity is unchanged. Furthermore, we compare our results to traditional estimation techniques. Column (10) of Table 4 reports result from production function estimated with the cost share procedure, see Foster et al. (2017). Results are

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\(^{25}\)Namely, the size of the loan relative to borrower’s total credit received, size of th loan relative to lender’s total credit granted, interest rate, length of the lending relations, type of credit instrument used, presence of past non-performing loans.

\(^{26}\)That is, we divide all firms into subsamples A and B. For each bank, we estimate two credit supply shocks, \( \phi_{A,b,t} \) and \( \phi_{B,b,t} \), using data about credit given to firms belonging to only one subsample at time. Then, we compute firm-level idiosyncratic shocks as the weighted average of the bank-level credit supply shocks estimated with data on firms of the other subsample. For instance, if firm \( i \) belongs to subsample A, we estimate its credit supply shocks as \( \phi_{i,t} = \sum_b w_{i,b,t-1} \cdot \phi_{A,b,t} \) where \( w_{i,b,t-1} \) is the share of credit to firm \( i \) granted by bank \( b \) in the previous period.

\(^{27}\)An alternative model of production with heterogeneous credit constraints is presented in section B.2, together with relative results, which do not differ significantly with respect to baseline estimation.

\(^{28}\)Under Cobb-Douglas production function, the share of the expenditure of any flexible input on income is equal to the elasticity of the output with respect to this input. Therefore, assuming labor and intermediate inputs are fully flexible, we estimate their sectoral elasticities as the median share of expenditure on each input on total
in the ballpark of the baseline estimation.

An alternative approach is to refrain from estimating the production function and, instead, study how the estimated effect of credit supply shocks on productivity varies as a function of the unknown parameters of the production function. The simplest production function is a Cobb-Douglas in value added:

\[ va_{i,t} = \omega_{i,t} + \rho \cdot (\beta_k \cdot k_{i,t} + (1 - \beta_k) \cdot l_{i,t}) \]

where \( \rho \) disciplines the returns to scale and \( \beta_k \) the (relative) elasticity of value added to capital. Then, given a couple \((\tilde{\rho}, \tilde{\beta}_k)\) we can back out productivity as

\[ \omega_{i,t}(\tilde{\rho}, \tilde{\beta}_k) = va_{i,t} - \tilde{\rho} \cdot (\tilde{\beta}_k \cdot k_{i,t} + (1 - \tilde{\beta}_k) \cdot l_{i,t}) \]

and estimate \( \gamma(\tilde{\rho}, \tilde{\beta}_k) \) as the coefficient of

\[ \Delta \omega_{i,t}(\tilde{\rho}, \tilde{\beta}_k) = \psi_i + \psi_{p,s,t} + \gamma(\tilde{\rho}, \tilde{\beta}_k) \cdot \phi_{i,t} + \eta_{i,t} \quad (8) \]

We let \( \rho \) vary from 0.3 to 2 and \( \beta_k \) from 0.01 to 0.9, so that our grid encompasses any plausible value of the return to scale and elasticity of value added to capital. Results are presented in graphical form in figure 6, showing that we find a positive (and statistically significant) effect of credit supply shocks on value added productivity growth for any point in the grid. Moreover, while higher values of the parameters tend to decrease the point estimates, \( \gamma(\tilde{\rho}, \tilde{\beta}_k) \) stays between 0.07 and 0.1 within the whole support.

The collection of evidence reported in this section clarifies that any misspecification of the production function estimation, although it might bias the point-estimate of the effect of credit supply on productivity, it is unlikely to change significantly its magnitude.

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revenue (or value added). The elasticity of capital is given by one (constant returns to scale) minus the elasticities of labor and intermediates. Foster et al. (2017) describe the theoretical and empirical differences between cost share approach and control function (which they classify as a “regression based” method). We divide intermediate inputs into expenditure for services and expenditure for materials, in order to show that merging them together does not drive the baseline results of the paper. Doing so, we lose some observations since not all income statements report separately expenditure in the two items.
5.2 Heterogeneity

Are all firms’ equally affected by credit supply shocks? Firm’s size might be a good predictor of its ability to find alternative source of funds in case of dry up of credit from current lenders. Furthermore, larger firms are less likely to be credit constrained. Therefore, for each year, we compute an indicator for whether or not a firm is in the top quartile of the size distribution in terms of assets value or number of employees. Then, we estimate the equation:

$$\Delta \omega_{i,t} = \psi + \psi_{s,p,t} + (\gamma + \gamma_{big} \cdot Big_{i,t-1}) \cdot \phi_{i,t} + \psi_{Big} \cdot Big_{i,t-1} - 1 + \eta_{i,t}$$

Results are reported in column (1) and (2) of Table 5, which refer to Cobb-Douglas revenue productivity. The parameter $\gamma_{big}$ is estimated to be negative, therefore large firms are less affected by credit supply shocks. The difference between the two groups is much larger and statistically significant in manufacturing.

Furthermore, we are interested in understanding whether having a larger number of lenders might help firms to find source of finance in case of negative credit supply shocks. Therefore, we estimate the model by allowing the coefficient to be different for firms in the bottom quartile for number of lending relations during previous period.\(^{29}\) Results in column (3) documents that borrowers with less lenders are much more affected by credit supply shocks.

An important dimension of the relevance of credit supply shocks is firms’ reliance on external funds. We classify industries in above and below the median according to the mean leverage (debt over assets) in the sample. Column (4) of Table 5 shows that the effect of credit supply shocks on revenue productivity is stronger in sectors with high leverage. Perhaps surprisingly, we do not find any significant pattern analyzing heterogeneity according to sectoral cash flow over assets, see column (5).

5.3 Persistence

The effect of credit supply shock on productivity is persistent. We compute innovation to the shock, which are defined as $\zeta_{i,t} := \phi_{i,t} - E [\phi_{i,t} | \phi_{t-1}]$. Then, we estimate the model

\(^{29}\)It was suggested by few seminar participants to differentiate the effect of credit shocks between firms with one and multiple lending relationships. Unfortunately, less than 5% of observations in CADS have only one lenders, therefore the relative coefficient would not be reliably estimated.
\[ \omega_{i,t} = \psi_i + \psi_{p,s,t} + \sum_{\tau=-T}^{T} \gamma_\tau \cdot \zeta_{i,t}^\tau + \eta_{i,t} \]  

(9)

We choose \( T = 3 \), since our empirical strategy is unfit to estimate the regression at longer horizon.\(^{30}\) Figure 5 provides graphical results of coefficients \( \gamma_\tau \) for firms active in manufacturing (bottom panel) and all industries (top panel). They document that the peak in productivity is experienced one year after the shock, and the effect remains positive and significant for at least 3 years after an expansion in credit supply. This finding underlines that a temporary credit contraction can have persistent effects on productivity. It also rules out the potential concern that the effect we measure on revenue productivity is short-lived and due to factor hoarding caused by adjustment costs of labor and capital.

We do not find any statistically significant pre-trend. Our main results rely on pre-existing lending relations being orthogonal with respect to productivity innovations. Therefore, the absence of pre-trend supports the claim that credit supply shocks have a causal effect on productivity.

5.4 Concavity of the credit-productivity relation

The main goal of this paper is to measure and explain the productivity effects of changes in the quantity of credit supplied, focusing on its first moment: is more credit bad or good? This section, instead, investigates the shape of relation between productivity and credit supply shocks, in order to understand whether higher moments of the credit supply shocks’ distribution might have an impact on average firm productivity.

We divide \( \phi_{i,t} \) into quintiles \( q = 1, 2, 3, 4, 5 \) and estimate:

\[ \Delta \omega_{i,t} = \psi_i + \psi_{p,s,t} + \sum_{q=1,q\neq3}^{5} \gamma^q \cdot 1(\phi_{i,t} \in q) + \eta_{i,t} \]

where \( 1(\phi_{i,t} \in q) \) is an indicator function taking value one iff the credit supply shock of firm \( i \) in year \( t \) belongs to the \( q \) quantile of its distribution; the third (or median) quintile \( q = 3 \) is the omitted category with \( \gamma^3 = 0 \). Results are shown in graphical form in Figure 7. The relations between credit

\(^{30}\) The within firm estimator, while allowing to control for firm unobserved heterogeneity, creates a mechanical negative correlation between observation means at different lags. In fact, regression of firm productivity on past productivity yields a coefficient between .9 and .98 if no FEs are included and between .3 and .4 if the standard set of FEs is included. Therefore, a shock to productivity of magnitude 1 \( \cdot \) \( m \), is expected to show up as a change in productivity of only 0.03 \( \cdot \) \( m \) to 0.06 \( \cdot \) \( m \) after 3 years.
supply and revenue productivity seem to be concave. That is, firms connected with banks with relatively low supply of credit experience lower revenue productivity growth with respect to their competitors; firms connected to banks with particularly strong increase in credit do not seem grow at particularly high rate. It is important not to be connected with banks experiencing bad credit supply shocks, but it is not useful to be connected with banks increasing their supply of credit particularly fast. To strengthen this intuition, we re-estimate equation (9), which is used to study the persistence of credit supply shocks, by differentiating between positive and negative shocks. Figure 8 presents the results in graphical form. The coefficients relative to negative credit supply shocks are shown with negative values. The effect of credit supply shocks on productivity is driven by firms connected with banks experiencing relatively negative credit supply dynamics. Additionally, in section 6 we argue that credit supply shocks are particularly important when credit dries up.

These empirical findings imply that an increase in credit supply cannot undue the harm of a negative shock of the same size. Therefore, it is not only the quantity of credit that matters, but also the stability of its provision. They analogously suggest that a credit crunch followed (or preceded) by a credit expansion of the same magnitude leads to a net loss in firm average productivity. We conclude that volatility of banking sector’s supply can be detrimental to firm productivity.

6 The Interbank Market Collapse as a Natural Experiment

The credit supply shock derived in section 3.1 has the value of being general, in that it can be attributed to all firms (both multiple and single-borrowers) and measured in all years for which there is bank-firm data on credit granted. This feature is exploited in section 7. Furthermore, the panel variation of $\phi_{i,t}$ is essential for production function estimation, see section 3.2. However, since its construction relies on firm-bank connections, estimates of equation (7) might suffer from the identification problems highlighted in section 5.1. While there we discussed several robustness exercises to mitigate such concerns, here we propose an alternative strategy to strengthen the robustness of our results. We use the 2007-2008 market collapse of the interbank market as a specific “natural experiment” in which credit supply shifts were arguably exogenous with respect to firm observed and unobserved characteristics. In addition, such variation was unexpected to both lenders and borrowers, thus overcoming the problem of assortative matching.

The interbank market represents a critical source of funding for banks: it allows them to readily fill

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31 This is not the first paper to rely on natural experiments to identify idiosyncratic credit supply shocks: for instance, see Khwaja & Mian (2008), Chodorow-Reich (2013) and Paravisini et al. (2014).
liquidity needs of different maturities through secured and unsecured contracts. Total gross interbank funding represented over 13.3% of total assets of Italian banks at the end of 2006. Market transactions begun shrinking in July 2007, when fears about the spread of toxic assets in banks’ balance-sheets made the evaluation of counterparty risk extremely difficult (Brunnermeier, 2009); the situation worsened further after Lehman’s default in September 2008. As a consequence, total transactions among banks fell significantly. In Italy, in particular, they plummeted from €24bn. in 2006 to €4.8bn. at the end of 2009. At the same time, the cost of raising funds in the interbank market rose sharply: the Euribor-Eurepo spread, which was practically zero until August 2007, reached over 50 basis points for all maturities in the subsequent year; it then increased by 5 times after the Lehman crisis, and remained well above 20 basis points in the following years. Two recent papers have exploited the collapse of the interbank market as a source of exogenous shock to credit supply. Iyer et al. (2013) used Spanish data to show that bank pre-crisis exposure to the interbank shock, as measured by the ratio between interbank liabilities and assets, was a significant predictor of a drop in credit granted during the crisis. Cingano et al. (2016) focus on CADS data for Italy to show that this drop had a significant negative effect on firm’s capital accumulation. These researches reported results of several empirical tests showing that bank pre-crisis exposure was not correlated with its borrowers’ characteristics, such as investment opportunities and firm growth potential, thus making this variable particularly suitable to instrument the impact of credit supply on firm’s outcomes. We focus on the period 2007-2009 when credit dried up the most. Subsequently, ECB interventions partially offset the impact of the interbank market shock. Our measure of firm exposure to the credit supply tightening is the average 2006 interbank exposure of Italian banks at the firm level, using firm’s specific credit shares in 2006 as weights. Because firm exposure is time-invariant, we use cross-sectional variation. We include observations over the three years window. Formally, for each firm i active in industry s and province p over the years t ∈ [2007, 2009], we estimate the equations:

\[ \Delta \omega_{i,t} = \psi_{p,s,t} + \gamma \cdot INTBK_{i,2006} + \eta_{i,t} \]  

(10)

where \( \omega_{i,t} \) is firm idiosyncratic productivity, \( INTBK_{i,2006} \) is the pre-crisis reliance on the interbank market and \( \psi \) is a set of province×industry×year fixed effects. Results are shown in Table 6. Firms whose lenders were more reliant from the interbank market in 2006, experienced a significantly lower revenue and value added productivity growth during the credit crunch. This strengthen the causal interpretation of the relations between credit supply and productivity growth documented in section 5. An increase in average bank dependence from the Interbank market of 1% decreases average value
added productivity growth of \( \approx 0.05\% \) and revenue productivity of \( \approx 0.02\% \). Consequently, the same interbank shock which decrease credit growth by 1\% also decrease value added productivity of 0.25\% and revenue productivity of a tenth of a percent for the whole sample. These effects are between 2 and 5 times larger than the baseline estimate of Table 3, suggesting that accessing a reliable source of credit supply is particularly important during financial turmoils.

6.1 Placebo and Robustness Tests

Estimation of (10) provides evidence that firms hit harder by the credit crunch decrease their relative productivity. What if banks relying more heavily on interbank were just matched to worst borrowers? To disprove this concern, we run equation (10) including only years before the freeze of the interbank market, that is \( t \in [2004, 2006] \). Results are shown in columns (1)-(4) of Table 7 which illustrate that firms more exposed to the freeze of the interbank market did not have statistically different growth rate of productivity before the credit crunch. Additional results show that firms more exposed to the interbank shock were not more sensitive to business cycle fluctuation before 2007. Details are in appendix D. We implement an additional placebo test. That is, we investigate the effect of a hypothetical freeze of interbank market in 2003. Therefore, for \( t \in [2003, 2005] \) we estimate the model:

\[
\Delta \omega_{i,t} = \psi_{p,s,t} + \gamma \cdot INTBK_{i,2002} + \eta_{i,t}
\]

Columns (5)-(8) of Table 7 show that the placebo collapse is not a significant predictor of firms’ subsequent productivity growth. The collection of evidence presented in this section should eliminate the concern that the relations between credit supply and productivity documented in section 5 is driven by correlated unobservable, reverse causality or assortative matching.

7 Beyond Measurement: Channels

How does credit supply improve productivity? In this section we investigate the relations between the credit supply shocks and several productivity enhancing activities. As described in section 2, INVIND provides information about R&D investment, Export, IT adoption and self reported “obstacles to innovation” for a sample of Italian companies in services and manufacturing. Both questions and respondents vary between waves, therefore each single specification of this section relies on a different sample. Furthermore, sample size is much smaller than in the previous sections, limiting our ability
to use our preferred specification.

In section 5.3 we show that credit supply shocks affect productivity immediately. We detect additional productivity growth for, at least, two years and higher productivity level for, at least, four years. Unfortunately, our empirical framework is unfit to investigate the effect at longer horizon. Some of the productivity-enhancing strategies studied in this section, such as IT adoption or better management practices, are likely to affect productivity from the very moment they are implemented. Others, such as R&D, might take few years to start producing substantial improvement. Therefore, this section does not only explore the potential mechanisms behind the effect we measure in section 5, but also suggests that credit availability might lead to additional productivity gains in the long run.

7.1 IT-intensity of Capital Stock

Speed of adoption of IT technologies caused large difference in productivity between US and European companies, as shown by Bloom et al. (2012). According to Pellegrino & Zingales (2014) failure to take full advantage of the IT revolution is one of the main drivers of Italy’s low productivity growth. Data on personal computers used is available from INVIND for the years 1999-2001. Purchases of PCs are accounted as investments. Therefore, they enter the computation of capital stock. Slacker credit constraints might allow firms to stay closer to the technological frontier. By making more technological investments, unconstrained firms might be endowed of a “better” capital stock. Since researchers do not have detailed information on “quality” or “closeness to the frontier” of inputs, this quality is picked up by the productivity residual. To test this hypothesis, we measure “IT-intensity” of firm capital stock as (log) number of PCs per 1,000 euros of capital.

\[
IT_{i,t} = \psi_i + \psi_{s,p,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t}
\]

Results are presented in Table 8, column (1). Firms are more likely to increase the IT-intensity of their capital stock when they receive a positive credit supply shocks. This finding suggests that financial frictions worsen the quality of capital inputs used in production.
7.2 Innovation and Export

Innovation activities, such as R&D, can increase firm productivity by improving both product quality and process efficiency. Similarly, export can have beneficial effects on revenue productivity through two channels. Firstly, it allows firms to access markets with higher margins. Secondly, it can improve firms’ know-how through the so-called “learning-by-exporting”. The sensitivity of international trade to financial frictions has been studied by several authors. For instance, see Manova (2012). INVIND survey is also used to identify firms who engage in export and have positive R&D expenditures. We focus on the extensive margin and estimate two linear probability models:

\[
Pr(R&D_{i,t} = 1) = \psi_i + \psi_t + \gamma \cdot \phi_{i,t} + \eta_{i,t}
\]

\[
Pr(Export_{i,t} = 1) = \psi_i + \psi_t + \gamma \cdot \phi_{i,t} + \eta_{i,t}
\]

Where \(R&D_{i,t}\) and \(Export_{i,t}\) are dummy variables indicating whether firm \(i\) engages in R&D or Export in year \(t\). Results, presented in column (4) and (5) of Table 8, show that there is a positive and statistically significant relation between credit supply and the propensity to perform these productivity enhancing activities. This indicates that companies are more likely to start (and, less likely to stop) exporting and performing R&D when they experience easier access to external finance.

Innovative effort is much broader than just formal R&D or IT-adoption. The 2011 survey wave investigates the main constraints to innovative effort. One question asks how important were difficulties to collect external funds in limiting innovation (in 2010) on a four-items scale. We build the variable \(FinCon_{i,2010}\) equal to one if and only if difficulties to get external funds is thought to be “somehow important” or “very important” as an obstacle to innovation. Then, we estimate the linear probability model:

\[
Pr(FinCon_{i,2010} = 1) = \psi_{s,p} + \gamma \cdot \phi_{i,2010} + \eta_i
\]

Results are presented in column (6) of Table 8 which documents that firms receiving positive credit supply shocks are less likely to consider external funds as a substantial obstacle to innovation. Since the question was asked for only one year of the survey, we cannot use panel variation. Nonetheless, this exercise is an indirect, yet insightful, test to the hypothesis that financial frictions dampen firms’ innovative efforts.
Patenting activities have been extensively used as a proxy for firm-level knowledge creation, see Bernstein (2015) and Kogan et al. (2017) for recent examples. We obtain information for patent applications for a large fraction of Italian companies from PatStat, as described in section 2. To investigate whether availability of credit boosts patent applications, we estimate the models:

\[ \text{PatentApp}_{i,t} = \psi_t + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t} \]

\[ \text{PatentApp}_{i,t} | \text{PatentApp}_{i,t} > 0 = \psi_t + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t} \]

Results are reported in columns (2) and (3) of Table 8. Italian firms patent more when they receive positive credit supply shocks. The effect is driven by the intensive margin.

### 7.3 Management Practices

Management matters for firm performances as shown by Bloom et al. (2013) for India and Giorcelli (2016) in the Italian setting. We use credit supply shocks to investigate whether firms improve their management when facing slacker financial constraints. The direction of the relations is not obvious. Firms might be pushed to improve their internal organization by scarcity of resources. Conversely, improvement in management practices might require stable financial resources, for instance to hire professional consulting services or to re-structure a production facility. Bhattacharya et al. (2013) propose a model where frictions distort optimal investment in managerial skills.

We obtain firm-level data on management practices from the World Managenet Survey. As it can be read from the website, WMS “developed an in-depth survey methodology and constructed a robust measure of management practices in order to investigate and explain differences in management practices across firms and countries in different sectors”. Information on data construction can be found in Bloom & Van Reenen (2007). They state: “practice evaluation tool defines and scores from one (worst practice) to five (best practice) across eighteen key management practices used by industrial firm”. Merging WMS of Italian companies by name, we obtain a sample of 183 observations. We have only one or two survey waves for each firm and therefore, we estimate the cross-sectional model:

\[ MS_{i,t} = \psi + \gamma \cdot \phi_{i,t} + \eta_{i,t} \]

32 See http://worldmanagementsurvey.org/. We are grateful for the data provided.
where $MS_{i,t}$ is the overall management score for firm $i$ surveyed in year $t$. Results are presented in column (7) of Table 8, which indicates that an increase in credit supply stimulates the adoption of superior management practices. While the small sample size might raise concern on the robustness of this result, the relation between credit supply shock and management is largely unaffected to the inclusion of a large set of firm-level controls.

### 7.4 Managerial Inattention

We propose a novel theory to explain why firms subject to negative credit shocks might decrease their productivity. Dealing with investors and creditors take a substantial share of executive time. Bandiera et al. (2011) study use of time of 94 CEO of top 600 Italian companies. They document that finance is the topic for which the CEO spend most time talking with firm insiders. Furthermore, investors and bankers are, respectively, the third and the fifth categories of outsiders with whom CEO spend more time. This is true for Italian top 600 companies which are all likely to have a professional CFO and other finance related personnel. Therefore, for managers/entrepreneurs of smaller private companies, which are the bulk of our sample, the time and effort required to establish and maintain relations with lenders might be even more demanding. Since their time is limited (as in a “temporal” limited span of control\footnote{See Akcigit et al. (2016) for an example of the harm caused by the lack of managerial delegation in developing countries.}), then the more difficult (or time-consuming) it is to find external funds, the less they can work on improving their core business. Entrepreneurs connected to lenders who contract their credit supply, might need to spend more time and energy to establish new lending relations. Therefore, they might exert less effort to improve their firm’s productivity. As a colorful piece of anecdotal evidence to support this theory, the aunt of one of the authors was managing the family business during the credit crunch. When asked about the firm performances, she used to reply “I barely have time to go to the factory, I spend most of my mornings at banks trying to get some money”. As an indirect test of this mechanism, appendix A.2 and relative results in Table A.1 show that firms receiving positive credit supply shocks are less likely to try to establish new lending relations. A more direct and complete investigation of this hypothesis is left to future research.

### 8 Conclusion

To grow and thrive firms need reliable access to external funding. In particular, this paper carefully documents that credit supply is an essential element of firms’ performance improvements, both in...
the short- and in the long-term.

To this purpose, we study the impact of banks’ credit supply on production of a large sample of Italian corporations. We exploit the universe of bank-firm credit relations over the period 1997-2013 to estimate an additive growth rate model and separate demand from supply shocks using firm-time and bank-time fixed effects. We improve on the literature by considering two important extensions to this framework. Then, we use the estimated bank-level supply shocks and the stickiness of lending relations in order to build a measure of firm-specific shocks to credit supply. We document that firms connected to banks which are expanding their supply of credit, acquire more inputs and produce more outputs with respect to competitors. We show that the effect on output is relatively stronger than the effect on inputs, suggesting productivity is affected by credit availability.

We build a model of production with heterogeneous credit constraints, in order to estimate industry-specific production function and isolate firm idiosyncratic productivity dynamics. Then, we show that credit supply boosts productivity growth and that these effects are sizable, persistent and robust. Moreover, they are stronger for smaller firms and for companies which operate in sectors relying heavily on banking credit. Furthermore, we exploit the 2007-2008 freeze of the interbank market as a natural experiment to support the causal interpretation of our estimates and show they are not driven by the assortative matching of borrowers and lenders or by reverse causality. Our results imply that financial turmoils can have persistent effect on aggregate output because they depress firms’ TFP in the short- and long-run. Furthermore, they suggest that financial frictions are not harmful only because of their detrimental effects on allocative efficiency.

We show that a negative credit supply shock produces stronger effects than a positive one of the same magnitude. This finding implies that it is not only the quantity of credit supply that matters, but also its stability.

Finally, this paper investigates the mechanisms behind the connection between credit supply and productivity growth. We show that several productivity enhancing activities, such as IT-adoption, sound management practices, export and innovation are stimulated by credit availability. Furthermore, we conjecture that a lender’s credit supply reduction might force borrowers’ managers/entrepreneurs to consume time and energy in order to establish new lending relations. Consequently, they might exert less effort to improve business performances. We document that firm attempts to create new lending relations are indeed more frequent when experiencing negative credit supply shocks.
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Figures

Figure 2: Growth rate of credit and productivity for a large sample of Italian corporations. Credit is total outstanding credit granted (loans and credit lines) by any financial institution at the end of the year. All series are de-trended (linear trend). Labor productivity is value added per employee and it is winsorized at 2 percent at firm level before being averaged. Estimation of firm-level TFP is detailed in section 3.2. TFP growth is averaged after being winsorized at 2 percent at firm level. Correlation coefficients are $\approx 0.3$. Data and sample selection are described in section 2.

Figure 3: Histogram of credit supply shock. Normal distribution is superimposed. See section 3.1 for details.
Figure 4: Histogram of productivity growth. Productivity is estimated as a residual from (log) revenues production function. Cobb-Douglas (top panel) or Trans-Log (bottom panel) functional form is assumed. Normal distribution is superimposed. See section 3.2 for details.
Figure 5: Productivity before and after an unexpected credit supply shock, see section 5.3 for details on the estimated equation. Top panel refers to all industries, while bottom panel refers to manufacturers. Productivity is estimated as residual from a (log) revenue production function. Functional form is either Cobb Douglas or Trans-Log. Details on productivity estimation are in section 3.2.
Figure 6: Credit Supply Shock and VA Productivity for different parameters of Cobb Douglas production function. The z-axis reports the estimated parameter $\gamma_{\rho,\beta_k}$ (top figures) or relative z-stats (bottom figures), from regression $\Delta \omega_{i,t}(\rho, \beta_k) = \psi_i + \psi_{s,t,p} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$. $\rho$ is the return to scale while $\beta_k$ is the relative elasticity of value added to capital. One observation is one firm for one year between 1998 and 2013 (unbalanced panel). The RHS variable $\phi_{i,t}$ represents idiosyncratic shock to firm credit supply, and its construction is detailed in section 3.1. The LHS variable is the first difference of Hicks-neutral productivity residual: $\Delta \omega_{i,t}(\rho, \beta_k) = \Delta va_{i,t} - \Delta \rho(\beta_k k_{i,t} + (1 - \beta_k) l_{i,t})$ where $va$ is log of of value added, $k$ is the log of capital stock and $l$ is log of labor (wagebill). Left and right panels show same patterns from two different angles.
Figure 7: Growth rate of productivity in manufacturing per quintile of credit supply shock. The third quintile (which includes the median credit supply shocks) is normalized to zero. Productivity is residual from a Cobb-Douglas revenues production function (left side) or Trans-Log revenues production function (right side).

Figure 8: Revenue productivity before and after a credit supply shock - negative vs positive shocks
### Tables

**Table 1: Descriptive Statistics - main firm-level variables**

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Median</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Median</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Industries</td>
<td>Manufacturing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Added</td>
<td>5,312</td>
<td>33,819</td>
<td>1,641</td>
<td>656,960</td>
<td>5,409</td>
<td>21,699</td>
<td>1,943</td>
<td>347,990</td>
</tr>
<tr>
<td>Net Revenues</td>
<td>27,073</td>
<td>156,638</td>
<td>8,813</td>
<td>656,960</td>
<td>25,351</td>
<td>164,054</td>
<td>8,209</td>
<td>347,990</td>
</tr>
<tr>
<td>Wagebill</td>
<td>3,377</td>
<td>19,693.9</td>
<td>1,062</td>
<td>656,960</td>
<td>3,466</td>
<td>13,452.4</td>
<td>1,299</td>
<td>347,990</td>
</tr>
<tr>
<td>Capital Stock</td>
<td>8,636</td>
<td>153,346</td>
<td>1,545</td>
<td>656,960</td>
<td>7,111</td>
<td>40,357</td>
<td>2,058</td>
<td>347,990</td>
</tr>
<tr>
<td>Intermediate Inputs</td>
<td>21,888</td>
<td>137,390</td>
<td>6,873</td>
<td>656,960</td>
<td>20,057</td>
<td>150,610</td>
<td>6,119</td>
<td>347,990</td>
</tr>
<tr>
<td>Credit Granted</td>
<td>7,924</td>
<td>3,6445</td>
<td>2,737</td>
<td>650,664</td>
<td>8,039</td>
<td>29,760</td>
<td>3,013</td>
<td>345,700</td>
</tr>
<tr>
<td>Employees</td>
<td>80</td>
<td>472</td>
<td>28</td>
<td>656,960</td>
<td>79</td>
<td>269</td>
<td>35</td>
<td>347,990</td>
</tr>
</tbody>
</table>

*Notes:* One observation is one firm for one year, between 1998 and 2013 (unbalanced panel). All variables (except for number of employees) are expressed as thousands of 2010 euros using sector-level deflators from national accounts.

*Source:* CADS and Credit Register.

**Table 2: Credit, Inputs and Outputs response to Credit Supply Shocks**

<table>
<thead>
<tr>
<th>VARIABLES (in delta Log)</th>
<th>Credit Received (1)</th>
<th>Value Added (2)</th>
<th>Net Revenues (3)</th>
<th>Capital Stock (4)</th>
<th>Wagebill (5)</th>
<th>Number of Employees (6)</th>
<th>Intermediate Inputs (7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>φ_{i,t}</td>
<td>0.949***</td>
<td>0.123***</td>
<td>0.0474***</td>
<td>0.0619***</td>
<td>0.0154*</td>
<td>0.00608</td>
<td>0.0220*</td>
</tr>
<tr>
<td></td>
<td>(0.0196)</td>
<td>(0.0162)</td>
<td>(0.0109)</td>
<td>(0.0128)</td>
<td>(0.00926)</td>
<td>(0.00889)</td>
<td>(0.0114)</td>
</tr>
<tr>
<td>Observations</td>
<td>609,195</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
</tr>
<tr>
<td>R²</td>
<td>0.239</td>
<td>0.224</td>
<td>0.302</td>
<td>0.259</td>
<td>0.324</td>
<td>0.319</td>
<td>0.302</td>
</tr>
</tbody>
</table>

| Manufacturing           |                      |                 |                  |                   |              |                        |                        |
| φ_{i,t}                 | 0.966***             | 0.134***        | 0.0436***        | 0.0610***         | 0.00388      | -0.00892               | 0.00716                |
|                         | (0.0253)             | (0.0201)        | (0.0143)         | (0.0169)          | (0.0116)     | (0.0108)               | (0.0152)               |
| Observations            | 324,926              | 347,990         | 347,990          | 347,990           | 347,990      | 347,990                | 347,990                |
| R²                      | 0.224                | 0.241           | 0.309            | 0.253             | 0.326        | 0.317                  | 0.308                  |

*Notes:* Results of estimating model:

\[
\Delta x_{i,t} = \psi_i + \psi_{s,t,p} + \gamma \cdot \phi_{i,t} + \eta_{i,t}
\]

One observation is one firm for one year between 1998 and 2013 (unbalanced panel). \(\Delta x_{i,t}\) is the delta-log of the variable described on top of each column, in real terms (2010 euros). \(\phi_{i,t}\) is an idiosyncratic shock to firm credit supply, whose construction is detailed in section 3.1. Firm FEs and province×industry×year FEs are included. Singleton observations are dropped. A 1% increase in \(\phi_{i,t}\) is the supply shock needed to increase the credit granted to firm \(i\) by 1%. The first column has less observation because some firms might have no credit granted in one year, and therefore delta logs are ill-defined. Standard errors (in parentheses) are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.
Table 3: Credit Supply Shocks and Productivity Growth

<table>
<thead>
<tr>
<th>VARIABLES (in delta Log)</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional Form</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output Measure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cobb-Douglas</td>
<td>Value Added</td>
<td>Trans-Log</td>
<td>Value Added</td>
<td>Trans-Log</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>All industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.0946***</td>
<td>0.109***</td>
<td>0.0190***</td>
<td>0.0259***</td>
</tr>
<tr>
<td></td>
<td>(0.0155)</td>
<td>(0.0160)</td>
<td>(0.00477)</td>
<td>(0.00491)</td>
</tr>
<tr>
<td>Observations</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.172</td>
<td>0.185</td>
<td>0.178</td>
<td>0.195</td>
</tr>
<tr>
<td>Manufacturing</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.115***</td>
<td>0.121***</td>
<td>0.0303***</td>
<td>0.0323***</td>
</tr>
<tr>
<td></td>
<td>(0.0178)</td>
<td>(0.0186)</td>
<td>(0.00595)</td>
<td>(0.00649)</td>
</tr>
<tr>
<td>Observations</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.186</td>
<td>0.200</td>
<td>0.144</td>
<td>0.180</td>
</tr>
</tbody>
</table>

Notes: Results of estimating model:

$$\Delta \omega_{i,t} = \psi_i + \psi_{s,t,p} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$$

One observation is one firm for one year between 1998 and 2013 (unbalanced panel). Firm FEs and province×industry×year FEs are included. Singleton are dropped. The RHS variable $\phi_{i,t}$ represents idiosyncratic shock to firm credit supply, and its construction is detailed in section 3.1. A 1% increase in $\phi_{i,t}$ is the supply shock needed to increase the credit granted to firm $i$ by 1%. The LHS variable is the first difference of Hicks-neutral productivity residual: $\Delta \omega_{i,t} = \Delta y_{i,t} - \Delta f(x_{i,t}, \beta)$ where $y$ is log of net revenues (or log of value added) and $x$ is a set of inputs. Capital stock, labor, and (for the revenue case only) intermediate inputs are included in $x$. $f(\cdot, \beta)$ is either a first (Cobb-Douglas) or second (Trans-Log) order polynomial in log inputs. Estimation of parameters $\beta$ is described in section 3.2. Standard errors, in parentheses, are (two-way) clustered at firm and main-lender×year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Table 4: Credit Supply Shocks and Productivity Growth: Robustness - Cobb-Douglas Revenue Productivity

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
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<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>(delta Logs)</td>
<td>Baseline</td>
<td>Firm Controls</td>
<td>Important Borrowers</td>
<td>Pooled Estimator</td>
<td>Alternative FE structure</td>
<td>Match Controls</td>
<td>Split Sample</td>
<td>4 Digits Sector</td>
<td>Endogenous Exit</td>
<td>Cost Share</td>
</tr>
<tr>
<td>Model</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
<td>(10)</td>
</tr>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.0190***</td>
<td>0.0248***</td>
<td>0.0182***</td>
<td>0.0131***</td>
<td>0.0171***</td>
<td>0.0234***</td>
<td>0.0197***</td>
<td>0.0278***</td>
<td>0.0166***</td>
<td>0.0256***</td>
</tr>
<tr>
<td>(0.00477)</td>
<td>(0.00534)</td>
<td>(0.00540)</td>
<td>(0.00327)</td>
<td>(0.00471)</td>
<td>(0.00604)</td>
<td>(0.00503)</td>
<td>(0.00585)</td>
<td>(0.00465)</td>
<td>(0.00736)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>656,960</td>
<td>483,665</td>
<td>521,741</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>587,873</td>
<td>656,960</td>
<td>545,162</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.178</td>
<td>0.184</td>
<td>0.192</td>
<td>0.006</td>
<td>0.096</td>
<td>0.178</td>
<td>0.178</td>
<td>0.272</td>
<td>0.177</td>
<td>0.185</td>
</tr>
<tr>
<td>Manufacturing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.0303***</td>
<td>0.0362***</td>
<td>0.0330***</td>
<td>0.0188***</td>
<td>0.0321***</td>
<td>0.0331***</td>
<td>0.0292***</td>
<td>0.0401***</td>
<td>0.0295***</td>
<td>0.0537***</td>
</tr>
<tr>
<td>(0.00595)</td>
<td>(0.00657)</td>
<td>(0.00698)</td>
<td>(0.00443)</td>
<td>(0.00600)</td>
<td>(0.00739)</td>
<td>(0.00633)</td>
<td>(0.00731)</td>
<td>(0.00639)</td>
<td>(0.0104)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>347,990</td>
<td>262,308</td>
<td>280,346</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
<td>309,887</td>
<td>347,990</td>
<td>291,071</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.144</td>
<td>0.153</td>
<td>0.150</td>
<td>0.004</td>
<td>0.071</td>
<td>0.144</td>
<td>0.144</td>
<td>0.259</td>
<td>0.166</td>
<td>0.161</td>
</tr>
</tbody>
</table>

Notes: Results of estimating model:

$\Delta \omega_{i,t} = \psi_{i,t} + \psi_{s,i,p} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$

One observation is one firm for one year between 1998 and 2013 (unbalanced panel). Firm FE's and province×industry×year FE's are included. Singletons are dropped. $\phi_{i,t}$ is an idiosyncratic shock to credit supply, whose construction is detailed in section 3.1. A 1% increase in $\phi_{i,t}$ is the supply shock needed to increase the credit granted to firm $i$ by 1%. The LHS variable is the first difference of productivity residual: $\Delta \omega_{i,t} = \Delta y_{i,t} - \beta_k \cdot \Delta k_{i,t} - \beta_l \cdot \Delta l_{i,t} - \beta_m \cdot \Delta m_{i,t}$ where $y$ is log of net revenues, $k$ is log of capital stock, $l$ is labor (measured by log of wage bill) and $m$ is log of intermediate inputs. Estimation of parameters $\beta$ is described in section 3.2. Column (2) add a set of lagged controls to baseline specification: polynomial in size (assets) and the ratios of value added, liquidity, cash flow and bank debt to assets. It excludes observation with missing or zero values for any control variable. Column (3) excludes any firm that, at any point in time, was the recipient of more than 1% of the total credit of any financial intermediary. Column (4) excludes firm FE's. Column (5) includes additively firm FE's, province FE's, year FE's, and industry FE's. Column (6) uses an alternative measure of credit supply shocks which control for match-specific covariates, see section 3.1. Column (7) uses an alternative credit supply shocks estimated with a “split sample” procedure, in order to control for finite sample biases. Column (8) uses a 4-digits (rather than 2) industry definition. It is estimated over less observations because of more singletons. Column (9) estimate productivity allowing for endogenous firm exit, as in Olley & Pakes (1996). Column (10) estimates productivity using the cost share method. It contains less observation because services and materials are entered additively, and not all firms report both intermediates. Standard errors, in parentheses, are (two-way) clustered at firm and main-lender×year level. *** p<0.01, ** p<0.05, * p<0.1
Table 5: Credit Supply Shocks and Productivity Growth - Heterogeneity - Cobb-Douglas Revenue Productivity

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heterogeneity Dimension</td>
<td>(Assets) (1)</td>
<td>(Workforce) (2)</td>
<td>Few Lenders (3)</td>
<td>High Sectoral Leverage (4)</td>
<td>High Sectoral Cash Flow (5)</td>
</tr>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.0219***</td>
<td>0.0197***</td>
<td>-0.0143</td>
<td>0.00872</td>
<td>0.0206***</td>
</tr>
<tr>
<td>(0.00503)</td>
<td>(0.00557)</td>
<td>(0.0185)</td>
<td>(0.00786)</td>
<td>(0.00513)</td>
<td></td>
</tr>
<tr>
<td>Interaction</td>
<td>-0.00413</td>
<td>0.00170</td>
<td>0.0348*</td>
<td>0.0168*</td>
<td>-0.00340</td>
</tr>
<tr>
<td>(0.00997)</td>
<td>(0.00907)</td>
<td>(0.0183)</td>
<td>(0.00942)</td>
<td>(0.00940)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>637,989</td>
<td>637,989</td>
<td>656,700</td>
<td>656,960</td>
<td>656,960</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.176</td>
<td>0.176</td>
<td>0.178</td>
<td>0.178</td>
<td>0.178</td>
</tr>
</tbody>
</table>

Manufacturing

| $\phi_{i,t}$ | 0.0365*** | 0.0354*** | -0.0128 | 0.0105 | 0.0352*** |
| (0.00718) | (0.00776) | (0.0244) | (0.0105) | (0.00725) |
| Interaction | -0.0258** | -0.0223* | 0.0445* | 0.0309** | -0.0138 |
| (0.0125) | (0.0123) | (0.0245) | (0.0127) | (0.0131) |
| Observations | 339,747 | 339,747 | 347,916 | 347,990 | 347,990 |
| R-squared | 0.141 | 0.141 | 0.144 | 0.144 | 0.144 |

Notes: Model is $\Delta \omega_{i,t} = \psi_i + \psi_{s,t,p} + \psi_{t} \cdot D_{i,t} + \gamma \cdot \phi_{i,t} + \gamma_{het} \cdot \phi_{i,t} \cdot D_{i,t} + \eta_{i,t}$ One observation is one firm for one year between 1998 and 2013 (unbalanced panel). Firm FE$s$ and province×industry×year FE$s$ are included. Singleton are dropped. The RHS variable $\phi_{i,t}$ represents idiosyncratic shock to firm credit supply, and its construction is detailed in section 3.1. A 1% increase in $\phi_{i,t}$ is the supply shock needed to increase the credit granted to firm $i$ by 1%. The LHS variable is the first difference of productivity residual: $\Delta \omega_{i,t} = \Delta y_{i,t} - \beta_k \cdot \Delta k_{i,t} - \beta_l \cdot \Delta l_{i,t} - \beta_m \cdot \Delta m_{i,t}$ where $y$ is log of net revenues, $k$ is log of capital stock, $l$ is labor (measured by log of wagebill) and $m$ is log of intermediate inputs. Estimation of parameters $\beta$ is described in section 3.2. Each specification add a categorical dummy $D_{i,t}$ and the interaction term between the category and $\phi_{i,t}$. Categorical dummy $D_{i,t}$ is equal to one iff: for column (1), firm is in the upper quartile for size, according to previous year assets, for column (2), firm is in the upper quartile for size, according to previous year number of employees, for column (3), firm is in the bottom half according to previous year number of lenders, for column (4), firm is in the top half according to sectoral mean leverage (debt over assets), and for column (5), firm is in the top half according to sectoral mean cash flow over book value of capital. Standard errors, in parentheses, are (two-way) clustered at firm and main-lender×year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 

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Table 6: Exposure to Interbank Market and Productivity Growth

<table>
<thead>
<tr>
<th>VARIABLES (in delta Log)</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional Form</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output Measure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cobb-Douglas Value Added</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$ITBK_{i,2006}$</td>
<td>-0.0477**</td>
<td>-0.0574**</td>
<td>-0.0172**</td>
<td>-0.0222***</td>
</tr>
<tr>
<td></td>
<td>(0.0239)</td>
<td>(0.0257)</td>
<td>(0.00757)</td>
<td>(0.00781)</td>
</tr>
<tr>
<td>Observations</td>
<td>110,746</td>
<td>110,746</td>
<td>110,746</td>
<td>110,746</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.112</td>
<td>0.117</td>
<td>0.101</td>
<td>0.122</td>
</tr>
<tr>
<td>Manufacturing</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$ITBK_{i,2006}$</td>
<td>-0.0802**</td>
<td>-0.106***</td>
<td>-0.00837</td>
<td>-0.0178*</td>
</tr>
<tr>
<td></td>
<td>(0.0329)</td>
<td>(0.0361)</td>
<td>(0.00960)</td>
<td>(0.0106)</td>
</tr>
<tr>
<td>Observations</td>
<td>58,191</td>
<td>58,191</td>
<td>58,187</td>
<td>58,187</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.134</td>
<td>0.143</td>
<td>0.086</td>
<td>0.113</td>
</tr>
</tbody>
</table>

Notes: Model is $\Delta \omega_{i,t} = \psi_{i,t,p} + \gamma \cdot ITBK_{i,2006} + \eta_{i,t}$ One observation is one firm for one year between 2007 and 2009 (unbalanced panel). Province×industry×year FE s are included. Singleton are dropped. The RHS variable $ITBK_{i,2006}$ is the weighted average of firm’s $i$ lenders’ liability on the interbank market over assets in 2006. The LHS variable is the first difference of Hicks-neutral productivity residual: $\Delta \omega_{i,t} = \Delta y_{i,t} - \Delta f(x_{i,t}, \beta)$ where $y$ is log of net revenues (or log of value added) and $x$ is a set of inputs. Capital stock, labor, and (for the revenue case only) intermediate inputs are included in $x$. $f(\cdot, \beta)$ is either a first (Cobb-Douglas) or second (Trans-Log) order polynomial in log inputs. Estimation of parameters $\beta$ is described in section 3.2. Standard errors (in parentheses) are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.
Table 7: Exposure to Interbank Market and Productivity Growth - Placebos

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional Form</td>
<td>Output Measure</td>
<td>Value Added</td>
<td>Net Revenues</td>
<td>Value Added</td>
<td>Net Revenues</td>
<td>Value Added</td>
<td>Net Revenues</td>
<td></td>
</tr>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$ITBK_{i,2006}$</td>
<td>-0.0148</td>
<td>-0.0133</td>
<td>-0.00560</td>
<td>-0.00702</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0225)</td>
<td>(0.0246)</td>
<td>(0.00798)</td>
<td>(0.00793)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$ITBK_{i,2002}$</td>
<td>-0.0195</td>
<td>-0.0379</td>
<td>0.00476</td>
<td>-0.00486</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0247)</td>
<td>(0.0266)</td>
<td>(0.00873)</td>
<td>(0.00832)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>115,042</td>
<td>115,042</td>
<td>115,042</td>
<td>115,042</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>$R^2$</td>
<td>0.074</td>
<td>0.079</td>
<td>0.090</td>
<td>0.112</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$ITBK_{i,2006}$</td>
<td>0.00230</td>
<td>0.0194</td>
<td>-0.0134</td>
<td>-0.0169</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0307)</td>
<td>(0.0340)</td>
<td>(0.0100)</td>
<td>(0.0119)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$ITBK_{i,2002}$</td>
<td>0.0106</td>
<td>-0.00820</td>
<td>0.00118</td>
<td>0.00908</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0337)</td>
<td>(0.0372)</td>
<td>(0.0106)</td>
<td>(0.0122)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
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<td>58,949</td>
<td>58,949</td>
<td>58,949</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.086</td>
<td>0.090</td>
<td>0.081</td>
<td>0.108</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Model is $\Delta \omega_{i,t} = \psi_{s,t,p} + \gamma \cdot ITBK_{i,t} + \eta_{i,t}$. One observation is one firm for one year between 2004 and 2006 or between 2003 and 2005 (unbalanced panel). Province×industry×year FEs are included. Singleton are dropped. The RHS variable $ITBK_{i,2006}$ is the weighted average of firm’s $i$ lenders’ liability on the interbank market over assets in 2006. The LHS variable is the first difference of Hicks-neutral productivity residual: $\Delta \omega_{i,t} = \Delta y_{i,t} - \Delta f(x_{i,t}, \beta)$ where $y$ is log of net revenues (or log of value added) and $x$ is a set of inputs. Capital stock, labor, and (for the revenue case only) intermediate inputs are included in $x$. $f(\cdot, \beta)$ is either a first (Cobb-Douglas) or second (Trans-Log) order polynomial log inputs. Estimation of parameters $\beta$ is described in section 3.2. Standard errors (in parentheses) are clustered at firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 


### Table 8: Credit Supply Shock and Productivity-Enhancing Activities

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>PCs per Unit of Capital</th>
<th>No. of Patents if Patents &gt; 0</th>
<th>R&amp;D</th>
<th>Export</th>
<th>FinCon&lt;sub&gt;2010&lt;/sub&gt;</th>
<th>Management Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Φ&lt;sub&gt;i,t&lt;/sub&gt;</td>
<td>0.808***</td>
<td>0.0645**</td>
<td>7.625**</td>
<td>0.238*</td>
<td>0.152*</td>
<td>-1.629***</td>
</tr>
<tr>
<td></td>
<td>(0.289)</td>
<td>(0.0323)</td>
<td>(3.530)</td>
<td>(0.128)</td>
<td>(0.085)</td>
<td>(0.594)</td>
</tr>
<tr>
<td>Observations</td>
<td>3,632</td>
<td>562,684</td>
<td>5,613</td>
<td>5,991</td>
<td>13,249</td>
<td>506</td>
</tr>
<tr>
<td>R²</td>
<td>0.968</td>
<td>0.759</td>
<td>0.812</td>
<td>0.872</td>
<td>0.843</td>
<td>0.421</td>
</tr>
</tbody>
</table>

**Notes:** Columns (1) to (5): model \( Y_{i,t} = \psi_i + \psi_{s,p} + \gamma \cdot \phi_{i,t} + \eta_{i,t} \) One observation is one firm for one year between 1999 and 2001 (unbalanced panel). Firm FEs and province×industry×year FEs are included. Singleton are dropped. LHS of column (1) is the log of number of PCs per 1,000 euros of capital. The LHS variable in column (2) is the number of patent application made from company \( i \) in year \( t \). Column (3) is the number of patent application made by company \( i \) in year \( t \), conditional on making any patent application. Columns (4) and (5): model is \( D_{i,t} = \psi_i + \psi_t + \gamma \cdot \phi_{i,t} + \eta_{i,t} \). \( D_{i,t} \) is a dummy variable taking value 1 iff firm \( i \) in year \( t \) has positive investment in R&D, column (4), or a dummy variable taking value 1 iff firm \( i \) in year \( t \) has positive export revenues, column (5). Column (6): linear probability model is \( FinCon_{i,2010} = \psi_{s,p} + \gamma \cdot \phi_{i,2010} + \eta_i \). One observation is one firm (cross section). Province×Industry fixed effects are included. \( FinCon_{i,2010} \) is a dummy taking value one iff firm \( i \) reports “difficulties to get external funds” as an important or somehow important obstacle to innovation. Number of PCs, export activity, R&D investments, and self-reported obstacle to innovation are taken from INVIND. Column (7): model is \( MS_{i,t} = \psi + \gamma \cdot \phi_{i,t} + \eta_{i,t} \). One observation is one firm observed for one or two years (cross section). \( MS_{i,t} \) is firm \( i \) overall management score provided by the World Management Survey (Bloom & Van Reenen, 2007). It takes value from 1-5. The RHS variable \( \phi_{i,t} \) represents idiosyncratic shock to firm credit supply, and its construction is detailed in section 3.1. A 1% increase in \( \phi_{i,t} \) is the supply shock needed to increase the credit granted to firm \( i \) by 1%. Standard errors (in parentheses) are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. See section 8 for more details.
A Additional Materials on Estimation of Credit Supply Shocks

A.1 Extensions of the additive growth rate model

A.1.1 Substitution Patterns

Various forms of the empirical model (1) are widely used in the literature on borrower-lender relations and real effect of financial shocks. However, it does not come without loss of generality. In particular, since companies might have multiple lending relationships, we can expect supply shocks of other connected bank to be included in (1). For instance, letting \( b \) and \( b' \) be the lenders of firm \( i \), a more complete model of credit is

\[
\frac{C_{i,b,t}}{C_{i,b,t-1}} = \frac{C(J_{t-1}, D_{i,t-1}, S_{b,t-1}, S_{b',t-1}, X_{i,b,t})}{C(J_{t-1}, D_{i,t-1}, S_{b,t-1}, S_{b',t-1}, X_{i,b,t-1})}
\]

which, leads to

\[
\Delta c_{i,b,t} = j_t + d_{i,t} + \phi_{b,t} + \alpha \cdot \phi_{b',t} + \epsilon_{i,b,t}
\]  
(11)

Building and estimating a credit demand and supply model with multiple lending relations and more realistic substitution patterns is beyond the scope of this project. Nonetheless, we perform several empirical exercise to assess the consequences of the exclusion of other banks’ supply from (1). To do so, we firstly estimate the credit supply shock from the restricted model (1): let \( \hat{\phi}_{0,b,t} \) be the resulting estimate. For each bank-firm pair, we define \( b' \) as the main substitute for \( b \) as the main lender of firm \( i \) during period \( t - 1 \). In case \( b \) is the main lender of firm \( i \), then \( b' \) is the second main lender of \( i \) in period \( t - 1 \). Then, we include the first-stage estimate of credit shock of bank \( b' \) as an additional control in (1). That is, we estimate:

\[
\Delta c_{i,b,t} = j_t + d_{i,t} + \phi_{b,t} + \alpha \cdot \hat{\phi}_{0,b',t} + \epsilon_{i,b,t}
\]  
(12)

Defining \( \hat{\phi}_{1,b,t} \) the estimate of \( \phi_{b,t} \) from (12), the correlation between \( \hat{\phi}_{1,b,t} \) and \( \hat{\phi}_{0,b,t} \) is \( \approx 0.99 \) for all years \( t \), suggesting that the exclusion of supply shocks of other potential borrowers from (3) is extremely unlikely to affect significantly our results. We conclude that ignoring substitution and complementarity does not significantly affect the impact of credit supply shocks on productivity.\(^{34}\)

A.1.2 Loan and Relation Characteristics

We may relax Assumption 2, by imposing Assumption 2b:

\[
\epsilon_{i,b,t} = \alpha \cdot \delta_{i,b,t-1} + \tilde{\epsilon}_{i,b,t}
\]

and

\[
\tilde{\epsilon}_{i,b,t} \perp D_t, S_b
\]

\(^{34}\)Specification (12) considers only the effect of the main alternative lender. However, firms’ financing decision might be affected by idiosyncratic shocks to all other connected lenders. Therefore, for each bank-firm pair, we compute \( \hat{\phi}_{0,b',t} \) as the average of \( \hat{\phi}_{b',t} \) of all banks lending to \( i \) but \( b \). Then, we consider the model:

\[
\Delta c_{i,b,t} = j_t + d_{i,t} + \phi_{b,t} + \alpha_t \cdot \hat{\phi}_{0,b',t} + \epsilon_{i,b,t}
\]  
(13)

Supply shocks estimated from (13) are, again, extremely highly correlated with the ones estimated from the main specification (3) (correlation coefficient is around 98 per cent for all years). Replicating our main specification using credit supply shocks estimated in (12) and (13) confirms our results.
with $o_{i,b,t-1}$ are observable characteristics of the lending relations between firm $i$ and financial intermediary $b$. The vector $o_{i,b,t-1}$ includes: size of the loan relative to borrower’s total credit received, size of loan relative to lender’s total credit granted, interest rate, length of the lending relations, type of credit instrument used, presence of past non-performing loans.

Assumption 2b allows to estimate bank and firm factors from

$$\Delta c_{i,b,t} = c_t + d_{i,t} + \phi_{b,t} + \alpha \cdot x_{i,b,t-1} + \epsilon_{i,b,t} + \text{approx}_{i,b,t}$$  \hspace{1cm} (14)$$

As match-specific controls, we include interest rates, length of lending relations, share of $C_{i,b,t-1}$ in the portfolio of the lender and in the portfolio of the borrower, type of credit instrument used, share of non-performing loans, share of credit covered by collateral. Supply shocks estimated from equation (14) and (3) show correlations above 94% for most years, which mitigate concern that unobservable elements of $\epsilon_{i,b,t}$ are significantly biasing estimate of $\phi_{b,t}$. Section 5.1 shows that the main results of the paper are unaffected by using the alternative credit supply shocks derived from decomposition (14).

Summing-up, we develop new tests to estimate whether substitution and complementarity patterns between lenders, and bank-firm match-specific shocks affect our results on the impact of credit supply on productivity. In our data, this does not seem to be the case. Yet, notice that this may not be the case in other more specialized or concentrated markets, such as the one of syndicated loans. Given the widespread use of additive growth rate model, we suggest that our tests represent an important sanity check to be performed by researchers.

A.2 Credit Supply Shocks and Credit Applications to new Lenders

The credit register contains information about firms’ application for loans or credit lines with new lenders.\(^{36}\) We expect a borrower to be less likely to apply for credit with new lenders when the lenders with whom it is already connected are expanding credit supply. On the other side, if the additive growth rate model is severely misspecified, then what we define as credit supply might be contaminated by demand-side factors. Consequently, we would expect a positive correlation between these demand-side factors and loans applications with all lenders (and, therefore, with new lenders as well). Therefore, we estimate the model:

$$App_{i,t} = \psi_i + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$$

$$Pr(App_{i,t} > 0) = \psi_i + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$$

$$App_{i,t}|App_{i,t} > 0 = \psi_i + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$$

where $App_{i,t}$ is the number of previously unconnected lenders receiving a credit application from $i$ in period $t$. Results are reported in Table A.1, which shows that firms receiving positive credit supply shocks decrease their search for alternative lenders both on the intensive and on the extensive margin. They confirm the soundness of the procedure to disentangle supply-side variation from demand-side factors.

\(^{35}\)We need to impute interest rates for roughly a third of the observations.

\(^{36}\)The very reason of having a national credit register is to provide lenders with information about potential borrowers’ credit history. When a lender submits a query to the credit register to seek information about a firm which is not among its current borrowers, the researcher infer that the firm applied for a loan or a credit line with that bank.
B Production with Heterogeneous Credit Constraints

B.1 Main model

Firm $i$, operates in sector $s$ and province $p$. For simplicity, we omit the subscript $s$, although all parameters, prices and functions should be thought as industry-specific. In each year $t$, firm combines capital, labor and materials to generate revenues:

$$Y_{i,t} = \exp\{\omega_{i,t}\}F(L_{i,t}, K_{i,t}, M_{i,t}, \beta)$$

or value added

$$VA_{i,t} = \exp\{\omega_{i,t}\}F(L_{i,t}, K_{i,t}, \beta)$$

As it is common in the literature, we assume that productivity can be decomposed in two components:

$$\omega_{i,t} = \tilde{\omega}_{i,t} + \epsilon_{Y,i,t}$$

$\tilde{\omega}_{i,t}$ is correlated over time and it is known by the firm before starting production. Therefore, it affects inputs acquisition and other firm’s decisions. $\epsilon_{Y,i,t}$ is an $iid$ shock, which takes place after input decisions have been made and does not convey information about future productivity. It is often referred as measurement error of output, although we prefer to interpret it as “pure luck”.

Capital stock is accumulated according to the following law of motion:

$$K_{i,t} = I_{i,t} + (1 - \delta_t)K_{i,t-1}$$

Prices

Firms are price-takers on the input markets. Prices of materials are assumed to be shaped by national prices of inputs and by local inflation shocks (measured by local CPI):

$$P_{p,t}^M = P_t^M \cdot P(cpi_{p,t})$$

we do not observe firm level or local level prices of intermediate inputs, so we need to assume a form for $P(\cdot)$.

Variable Profits and Utility Function

We focus the discussion on revenue productivity. The value added case is a straightforward simplification. Variable profits are:

$$\pi (K_{i,t}, L_{i,t}, \tilde{\omega}_{i,t}, w_t, P_{p,t}^M, \epsilon_{Y,i,t}) =$$

$$= \exp\{\omega_{i,t} + \epsilon_{Y,i,t}\}F(L_{i,t}, K_{i,t}, M_{i,t}, \beta) - w_tL_{i,t} - M_{i,t}P_{p,t}^M$$

The firm maximizes owner’s utility from the dividend stream $Div_{i,t}$:

---

37 For instance, see Olley & Pakes (1996).
38 See section 2.
39 For a discussion see Ackerberg et al. (2015) and De Loecker & Scott (2016).
\[ u(Div_{i,t}, \epsilon_t^U) + E \left[ \sum_{\tau > t} \left( \frac{1}{1 + R} \right)^{\tau-t} u(Div_{i,\tau}, \epsilon_{\tau}^U) \right] \]

Credit Supply Shocks

At the beginning of the period, firm \( i \) is connected to a subset of the banks operating in the country, \( B_{i,t-1} \). Each bank “experience” a credit supply shock \( \phi_{b,t} \). Firm \( i \) receives a credit supply shock equal to \( \phi_{i,t} = \sum_{b \in B_{i,t-1}} \phi_{b,t} \cdot wc_{b,i,t-1} \) where weights are proportional to the share of credit received from firm \( i \) from each lender in previous period.

We assume \( B_{i,t} \) and \( \{wc_{b,i,t-1}\} \) evolve exogenously, while the quantity of debt is endogenously chosen. In section 6 we exploit a natural experiment to control for assortative matching between borrowers and lenders and we show that our empirical results hold.

Budget and Credit constraints

Firm faces a budget constraint:

\[ Div_{i,t} + K_{i,t} + B_{i,t-1} (1 + r_{i,t}) + Adj \left( L_{i,t}, L_{i,t-1}, K_{i,t}, K_{i,t-1}, J_t, \epsilon_{i,t}^{adj} \right) = \pi_{i,t} + B_{i,t} + (1 - \delta_t) K_{i,t-1} \]

where \( B_{i,t} \) is the quantity of euros borrowed, \( Adj (\cdot) \) are adjustment costs for labor and capital, \( J_t \) is the set of all industry-wide state variables. Interest rate is a function of firms’ characteristics and credit supply shocks, plus random shocks

\[ r_{i,t} = r \left( B_{i,t-1}, J_t, \phi_{i,t}, \epsilon_{i,t}^K \right) \]

credit constraint

\[ B_{i,t} \leq K_{i,t-1} \cdot \Gamma \left( B_{i,t-1}, \phi_{i,t}, \tilde{\omega}_{i,t}, J_t \right) \]

we also allow single inputs to have specific financially-generated constraints.

\[ M_{i,t} \leq K_{i,t-1} \cdot \Gamma^M \left( B_{i,t-1}, \phi_{i,t}, \tilde{\omega}_{i,t}, J_t \right) \]
\[ K_{i,t} \leq K_{i,t-1} \cdot \Gamma^K \left( B_{i,t-1}, \phi_{i,t}, \tilde{\omega}_{i,t}, J_t \right) \]
\[ L_{i,t} \leq K_{i,t-1} \cdot \Gamma^L \left( B_{i,t-1}, \phi_{i,t}, \tilde{\omega}_{i,t}, J_t \right) \]

furthermore, we assume the function \( \Gamma^M \) is increasing in its second and third arguments.

The presence of general credit constraints does not imply that intermediate inputs are constrained. However, we want to allow for this possibility, since firms might need to pay in advance part of the material inputs and availability of credit (especially credit lines) might limit their ability to do so. Whether or not an input is effectively contained by availability of external funds depends on the
relative cash cycle. For instance, capital investments might be more sensitive to credit availability than labor because they have to be paid fully in advance. However, while firms make financial and real decision in continuous time (or every day), our model discretize time in yearly periods, as it is commonly do by the literature because balance-sheets data are available at yearly frequency. Allowing for input-specific constraints is a way to partly reconcile the model with reality.

**Timing**

At the beginning of the period firms observe \( \tilde{\omega}_{i,t} \), \( \epsilon_{K,i,t} \), \( \phi_{i,t} \) and all elements of \( J_t \) (like \( \epsilon_u \) and \( cpi_{p,t} \)). Then, it choose jointly \( B_{i,t} \) and all inputs \( K_{i,t}, L_{i,t} \) and \( M_{i,t} \). Firms do not observe the non transmitted error \( \epsilon_{i,t}^Y \) until the end of the period. When the random shock \( \epsilon_{i,t}^Y \) is realized, \( Div_{i,t} \) is set as residual from the budget constraint and it is consumed.

**Law of Motion**

The non transmitted shock \( \epsilon_{i,t}^Y \) is pure luck and, therefore, it is i.i.d and independent of any other component of the model. Without loss of generality, we set \( E[\exp\{\epsilon_{i,t}^Y\}] = 1 \). The law of motion of all other shocks \( \epsilon_{i,t} \) is left unrestricted. However, notice that the absence of any shock directly affecting intermediate inputs is essential for identification.

Following the tradition of the control function, we impose a law of motion for productivity. That is,

\[
E[\tilde{\omega}_{i,t}|\mathcal{I}_{t-1}] = E[\tilde{\omega}_{i,t-1}, \phi_{i,t-1}, J_{t-1}] 
\]  

(16)

where \( \mathcal{I}_{t-1} \) is firm’s information set at time \( t-1 \). Assumption 16 relaxes the classical Markovian structure by allowing credit supply to affect productivity dynamics.\(^{40}\)

Furthermore, defining:

\[
\zeta_{i,t} := \tilde{\omega}_{i,t} - E[\tilde{\omega}_{i,t}|\mathcal{I}_{t-1}] 
\]  

(18)

and

\[
\zeta_{i,t}^\phi := \phi_{i,t} - E[\phi_{i,t}|\mathcal{I}_{t-1}] 
\]  

(19)

we assume \( \zeta_{i,t}^\phi \) is independent of all \( \epsilon \)'s.

**Demand for intermediate inputs**

The optimal quantity of intermediate input is

\[
E[\tilde{\omega}_{i,t}|\mathcal{I}_{t-1}] = E[\tilde{\omega}_{i,t-1}, \phi_{i,t-1}, \text{Lev}_{i,t-1}, J_{t-1}] 
\]  

(17)

where \( \text{Lev}_{i,t-1} = \frac{B_{i,t-1}}{K_{i,t-1}} \) is a measure of leverage. The main results of the paper are robust to this alternative law of motion.

\(^{40}\)Alternatively, the researcher can allow the endogenous choice of leverage to mediate the effect of exogenous financial shocks. Then, one should modify the Markovian process as:

\[
E[\tilde{\omega}_{i,t}|\mathcal{I}_{t-1}] = E[\tilde{\omega}_{i,t-1}, \phi_{i,t-1}, \text{Lev}_{i,t-1}, J_{t-1}] 
\]  

(17)
\[ M^*(K_{i,t}, L_{i,t}, K_{i,t-1}, \tilde{\omega}_{i,t}, J_t, B_{i,t-1}, P_{p,t}^M) = \min\{M^{unc}(K_{i,t}, L_{i,t}, \tilde{\omega}_{i,t}, P_{p,t}^M); K_{i,t-1} \cdot \Gamma^M(B_{i,t-1}, \phi_{i,t}, \tilde{\omega}_{i,t}, J_t)\} \]

where \(M^{unc}\) solves

\[ \frac{\partial F(L_{i,t}, K_{i,t}, M, \beta)}{\partial M} \exp\{\tilde{\omega}_{i,t}\} = P_{p,t}^M \]

under assumptions above, \(^{41}\) \(M^*\) is increasing in productivity for each level of the other factors. Therefore, \(\exists\) an unknown function \(M^{-1}\) such that:

\[ \tilde{\omega}_{i,t} = M^{-1}(K_{i,t}, L_{i,t}, K_{i,t-1}, \phi_{i,t}, c_{p,t}, J_t) \]

which allows to write

\[ Y_{i,t} = \exp\{\epsilon^Y_{i,t}\} F(L_{i,t}, K_{i,t}, M_{i,t}, \beta) \exp\{M^{-1}(K_{i,t}, L_{i,t}, K_{i,t-1}, \phi_{i,t}, c_{p,t}, J_t)\} \]

therefore, for some unknown function \(\tilde{\Psi}\)

\[ Y_{i,t} = \exp\{\epsilon^Y_{i,t}\} \tilde{\Psi}(L_{i,t}, K_{i,t}, M_{i,t}, K_{i,t-1}, \phi_{i,t}, c_{p,t}, J_t) \]

\(^{42}\)

\[ Y_{i,t} = \Psi(l_{i,t}, k_{i,t}, m_{i,t}, k_{i,t-1}, \phi_{i,t}, c_{p,t}, J_t) + \epsilon^Y_{i,t} \]

for some unknown function \(\Psi\). Following Ackerberg et al. (2015), we estimate the model in two stages. In the first stage we purge the output from the noise \(\epsilon^Y_{i,t}\). We estimate \(\Psi\) as

\[ E_t[y_{i,t}|l_{i,t}, k_{i,t}, m_{i,t}, k_{i,t-1}, \phi_{i,t}, c_{p,t}, J_t]. \]

\(^{41}\)Formally, we assume that \(M\) is chosen within a set \(A_M\) such that \(F(K, L, \cdot)\) is increasing in its last argument for each value of \(K\) and \(L\). Then, \(M^{unc}\) is increasing in \(\tilde{\omega}\) by Topkis theorem. This is trivially true for the Cobb Douglas case, as long as \(K > 0\) and \(L > 0\).

\(^{42}\)\(E_t[y_{i,t}|x_{i,t}, J_t] = \psi(x_{i,t}, J_t)\) for some unknown \(\psi\), which we approximate as a polynomial in \(x\) plus year FEs. We follow this approximation procedure through the paper.
From equation (16) we can write

\[ \tilde{\omega}_{i,t} = g_t (\tilde{\omega}_{i,t-1}, \phi_{i,t-1}) + \zeta_{i,t} \]

with \( g_t \) unknown.

By definition, we have

\[ E \left[ \zeta_{i,t} + \epsilon_{i,t}^Y | I_{t-1} \right] = 0 \]

therefore,

\[ E \left[ y_{i,t} - f(l_{i,t}, k_{i,t}, m_{i,t}, \beta) - g_t (\Psi_{i,t-1} - f(l_{i,t-1}, k_{i,t-1}, m_{i,t-1}, \beta), \phi_{i,t-1}) | I_{t-1} \right] = 0 \]

leading to the moment condition

\[ E \begin{bmatrix} \Psi_{i,t} - f(l_{i,t}, k_{i,t}, m_{i,t}, \beta) - g_t (\Psi_{i,t-1} - f(l_{i,t-1}, k_{i,t-1}, m_{i,t-1}, \beta), \phi_{i,t-1}) \\ l_{i,t-1} \\ m_{i,t-1} \\ \text{inv}_{i,t-1} \end{bmatrix} = 0 \quad \tag{23} \]

Moment (23) allows joint estimation of the structural parameter \( \beta \) and of the unknown function \( g_t \).

We parametrize \( f(\cdot) \) as either linear in logs (Cobb-Douglas\(^{44}\)) or quadratic (translog). These two functions can be seen as a first and second order log-linear approximation of any smooth production function in level \( F(\cdot) \). Given that all our results are extremely similar between Cobb-Douglas and translog, we do not believe it is useful to add higher order terms. Production functions are industry-specific. We drop sectors for which less than 300 firm-year observations are available, because of difficulties in estimating production function with few observations.

The control function approach allows to estimate production function parameters by controlling for simultaneity bias in the choice of inputs.\(^{45}\) Furthermore, the inclusion of local price shocks \( cpi_{p,t} \) in the control function overcomes the non-identification results of Gandhi et al. (2011). In our baseline specification, we do not include endogenous exit decision in the model. Section 5.1 shows that such an inclusion does not significantly affect the main results of this paper.

If credit supply affects productivity, then it is correlated with \( \zeta_{i,t} \). Moreover, \( \phi_{i,t} \) is correlated over

\[^{43}\text{We follow De Loecker & Warzynski (2012) and we perform this second stage in two steps. For each guess a parameter value } \beta_{\text{guess}}, \text{we can compute a corresponding } \omega_{i,t}(\beta_{\text{guess}}). \text{Then, by regressing } \omega_{i,t}(\beta_{\text{guess}}) \text{on a polynomial in } \omega_{i,t-1}(\beta_{\text{guess}}) \text{and } \phi_{i,t-1} \text{plus year fixed effects we get a sample analog of } \zeta(\beta_{\text{guess}}). \text{We estimate } \beta \text{ by minimizing then sample analog of } E \left[ (\beta_{\text{guess}}) \cdot \text{instruments}_{i,t-1} \right]. \]

\[^{44}\text{See Cobb \\& Douglas (1928).} \]

\[^{45}\text{That is, since more productive firms are likely to acquire more inputs, a simple regression of output on inputs does not recover the structural parameters of interest.} \]
time: in fact, regression of $\phi_{i,t}$ on $\phi_{i,t-1}$ gives a coefficient of $\approx 0.5$ if no fixed effect is included and $\approx 0.2$ if firm fixed effects are included. Furthermore, it affects input acquisition, as documented by section 4. Therefore, if one excludes credit supply shocks from the model, past inputs are correlated with the productivity innovation, and there are no valid instruments to identify the parameter of interests.

Results

Table A.2 provides some descriptives for the Cobb-Douglas production function estimates.\footnote{As it is shown in section 5 the relations between productivity and credit does not change if one consider CD or Trans-Log production function, therefore we do not find it useful to analyses in detail the more complicated case.} The mean\footnote{We take averages weighted for number of observation in the sample of the main specification.} elasticity of value added to capital (to labor) is $\approx 0.17 (\approx 0.64)$ for the whole economy and $\approx 0.19 (\approx 0.62)$ for manufacturing. The mean elasticity of net revenues to capital (to labor) is $\approx 0.07 (\approx 0.14)$ for the whole economy and $\approx 0.04 (\approx 0.13)$ for manufacturing. The mean elasticity of net revenues to intermediate inputs is $\approx 0.81$ for both manufacturing and all industries.\footnote{Under the assumption of single good producers, we can translate these revenue production function estimate into a quantity production function. The relations depend on the competitive structure of the product market, see, for instance, De Loecker (2011). If firms are price takers on the output market, then the quantity elasticities are equal to revenue elasticities. However, if firms compete under monopolistic competition and consumers have CES utility, then, for each input $x$ the relations between quantity and revenue elasticity is $\beta_{x,\text{quantity}} = \beta_{x} \cdot \frac{\sigma}{\sigma - 1}$ where $\sigma$ is the elasticity of demand. We compute sector level estimate of $\sigma$ following Pozzi & Schivardi (2016) in order to calculate the mean quantity-elasticities for manufacturing, which are, respectively $\approx 0.05$ for capital, $\approx 0.17$ for labor and $\approx 1.06$ for intermediate inputs.}

B.2 An alternative empirical model of production

The credit supply shock $\phi_{i,t}$ is a weighted average of supply shocks $\phi_{b,t}$ of the banks connected to firm $i$ in the previous period. A potential critique of the main model is that it includes credit supply changes as an element of the level of the constraint faced each period by the firm. Indeed, one might prefer to include $S_{b,t}$ (i.e., all the bank-level factors affecting b’s ability and willingness to provide credit to its borrowers) into the credit constraint function $\Gamma$. An additional potential problem is that, to perform the inversion of the error, the researcher need to observe the exact value of $\phi_{i,t}$. The credit shifter estimated as in section 3.1 might be considered a proxy of the real variation in credit constraints. For instance, the actual credit supply faced by a firm can be affected by new banks it connects to during the year. In this section, we provide an alternative model of production with credit constraints that address all these issues, at the cost of relying on a first-order log-linearization of the estimating equations.\footnote{For a critique of the use of log-linear approximation, see Carroll (2001).} This model provides an alternative firm-specific estimate of productivity growth: the impact of credit supply shocks on it is qualitatively and quantitatively similar.

Production, utility and budget constraints are as in section (3.2). Credit constraints are:

$$B_{i,t} \leq K_{i,t-1} \cdot \Gamma \left( B_{i,t-1}, S_{b(i),t}, \tilde{\omega}_{i,t}, J_t \right)$$
and

\[
\begin{align*}
M_{i,t} & \leq K_{i,t-1} \cdot \Gamma^M \left( B_{i,t-1}, S_{b(i),t}, \tilde{\omega}_{i,t}, J_t \right) \\
K_{i,t} & \leq K_{i,t-1} \cdot \Gamma^K \left( B_{i,t-1}, S_{b(i),t}, \tilde{\omega}_{i,t}, J_t \right) \\
L_{i,t} & \leq K_{i,t-1} \cdot \Gamma^L \left( B_{i,t-1}, S_{b(i),t}, \tilde{\omega}_{i,t}, J_t \right)
\end{align*}
\]

where \( b(i) \) is the set of banks connected to \( i \) at the beginning of the period, and \( S_{b(i),t} \) are bank-level factors determining credit supply. Log output is:

\[
Y_{i,t} = \tilde{\Psi} \left( L_{i,t}, K_{i,t}, M_{i,t}, K_{i,t-1}, S_{b(i),t}, cpi_{p,t}, J_t \right) + \epsilon^Y_{i,t}
\] (24)

and the law of motion of productivity is

\[
E[\exp \{ \tilde{\omega}_{i,t} \} | \mathcal{I}_{t-1}] = E[\exp \{ \tilde{\omega}_{i,t} \} | \mathcal{W}_{t-1}, S_{b(i),t-1}, J_{t-1}] = G_t \left( \tilde{\omega}_{i,t-1}, S_{b(i),t-1} \right)
\] (25)

log-linearizing equations (24) and (25) and taking first differences yields:

\[
\Delta y_{i,t} = \psi_t + \psi_l \Delta l_{i,t} + \psi_k \Delta k_{i,t} + \psi_m \Delta m_{i,t} + \psi_{km} \Delta k_{i,t} + \psi_{\phi} \phi_{b(i),t} + \psi_{cpi} \Delta cpi_{p,t} + approx^y_{i,t} + \Delta \epsilon^Y_{i,t}
\] (26)

and

\[
\Delta \tilde{\omega}_{i,t} = g_t + g_\omega \cdot \Delta \tilde{\omega}_{i,t-1} + g_\phi \cdot \phi_{b(i),t-1} + \nu_{i,t} + approx^\phi_{i,t}
\] (27)

where \( \phi_{b(i),t} = c_3 \Delta s_{b(i),t} \) as defined in section 3.1, and \( \zeta_{i,t} \) is an expectation error and \( approx^\phi_{i,t} \) approximation error. The econometrician observe \( \hat{\phi}_{i,t} \) which is a noisy proxy of \( \phi_{b(i),t} \):

\[
\hat{\phi}_{i,t} = \phi_{b(i),t} + \epsilon^\phi_{i,t}
\] (28)

the measurement error \( \epsilon^\phi_{i,t} \) is assumed to be i.i.d and uncorrelated over time. We can rewrite the equations as

\[
\Delta y_{i,t} = \Delta \psi_{i,t} + approx^y_{i,t} + \Delta \epsilon^Y_{i,t} = \\
\Delta \psi_{i,t} + \psi_l \Delta l_{i,t} + \psi_k \Delta k_{i,t} + \psi_m \Delta m_{i,t} + \psi_{km} \Delta k_{i,t-1} + \\
+ \psi_{\phi} \cdot \hat{\phi}_{i,t} + \psi_{cpi} \Delta cpi_{p,t} + approx^y_{i,t} - \epsilon^\phi_{i,t} + \Delta \epsilon^Y_{i,t}
\]

In the first stage, we produce an estimate for \( \Delta \psi_{i,t} \) from equation . Since \( \epsilon^\phi_{i,t} \) is correlated with input acquisition at period \( t \), we use past values of inputs as instrument, together with contemporaneous value of \( \phi_{i,t} \) and \( cpi \).

Then, we consider the log-lin approximation of the expected value of productivity
\[ \Delta \tilde{\omega}_{i,t} = g_t + g_\omega \cdot \Delta \tilde{\omega}_{i,t-1} + g_\phi \cdot \phi_{i,t-1} - \epsilon^\psi_{i,t-1} + \Delta \zeta_{i,t} + \Delta \text{approx}_{i,t}^{\omega} \]  

(29)

to estimate the model we need to add an assumption on the approximation error:

\[ E[\Delta \text{approx}_{i,t}^{\omega} | I_{t-2}] = 0 \]

implying moment conditions

\[ E[-\epsilon^\psi_{i,t-1} + \Delta \zeta_{i,t} + \Delta \text{approx}_{i,t}^{\omega} | I_{t-2}] = 0 \]

or, equivalently

\[ E \left[ \Delta \psi_{i,t} - \Delta f(l_{i,t}, k_{i,t}, m_{i,t}, \beta) - g_t - g_\omega \cdot (\Delta \psi_{i,t-1} - \Delta f(l_{i,t-1}, k_{i,t-1}, m_{i,t-1}, \beta)) - g_\phi \cdot \phi_{i,t-1} | \Psi_{i,t-2}^{\text{inv}_{i,t-2}}, \Psi_{i,t-2}^{m_{i,t-2}} \right] = 0 \]

which allow to estimate the parameter \( \beta \) and recover productivity residual \( \omega_{i,t} \). Table A.3 shows that the effect of credit supply shock on productivity is extremely similar if production function is estimated with this alternative procedure rather than baseline of Table 3.

C Additional Materials on Credit Supply and Productivity Growth

C.1 TFP, TFPR and TFPQ - cont’d

We follow De Loecker (2011) and consider a firm producing quantity \( Q_{i,t} \) of a single differentiated good, at price \( P_{i,t} \), and facing a CES demand function. Let its production function be a Cobb-Douglas. Quantity produced (supply) is

\[ Q_{i,t} = \exp\{\omega_{i,t}^{q} + \Delta f(l_{i,t}, k_{i,t}, m_{i,t}, \beta)\} = \exp\{\omega_{i,t}^{q} + \beta_{l}^{q} \cdot l_{i,t} + \beta_{k}^{q} \cdot k_{i,t} + \beta_{m}^{q} \cdot m_{i,t}\} \]

Quantity sold (demand) is:

\[ Q_{i,t} = \left(\frac{P_{i,t}}{P_t}\right)^{-\sigma} \exp\{\theta_{i,t}\} \]

where \( P_t \) is national deflator and \( \theta_{i,t} \) reflects demand conditions, both endogenous (e.g. quality of the product offered) and exogenous (e.g. local economic shocks) with respect to firm’s activity. We follow Pozzi & Schivardi (2016) and refer to \( \theta \) as “market appeal”. Then, the deflated revenues are:
\[ Y_{i,t} = \frac{P_{i,t} \cdot Q_{i,t}}{P_t} = Q_{i,t}^{\frac{\sigma-1}{\sigma}} \cdot \exp\{\theta_{i,t}\} \]

therefore, taking logs:

\[ y_{i,t} = \frac{1}{\sigma} \cdot \theta_{i,t} + \frac{\sigma-1}{\sigma} \cdot \omega_{i,t}^q + \frac{\sigma-1}{\sigma} \cdot f(l_{i,t}, k_{i,t}, m_{i,t}, \beta) = \]

\[ = \frac{1}{\sigma} \cdot \theta_{i,t} + \frac{\sigma-1}{\sigma} \cdot \omega_{i,t}^q + \beta_l \cdot l_{i,t} + \beta_k \cdot k_{i,t} + \beta_m \cdot m_{i,t} \]

with \( \beta_x = \frac{\sigma-1}{\sigma} \cdot \beta_x^q \). The growth rate of productivity is:

\[ \Delta \omega_{i,t} = \frac{1}{\sigma} \cdot \Delta \theta_{i,t} + \frac{\sigma-1}{\sigma} \cdot \Delta \omega_{i,t}^q = \psi_i + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t} \]

Equation (30) underlines the additional empirical challenges arising from having revenues rather than quantity productivity on the LHS. In fact, both technology and demand shocks enter the error terms. The demand shocks are especially pernicious, since there are many reasons why they might create spurious correlations between credit supply and revenue productivity. For instance, if the output market of the borrower and the lending market of the lender overlap, then healthier lenders are also connected to firms receiving positive demand shocks. Consequently, the exclusion restriction underlying equation (30) is that all the external demand or technology shocks, which might create spurious correlations, are captured by the set of fixed effects \( \psi_{p,s,t} \) and \( \psi_i \). Sections 5.1 and 6 present results supporting the soundness of this exclusion restriction.

An additional concern is that under a more general (inverse) demand function, \( P_{i,t} = D(Q_{i,t}, \theta_{i,t}, P_t) \), credit supply might alter pricing incentives and create an increase in measured revenue productivity even without a change in technical efficiency \( \omega_{i,t}^q \) or market appeal \( \theta_{i,t} \). In fact, productivity growth can be also written as:

\[ \Delta \omega_{i,t} = \Delta \omega_{i,t}^q + \Delta \omega_{i,t}^q \]

However, this is a not a very worrisome concern. In fact, it is shown in the paper that positive credit supply shocks increase input acquisition. Therefore, even if productivity does not respond to credit shocks, quantity produced also goes up. As long as demand is decreasing in prices (implying
inverse demand is decreasing in quantity), a firm has to set lower prices in order to sell the additional quantity produced. Then, a positive credit supply shocks decreases prices and, consequently, revenue productivity, for a given level of technical efficiency and product appeal. We show, instead, a positive effect of credit on productivity.\footnote{It is possible that more complex interaction between financial constraints and pricing incentives might arise because of the presence of demand dynamics (e.g. demand today depends on prices set yesterday). It is not possible to exclude that this might be the case under some assumptions. However, Chevalier & Scharfstein (1996) show that more financially constrained firms set higher prices (at least in the supermarket industry, during recessions) because they are more likely to exit the market and, therefore, “care less” about future demand, which support the causal interpretation of our results.}

Does $\theta$ or $\omega^q$ respond more strongly to a credit supply shocks? Let us consider again the case of monopolistic competition and CES demand. Let us assume that equation (30) can be decomposed in two parts

$$
\Delta\theta_{i,t} = a_i + a_{p,s,t} + \gamma^\theta \cdot \phi_{i,t} + \epsilon^\theta_{i,t} \\
\Delta\omega^q_{i,t} = b_i + b_{p,s,t} + \gamma^q \cdot \phi_{i,t} + \epsilon^q_{i,t}
$$

therefore

$$
\frac{1}{\sigma} \cdot \Delta\theta_{i,t} + \frac{\sigma - 1}{\sigma} \cdot \Delta\omega^q_{i,t} = \psi_i + \psi_{p,s,t} + \left(\frac{1}{\sigma} \cdot \gamma^\theta + \frac{\sigma - 1}{\sigma} \cdot \gamma^q\right) \cdot \phi_{i,t} + \eta_{i,t}
$$

under the exclusion restrictions of uncorrelation of $\phi_{i,t}$ with respect to $\eta_{i,t} = \epsilon^q_{i,t} + \epsilon^\theta_{i,t}$ (conditional on fixed effects), then, the parameter recovered by estimating the main equation (7) is

$$
\gamma = \left(\frac{1}{\sigma} \cdot \gamma^\theta + \frac{\sigma - 1}{\sigma} \cdot \gamma^q\right)
$$

The derivative of $\gamma$ with respect to $\sigma$ is

$$
\frac{\partial \gamma}{\partial \sigma} = \frac{1}{\sigma^2} \cdot (\gamma^q - \gamma^\theta)
$$

implying

$$
\frac{\partial \gamma}{\partial \sigma} > 0 \iff \gamma^q > \gamma^\theta
$$

That is, the effect of credit supply shocks on revenue productivity is increasing in the elasticity of demand if the effect of credit supply shocks on technical efficiency is stronger than the effect on market appeal, and viceversa. Consequently, under the (strong) assumption that $\gamma^q$ and $\gamma^\theta$ are both constant across all industries, we can use sectoral variation in $\sigma$ to test whether $\gamma^q > \gamma^\theta$ or viceversa. To do so, we estimate the heterogeneity model:
\[
\Delta \omega_{i,t} = \psi_i + \psi_{p,s,t} + (\gamma + \gamma' \cdot HE_s) \cdot \phi_{i,t} + \eta_{i,t}
\]

where \(HE_s\) is a dummy equal to one if the industry has an elasticity of demand above the median. As in appendix B.1, we follow Pozzi & Schivardi (2016) and estimate elasticity of demand from INVIND self-reported elasticities.\(^{51}\)

Results are reported in Table A.4. The effect of credit supply shocks on revenues productivity is significantly stronger in industries with higher elasticity of demand. Demand elasticity can be correlated with many technological or economic factors. Therefore, this empirical finding should be interpreted with extreme caution. Nonetheless, Table A.4 suggests that the effect of credit supply on technical efficiency is likely larger than the effect on market appeal, at least in manufacturing.

C.2 Unobservable Selection and Coefficient Stability (Oster, 2016)

Oster (2016) develops a framework to evaluate coefficient stability and changes in \(R^2\) when including observable controls. This framework, which builds on work by Altonji et al. (2005), is tailored to study how much the coefficient of a linear regression is robust to the presence of unobservable variables. It formalizes a commonly used intuitive approach: if the researcher includes relevant controls in a linear regression and the coefficient associated with the variable of interest does not vary, then it is “unlikely” that omitted variables are significantly affecting the results.

In order to implement this approach in our setting, let us define \(R_{un}\) and \(\gamma_{un}\) as the \(R^2\) and the coefficient of interest of the unrestricted regression (full set of fixed effects) and \(R_{con}\) and \(\gamma_{con}\) as their restricted counterpart (from regression with only province and sector and year fixed effect, but no interaction). They can be found in columns (1) and (5) of table 4 (for the revenue Cobb-Douglas case), see section 5.1. The formula at the end of section 3.2 of the 2016 working paper version of Oster (2016) defines as “approximated bias adjusted treatment effect” the coefficient

\[
\gamma(\delta, R_{\max}) = \gamma_{un} - \delta \cdot (\gamma_{con} - \gamma_{un}) \cdot \frac{R_{\max} - R_{un}}{R_{un} - R_{con}}
\]

where \(\delta, R_{\max}\) are two parameters to be chosen by the researcher. \(R_{\max}\) is the maximum \(R^2\) that a regression including all the observable and unobservable variables can attain. We set \(R_{\max}\) equal to 1, that is the most conservative value. \(\delta\) is a parameter governing the relative importance of unobservable variables with respect to the observable controls. It is common to set \(\delta = 1\), that is, to assume that observable and unobservable have the same correlation with the variable of interest. However, we choose \(\delta = 2\) in order to be very conservative. As suggested in section 3.4 of Oster (2016), we build bounding set for \(\gamma\) using \(\gamma_{uc}\) and \(\gamma(\delta = 2, R_{\max} = 1)\) as extreme points. Results, which are presented in Table A.6, show that these bounding sets never contain 0. Therefore, our results on the effect of credit shocks on productivity growth (section 5) are “robust” to the presence of unobservable shocks.

\(^{51}\)We assume each two digit industry has a single elasticity and take the median value among all the responses. We drop responses implying negative values of \(\sigma\). We use both 2007 and 1996 survey waves.
C.3 Measurement Error

Most of the production function literature assume that inputs are measured without error. However, the complete absence of any measurement error is an utopia. Therefore, the reader might be concerned that the mismeasurement of inputs with respect to output is an important driver of our results. Section 5.1 deals with robustness of the findings with respect to misspecification of the production functions. A further concern is that we find a residual effect of the credit supply shocks on productivity because we are not able to fully control for inputs. In fact, we can re-write equation (7) as:

\[ \Delta y_{i,t} = \psi_t + \psi_{p,s,t} + \Delta f (k_{i,t}, l_{i,t}, m_{i,t}, \beta) + \gamma \cdot \phi_{i,t} + \eta_{i,t} \]

where the \( \beta \) parameters are computed on a first stage. Given that \((k_{i,t}, l_{i,t}, m_{i,t})\) are correlated, measurement error in the inputs might lead inconsistent estimates for \( \gamma \). Table 2, where inputs are on the left hand side, mitigates these concern. Measurement error on the dependent variable worsen estimates precision, but does not lead to inconsistent estimates. Therefore, the finding that output respond more than inputs (except capital), which is the statistical finding informing the productivity results, cannot be generated by classical mismeasurement.

The combination of factor hoarding and adjustment costs might generate more pernicious forms of misurement errors and create spurious correlation between credit supply and productivity. For instance, as a consequence of a tightening in the credit constraint, a firm might immediately scale down production by acquiring less intermediate inputs and, let’s say, disinvest part of the capital goods. However, because of employment protection legislation, firing workers might take some time even though these are factually out of production. Therefore, the researcher would observe a wagebill or headcount overestimating the real workforce. Similarly, we observe only capital stock and not its utilization. If using capital is costly, for instance because of endogenous deterioration, firms might respond to negative credit supply shocks partially by changing utilization rate rather than investments. While these concerns are well grounded, and our empirical analysis would be more complete if we could observed capital utilization and hours worked, they cannot be a main driver of our results. In fact, these stories are based on delayed adjustments and they could create short-term productivity loss from negative shocks. Conversely, section 5.3 shows that effect of credit supply shocks last for, at least, few years.

C.4 Small vs large lenders

Is the effect of credit supply on productivity driven by small or large banks? To answer to this question, we compute, for each borrower firms, the average size of its lenders:

\[ LenderSize_{i,t} = \sum_b \frac{Assets_{b,t-1} \cdot C_{b,i,t-1}}{\sum_b C'_{b,i,t-1}} \]

where \( Assets_{b,t-1} \) is the total asset size of bank \( b \) and \( C_{b,i,t-1} \) is the credit granted by \( b \) to firm \( i \). Then, we re-estimate the main equation (7) excluding firms in the top (“large banks”) or bottom (“small banks”) quartile of the (year-specific) distribution of \( LenderSize_{i,t} \). Results are reported in Table A.7. The effect of credit supply on productivity is robust to the exclusion of firms borrowing

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52There are few notable exceptions, such as Collard-Wexler & De Loecker (2016).
53The difference of two classical measurement errors is still a classical measurement error.
from large or small lenders. This finding implies that our main results are not driven by banks of a specific size.

D Additional Materials on Interbank Shock

D.1 Credit Granted and Credit Supply

This section investigates whether the exposure to the interbank market was a significant negative credit supply shock, as we argue in section 6. For each firm $i$ active in industry $s$ and province $p$ over the years $t \in [2007, 2009]$, we estimate the equations:

$$\Delta credit_{i,t} = \psi_{p,s,t} + \gamma \cdot INTBK_{i,2006} + \eta_{i,t}$$

$$\phi_{i,t} = \psi_{p,s,t} + \gamma \cdot INTBK_{i,2006} + \eta_{i,t}$$

Results are shown in Table A.5, which documents that firms more exposed to the collapse of the interbank market decrease more the credit received with respect to others operating in the same industry and location. An increase of dependence from the interbank market of 1%, lead to a decrease of the growth rate of credit granted between a quarter and a fifth of a percentage point, see columns (2) and (4). Furthermore, columns (1) and (3) show that the measure of credit supply shocks $\phi_{i,t}$ does respond negatively to the interbank shocks.

D.2 Interbank and Sensitivity to Business Cycle

A further concern is that, although firms more exposed to interbank market had equal average productivity growth before the credit crunch, they were more sensitive to business cycle fluctuation and, therefore, they suffered more during the recession following the financial turmoil. For each firm in the sample, we estimate its sensitivity to business cycle from equation:

$$\Delta y_{i,t} = \alpha_i + \beta_i \cdot GDP_{gr_t} + \epsilon_{i,t}$$

where $GDP_{gr_t}$ is the growth rate of Italian GDP in year $t$ and $y_{i,t}$ is one of two outcomes: (logs) value added or (logs) revenues. The model is estimated using all available years before 2006. Then, we study the correlation between the three measures of sensitivity to fluctuation and the interbank exposure in 2006. Table A.8 shows that firms more exposed to the collapse of the interbank market were not significantly more sensitive to downturns before 2006.

E Additional Materials on Mechanisms

E.1 Notes on R&D and Export

In section 7 we estimate equations:

$$Pr(R&D_{i,t} = 1) = \psi_i + \psi_t + \gamma \cdot \phi_{i,t} + \eta_{i,t}$$

$$Pr(Export_{i,t} = 1) = \psi_i + \psi_t + \gamma \cdot \phi_{i,t} + \eta_{i,t}$$
If we include the full set of province×industry×year fixed effects to control for local business cycle and industry-specific shocks the sample size halves (because of singletons). While the estimated coefficients stay in the same ballpark, the standard errors raise enough that we are not able to reject the null of no effect on R&D at the conventional level.
Additional Figures

Figure A.1: Credit intensity per quintile of asset size. Credit intensity is the ratio of credit granted over net revenues and it is winsorized at top 2%.

Figure A.2: Industry (2-digits) average credit intensity and capital to labor ratio (left panel) or liquidity (right panel). Credit intensity is the ratio of credit granted over net revenues and it is winsorized at top 2% before taking averages. Capital to labor ratio is the ratio of capital stock over total wagebill. Liquidity is the ratio of liquid assets over book value of capital.
Figure A.3: Industry (2-digits) average credit intensity and share of companies engaging in export (left panel) or R&D (right panel). Credit intensity is the ratio of credit granted over net revenues and it is winsorized at top 2% before taking averages. Data on export and R&D are taken from INVIND survey (see sections 2 and 7) and represent noisy estimate of the effective export and R&D intensity. The slope of the fitted line in left panel is significantly larger from zero, while the one in the right panel is statistically indistinguishable from zero.

Figure A.4: Average productivity growth per quintile of credit supply shock

Figure A.5: Industry×year average revenue productivity growth and credit supply shocks. Fitted lines in both panels have a slope significantly larger than zero (1% confidence). We drop two observations with extremely negative value of average the credit supply shock
Figure A.6: Figures display evolution of Credit Supply Shock experienced by a 1.5% random sample. Right panel shows residualized values after taking out FEs.

Figure A.7: Figures display evolution of Productivity (Cobb-Douglas, Value Added) for 1.5% random sample. Right panel shows residualized values after taking out FEs.
Figure A.8: Distribution of $\gamma$ from equation $\Delta \omega_{i,t} = \psi_t + \psi_{p,s,t} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$. See section 5 for details. Distribution is computed from 50 (firm-level) bootstrapped sample. Industry level production function and firm level productivity growth is re-estimated for each bootstrapped sample. Estimates are all above zero (red vertical line) for all samples.

Figure A.9: Distribution of $\gamma$ from equation $\Delta \omega_{i,t} = \psi_{p,s,t} + \gamma \cdot ITBK_{i,2006} + \eta_{i,t}$. See section 6 for details. Distribution is computed from 50 (firm-level) bootstrapped sample. Industry level production function and firm level productivity growth is re-estimated for each bootstrapped sample. Estimates are all below zero for all samples except one (one of the estimates related to the revenue- trans log productivity case).
## Table A.1: Credit Supply Shock and Loan Applications to New Lenders

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>N. of PI (1)</th>
<th>N. of PI</th>
<th>N &gt; 0</th>
<th>Pr(N. of PI &gt; 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>-0.537***</td>
<td>-0.458***</td>
<td>-0.0780***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0796)</td>
<td>(0.113)</td>
<td>(0.0173)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>656,960</td>
<td>456,888</td>
<td>656,960</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.500</td>
<td>0.477</td>
<td>0.348</td>
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</tr>
<tr>
<td>Manufacturing</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>-0.424***</td>
<td>-0.355**</td>
<td>-0.0583**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td>(0.161)</td>
<td>(0.0242)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>347,990</td>
<td>246,453</td>
<td>347,990</td>
<td></td>
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<tr>
<td>$R^2$</td>
<td>0.491</td>
<td>0.462</td>
<td>0.349</td>
<td></td>
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</table>

**Notes:** One observation is one firm for one year between 1998 and 2013 (unbalanced panel). Firm FEs and province×industry×year FEs are included. Singleton are dropped. The RHS variable $\phi_{i,t}$ represents idiosyncratic shock to firm credit supply, and its construction is detailed in section 3.1. A 1% increase in $\phi_{i,t}$ is the supply shock needed to increase the credit granted to firm $i$ by 1%. The LHS variables are built from the number of banks which request information about firm $i$ in year $t$ and they proxy for the number of firm $i$’ applications with previously unconnected lenders. Column (1) conflates both intensive and extensive margin, while (2) is a linear probability model for the probability of making any application. Column (3) considers the extensive margin only. Standard errors (in parentheses) are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1
Table A.2: Descriptive Statistics - Cobb Douglas Parameters

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
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<td></td>
<td></td>
<td>(Quantity)</td>
<td></td>
<td>(Quantity)</td>
</tr>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Value Added</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_l$</td>
<td>.64</td>
<td>.16</td>
<td>.85</td>
<td>.25</td>
</tr>
<tr>
<td>$\beta_k$</td>
<td>.17</td>
<td>.14</td>
<td>.22</td>
<td>.19</td>
</tr>
<tr>
<td>Revenues</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_l$</td>
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<td>.17</td>
<td>.18</td>
<td>.22</td>
</tr>
<tr>
<td>$\beta_k$</td>
<td>.06</td>
<td>.06</td>
<td>.08</td>
<td>.08</td>
</tr>
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<td>$\beta_m$</td>
<td>.81</td>
<td>.11</td>
<td>1.08</td>
<td>.25</td>
</tr>
<tr>
<td>Manufacturing</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Value Added</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_l$</td>
<td>.62</td>
<td>.15</td>
<td>.81</td>
<td>.22</td>
</tr>
<tr>
<td>$\beta_k$</td>
<td>.19</td>
<td>.16</td>
<td>.24</td>
<td>.21</td>
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<tr>
<td>Revenues</td>
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<td></td>
</tr>
<tr>
<td>$\beta_l$</td>
<td>.13</td>
<td>.05</td>
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<td>.07</td>
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<td>$\beta_k$</td>
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<td>.02</td>
<td>.05</td>
<td>.03</td>
</tr>
<tr>
<td>$\beta_m$</td>
<td>.81</td>
<td>.1</td>
<td>1.06</td>
<td>.12</td>
</tr>
</tbody>
</table>

Notes: $\beta_x$ is the estimated elasticity of output with respect to input $x$. Estimation of the parameters is performed at sector level, details are provided in section 3.2. Standard deviation represent sectoral variations and not estimation error. "Quantity" parameters are calculated by multiplying the estimate of sales-generating production function by the correction term $\sigma^{-1}$, where $\sigma$ is the elasticity of demand. The correction is exact if firms are monopolistic competitors, see De Loecker (2011). $\sigma$ is estimated from self-reported elasticity of demand, as in Pozzi & Schivardi (2016).

Table A.3: Credit Supply Shock and Productivity Growth (alternative model)

<table>
<thead>
<tr>
<th>VARIABLES (in delta Log)</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.117***</td>
<td>0.0347***</td>
<td>0.106***</td>
<td>0.0231***</td>
</tr>
<tr>
<td></td>
<td>(0.0178)</td>
<td>(0.00589)</td>
<td>(0.0145)</td>
<td>(0.00412)</td>
</tr>
<tr>
<td>Observations</td>
<td>347,990</td>
<td>347,990</td>
<td>656,960</td>
<td>656,960</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.194</td>
<td>0.146</td>
<td>0.182</td>
<td>0.172</td>
</tr>
<tr>
<td>Functional Form</td>
<td>Cobb-Douglas</td>
<td>Cobb-Douglas</td>
<td>Cobb-Douglas</td>
<td>Cobb-Douglas</td>
</tr>
<tr>
<td>Output Measure</td>
<td>Value Added</td>
<td>Net Revenues</td>
<td>Value Added</td>
<td>Net Revenues</td>
</tr>
<tr>
<td>Sample</td>
<td>Manufacturing</td>
<td>Manufacturing</td>
<td>All</td>
<td>All</td>
</tr>
</tbody>
</table>

Notes: One observation is one firm for one year (panel). Firm FE and province×industry×year FE are included. The RHS variable $\phi_{i,t}$ represents idiosyncratic shock to firm credit supply, and its construction is detailed in section A.1. Productivity is estimated following the model in section B.2. Standard errors (in parentheses) are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1
Table A.4: Credit Supply Shock and Productivity Growth - Heterogeneity by Demand Elasticity

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Productivity (in delta Log)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.0854***</td>
<td>0.101***</td>
<td>0.0146***</td>
<td>0.0199***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0169)</td>
<td>(0.0175)</td>
<td>(0.00445)</td>
<td>(0.00470)</td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t} \cdot HS_s$</td>
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<td>0.0345</td>
<td>0.0156</td>
<td>0.0221*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0321)</td>
<td>(0.0342)</td>
<td>(0.0134)</td>
<td>(0.0121)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>649,662</td>
<td>649,662</td>
<td>649,662</td>
<td>649,662</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.170</td>
<td>0.182</td>
<td>0.176</td>
<td>0.188</td>
<td></td>
</tr>
</tbody>
</table>

| Manufacturing             |                            |     |     |     |     |
| $\phi_{i,t}$              | 0.0774***                  | 0.0906*** | 0.0201** | 0.0171* |
|                           | (0.0255)                  | (0.0260) | (0.00823) | (0.00938) |
| $\phi_{i,t} \cdot HS_s$  | 0.0787**                   | 0.0623*  | 0.0212* | 0.0316** |
|                           | (0.0354)                  | (0.0374) | (0.0121) | (0.0132) |
| Observations              | 347,990                    | 347,990 | 347,990 | 347,990 |
| R-squared                 | 0.186                      | 0.200  | 0.144 | 0.180 |

Notes: $\Delta \omega_{i,t} = \psi_{i} + \psi_{s,t,p} + (\gamma + \gamma^s \cdot HE_s) \cdot \phi_{i,t} + \eta_{i,t}$. One observation is one firm for one year between 1998 and 2013 (unbalanced panel). Firm FEs and province×industry×year FEs are included. Singleton are dropped. The RHS variable $\phi_{i,t}$ represents idiosyncratic shock to firm credit supply, and its construction is detailed in section 3.1. A 1% increase in $\phi_{i,t}$ is the supply shock needed to increase the credit granted to firm $i$ by 1%. The LHS variable is the first difference of Hicks-neutral productivity residual: $\Delta \omega_{i,t} = \Delta y_{i,t} - \Delta f(x_{i,t}, \beta)$ where $y$ is log of net revenues (or log of value added) and $x$ is a set of inputs. Capital stock, labor, and (for the revenue case only) intermediate inputs are included in $x$. $f(\cdot, \beta)$ is either a first (Cobb-Douglas) or second (Trans-Log) order polynomial in log inputs. Estimation of parameters $\beta$ is described in section 3.2. $HE_s$ is a dummy variable equal to one iff firm $i$ is in an industry with elasticity of demand above the sample median. Sectoral elasticities are calculated from INVIND (1996 and 2007 waves) self-reported elasticity of demand (we take median of all responses within a 2-digits industry). Standard errors (in parentheses) are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1
### Table A.5: Exposure to Interbank Market, Credit Supply Shocks and Credit Granted

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Credit Supply</th>
<th>Credit Granted</th>
<th>Credit Supply</th>
<th>Credit Granted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>$ITBK_{i,2006}$</td>
<td>-0.137***</td>
<td>-0.203***</td>
<td>-0.160***</td>
<td>-0.253***</td>
</tr>
<tr>
<td></td>
<td>(0.00624)</td>
<td>(0.0383)</td>
<td>(0.00900)</td>
<td>(0.0509)</td>
</tr>
<tr>
<td>Observations</td>
<td>110070</td>
<td>108267</td>
<td>57986</td>
<td>57349</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.187</td>
<td>0.093</td>
<td>0.194</td>
<td>0.089</td>
</tr>
</tbody>
</table>

Notes: Models are $\phi_{i,t} = \psi_{s,t,p} + \gamma \cdot ITBK_{i,2006} + \eta_{i,t}$ and $\Delta cred_{i,t} = \psi_{s,t,p} + \gamma \cdot ITBK_{i,2006} + \eta_{i,t}$. One observation is one firm for one year between 2007 and 2009 (unbalanced panel). Province×industry×year FEs are included. Singleton are dropped. The RHS variable $ITBK_{i,2006}$ is the weighted average of firm’s $i$ lenders’ liability on the interbank market over assets in 2006. The first LHS variable is the credit supply shocks $\phi_{i,t}$, construction is detailed in section 3.2. The second LHS is the first difference of the log of the credit granted to firm $i$ by all financial intermediaries at the end of year $t$. Standard errors (in parentheses) are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

### Table A.6: Credit Supply Shocks and Productivity Growth - bounding sets (Oster, 2016)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(in delta Log)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Functional Form</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output Measure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cobb-Douglas Value Added</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Added</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>[0.043 ; 0.095]</td>
<td>[0.057 ; 0.11]</td>
<td>[0.019 ; 0.066]</td>
<td>[0.026 ; 0.071]</td>
</tr>
<tr>
<td>Observations</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
</tr>
<tr>
<td>Manufacturing</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>[0.069 ; 0.115]</td>
<td>[0.097 ; 0.121]</td>
<td>[0.014 ; 0.030]</td>
<td>[0.032 ; 0.126]</td>
</tr>
<tr>
<td>Observations</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
</tr>
</tbody>
</table>

Notes: $\Delta \omega_{i,t} = \psi_{i} + \psi_{s,t,p} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$. One observation is one firm for one year between 1998 and 2013 (unbalanced panel). Bounding sets are built following Oster (2016), see appendix C.2 for details.
Table A.7: Credit Supply Shock and Productivity Growth - Exclusion of small or large lenders

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(in delta Log)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exclude Banks</td>
<td>Small</td>
<td>Large</td>
<td>Small</td>
<td>Large</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td></td>
</tr>
<tr>
<td>Manufacturing</td>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi_{i,t} )</td>
<td>0.0176**</td>
<td>0.0335***</td>
<td>0.0174***</td>
<td>0.0188***</td>
</tr>
<tr>
<td>(0.00712)</td>
<td>(0.00738)</td>
<td>(0.00544)</td>
<td>(0.00552)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>261,375</td>
<td>260,308</td>
<td>492,427</td>
<td>489,502</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.164</td>
<td>0.172</td>
<td>0.197</td>
<td>0.211</td>
</tr>
</tbody>
</table>

**Notes:** \( \Delta \omega_{i,t} = \psi_i + \psi_{s,t,p} + \eta_{i,t} \). One observation is one firm for one year between 1998 and 2013 (unbalanced panel). Firm FE and province×industry×year FE are included. Singleton are dropped. Appendix C.4 details the classification of firms as “large bank” and “small bank” groups. The RHS variable \( \phi_{i,t} \) represents idiosyncratic shock to firm credit supply, and its construction is detailed in section 3.1. A 1% increase in \( \phi_{i,t} \) is the supply shock needed to increase the credit granted to firm \( i \) by 1%. The LHS variable is the first difference of productivity residual: \( \Delta \omega_{i,t} = \Delta y_{i,t} - \beta_k \cdot \Delta k_{i,t} - \beta_l \cdot \Delta l_{i,t} - \beta_m \cdot \Delta m_{i,t} \) where \( y \) is log of net revenues, \( k \) is log of capital stock, \( l \) is labor (measured by log of wagebill) and \( m \) is log of intermediate inputs. Estimation of parameters \( \beta \) is described in section 3.2. Standard errors (in parentheses) are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1

Table A.8: Exposure to Interbank in 2006 and pre-2006 sensitivity to business cycle fluctuations.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Sensitivity to business cycle</th>
<th>Sensitivity to business cycle</th>
<th>Sensitivity to business cycle</th>
<th>Sensitivity to business cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>All Industries</td>
<td>Manufacturing</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( ITBK_{i,2006} )</td>
<td>0.0767</td>
<td>0.0604</td>
<td>0.195</td>
<td>-0.0292</td>
</tr>
<tr>
<td>(0.108)</td>
<td>(0.0377)</td>
<td>(0.225)</td>
<td>(0.0464)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>34,004</td>
<td>34,004</td>
<td>17.759</td>
<td>17.759</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.030</td>
<td>0.104</td>
<td>0.026</td>
<td>0.091</td>
</tr>
<tr>
<td>Output measure</td>
<td>Value Added</td>
<td>Revenues</td>
<td>Value Added</td>
<td>Revenues</td>
</tr>
<tr>
<td>(delta log)</td>
<td>(delta log)</td>
<td>(delta log)</td>
<td>(delta log)</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** Model is \( \beta_i = \psi + \gamma \cdot ITBK_{i,2006} + \eta_i \). The RHS variable \( ITBK_{i,2006} \) is the weighted average of firm’s \( i \) lenders’ liability on the interbank market over assets in 2006. The LHS variable \( \beta_i \) is the estimated parameter from the model \( \Delta y_{i,t} = \alpha_i + \beta_i \cdot GDP_{gr} + \epsilon_{i,t} \) where \( \Delta y_{i,t} \) is the delta log of revenues or value added produced by firm \( i \) in year \( t < 2006 \) and \( GDP_{gr} \) is the growth rate of Italy’s GDP.
Table A.9: Credit Supply Shocks and Productivity Growth: Robustness - Cobb-Douglas Value Added Productivity

<table>
<thead>
<tr>
<th>VARIABLES (delta Logs)</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Baseline</td>
<td>Firm Controls</td>
<td>Important Borrowers</td>
<td>Pooled Estimator</td>
<td>Alternative FEs structure</td>
<td>Match Controls</td>
<td>Split Sample</td>
<td>4 Digits</td>
<td>Endogenous Exit</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
</tr>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.0946***</td>
<td>0.106***</td>
<td>0.0865***</td>
<td>0.0436***</td>
<td>0.0968***</td>
<td>0.101***</td>
<td>0.0932***</td>
<td>0.0988***</td>
<td>0.0898***</td>
</tr>
<tr>
<td>(0.0155)</td>
<td>(0.0175)</td>
<td>(0.0172)</td>
<td>(0.00963)</td>
<td>(0.0151)</td>
<td>(0.0188)</td>
<td>(0.0164)</td>
<td>(0.0183)</td>
<td>(0.0156)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>656,960</td>
<td>483,665</td>
<td>521,741</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>587,873</td>
<td>656,960</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.172</td>
<td>0.191</td>
<td>0.185</td>
<td>0.021</td>
<td>0.104</td>
<td>0.172</td>
<td>0.172</td>
<td>0.267</td>
<td>0.175</td>
</tr>
<tr>
<td>Manufacturing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.115***</td>
<td>0.122***</td>
<td>0.126***</td>
<td>0.0405***</td>
<td>0.116***</td>
<td>0.114***</td>
<td>0.114***</td>
<td>0.127***</td>
<td>0.111***</td>
</tr>
<tr>
<td>(0.0178)</td>
<td>(0.0211)</td>
<td>(0.0196)</td>
<td>(0.0120)</td>
<td>(0.0180)</td>
<td>(0.0216)</td>
<td>(0.0188)</td>
<td>(0.0208)</td>
<td>(0.0180)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>347,990</td>
<td>262,308</td>
<td>280,346</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
<td>309,887</td>
<td>347,990</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.186</td>
<td>0.209</td>
<td>0.198</td>
<td>0.032</td>
<td>0.110</td>
<td>0.186</td>
<td>0.186</td>
<td>0.278</td>
<td>0.191</td>
</tr>
</tbody>
</table>

Notes: Model is $\Delta \omega_{i,t} = \psi_i + \psi_{s,t,p} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$ One observation is one firm for one year between 1998 and 2013 (unbalanced panel). Firm FEs and province×industry×year FEs are included. Singleton are dropped. The RHS variable $\phi_{i,t}$ represents idiosyncratic shock to firm credit supply, and its construction is detailed in section 3.1. A 1% increase in $\phi_{i,t}$ is the supply shock needed to increase the credit granted to firm $i$ by 1%. The LHS variable is the first difference of productivity residual: $\Delta \omega_{i,t} = \Delta va_{i,t} - \beta_k \cdot \Delta k_{i,t} - \beta_l \cdot \Delta l_{i,t}$ where $va$ is log of net value added, $k$ is log of capital stock and $l$ is labor (measured by log of wagebill). Estimation of parameters $\beta$ is described in section 3.2. Column (2) add a set of lagged controls to baseline specification: polynomial in size (assets) and the ratios of value added, liquidity, cash flow and bank debt to assets. It excludes observation with missing or zero values for any control variable. Column (3) excludes any firm that, at any point in time, received more than 1% of the credit by any financial intermediary. Column (4) use pooled estimator (rather than “within”) by dropping firm FEs. Column (5) includes firm FEs, province FEs, year FEs and industry FEs, but do not include province×year×industry FEs. Column (6) uses an alternative measure of credit supply shocks which control for match-specific covariates, see section 3.1. Column (7) uses, as an instrument, an alternative credit supply shocks estimated with a “split sample” procedure, in order to control for finite sample biases. Column (8) uses a 4-digits (rather than 2) industry definition both for the estimation of productivity parameters and for the FEs structure. It contains less observations because of the singleton dropping. Column (9) estimate productivity allowing for endogenous firm exit, as in Olley & Pakes (1996). Standard errors, in parentheses, are (two-way) clustered at firm and main-bank×year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Table A.10: Credit Supply Shocks and Productivity Growth: Robustness - Translog Revenue Productivity

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Baseline</th>
<th>Firm Controls</th>
<th>Important Borrowers</th>
<th>Pooled Estimator</th>
<th>Alternative FEs structure</th>
<th>Match Controls</th>
<th>Split Sample</th>
<th>4 Digits Sector</th>
<th>Endogenous Exit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(delta Logs)</td>
<td>Productivity</td>
<td>Productivity</td>
<td>Productivity</td>
<td>Productivity</td>
<td>Productivity</td>
<td>Productivity</td>
<td>Productivity</td>
<td>Productivity</td>
<td>Productivity</td>
</tr>
<tr>
<td>Model</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
</tr>
<tr>
<td>All Industries</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.0259***</td>
<td>0.0268***</td>
<td>0.0246***</td>
<td>0.0210***</td>
<td>0.0244***</td>
<td>0.0297***</td>
<td>0.0261***</td>
<td>0.0274***</td>
<td>0.0242***</td>
</tr>
<tr>
<td></td>
<td>(0.00491)</td>
<td>(0.00563)</td>
<td>(0.00571)</td>
<td>(0.00367)</td>
<td>(0.00492)</td>
<td>(0.00621)</td>
<td>(0.00521)</td>
<td>(0.00573)</td>
<td>(0.00452)</td>
</tr>
<tr>
<td>Observations</td>
<td>656,960</td>
<td>483,665</td>
<td>521,741</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>656,960</td>
<td>586,012</td>
<td>656,960</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.195</td>
<td>0.202</td>
<td>0.207</td>
<td>0.007</td>
<td>0.100</td>
<td>0.195</td>
<td>0.195</td>
<td>0.267</td>
<td>0.182</td>
</tr>
<tr>
<td>Manufacturing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_{i,t}$</td>
<td>0.0323***</td>
<td>0.0363***</td>
<td>0.0343***</td>
<td>0.0304***</td>
<td>0.0274***</td>
<td>0.0335***</td>
<td>0.0315***</td>
<td>0.0361***</td>
<td>0.0299***</td>
</tr>
<tr>
<td></td>
<td>(0.00649)</td>
<td>(0.00710)</td>
<td>(0.00765)</td>
<td>(0.00483)</td>
<td>(0.00659)</td>
<td>(0.00809)</td>
<td>(0.00693)</td>
<td>(0.00820)</td>
<td>(0.00644)</td>
</tr>
<tr>
<td>Observations</td>
<td>347,990</td>
<td>262,308</td>
<td>280,346</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
<td>347,990</td>
<td>309,252</td>
<td>347,990</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.180</td>
<td>0.191</td>
<td>0.185</td>
<td>0.012</td>
<td>0.093</td>
<td>0.180</td>
<td>0.180</td>
<td>0.277</td>
<td>0.164</td>
</tr>
</tbody>
</table>

Notes: Model is $\Delta \omega_{i,t} = \psi_i + \psi_{s,t,p} + \gamma \cdot \phi_{i,t} + \eta_{i,t}$ One observation is one firm for one year between 1998 and 2013 (unbalanced panel). Firm FE and province×industry×year FEs are included. Singleton are dropped. The RHS variable $\phi_{i,t}$ represents idiosyncratic shock to firm credit supply, and its construction is detailed in section 3.1. A 1% increase in $\phi_{i,t}$ is the supply shock needed to increase the credit granted to firm $i$ by 1%. The LHS variable is the first difference of productivity residual: $\Delta \omega_{i,t} = \Delta y_{i,t} - f(k_{i,t}, l_{i,t}, m_{i,t}, \beta)$ where $y$ is log of net revenues, $k$ is log of capital stock, $l$ is labor (measured by log of wagebill), $m$ is log of intermediate inputs, and $f(\cdot, \beta)$ is a second order polynomial. Estimation of parameters $\beta$ is described in section 3.2. Column (2) add a set of lagged controls to baseline specification: polynomial in size (assets) and the ratios of value added, liquidity, cash flow and bank debt to assets. It excludes observations with missing or zero values for any control variable. Column (3) excludes any firm that, at any point in time, received more than 1% of the credit by any financial intermediary. Column (4) use pooled estimator (rather than “within”) by dropping firm FEs. Column (5) includes firm FEs, province FEs, year FEs and industry FEs, but do not include province×year×industry FEs. Column (6) uses an alternative measure of credit supply shocks which control for match-specific covariates, see section 3.1. Column (7) uses, as an instrument, an alternative credit supply shocks estimated with a “split sample” procedure, in order to control for finite sample biases. Column (8) uses a 4-digits (rather than 2) industry definition both for the estimation of productivity parameters and for the FEs structure. It contains less observations because of the singleton dropping. Column (9) estimate productivity allowing for endogenous firm exit, as in Olley & Pakes (1996). Standard errors (in parentheses) are clustered at firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$