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ALLOCATIVE EFFICIENCY AND FINANCE

by Andrea Linarello[*], Andrea Petrella[*] and Enrico Sette[*]

Abstract

This paper studies the effect of bank lending shocks on aggregate labor productivity. Exploiting a unique administrative dataset covering the universe of Italian manufacturing firms between 2000 and 2015, we apply the Melitz and Polanec (2015) decomposition at the 4-digit industry level to distinguish the contribution to aggregate productivity growth of: changes in surviving firms' average productivity, market share reallocation among surviving firms, and firm entry and exit. We estimate the impact of credit shocks on each of these components, using data from the Italian Credit Register to construct industry-specific exogenous credit supply shocks. Only for the 2008-2015 period, we find that a tightening in the supply of credit lowers average productivity but increases the covariance between market share and productivity among incumbents, thus boosting the reallocation of labor. We find no significant effects of credit supply shocks on the contribution made by firm entry and exit. We find that the effects of negative credit shocks on average productivity and reallocation are concentrated in industries with a lower share of tangible capital and collateralized debt.

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Keywords: credit supply shocks, labor productivity, allocative efficiency.

Contents

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1 Introduction

Productivity is the engine of economic growth. After the Great Recession, which has been triggered by a credit crunch in many developed countries, a growing body of research has tried to quantify to what extent credit shocks, especially negative ones, affect aggregate productivity. Negative credit shocks can impact aggregate productivity through several channels. First, they can lower firm-level productivity by exacerbating credit constraints, thus preventing firms from investing, hiring workers and innovating (Aghion et al., 2010; Chodorow-Reich, 2014; Hall and Lerner, 2010). Second, credit shocks could increase firm exit, which may benefit aggregate productivity, to the extent that low productivity firms are those that are forced to leave the market (Caballero and Hammour, 1994; Foster et al., 2016a). Third, negative credit supply shocks may affect the entry rate of firms: typically, the productivity of entrants is higher during downturns (Lee and Mukoyama, 2015), but negative credit shocks could attenuate this positive selection, and may delay the growth of new entrants (Midrigan and Xu, 2014). These channels, however, do not account for the full impact of credit shocks on aggregate productivity, which may also flow through the reallocation of inputs: if credit constraints force low productivity firms to shrink, unconstrained high productivity firms may be able to expand, thus fostering the reallocation of production factors towards more productive uses (Banerjee and Duflo, 2005).

In this paper we measure the effect of credit supply shocks on aggregate productivity. Importantly, we go beyond the study of the impact of credit supply shocks on firm-level productivity, but also study its effect through the reallocation of labor across firms, and through the exit and entry margin. We are in an ideal position to address this question, since we have access to a unique dataset including the universe of Italian manufacturing firms covering the period 2000–2015. This is crucial to obtain a complete picture of the reallocation process and of the entry and exit of firms. Our empirical approach hinges upon the aggregate Melitz and Polanec (2015) productivity decomposition. This allows us to measure the effect of credit supply shocks on productivity through different channels: i) the impact of the credit shock on the growth of incumbent firms' productivity; ii) the contribution to the covariance between market share and productivity (which measures the extent of reallocation); iii) the extensive margin, looking at the impact of the credit shock on the contribution of firms entry and exit.

We isolate credit supply shocks using detailed microdata from the Italian Credit Register. As our focus is on the extent to which credit shocks affect each component of aggregate productivity, we need to define a level of aggregation of the data. We document that in our data most of the reallocation occurs within a 4-digit industry. As a consequence we estimate the credit supply shocks at the sector (4-digit) level. We first regress the growth rate of credit by each bank to each firm including a full set of firm-time and bank-time fixed effects. The former control for firm-level time varying observed and unobserved heterogeneity, including demand for credit and firm riskiness. The latter represent the bank-specific credit supply shocks, which we then aggregate at the 4-digit industry level, using the share of credit of each bank in each industry. This approach allows us to purge our estimates from demand effects, which typically affect the dynamics of credit (Khwaja and Mian, 2008; Greenstone et al., 2014; Amiti and Weinstein, 2013), as the credit supply shocks are, by construction, orthogonal to the firms' demand for credit.[1].

Importantly, our data encompass both a period in which the Italian economy experienced good economic growth and the two deep recessions following the default of Lehman (2009–2010) and the European sovereign debt crisis (2011–2014). This allows us to study the impact of credit supply shocks on productivity during financially-driven recessions, and to test for differential effects of credit shocks in good as opposed to crises times.

[1]Estimating the credit shock conditional on firm*time fixed effects we improve upon the procedure used in Greenstone et al. (2014) since we estimate bank*time fixed effects, i.e. the bank supply shocks conditional on firm*time unobservables and not industry*time, which may be less able to properly capture demand effects.

Our findings show that credit shocks affect mainly average firm productivity and the reallocation component. This occurs in the crisis period, only. We find that negative credit shocks (such as those prevailing during the crisis years) depress productivity because they lower firms' average productivity. However, they also have a positive effect on aggregate productivity through the reallocation of the share of workers from the least productive to the most productive firms. As a consequence, the total direct effect of credit shocks on aggregate productivity are small. Before the crisis the impact of credit shocks on any of the components of the productivity decomposition is small and imprecisely estimated. The effects are economically significant. In our preferred specification, during the crisis period, a one standard deviation lower credit shock leads to a negative contribution to aggregate productivity growth of average productivity by 3.6 p.p. and a positive contribution of reallocation of 2.4 p.p, that is about 60% of the observed average annual contributions in our data.

We also find that the effects of the credit shocks on the reallocation component are heterogeneous across sectors. They are stronger in industries in which the concentration in product market is higher, export intensity is higher or import competition is lower. Moreover, consistent with recent evidence suggesting that industries with less collaterizable assets are those in which factors of production are allocated best, we find that the effects of negative credit shocks on reallocation are concentrated in industries with a lower share of tangible capital and collateralized debt. The effects of credit shocks on average productivity are instead more homogeneous across industries.

In addition, results are similar if we perform the (Melitz and Polanec, 2015) decomposition at the local labor market level (Sistema locale del lavoro, conceptually similar to Metropolitan Statistical areas). Credit shocks affect positively the average productivity and negatively the reallocation component, only during the crisis years. This is important since it shows that credit shocks affect the reallocation of workers also within local labor markets. Overall, our findings are robust to other exercises concerning the specification (including different sets of industry and time fixed effects, weighting by industry size) and on the way the measure of credit supply shock is built.

Our findings extend the large literature on misallocation and productivity. Following the pioneering contribution of Hsieh and Klenow (2009), who find sizable misallocation of inputs in China and India, a large literature identifies the reasons and consequences of frictions in the labor or credit markets, or in law enforcement, on the allocation of production factors and in this way on TFP growth. Financial frictions in particular, have been the focus of a large and growing literature. Buera and Shin (2013) find that financial frictions have a large impact along the transition to the steady state, prolonging the adverse consequences of the initial resource misallocation. In addition Moll (2014) suggests that financial frictions amplify TFP shocks in the short run, and firms find it difficult to save out of borrowing constraints. Larrain and Stumpner (2012) find that a capital account liberalization decreases resources misallocation by improving the allocation of finance. Midrigan and Xu (2014) challenge these findings suggesting that financial frictions play a limited role in the misallocation of resources, and they do so by creating a distortion in entry and exit rates. A recent work by Gopinath et al. (2015) finds that, following the beginning of the European monetary union, the decline in the real interest rate —often attributed to the Euro convergence process— led to a significant decline in sectoral total factor productivity, as capital inflows were misallocated toward firms that had higher net worth but were not necessarily more productive. This phenomenon had been especially pronounced in Spain.

Two recent works focusing on Italy study the effect of credit supply on TFP. Manaresi and Pierri (2016) show that an expansion in the credit supply increases both input accumulation and firms' ability to generate value added for a given level of inputs, in this way enhancing productivity. More indirectly, Schivardi et al. (2017) find evidence of zombie lending in Italy during the financial and sovereign debt crises, but the real effects of this misallocation of credit are limited: sales, investment and employment of non-zombie firms are hardly affected by the intensity of zombie lending.

Our work contributes to this literature in several ways. First, we explore the effect of credit market frictions on the components of aggregate productivity, thus shedding light on the channels (average firm productivity, reallocation, entry/exit margin) through which credit shocks affect productivity. Second, we use a unique dataset covering the universe of Italian firms, which allows us to fully gauge reallocation and the contribution of entering and exiting firms. Our findings suggest that negative shocks to bank credit contribute to "cleanse" the economy by favoring the reallocation of resources and market shares from low to high productivity firms, and thus can contribute to dampen the drop in aggregate productivity growth that occurs during crises. In this way our work shows a channel through which recessions may be, at least in part, "cleansing" (Foster et al. (2016a)).

The paper is organized as follows. Section 2 presents the data used in this paper. Section 3 documents the dynamics of aggregate labor productivity and presents the results of the Melitz and Polanec (2015) decomposition, providing some suggestive evidence on the connection between the conditions of credit supply and the extent of reallocation and selection. Section 4 illustrates the estimation method of the credit supply shocks, and shows some basic stylized facts on firm data and the estimated shocks. Section 5 discusses the empirical strategy and section 6 illustrates the main results. In section 7 we present some robustness checks and extend our results to account for sectoral heterogeneity. In section 8 we perform our main test on data at the geography level. Finally, section 9 concludes.

2 Data

The paper relies on two different data sources. The first is a unique firm-level dataset that covers the universe of manufacturing firms from 2000 to 2015. The dataset has been jointly developed by the Bank of Italy and the Italian National Statistical Agency (ISTAT); it combines the information of the Italian Register of Active Firms (ASIA) with data retrieved from statistical, administrative and fiscal sources. The dataset contains information on firms' location, incorporation date, industry classification (Nace rev. 2), number of employees and sales.[2] We deflate the data on sales to 2010 prices, using sector-level price indexes for sales. We exploit administrative information to obtain a measure of entry and exit of firms purged from errors (that is, from false events). Finally, we are able to single out extraordinary events in the life of a firm —such as mergers, acquisitions, etc…—, which may be at the root of the unrealistically strong variations (of sales or employees, for example) which often introduce noise in microdata with characteristics similar to ours.

The quality of our micro-aggregated data can be gauged by comparing them with National Accounts data. Panel (a) of Figure 1 compares the value of production from National Accounts with the total value of sales from ASIA dataset, both evaluated at current prices.[3] The two series are very similar over the entire period of observation, the correlation is .933. The National account series usually remains above the ASIA data, because the former includes estimates of the underground economy and illegal workforce; occasionally, the National Account series lies below the ASIA one, as a consequence of the dynamics of inventories, which are not accounted for by our dataset. The similarity with the National Accounts also emerges when looking at the growth rates, as shown in panel (b); the two series are remarkably close in the central part of our sample and in correspondence to the great trade collapse episode (the correlation is .969).

The second data source we rely upon is the comprehensive Italian Credit Register, a database owned by the Bank of Italy, which contains data on all individual bank-borrower relationships

[2]See Abbate et al. (2017) for a detailed description of the dataset.

[3]The comparison is made at current prices, in order to exclude the discrepancies deriving from the use of price deflators at different levels of disaggregation.

with an exposure of at least 75,000 Euros until 2008, and 30,000 since 2009. The Credit Register lists outstanding balances of loan amounts at the lender-borrower level aggregated into 3 categories: overdraft loans, term loans, loans backed by receivables, and it also flags non-performing loans. Banks routinely use the Credit Register to assess the creditworthiness of current and prospective borrowers, which ensures a high quality of the data. Unique identifiers of banks and borrowers allow us to track them over time. The Credit Register contains both granted (committed) credit and actually used (drawn) credit. We focus on the former as it represents a better measure of credit supply, while the latter is heavily influenced by borrowers' decisions to utilize available credit.

As the main goal of the paper is to study the effects of credit shocks on the individual components of productivity identified by the Melitz-Polanec decomposition, we perform our empirical analysis at the industry-level (4-digit).[4] In an extension we also explore the effects of credit shocks within a geographical area, the "sistemi locali del lavoro" (SLL) which are similar to Metropolitan Statistical Areas in the U.S.

During our sample period (2000–2015), Italian manufacturing shrunk significantly. Table 1 reports descriptive statistics of the firms in our sample. Starting in 2002, the number of firms declined every year: in 2015 there were about 110,000 firms less than in 2001. As a consequence, the number of employees dropped by more than 600,000 units. Average firm size —measured in terms of employees per firm— experienced an increase, almost exclusively concentrated in the first half of our sample. The financial crisis heavily contributed to depress the economic performance of Italian manufacturing firms, although their sales started dropping even before the crisis.

Aggregate labor productivity —measured as real sales per worker[5] — decreased during economic downturns: in 2002–03, and more strongly during the Great Recession (2008–09) and that following the European sovereign debt crisis (2012–13). The double-dip recession had a severe effect on Italian aggregate labor productivity, which in 2014 was only slightly above its 2007 levels.

3 The dynamics of aggregate productivity and its components

In this section we provide a brief sketch of the evolution of aggregate manufacturing productivity in Italy between 2000 and 2015, focusing on the driving forces that have shaped its dynamics and proposing some suggestive evidence on its relationship with the fluctuations of credit supply. A comprehensive assessment of these trends is shown in Figure 2, where the grayed out areas help identifying the periods of recession for the manufacturing sector.

Over the period of observation, the dynamics of value added in manufacturing has been particularly sluggish, experiencing a 7.1% drop between 2000 and 2015, as shown in panel (a). As a matter of fact, the sector experienced a contraction in half of the observed years, while not attaining a consistently fast-paced growth in the remaining ones. A first period of stagnation and recession can be found at the very beginning of our sample (2001–03), followed by the massive drop —and subsequent rebound— of value added in correspondence to the the global financial crisis (2008–09), and a more moderate contraction during the sovereign debt crisis (2012–13).

[4]Hence, we do not work at the firm-level. In particular, defining reallocation is only possible within a set of firms which are part of a relevant aggregation, such as an industry, or a geographical area.

[5]Labor productivity is usually measured as value added per worker. We use sales per worker instead for two main reasons: on one hand, using sales we are able to exploit a longer time series, allowing us to study also the years before the crisis; on the other, the decomposition technique of Melitz and Polanec (2015) requires to express productivity in logs, which would have implied a substantial information loss if we had used value added, which is often negative, especially during the crisis. Moreover, in the literature it is not uncommon to use sales per worker as a valid alternative for measuring labor productivity (as in Bartelsman et al. (2013)). Though displaying some differences, in Italy value added per worker and sales per worker broadly share similar dynamics, as shown by Linarello and Petrella (2017).

The dynamics of manufacturing value added should be read in parallel to the chart displayed in panel (b), depicting the evolution of the total credit granted to manufacturing firms. Bank loans have grown at positive rates until the global financial crisis: during the 2001–2003 recession, which didn't have a financial nature, the growth of credit remained positive —despite slightly declining— and then increased in magnitude until 2006. After the outbreak of the crisis, the massive liquidity drought in interbank markets mirrored on the rapid shrinkage of credit; the pace of contraction slowed down in correspondence to the partial recovery of 2010, but another and more severe period of credit restriction was fostered by the sovereign debt crisis. A faint recovery emerged from 2014 on.

How does the dynamics of aggregate labor productivity fit into these broad macroeconomic patterns? To provide a more insightful answer to this question, it is crucial to distinguish the role played by the reallocation of resources across firms from that played by the processes of firm entry and exit to/from the market.

To quantify the relative contribution of different groups of firms to the dynamics of aggregate labor productivity, we exploit the decomposition proposed by Melitz and Polanec (2015). This is known as "dynamic Olley and Pakes decomposition", since it represents a dynamic extension of the widely-used decomposition by Olley and Pakes (1996) to distinguish between the efficiency gains deriving from the reallocation of resources towards the most productive firms (measured by the so-called OP covariance term), and those arising from the productivity growth of individual firms (captured by average firm productivity).

Following Melitz and Polanec (2015), we define aggregate labor productivity as the average of firm-level log productivities, weighted by their share of employees. We then divide firms into three groups: entrants (E), exiting (X) and incumbent firms (S). Considering two consecutive time periods, it is possible to express the aggregate productivity of the first period (Φ_1) as the weighted average of the productivity of the firms that survive and the one of the firms that exit the market; analogously, the aggregate productivity of the second period (Φ_2) can be expressed as the weighted average of the productivity of the firms that survived and the one of the firms that have entered the market:

$$\Phi_1 = \Phi_{S1}\omega_{S1} + \Phi_{X1}\omega_{X1} \tag{1}$$

$$\Phi_2 = \Phi_{S2}\omega_{S2} + \Phi_{E2}\omega_{E2} \tag{2}$$

where Φ_{gp} is the aggregate productivity of group g in period p, and ω_{gp} is the share of employees in each group.

The difference between Φ_2 and Φ_1 returns the variation in aggregate productivity:

$$\Phi_2 - \Phi_1 = (\Phi_{S2} - \Phi_{S1}) + \omega_{E2}(\Phi_{E2} - \Phi_{S2}) + \omega_{X1}(\Phi_{S1} - \Phi_{X1}) \tag{3}$$

where the first term represents the productivity variation for the firms that are active on the market in both periods (the incumbents); the second is the contribution of entrants, which is positive (negative) if their productivity is higher (lower) than the one of the incumbent firms; the third is the contribution of firms that exit the market, which is positive (negative) if their productivity is lower (higher) than the one of the incumbents.[6]

Making use of the Olley and Pakes (1996) decomposition, the term $(\Phi_{S2} - \Phi_{S1})$ can be further decomposed in the variation of the incumbents' average productivity and the one of the covariance between incumbents' productivity and the share of employees, capturing the intensity

[6]For sake of simplicity, here we have only referred to three groups (entering, exiting and incumbent firms). When we apply the decomposition, however, we define additional groups, capturing the contribution of false entry/exit (in the spirit of Geurts and Van Biesebroeck (2014)) and extraordinary events. That is intended both to provide an exact decomposition and a neater definition of phenomena: the demographic components will measure the contributions of the firms that are truly entering or exiting the market, and the data on incumbents will be net of those incumbents that have undergone extraordinary operations in one of two adjacent years. Overall, these additional components typically account for a small share of the variation in aggregate productivity.

of the reallocation process. To sum up, the variation of aggregate productivity can be expressed as the sum of the following four components:

$$\Phi_2 - \Phi_1 = \underbrace{\Delta\bar{\varphi}_S}_{\text{Avg. prod.}} + \underbrace{\Delta\mathrm{Cov}_S}_{\text{Reallocation}} + \underbrace{\omega_{E2}(\Phi_{E2} - \Phi_{S2})}_{\text{Entry}} + \underbrace{\omega_{X1}(\Phi_{S1} - \Phi_{X1})}_{\text{Exit}} \tag{4}$$

How did these components evolve in our reference period? Going back to Figure 2, the dynamics of aggregate labor productivity —measured from our data as aggregate sales per worker and depicted in panel (a)— has been substantially similar to that of manufacturing value added, as reported by National Accounts. As panel (c) shows, reallocation has always provided a positive contribution to aggregate labor productivity, partially offsetting the dynamics of average firm productivity, whose contribution was negative in 13 out of 15 years (see also Table 2). The contribution of reallocation moderately rose until 2006, and then momentarily slowed down, just before peaking in the wake of the two crisis episodes. It is interesting to note that the rise in the reallocation component seem to mirror the trough experienced by credit supply.

Panel (d) displays the contribution of entry and exit. The contribution of entering (exiting) firms is always negative (positive), since their aggregate productivity in the first (last) year of life is typically lower than the one of incumbents.[7] The entry component fluctuates in a narrow band, between -2 and -1 percentage points, with few deviations over the entire period. The exit component remains remarkably stable during the first part of our sample, even during the first recession episode of 2001–03. After the global financial crisis, however, its contribution progressively increased; during the brief recovery of 2010–11, it then appeared to converge back to its before-crisis values, but experienced another increase after the burst of the sovereign debt crisis.

Overall, this broad picture provides some suggestive evidence of a possible link between the evolution of credit supply and certain components of aggregate labor productivity, with potentially opposing effects on aggregate labor productivity dynamics. In the remainder of this paper, we exploit our granular data to provide evidence in favor of this hypothesis, making continuous reference to the Melitz and Polanec (2015) decomposition to explore what are the mechanisms that give rise to the fluctuations we observe in the aggregate.

The Melitz and Polanec (2015) decomposition —as presented in equations (1)–(4)— can be applied at any level of aggregation of the original firm-level data; in this paper we aggregate data at the 4-digit Nace industry level. Even under the assumption that firms do not change sector over time,[8] the overall contribution of reallocation (the one in panel (c)) can not be expressed as a weighted average of sector-level components, but rather as a sum of two sets of components. The first part measures the direct contribution of the *within-sector* shifts in market share and productivity, whereas the second part captures the indirect contribution of the *between-sectors* shifts in market shares and productivities.

Table 3 shows the decomposition of the reallocation component into the within and between term. The first column reports the contribution to aggregate productivity growth of the reallocation component in the manufacturing sector as a whole (this is equal to the one reported in the second column of Table 2); the second and the third column report the within and the between sectoral terms, while the last column reports the share of within-sector reallocation.

[7]The negative contribution of the entry component stems from our definition of newborn firms as those in their first year of life, which is a direct consequence of the year-on-year decomposition adopted. One-year-old firms generally show a lower revenue per worker than incumbents for a variety of reasons, including for example that they have not yet undergone a selection process, that they tend to compress their prices to acquire market shares (Foster et al., 2016b), or that revenues materialize with some lag with respect to production. If considered over a longer time horizon, young firms stand out as an extraordinarily dynamic component and account for a relevant fraction of overall productivity growth (Haltiwanger et al., 2017).

[8]This assumption is useful to shut down a channel for intra-industry reallocation. Notice, however, that the share of firms that change sector of activity between two adjacent years is relatively small; therefore, such assumption despite simplifying the analysis does not introduce systematic bias in the results.

All in all, the table suggests that within-sector components are significantly larger than the between components. With some exceptions, the within component generally accounts for around 80% of the overall reallocation. These results are consistent with previous findings of a remarkable role of within-industry reallocation in shaping aggregate productivity growth.[9] Most of the analyses presented in the remainder of the paper will be centered around the within-sector components. In one exercise, rather than focusing on sectors, we are going to apply the decomposition at the level of local labor market (LLM); in that case, the weight of the within-LLM component of reallocation is even higher, accounting on average for more than 95%.

Finally, it is important to stress that the relative importance of the components in equation (4) displays substantial variation across industries. To highlight this fact, Table 4 reports the decomposition of productivity at the sector level by sub-period; for sake of compactness, results are presented at the 2-digit level. The table shows that there is a substantial heterogeneity across sectors in terms of aggregate productivity dynamics and its components. Nonetheless, some common pattern across sectors and in the two sub-period emerge: first, while average productivity is generally declining, the reallocation component is always positive (there are only 3 sectors before 2008 with negative reallocation components); second, the positive contribution of reallocation increases after 2008 in all sectors; third, the contribution of net demography is positive in the majority of cases before 2008, but after the burst of the crisis this feature spreads to all sectors while contemporaneously increasing in magnitude.

4 The credit supply shock: estimation and basic facts

To identify bank-specific credit shocks, we apply the methodology of Greenstone et al. (2014) on loan-level microdata from the Italian Credit Register data. We make an important improvement, though: since we can observe data on individual bank-firm relationships, we estimate the bank-specific credit shocks conditional on a full set of firm*time fixed effects, to control for firm observable and unobservable time varying characteristics, including demand for credit, firm riskiness, etc. This provides a better control for these crucial feature of credit allocation than the inclusion of industry*time fixed effects.

In practice we estimate the following model:

$$\Delta \ln(L_{bit}) = \alpha_{bt} + \gamma_{it} + \epsilon_{bit} \tag{5}$$

where $\Delta \ln(L_{bit})$ is the log change in credit granted by bank b to firm i at time t. $\alpha_{b,t}$ are a set of bank*time fixed effects and γ_{it} are a set of unit of firm*time fixed effects. In practice, model (5) compares the growth of credit from different banks lending to the same firm in any year. The firm*time fixed effects control for changes in demand and economic conditions at the firm-level in each year, while the bank*time fixed effects $\alpha_{b,t}$ are the components of the credit dynamics that are common to each bank b across the credit relationships observed, and can therefore be interpreted as bank-specific, idiosyncratic credit supply shocks.[10] The set of bank-time fixed effects, $\alpha_{b,t}$, identifies a supply-induced change in credit under the assumption that the at the firm-time level there is no bank-specific demand for credit, so that the set of firm-time fixed effects fully control for changes in demand and in the riskiness and economic prospects of the firms. Under this condition, these shocks are uncorrelated with any characteristics of the firms and of the markets in which the banks operate. This assumption could be violated

[9] Obviously, the weight of the within-sector component of reallocation depends on the granularity of the data; more precisely, it is inversely proportional to the level of disaggregation at which the decomposition is applied. At the 2-digit sector level, the within component accounts on average for more than 85% of the overall reallocation.

[10] This approach to identify the bank-lending channel at the firm-level has been first proposed by Khwaja and Mian (2008). Manaresi and Pierri (2016) and Barone et al. (2018) apply a similar technique to estimate credit supply shocks for the Italian economy.

if a bank specialized in financing a specific category of firms. However, Amiti and Weinstein (2013) and Greenstone et al. (2014) formally show that, even if this assumption were violated, that would not affect the estimation of the bank*time fixed effects. Furthermore, controlling for time-varying fixed effects at the firm level makes the violation of such assumption less probable than if we were estimating bank shocks conditional on industry*time fixed effects alone: it is in fact more likely that banks specialize in certain industries (rather than in certain firms), also because of the presence of geographical clusters.

Since three of the components of Melitz and Polanec (2015) decomposition, reallocation, entry and exit need to be studied at the industry level, we then aggregate these bank-specific shocks to obtain a measure of the evolution of credit supply at the industry level, by computing the share of credit to each industry held by each bank. More specifically, we compute our credit supply shock as:

$$CSS_{st} = \begin{cases} \sum_b \theta^s_{b,1999} \widehat{\alpha}_{bt}, & \text{if } t \leq 2007 \\ \sum_b \theta^s_{b,2006} \widehat{\alpha}_{bt}, & \text{if } t > 2007 \end{cases} \tag{6}$$

where θ^s_{bt} is the market share of bank b in industry s (4-digit Nace rev. 2) in year t. These shares are computed aggregating the loans in the Credit Register at the industry level, as in the computation of the growth rates.

The estimated supply shock are essentially a weighted average of the bank*time fixed effects, in which the weights are the share of credit of each bank at the sector level as of 1999 and 2006. Due to the relatively long time span covered by our data, we have chosen to let the weights vary to obtain a cleaner measure of the bank shocks as of before the financial and the sovereign debt crises. On the one hand, fixing the market shares at their 1999 levels would make the estimated credit supply shock progressively less informative on the actual propensity to lend, as years move away from 1999; on the other hand, letting the weights vary every year would make our credit supply measure potentially endogenous to the economic performance within each sector.[11] Moreover, this formulation of the supply shock comes particularly handy when we split the sample in the period before and the one during the financial crisis: when we do that, each subsample contains a credit supply shock obtained from weights at the beginning of the period.

Since the bank shocks α_{bt} are identified up to a constant scaling factor, the credit supply shock cannot be attached an absolute quantitative interpretation. The differences among banks supply shocks both cross-sectionally and over time are, instead, preserved. For the sake of clarity, suppose that we estimate a credit supply shock of 5 and -5 for a given sector in time t and $t+1$, respectively: we are not able to state whether credit supply actually expanded or shrunk in the two periods (since it is not possible to derive the reference level), but we can assert that the growth rate of credit supply decreased by 10 percentage points; the same comparison can be performed across sectors. This means that —if we were interested in investigating the elasticity of a certain variable to the dynamics of credit supply in a regression framework— it would be perfectly fine to use our estimated credit supply shock as an explanatory variable, since the unknown reference level would not affect the estimate of the elasticity, and would instead be absorbed by the constant.

Importantly, this framework is useful to fully control for a generalized drop in credit demand. This would be absorbed by the firm fixed effects. While there is macroeconomic evidence that a large part of the drop in credit during the financial crisis is due to a drop in demand (Caivano et al. (2010)), models based of micro data evidence document a sizeable role of supply-side factors (Del Giovane et al. (2017)). Hence, our focus on credit supply is important to uncover a significant driver of economic activity during the crisis.

Table 5 shows the distribution of the credit supply shocks obtained as shown in equation (6), across industries (we show the distribution re-weighting the credit shocks at the 2-digit

[11] See section 7 for robustness checks on the definition of the weights.

Nace level for ease of exposition) and years. It is apparent that after the outbreak of the global financial crisis in 2008 the propensity of financial intermediaries to lend dramatically declined, with even greater intensity in the years of the sovereign debt crisis.[12] The dispersion of the credit supply shock across sectors slightly increased after the crisis. The distribution of the bank shocks by sectors suggests that the drop in credit supply growth during the crisis has been stronger in food, machinery, plastic and metal industries. Differences across sector, however, are less pronounced, with the credit supply shock being bounded between 4 and 5% before the crisis and between -7 and -6 % after its outbreak. This stylized fact goes in favor of our argument of the estimated credit supply shock being uncorrelated with sector-specific characteristics.

To provide further support to the identification of the bank-shocks, we test their correlation with key bank balance-sheet characteristics which are regarded as major drivers of banks' propensity to lend. To this aim, we exploit balance sheet information from the Supervisory Reports submitted by banks to the Bank of Italy. We regress the estimated bank shock relative to year t on bank-level characteristics measured as of December of year *t-1*.[13] Results, shown in Table 6 indicate that banks with higher capital, lower interbank funding, higher liquidity supply more credit. Credit supply is also negatively correlated with a higher share of (gross) non-performing loans. While these regressions estimate conditional correlations, they are reassuring as they indicate that banks with stronger (measured by capital and the bad loans ratio), more liquid, and with a less volatile funding structure (less interbank funding) are associated to higher values of the credit supply shock, suggesting higher credit supply relative to other banks. These results are also consistent with previous findings on the bank lending channel in Italy (di Patti and Sette (2016)) and in other countries (Khwaja and Mian (2008), Iyer et al. (2014), Jiménez et al. (2010)).

5 Empirical strategy

In this section we investigate the effect of credit supply on industry-level productivity dynamics, and on how this maps to the aggregate fluctuations documented in section 3. To guide our analyses, we will continuously make reference to the Melitz and Polanec (2015) decomposition discussed above.

In its most general form, the specification adopted for most of the analyses presented in this section is the following:

$$y_{st} = \beta CSS_{s,t} + \gamma_t + \delta_s + \varepsilon_{st} \tag{7}$$

where y_{st} is the dependent variable of interest at industry level (4-digit): it will correspond either to the growth rate of labor productivity or to one of the four components outlined in equation (4); $CSS_{s,t}$ is the credit supply shock, as defined in equation (6); γ_t are year fixed effects; δ_s are a set of sector fixed effects; ε_{st} is an error term. Standard errors are clustered at the sector level to account for serial correlation.

The coefficient of interest is β, capturing the effect of the credit supply shock. Since the period spanned by our data includes a disruptive event such as the global financial crisis, followed in Italy by a further downturn, as a consequence of the turmoil on the sovereign debt markets, we check if the effects of the credit supply shocks are heterogeneous across time, by splitting our dataset in two subsamples, containing information on the period before (until 2007) and during the crisis (from 2008 on).

Identification relies on the exogeneity of the credit supply shock with respect to the decisions and performance at the firm level. As alluded to in section 4, we claim this to be the case: on

[12] See di Patti and Sette (2016) and Bofondi et al. (2017) for evidence of the impact on credit supply of the post-Lehman and the sovereign shocks, respectively, in Italy.

[13] These regressions exclude foreign banks. They also exclude the year 2015, because of a major change in the reporting of supervisory information occurring in 2014, when supervision moved from the national central banks to the European Central Bank.

one side, the bank-specific shocks are by construction uncorrelated with any characteristics of the firms and the markets in which the banks operate; on the other, the market shares used to aggregate the bank-specific shocks are fixed in time (according to the scheme described in equation (6)), in order to avoid incorporating in our shock the banks' sectoral strategic positioning decisions, which could have been driven by the economic performance of firms within a given sector. In model (7), the sector fixed effects control are intended to address additional concerns on omitted variables correlated to both the economic and the credit cycles.

6 Main results: Industry-level analysis

We start by testing if and to what extent credit shocks affect each of the 4 components of the Melitz and Polanec (2015) decomposition at the 4-digit industry level. Results are displayed in Table 7, and are arranged so that each panel contains the estimates associated to a given dependent variable.[14] Different columns correspond to different specifications, including different sets of industry and time fixed effects.

The top panel shows that credit supply shocks have a positive and significant impact on average productivity: when banks' lending to industry s in period t experiences a relatively higher credit supply idiosyncratic shock, the growth rate of average productivity of firms in the industry increases. This result is in line with intuition and with other empirical findings for the case of Italy (Manaresi and Pierri, 2016). Coefficients increase both in magnitude and significance when we weigh observations by the number of employees in each industry (columns (2)–(4)) to provide an estimate of the aggregate impact of the bank shock. Our preferred specification is shown in column (2) and it includes 2-digit sector fixed effects and year fixed effects, but the result is robust to the inclusion of finer industry fixed effects and of a set of sector-year dummies to control for different business cycles at the sector level (columns 3 and 4). The effects are economically significant: a one-standard-deviation increase in the credit supply shocks increases the average productivity component by between one quarter and a half of a standard deviation.

The same battery of models has been applied to the other terms of the decomposition (and to aggregate labor productivity growth). In general, the estimates of the effect of a bank shock are non-significant. Overall, we are not able to identify an effect on aggregate productivity, as a consequence of the consistently negative estimates for the reallocation component, which —despite being non-significant (although marginally, most of the times)— partially offsets the positive effect found on average productivity.

The picture changes when we separately look at the crisis period. As shown in Table 8 credit supply shocks affect aggregate productivity both through the average productivity and through the reallocation component. The first panel shows that the credit supply shocks have a positive impact on average productivity. In particular, a one standard deviation fall in credit supply generates a 3.60 pp. negative contribution of average productivity, that is about 60% of the observed negative contribution (-5.75) over the period 2008-2015 (calculation from the preferred specification shown in column 2 of 8).

The second panel shows that the effect of credit supply shocks on the reallocation component is negative and significant: when credit supply shrinks, relative to other industries, the contribution of reallocation to the dynamics of aggregate productivity increases. Hence, the allocation of production factors (labor, in our case) improves when credit conditions worsen: this could either reflect the fact that more productive firms get bigger (i.e. hire more workers) at the expenses of the less productive firms that shrink, or that more productive firms lay off workers at a lower rate. Again, this is an economically significant effect: a one standard deviation lower bank shock is associated with a positive contribution of reallocation to aggregate productivity

[14] Each panel represents a different regression.

growth of 2.44 pp., which is a sizable number compared to the observed contribution over the same period – that is 3.97 –, again based on the preferred specification.

The contribution of firm demography to aggregate productivity does not seem to be affected by credit supply shocks during the crisis years. The coefficient of the credit supply shocks is small and not statistically significant neither for the entry nor for the exit component across all specifications.

Overall, we fail to identify an effect on aggregate labor productivity, as a consequence of the two opposing effects on average productivity and reallocation that offset each other.

To complete the picture, we estimate the model on the pre-crisis period (2000–2007). Table 9 shows that credit supply shocks do not have a significant effect on average productivity. This can be rationalized with the possibility that demand factors may be more relevant in shaping the firms' behavior in periods characterized by a generalized loosening of credit supply. The coefficient of credit shocks in the regressions on the reallocation term is not precisely estimated. If anything, a higher credit supply shock seems to foster an improvement in the reallocation term. Credit shocks seems to have a more robust effect on entry (third panel), whose contribution to aggregate productivity growth worsens as a consequence of a higher credit supply shock. That can be rationalized by thinking that looser credit conditions may either foster a higher entry rate (and therefore a greater mass of low-productivity firms), or allow less promising firms to enter the market. These effects, however, are not sizable enough to be reflected in a statistically significant impact on aggregate productivity, that once again is not affected by (idiosyncratic) credit supply shocks at the industry-level.

Overall, these findings suggest that most of the effects of credit supply shocks on the component of aggregate productivity take place during the crisis period, which was characterized by a widespread credit restriction that touched all sector, although with different intensities (see Table 5).

7 Extensions and robustness

7.1 Industry heterogeneity

We now turn to exploring whether the effect of credit supply shocks on the different items of the Melitz-Polanec decomposition are heterogeneous across industries (Table 10). We focus on a wide array of industry-level characteristics that could be relevant in shaping the response of firms to a credit supply shock. For each of these features, we estimate the model discussed above by interacting the credit supply shock with a dummy indicating industries located above and below the median value of that variable of interest. To perform this exercise, we adopt the specification with year and Nace 2-digit fixed effects, weighted by the number of employees in the industry (this is the specification shown in column 2 of Tables 7 to 9, and represents our preferred specification). We run these tests on the crisis period only, since this is the period in which we have shown the effect of credit supply shocks on the components of aggregate productivity to be stronger and more significant.

In the first panel we divide industries according to their concentration in the product market. Following Autor et al. (2017) we measure industry concentration as the share of sales of the superstar firms, that are the 20 largest firms in each industry. The results show that credit shocks reduce average productivity in all industries, while the effect on reallocation is much higher in industries where the market shares are more concentrated among superstar firms, the difference in the coefficients is significant at the .12 level. Because superstars are likely to be the most productive and financially unconstrained firms within industries, a negative credit supply shock is likely to have a negative impact only on small and unproductive firms, thus generating an increase in the employment share of superstars, and therefore a positive contribution of the covariance term to aggregate productivity growth. The same is not true for average productivity, while superstar firms account for a large share of revenues and employment, they are very few in number, therefore their contribution to average productivity growth is negligible (it actually goes to zero as the number of firms in the industry become very large).

The second industry characteristic that we consider is export intensity, that we measure as exports overt total sales. Exporters depend more on external financing because of the additional costs related to trade (e.g. higher working capital and fixed exporting costs); recent contributions in the literature have shown that negative shocks to credit reduce both the selection of firms into exporting (Manova, 2013) and the volume of exports for firms that continue exporting (Paravisini et al., 2015). Consistently with these findings, in the second panel we show that the effects on average productivity seem to be entirely concentrated among industries characterized by a high level of export intensity. While the effects on the covariance component are not statistically different between the two groups of industries, the point estimate in high export intensive industry is 5 times larger, thus suggesting that also reallocation is likely to be stronger in those industries: if negative shocks to credit affect more small exporters, larger exporters may benefit both in foreign markets by gaining market shares and at home by increase their employment shares.

In the third panel we classify industries according to their level of import competition, that is the ratio between imports and domestic absorption. Import competition – in particular from developing countries – can affect productivity through several channels. On the one hand, it can affect within-firm productivity by increasing innovation and technological change (Bloom et al., 2016); on the other hand, it can foster the reallocation of resources from the least to most productive firms (Melitz, 2003). The results show that no statistically-significant differences emerge in terms of the effects on average productivity between industries: both are negatively affected by a credit supply restriction. Although the effects of the credit shock on the reallocation component is not statistically different across subsamples, the point estimates in industries with import competition below the median is significant and three times larger.

The fourth panel shows how the effects of credit shocks are heterogeneous across industries with different levels of profitability, that we measure as the ratio of Ebitda to total assets.[15] With imperfect capital markets, industry profitability can affect aggregate productivity because it allows firms to relax credit constraints by using internal finance (Fazzari et al., 1987). While we do not find any significant difference in terms of average productivity between low- and high-profitability industries, the effects of credit shocks on the reallocation component is negative and significant only for less profitable industries, suggesting that in those industries credit shocks bite more due to tighter credit constraints among this group of firms.

In the following two panels (fifth and sixth) we distinguish industries according to their share of tangible capital and of collateralized debt. These two measures are strictly interconnected between each other. Industries with a lower share of tangible capital are those in which inputs are more easily redeployable; moreover, tangible capital can be easily collateralized by firms and allow them to access external bank finance, thus alleviating credit constraints. The results show that the effects of negative credit shocks on average productivity and reallocation are concentrated in industries with a lower share of tangible capital and collateralized debt. The differences are statistically significant. This suggests that the availability of collateral or guarantees are crucial to hamper or exacerbate the harshness of a financial restriction: less collateralized sectors suffer a drop in average within-firm productivity and experience a reallocation of labor shares from less to more productive units. Again, we find stronger effects in industries that are more likely to feature stronger credit constraints.

In the last panel we divide industries according to their level of leverage, finding little heterogeneity. This is not in contrast with the previous results, since leverage is not specific to bank debt, and therefore is a poor proxy for credit constraints.

An important question is whether our results differ depending on whether a credit shock hits an industry that is expanding as opposed to contracting. On the one hand, expanding industries

[15] Ebitda is Earnings before interest, taxes, depreciation, and amortization. It is a measure of operating profits.

are likely those that require more external finance, and thus in which credit constraints are more likely to bite. On the other hand, expanding industries may be those with better perspectives, in which firms may find it easier to access external finance. We perform this test by classifying industries as "expanding" if world imports in that sector (excluding Italy) grew in a given year, and as "shrinking" otherwise. We then repeat the estimation on the two subsamples of growing and shrinking industries. Results are shown in Table 11. Credit shocks affect average firm productivity in both shrinking and expanding industries, although the drop is significantly stronger for the former; this suggest that in a shrinking sector, that presumably has limited capacities of internal financing, a bank credit cut affects within-firm productivity with a greater intensity. By contrast, credit supply shocks affect the reallocation component only in expanding industries. This could be rationalized by thinking, on one hand, that a credit cut will hit with a relatively higher intensity the small and less productive firms (that are also likely to be the more financially constrained); on the other hand, that the bigger and more productive firms facing a positive international cycle will have the absorption capacity to embody additional resources freed within the industry.

7.2 Additional robustness checks

We already tested the robustness of our results to specifications including different sets of industry and time fixed effects. We now subject our findings to two additional robustness checks. The first concerns the definitions of the credit shock. As explained extensively in section 4, in our baseline specifications we chose to fix the weights used to compute the credit shocks to reduce the potential endogeneity of the share of credit of different banks in each industry. This concern is especially relevant when it comes to study the effect of credit shocks on the reallocation component: the reallocation of workers across firms may impact the shares of credit if more productive firms are systemically matched with banks experiencing a higher (or lower) than average credit supply shock. However, we experiment with two additional definitions of credit shocks focusing on the crisis period, which yields the most interesting results.The first uses a different definitions of fixed weights: these are now computed as the average of the three years preceding the crisis (2005–2007), to reduce concerns that using weights as of 2007 may drive results because that year is any way special. The second uses time-varying weights. Results are shown in Table 16. Results on the effects of credit shocks on average productivity are fully confirmed: positive credit shocks are associated with higher average productivity. Coefficients are also similar in magnitude across specifications. The picture is similar when we look at the reallocation component, with the exception of the specification with variable weights in the industry-level regressions. In column 6 the coefficient is marginally not significant with p-value 0.11.

The second robustness check concerns the timing of the effects. We test whether credit supply shocks have a lagged effect on each component of the Melitz-Polanec decomposition. To this aim, we estimate the following distributed lag model based on our baseline model (5): $y_t = \beta_0 * CSS_t + \beta_1 * CSS_{t-1} + \beta_2 * CSS_{t-2} + fixedeffects$, where y_t is each term of the Melitz-Polanec decomposition. The coefficient β_0 can be interpreted as the contemporaneous impact of the credit supply shock, while β_1 and β_2 are the effect one and two years later, respectively.[16] The findings are shown in figure 3. The effect on aggregate productivity is strong on impact, and then it becomes somewhat smaller (marginally not significant at t-1, significant at t-2). This points to some persistence in the effects of credit shocks on aggregate productivity. The effect of credit shocks on the covariance component become instead stronger, and significant, one year

[16] We resort a simple distributed lag model for two reasons. The first is that we aim at keeping this part of the analysis as simple as possible as it should be understood as a cursory exploration of potential lagged effects of the credit shocks on the decomposition. Second, the serial correlation of the credit shocks is not large, that between the time t and $t-1$ shocks 0.38, that between $t-1$ and $t-2$ 0.66, that between t and $t-2$ a mere 0.02. This suggests that estimating a simple lagged distributed model may be appropriate.

later. At t-2 it gets smaller, and statistically not significant. This suggests that the effect of credit shocks on the reallocation component die-out relatively quickly. The effects of entry and exit are never statistically significant, instead, as shown in the baseline estimates.

8 Geography-level analysis

Our findings show that during the crisis, negative credit shocks had a negligible effect on aggregate productivity, by contemporaneously depressing the growth of average within-firm productivity and fostering the reallocation of labor shares in favor of more productive firms. A natural extension to this result is to look at the same phenomena within local labor markets: on one side, it can be argued that bank credit shocks may be more localized, rather than affecting entire industries; on the other hand, narrower geographic areas may be the relevant observational unit to gauge the overall effect of a lending cut on labor (Huber, 2018).

To this aim we repeat the same analysis using the local labor market as a unit of analysis. This is defined by ISTAT as a "Sistema Locale del Lavoro" (SLL), i.e. geographical units defined on the basis of the extent of self-containment of the home-to-work commuting flows. Italy features 686 SLLs, and they are conceptually similar to the Metropolitan Statistical Areas defined for the United States.

Results are shown in Tables 12 for the full sample, and in Tables 13 and 14 for the crisis and pre-crisis period, respectively. In the full sample, credit shocks have a positive effect on average productivity; they instead have a negative and generally significant effect on the reallocation component. Table 13 shows that the effects of the credit shock on average productivity and on the reallocation component are concentrated in the crisis period, as occurs in the baseline specification. The effect on the reallocation component is marginally not significant in the demanding specification including SLL fixed effects and region*year fixed effects (p-values 0.16 and 0.14, respectively). These findings indicate that negative credit shocks increase the positive contribution of the reallocation component to aggregate productivity within local labor market. Thus, the effects can be detected not only within industries, but also within the relevant geographical area.

Credit shocks also appear to have a somewhat negative effect in the regressions on the exit component: local markets experiencing an higher than average expansion in credit feature a smaller contribution of the exit rate to aggregate productivity. This may be due to a lower share of employees in exiting firms: when a local market experiences a higher than average expansion in credit supply, fewer firms exit, and therefore the share of people working in the exiting firms is smaller.[17] Table 14 highlights that these effects are concentrated in the pre-crisis period, indicating that positive credit credit supply shocks imply a stronger reduction in the weight of exiters in good than in crisis times.

Overall, results on the geographical dimension seem to be somewhat stronger and easier to detect than in the industry dimension. While this may be partly due to a larger number of cross-sectional observations in the former than in the latter, it may also owe to the possibility to detect general equilibrium effects, going through local labor market externalities or indirect demand effects. Testing explicitly for these effects, though, is outside the scope of this paper and may be an interesting avenue for future research.

Finally, we have performed some additional exercises to verify whether these estimates also display some degree of heterogeneity with respect to certain characteristics of the SLLs. The results, again referring to the crisis period only, are displayed in Table 15.

The first panel distinguishes between SLLs that host (at least) an industrial district —in the definition of the National statistical agency, ISTAT— and those that do not. As a consequence of a lending cut, the latter category of SLLs experience both a sharper drop in average productivity and a more pronounced increase in the reallocation term with respect to industrial districts. This

[17] This is the ω_X term in Equation 4.

is coherent with the evidence of Finaldi Russo and Rossi (2001), who find that firms located in Italian districts display an advantage in terms of financial relations with the banking system, facing both a lower cost of credit and milder financial constraints.

The results on industrial districts are somehow mirrored in the second panel, which groups SLLs according to their degree of sectoral specialization. When credit shrinks, less specialized SLLs face a greater reduction of average productivity and a more sizable increase of reallocation with respect to specialized ones. This may be due on one hand to the higher financial constraints faced by less specialized areas (in analogy with the industrial districts case). On the other hand, it may owe to the possibility that less specialized SLLs display a greater scope for reallocation: effective credit shocks unevenly distribute across sectors within SLLs, therefore leaving room for a reallocation of labor shares from low-productivity firms in severely hit sectors to high-productivity firms in other ones; this channel may be less relevant for more specialized SLLs, where credit shock is more uniform across sectors.

The third and fourth panels confirm some of the results discussed in the section 7.1. In particular, they show that the effects of a credit cut are more pronounced for SLLs that display a higher export intensity and for those that are characterized by a lower degree of collateralization.

The bottom panel shows that a credit crunch entails more relevant effects —both in terms of average productivity and of reallocation— for SLLs characterized by a lower number of banks per capita. This captures the degree of substitutability across alternative funding strategies; hence, the real effects of a negative credit shock are triggered by the fact that —when the bank presence is low— firms may find themselves financially constrained once they have limited options to substitute for bank credit.

9 Conclusions

In this paper we study if and to what extent credit supply shocks account for fluctuations in aggregate labor productivity. To isolate the different channels through which credit supply affects productivity, we base our empirical approach on the decomposition proposed by Melitz and Polanec (2015), which breaks down the dynamics of aggregate productivity into four components: the variation of average firm productivity, the reallocation of resources towards more productive firms, the contribution of exit and the contribution of entry. Closely following this interpretation framework, we exploit a unique dataset on the universe of Italian manufacturing firms to study the impact of a credit supply shock at the industry-province level on each of these components. We isolate credit supply shocks applying the procedure proposed in Greenstone et al. (2014) on granular microdata from the Italian Credit Register.

The results of the decomposition show that the sluggish aggregate manufacturing productivity in Italy in the period 2000–2015 is primarily driven by the negative contribution of the average (within-firm) productivity. Reallocation of resources to more productive firms has instead sustained the dynamics of aggregate productivity in all years, though its relevance spiked during the global financial and the sovereign debt crises, which were characterized by a massive restriction of credit supply. The exit component of the productivity decomposition, which always contributes positively (since on average exiters are less productive than incumbents), increased in magnitude after 2009, too.

This evidence, suggesting that credit supply shocks may reverberate on aggregate productivity through various channels, has been more rigorously explored in a regression framework that looks at the industry-level components of the Melitz and Polanec (2015) decomposition. Accordingly, we test the effects of idiosyncratic industry credit supply shock on each of the 4 component: average productivity, reallocation, entry and exit margin.

Our findings show that a restriction in credit supply does not significantly affect aggregate productivity growth, but triggers important within-industry dynamics, especially in terms of reallocation: less productive firms shrink in size as a consequence of a negative credit supply shock, thus losing employment shares in favor of more productive ones. On the other hand, a negative credit supply shock hinders aggregate productivity growth through the within-firm productivity (because of the lower productivity growth of the incumbents). These effects are present only during the crisis years. Prior to the crisis we do not find significant effects of (idiosyncratic) credit supply shock on any of the components of aggregate productivity. We estimate a rather small and statistically insignificant effect of credit shocks on the entry and exit margins.

We find that the effects of credit shocks on the reallocation component are stronger in industries in which there is ex-ante more scope for reallocation: those that are more concentrated, that export more intensively, that display a lower profitability and a lower degree of collateralization. The impact is also stronger in sectors that are exposed to a growing international demand.

Finally, we show that results are qualitatively similar if we perform the same analysis within local labor markets (Sistemi Locali del Lavoro, similar to Metropolitan Statistical Areas). Over this dimension, the effects are stronger in areas with a lower sectoral specialization, in those that do not host an industrial district, and in those with a lower presence of banks in per capita terms.

Overall, our findings highlight the presence of a cleansing effect of negative credit shocks during the crisis which counterbalance its negative impact on firm's productivity.

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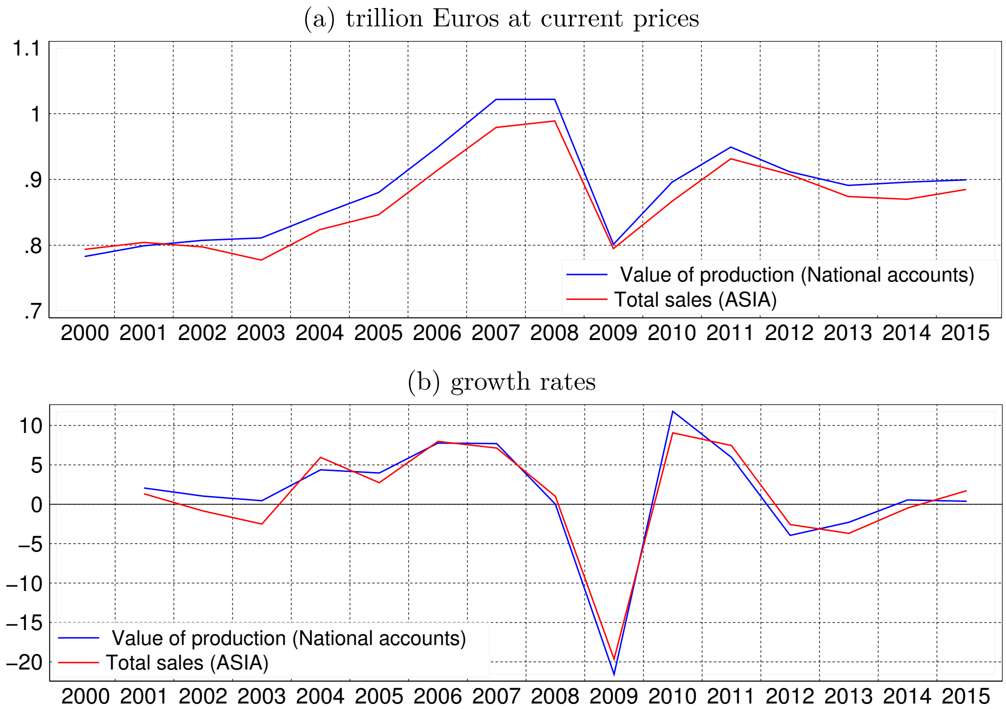
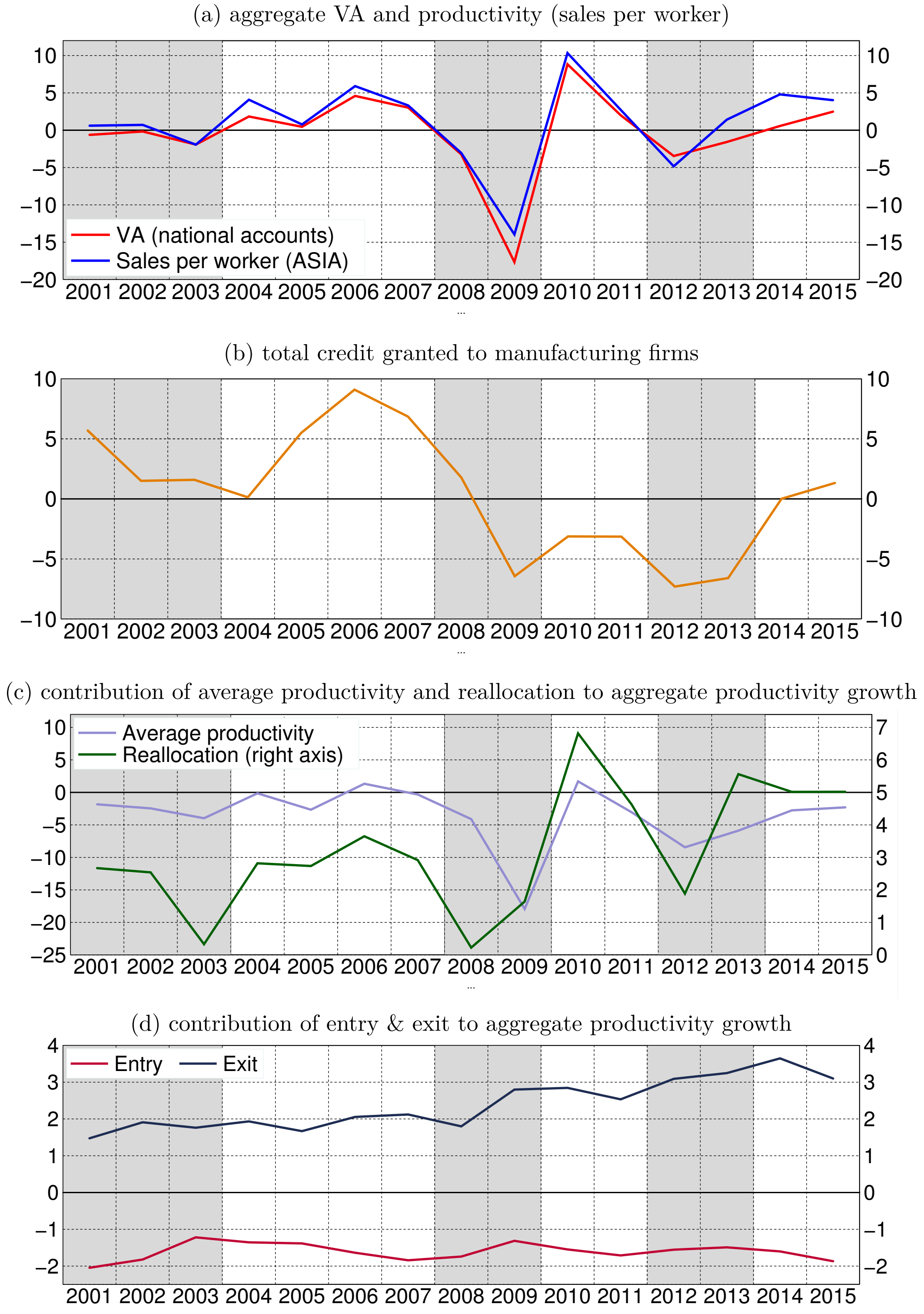
Figures

Figure 1: Comparison between National Accounts and ASIA dataset



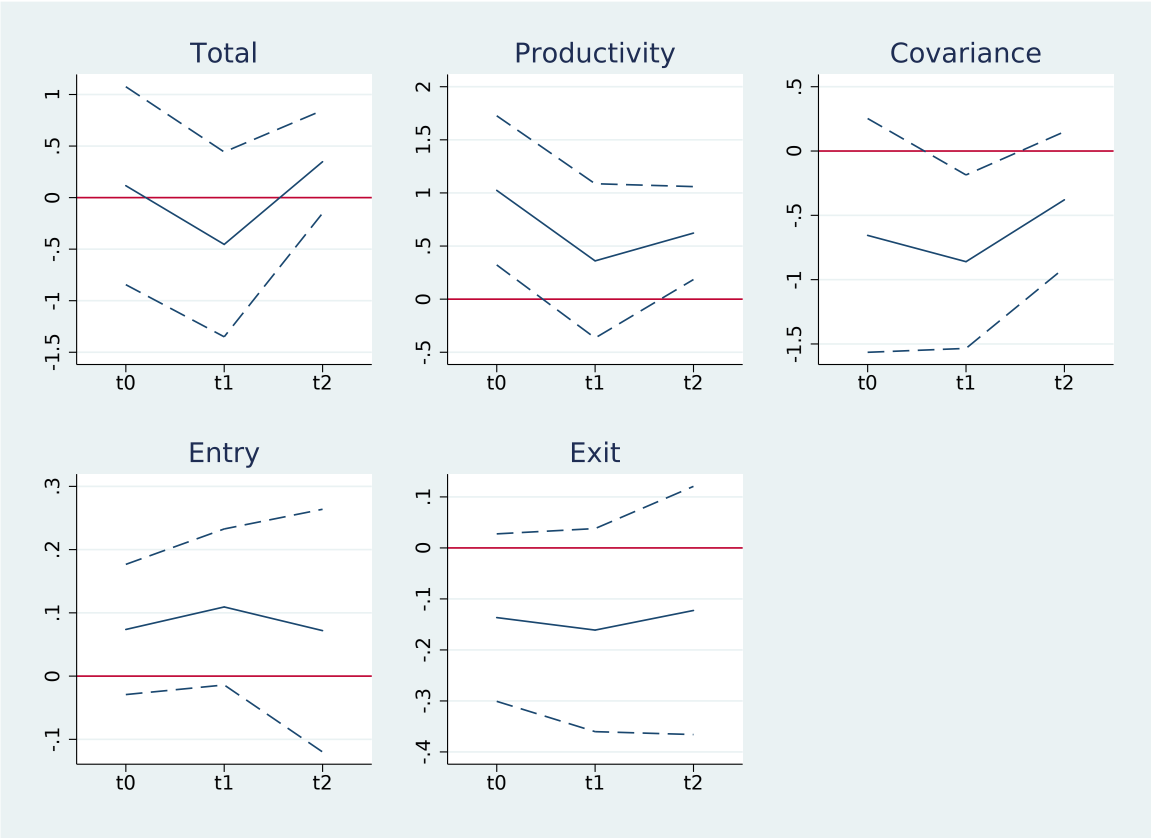
Source: National accounts and ASIA database.

Figure 2: Italian manufacturing, growth rates, years 2001–2015



Source: National accounts and own elaborations from Italian Credit Register and ASIA databases.
Notes: Grayed out areas correspond to years of recession for the manufacturing sector.

Figure 3: Lagged effects of credit shocks



Notes: The figure shows coefficients and confidence intervals of the coefficients of the following regression: $y_t = \beta_0 * CSS_t + \beta_1 * CSS_{t-1} + \beta_2 * CSS_{t-2} + fixedeffects$, where y_t is each term of the Melitz-Polanec decomposition. The coefficient β_0 can be interpreted as the contemporaneous impact of the credit supply shock, while $beta_1$ and $beta_2$ are the effect one and two years later, respectively.

Tables

Table 1: Descriptive statistics for manufacturing, years 2000–2015

	# firms	# employees	avg. size	sales	sales p.w.
2000	491,832	4,242,901	8.63	901,843	212,553
2001	492,835	4,266,155	8.66	898,200	210,541
2002	486,421	4,257,174	8.75	869,372	204,213
2003	476,138	4,280,588	8.99	837,524	195,656
2004	465,882	4,201,217	9.02	866,502	206,250
2005	459,262	4,138,802	9.01	857,071	207,082
2006	452,858	4,127,748	9.11	904,067	219,022
2007	447,206	4,170,744	9.33	944,626	226,489
2008	441,744	4,173,805	9.45	918,000	219,943
2009	426,710	3,992,769	9.36	766,893	192,071
2010	416,022	3,867,436	9.30	830,263	214,680
2011	414,430	3,873,660	9.35	867,249	223,884
2012	406,694	3,799,113	9.34	814,082	214,282
2013	398,092	3,717,963	9.34	806,218	216,844
2014	388,633	3,662,740	9.42	826,145	225,554
2015	383,407	3,660,049	9.55	854,755	233,536

Source: Own elaborations from ASIA dataset.
Notes: Sales data are expressed in million Euros. Both sales and sales per worker have been deflated to 2010 values. Average size is expressed in terms of employees per firm.

Table 2: Melitz–Polanec decomposition of the dynamics of Italian aggregate labor productivity in manufacturing

	Average productivity	Reallocation	Entry	Exit	Total productivity
2001	-1,83	2,67	-2,05	1,47	0,61
2002	-2,45	2,54	-1,82	1,91	0,71
2003	-3,98	0,33	-1,22	1,76	-1,93
2004	-0,14	2,82	-1,35	1,93	4,08
2005	-2,66	2,74	-1,38	1,67	0,77
2006	1,33	3,65	-1,64	2,05	5,90
2007	-0,32	2,92	-1,84	2,12	3,31
2008	-4,11	0,22	-1,74	1,80	-3,05
2009	-17,93	1,64	-1,31	2,80	-13,95
2010	1,70	6,82	-1,55	2,84	10,33
2011	-3,04	4,63	-1,71	2,53	2,74
2012	-8,44	1,89	-1,55	3,09	-4,83
2013	-5,89	5,56	-1,49	3,25	1,41
2014	-2,76	5,02	-1,60	3,65	4,80
2015	-2,30	5,02	-1,87	3,10	4,02

Source: Own elaborations from ASIA dataset.
Notes: Productivity is measured as sales per worker. The sum of the single components may not add up to the total variation, since the contribution of extraordinary events and false entry/exit is not displayed; overall, the impact of these components on the dynamics of aggregate productivity is negligible.

Table 3: Within and Between components of reallocation

	Total reallocation	Within	Between	% within
2001	2,67	2,63	0,04	98,3
2002	2,54	1,89	0,65	74,5
2003	0,33	0,58	-0,25	175,4
2004	2,82	1,95	0,87	69,1
2005	2,74	2,12	0,62	77,3
2006	3,65	2,57	1,08	70,4
2007	2,92	2,47	0,45	84,6
2008	0,22	0,16	0,06	72,6
2009	1,64	3,66	-2,02	223,1
2010	6,82	4,25	2,57	62,3
2011	4,63	3,28	1,35	70,8
2012	1,89	1,91	-0,02	101,2
2013	5,56	4,32	1,25	77,6
2014	5,02	3,70	1,31	73,9
2015	5,02	4,05	0,97	80,7
	Sub-period simple means			
2000–07	2,52	2,03	0,50	80,4
2008–15	3,85	3,17	0,68	82,3
2000–15	3,23	2,64	0,60	81,6

Source: Own elaborations from ASIA dataset.
Notes: Productivity is measured as sales per worker. Aggregate productivity is defined as the weighted average of firm-level log productivities. The sum of the within and between components add to the total reallocation. The within component indicate the within industry reallocation, while the between the across sectoral shifts.

Table 4: Melitz–Polanec decomposition by sector

Sector	Average productivity	Reallocation	Entry	Exit	Total productivity
		Period 2000–2007			
10	-2,12	1,33	-2,28	2,07	-0,09
11	-0,62	1,11	-1,10	0,78	0,29
13	-4,65	3,00	-1,16	2,01	-0,54
14	-3,94	4,80	-2,78	4,53	3,98
15	-3,01	3,83	-1,90	3,06	3,49
16	-0,59	1,24	-1,74	3,05	2,43
17	-0,16	1,42	-0,54	-0,39	2,08
18	-1,66	1,92	-1,34	1,95	1,21
19	-3,86	1,39	1,55	0,17	-10,68
20	-0,51	2,60	-0,53	0,56	2,20
21	4,69	-2,01	-0,21	0,05	3,32
22	-1,57	3,34	-0,73	0,81	2,28
23	-1,14	1,61	-1,34	1,40	0,69
24	-1,98	3,79	-0,48	0,21	2,71
25	-0,65	2,04	-1,50	1,81	2,24
26	-1,67	2,20	-0,80	1,59	-1,22
27	-2,24	4,79	-0,99	1,72	3,76
28	-1,32	3,67	-0,64	1,03	3,09
29	0,08	2,80	-0,39	0,15	2,15
30	1,00	-2,11	-1,71	1,11	-0,25
31	-1,65	1,94	-1,38	2,21	1,51
32	-0,18	0,21	-1,87	2,37	1,75
33	1,39	-0,13	-1,92	-0,03	-0,91
		Period 2008–2015			
10	-3,20	2,29	-2,28	2,93	-0,17
11	-3,03	2,17	-1,76	2,03	-0,30
13	-6,98	4,58	-1,25	4,19	0,70
14	-7,09	3,55	-4,43	7,42	-0,09
15	-6,02	4,57	-3,06	4,43	0,01
16	-6,13	1,77	-0,67	3,95	-1,12
17	-5,40	4,68	-0,61	1,53	0,57
18	-5,87	3,24	-0,95	3,16	-0,52
19	-4,30	5,54	-0,67	0,89	-1,47
20	-4,03	2,65	-0,55	0,89	-0,97
21	-1,54	3,85	0,03	0,03	2,60
22	-5,21	4,44	-0,69	1,62	-0,05
23	-6,85	3,80	-0,74	2,34	-1,32
24	-5,31	3,50	-0,46	0,84	-1,58
25	-5,15	3,51	-1,07	2,45	-0,13
26	-5,86	6,56	-0,55	0,71	2,35
27	-5,18	4,34	-0,73	1,46	0,76
28	-4,83	4,02	-0,46	0,94	-0,03
29	-6,23	6,16	-0,36	0,58	1,28
30	-9,50	10,31	-1,36	2,25	1,68
31	-6,81	3,72	-1,07	3,19	-0,94
32	-4,12	1,91	-1,35	2,78	-1,06
33	-5,44	2,93	-1,57	3,30	-0,90

Source: Own elaborations from ASIA dataset.

Notes: Simple averages over the results of year-on-year decompositions. Productivity is measured as sales per worker. Aggregate productivity is defined as the weighted average of firm-level log productivities. The sum of the single components may not add up to the total variation, since the contribution of extraordinary events and false entry/exit is not displayed; overall, the impact of these components on the dynamics of aggregate productivity is negligible.

Table 5: Summary statistics for the credit supply shock

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
2-digit Nace																
10	3.01	-0.46	0.37	-4.32	-5.15	1.5	4.55	2.32	-3.45	-10.61	-7.21	-10.75	-14.26	-13.45	2.82	4.95
11	1.93	-1.79	0.93	-3.56	-5.15	0.37	4.23	2.1	-3.95	-11.5	-6.39	-10.85	-14.95	-13.86	-2.78	-5.11
13	3.32	-0.53	0.68	-3.44	-5.64	1.68	5.32	2.34	-2.49	-10.46	-6.93	-9.94	-14.48	-13.18	-2.74	-5.39
14	3.41	1.53	0.67	-3.92	-4.87	1.8	5.81	3.06	-4.32	-14.28	-7.35	-11.07	-14.67	-13.6	-2.86	-6.62
15	3.68	1.68	1.39	-4.65	-5.09	1.09	4.35	4.02	-3.97	-11.08	-7.21	-10.68	-13.77	-12.88	-2.54	-5.77
16	3.88	1.5	1.58	-2.12	-3.61	2.14	5.07	3.67	-1.71	-9.43	-6.88	-10.45	-14.54	-12.94	-4.21	-5.93
17	2.55	-5.37	0.81	-3.33	-4.01	-2.18	0.79	3.81	-4.45	-13.39	-5.19	-10.72	-14.31	-12.91	-0.96	-5.26
18	3.74	0.55	1.04	-1.96	-4.82	1.96	5.16	3.21	-3.04	-10.17	-6.89	-10.62	-15.01	-12.6	-3.13	-5.29
19	2.95	-1.61	-1.26	-5.58	-6.04	1.84	2.7	1.08	-4.37	-11.43	-6.44	-11.81	-13.19	-13.29	-2.02	-5.94
20	1.01	-1.93	-1.62	-5.12	-7.33	1.03	6.24	0.71	-4.53	-12.04	-7.22	-9.96	-14.26	-13.64	-2.27	-4.48
21	1.4	-3.09	-2.17	-5.48	-8.43	1.11	3.87	2.71	-4.67	-12.97	-6.95	-9.03	-14.57	-14.52	0.35	-1.89
22	3.04	-0.38	-0.11	-3.2	-5.92	1.88	5.34	1.97	-4.09	-11.18	-7.48	-10.11	-14.8	-13.04	-2.49	-4.97
23	3.08	-0.24	0.11	-4.47	-4.83	1.2	4.45	2.29	-4.2	-11.85	-6.59	-11.1	-14.32	-13.31	-2.1	-5.87
24	2.43	-0.76	-0.3	-3.73	-6.52	1.45	5.57	1.94	-3.59	-11.24	-7.14	-10.47	-14.96	-13.95	-2.38	-5.39
25	3.55	0.27	1.16	-2.19	-4.57	2.22	5.41	3.28	-3.01	-10.18	-7.19	-10.4	-14.49	-12.84	-3.1	-5.45
26	2.45	-0.9	-1.1	-5.51	-5.65	1.81	4.58	1.38	-4.98	-11.35	-7.24	-10.3	-14.78	-13.53	-2.52	-5.28
27	2.16	-0.79	-0.32	-5.26	-5.52	1.72	5.48	2.11	-4.3	-12.09	-7.57	-10.29	-14.39	-13.27	-2.49	-5.55
28	2.93	-0.1	-0.19	-3.89	-5.94	1.47	5.43	0.81	-4.51	-11.54	-7.46	-10.47	-14.73	-13.72	-2.48	-5.07
29	1.59	-2.71	-0.58	-5.76	-6.16	0.52	6.78	0.91	-7.3	-12.54	-9.14	-8.95	-17.06	-14.85	-2.28	-3.49
30	3.29	-0.3	-0.31	-4.68	-4.87	-1.21	0.68	-10.73	-7.02	-17.25	-10.03	-12.17	-20.84	-12.12	-0.5	-4.74
31	4.38	1.6	1.83	-2.74	-3.54	1.87	4.97	3.47	-2.09	-9.65	-7.39	-10.08	-14.97	-13.04	-4.22	-6.33
32	3.42	1.82	0.17	-4.8	-4.18	1.56	5.04	2.69	-3.67	-10.8	-6.81	-10.31	-14.88	-14.21	-3.51	-7.93
33	3.34	0.3	1.09	-2.26	-4.33	2.33	4.73	2.14	-3.83	-10.35	-7.25	-10.28	-15.18	-12.94	-2.34	-5.72

Source: Own elaborations from Italian Credit Register data.

Table 6: Credit supply shocks and bank balance-sheet characteristics

	(1)	(2)	(3)
capital	0.0854	0.150***	0.122**
	(0.0605)	(0.0541)	(0.0560)
liquidity	0.165***	0.0923***	0.104***
	(0.0297)	(0.0329)	(0.0347)
roa	1.471**	0.157	0.371
	(0.586)	(0.608)	(0.601)
interbank	-0.298***	-0.0991**	-0.110**
	(0.0531)	(0.0470)	(0.0471)
non-performing	-0.747***	-0.556***	-0.518***
	(0.101)	(0.0916)	(0.0863)
size	-0.00200	0.000254	-0.00301
	(0.00165)	(0.00176)	(0.00213)
d(mutual)			-0.0235**
			(0.0101)
Constant	0.0108		
	(0.0194)		
Year FE	N	Y	Y
Observations	7,158	7,158	7,158
R^2	0.071	0.156	0.158

Source: Own elaborations from Italian Credit Register data.
Notes: Capital is the ratio of equity to total assets, liquidity is the ratio of cash and government bonds to total assets, roa is the ratio of profits (losses) to total assets, interbank is the ratio of interbank deposits including repos to total assets, non-performing is the ratio of gross non-performing loans to total assets, size is the log of total assets, d(mutual) is a dummy if the bank is a mutual banks. Standard errors clustered at the bank-level in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Industry-level results - Full sample

Dependent vars	Independent var	(1)	(2)	(3)	(4)
Average productivity	CSS_t	0.430*	0.801***	0.799**	0.545**
		[0.246]	[0.270]	[0.332]	[0.239]
Reallocation	CSS_t	-0.516	-0.462	-0.403	-0.473
		[0.345]	[0.393]	[0.530]	[0.319]
Entry	CSS_t	-0.014	0.031	0.086	-0.026
		[0.058]	[0.068]	[0.069]	[0.063]
Exit	CSS_t	0.180*	0.021	0.033	-0.011
		[0.107]	[0.115]	[0.123]	[0.111]
Aggregate productivity	CSS_t	0.0031	0.357	0.542	-0.043
		[0.273]	[0.375]	[0.527]	[0.249]
Year FE		Y	Y	Y	N
Nace 2-digit FE		Y	Y	N	N
Nace 4-digit FE		N	N	Y	N
Year*Nace 2-digit FE		N	N	N	Y
Weighted		N	Y	Y	Y
Observations		2,655	2,655	2,655	2,640

Source: Own elaborations from ASIA dataset.
Notes: Standard errors clustered at the industry (Nace 4-digit) level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 8: Industry-level results - Crisis period (2008–2015)

Dependent vars	Independent var	(1)	(2)	(3)	(4)
Average productivity	CSS_t	0.816***	1.244***	1.548***	0.722***
		[0.290]	[0.300]	[0.404]	[0.261]
Reallocation	CSS_t	-0.730**	-0.842**	-0.873*	-0.568*
		[0.357]	[0.366]	[0.485]	[0.325]
Entry	CSS_t	0.048	0.072	0.019	0.079
		[0.061]	[0.068]	[0.048]	[0.084]
Exit	CSS_t	0.0588	-0.0982	-0.0131	-0.135
		[0.109]	[0.104]	[0.119]	[0.110]
Aggregate productivity	CSS_t	0.203	0.423	0.805	0.118
		[0.331]	[0.429]	[0.615]	[0.256]
Year FE		Y	Y	Y	N
Nace 2-digit FE		Y	Y	N	N
Nace 4-digit FE		N	N	Y	N
Year*Nace 2-digit FE		N	N	N	Y
Weighted		N	Y	Y	Y
Observations		1,416	1,416	1,416	1,408

Source: Own elaborations from ASIA dataset.
Notes: Standard errors clustered at the industry (Nace 4-digit) level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 9: Industry-level results - Pre-crisis period (2000–2007)

Dependent vars	Independent var	(1)	(2)	(3)	(4)
Average productivity	CSS_t	-0.0794	0.113	-0.806	0.244
		[0.354]	[0.360]	[0.537]	[0.388]
Reallocation	CSS_t	-0.112	0.179	1.292**	-0.314
		[0.363]	[0.379]	[0.584]	[0.435]
Entry	CSS_t	-0.159	-0.239***	-0.203***	-0.204*
		[0.116]	[0.089]	[0.078]	[0.104]
Exit	CSS_t	0.368*	0.199	0.219	0.200
		[0.195]	[0.187]	[0.193]	[0.227]
Aggregate productivity	CSS_t	-0.249	0.026	0.154	-0.317
		[0.359]	[0.401]	[0.769]	[0.459]
Year FE		Y	Y	Y	N
Nace 2-digit FE		Y	Y	N	N
Nace 4-digit FE		N	N	Y	N
Year*Nace 2-digit FE		N	N	N	Y
Weighted		N	Y	Y	Y
Observations		1,239	1,239	1,239	1,232

Source: Own elaborations from ASIA dataset.
Notes: Standard errors clustered at the industry (Nace 4-digit) level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 10: Industry-level results - Sectoral heterogeneity

	Below/above median	Average productivity	Reallocation	Entry	Exit	Aggregate productivity
Market share of top 20 firms	below	1.267***	-0.310	-0.0185	0.0696	0.899*
		[0.373]	[0.238]	[0.0689]	[0.112]	[0.458]
	above	1.438**	-2.320***	0.201	-0.305	-0.765
		[0.591]	[0.854]	[0.136]	[0.205]	[0.669]
	below - above	0.141	1.286	-0.0809	0.505	1.697
	pval H0: below=above	0.829	0.122	0.570	0.0199	0.0320
Export intensity	below	-0.192	-0.211	-0.0822	-0.0427	-0.103
		[0.602]	[0.446]	[0.117]	[0.211]	[0.562]
	above	1.498***	-1.074**	0.0999	-0.1000	0.351
		[0.301]	[0.489]	[0.0791]	[0.123]	[0.575]
	below-above	-1.368	-0.243	0.0618	-0.144	-1.243
	pval H0: below=above	0.0232	0.765	0.671	0.503	0.104
Import competition	below	1.144**	-1.578**	0.204**	-0.160	-0.379
		[0.475]	[0.603]	[0.101]	[0.169]	[0.653]
	above	1.396***	-0.414	-0.0271	-0.0885	0.983**
		[0.367]	[0.431]	[0.0443]	[0.139]	[0.485]
	below - above	-0.412	-0.874	0.179	-0.0854	-1.298
	pval H0: below=above	0.499	0.255	0.149	0.640	0.126
Profitability (ROA)	below	1.489***	-1.365***	0.0557	-0.0595	0.212
		[0.344]	[0.510]	[0.0981]	[0.147]	[0.588]
	above	1.197**	-0.0673	0.00193	-0.0839	0.998*
		[0.569]	[0.456]	[0.0598]	[0.145]	[0.579]
	below - above	0.305	-1.298	0.0560	-0.00498	-0.769
	pval H0: below=above	0.643	0.0580	0.627	0.981	0.352
Share of tangible capital	below	1.594***	-1.256***	0.104	-0.141	0.377
		[0.362]	[0.446]	[0.0887]	[0.135]	[0.569]
	above	0.304	0.530	-0.113	-0.00555	0.619
		[0.616]	[0.735]	[0.122]	[0.153]	[0.648]
	below - above	1.123	-1.934	0.211	-0.149	-0.589
	pval H0: below=above	0.0988	0.0204	0.142	0.448	0.505
Share of collateralized debt	below	1.370***	-1.093**	0.102	-0.128	0.351
		[0.328]	[0.544]	[0.0761]	[0.151]	[0.652]
	above	-0.0206	-0.144	-0.100	0.135	-0.109
		[0.559]	[0.402]	[0.109]	[0.135]	[0.504]
	below - above	1.410	-0.874	0.176	-0.236	0.551
	pval H0: below=above	0.0438	0.195	0.226	0.259	0.497
Leverage	below	1.404***	-0.855	-0.0251	-0.0437	0.605
		[0.469]	[0.514]	[0.0390]	[0.169]	[0.657]
	above	1.249***	-0.922*	0.140	-0.192*	0.274
		[0.365]	[0.498]	[0.111]	[0.115]	[0.573]
	below - above	0.109	-0.0718	-0.146	0.136	0.137
	pval H0: below=above	0.858	0.921	0.237	0.504	0.877

Source: Own elaborations from ASIA dataset.
Notes: Standard errors clustered at the industry (Nace 4-digit) level in parentheses * p<0.10, ** p<0.05, *** p<0.01. All regressions are weighted by the number of employees in each industry; year and sector (Nace 2-digits) fixed effects included. Export intensity is the ratio of export and sales; import intensity is the share of imported goods on total intermediate inputs; import competition is the share of imports from developing countries in domestic consumption.

Table 11: Industry-level results - Sectoral heterogeneity

	(1) Productivity	(2) Covariance	(3) Entry	(4) Exit
shrinking # CSS	1.838***	0.150	0.0487	-0.212*
	[0.507]	[0.624]	[0.0746]	[0.124]
growing # CSS	0.709*	-1.674**	0.0750	0.00885
	[0.375]	[0.666]	[0.0822]	[0.141]
test shrink - grow	1.128	1.824	-0.0263	-0.221
pval H0: shrink=grow	0.0769	0.0804	0.714	0.190
N	1416	1416	1416	1416

Source: Own elaborations from ASIA dataset.
Notes: Industries are classified as growing in the year if world imports (excluding Italy) grew in that year. Industries are classified as shrinking if world imports (excluding Italy) contracted in that year. Standard errors clustered at the sector (Nace 2-digit) level in parentheses * p<0.10, ** p<0.05, *** p<0.01. All regressions are weighted by the number of employees in each industry; year and industry (Nace 2-digits) fixed effects included.

Table 12: LLM-level results - Full sample

Dependent vars	Independent vars	(1)	(2)	(3)
Average productivity	CSS_t	0.121***	0.085***	0.092***
		[0.025]	[0.026]	[0.022]
Reallocation	CSS_t	-0.068*	-0.049	-0.061*
		[0.036]	[0.040]	[0.034]
Entry	CSS_t	0.010	0.003	0.010
		[0.008]	[0.009]	[0.008]
Exit	CSS_t	-0.035**	-0.016	-0.034**
		[0.016]	[0.015]	[0.0150]
Aggregate productivity	CSS_t	0.118	0.107	0.056
		[0.079]	[0.084]	[0.051]
Year FE		Y	Y	N
Region FE		Y	N	N
LLM FE		N	Y	N
Year*Region FE		N	N	Y
Observations		8,498	8,498	8,498

Source: Own elaborations from ASIA dataset.
Notes: All regressions are weighted by the number of employees in each LLM. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 13: LLM-level results - Crisis period (2008–2015)

Dependent vars	Independent vars	(1)	(2)	(3)
Average productivity	CSS_t	0.178***	0.153***	0.118***
		[0.042]	[0.036]	[0.028]
Reallocation	CSS_t	-0.107**	-0.101	-0.0728
		[0.055]	[0.072]	[0.050]
Entry	CSS_t	0.015	0.000	0.009
		[0.010]	[0.007]	[0.011]
Exit	CSS_t	-0.024	-0.008	-0.016
		[0.017	[0.018]	[0.018]
Aggregate productivity	CSS_t	0.092	0.111	0.024
		[0.072]	[0.095]	[0.065]
Year FE		Y	Y	N
Region FE		Y	N	N
LLM FE		N	Y	N
Year*Region FE		N	N	Y
Observations		4,871	4,871	4,871

Source: Own elaborations from ASIA dataset.
Notes: All regressions are weighted by the number of employees in each LLM. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 14: LLM-level results - Pre-crisis period (2000–2007)

Dependent vars	Independent vars	(1)	(2)	(3)
Average productivity	CSS_t	0.030	-0.016	0.053*
		[0.037]	[0.049]	[0.031]
Reallocation	CSS_t	-0.023	-0.012	-0.044
		[0.044]	[0.051]	[0.047]
Entry	CSS_t	0.001	-0.011	0.012
		[0.011]	[0.012]	[0.010]
Exit	CSS_t	-0.058**	-0.022	-0.062***
		[0.023]	[0.021]	[0.024]
Aggregate productivity	CSS_t	0.141	0.053	0.103
		[0.119]	[0.112]	[0.082]
Year FE		Y	Y	N
Region FE		Y	N	N
LLM FE		N	Y	N
Year*Region FE		N	N	Y
Observations		3,592	3,592	3,592

Source: Own elaborations from ASIA dataset.
Notes: All regressions are weighted by the number of employees in each LLM. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 15: LLM-level results - Spatial heterogeneity

	Features	Average productivity	Reallocation	Entry	Exit	Aggregate productivity
Industrial districts	Non district (ND)	0.215***	-0.149*	0.0105	-0.0431**	0.125
		[0.0524]	[0.0761]	[0.0101]	[0.0206]	[0.0941]
	District (D)	0.0668	0.0400	0.0146	-0.00306	0.0773
		[0.0546]	[0.0614]	[0.0248]	[0.0436]	[0.0881]
	ND - D	0.148	-0.189	-0.00410	-0.0400	0.0481
	pval H0: ND=D	0.0511	0.0536	0.878	0.407	0.709
Specialization	below median	0.185***	-0.132**	-0.000635	-0.0229	0.0567
		[0.0486]	[0.0626]	[0.0114]	[0.0190]	[0.0692]
	above median	0.131**	-0.0380	0.0453*	-0.0225	0.188
		[0.0610]	[0.125]	[0.0262]	[0.0483]	[0.204]
	below - above	0.0537	-0.0942	-0.0459	-0.000431	-0.131
	pval H0: below=above	0.491	0.502	0.108	0.993	0.544
Export openness	below median	0.0333	0.0467	-0.00303	-0.0255	0.0318
		[0.0488]	[0.0987]	[0.0152]	[0.0261]	[0.0983]
	above median	0.206***	-0.150**	0.0203	-0.0285	0.0985
		[0.0447]	[0.0698]	[0.0126]	[0.0217]	[0.0936]
	below - above	-0.172	0.197	-0.0233	0.00299	-0.0667
	pval H0: below=above	0.00947	0.105	0.239	0.930	0.623
Share of guaranteed credit	below median	0.218***	-0.164**	0.0217	-0.0128	0.106
		[0.0493]	[0.0754]	[0.0149]	[0.0263]	[0.114]
	above median	0.0250	-0.00412	0.00446	-0.0327*	0.00261
		[0.0333]	[0.0671]	[0.0115]	[0.0178]	[0.0691]
	below - above	0.193	-0.160	0.0172	0.0199	0.104
	pval H0: below=above	0.00124	0.114	0.360	0.531	0.435
Banks per capita	below median	0.229***	-0.197*	0.0220	-0.0285	0.0644
		[0.0606]	[0.101]	[0.0160]	[0.0296]	[0.112]
	above median	0.103**	0.000188	0.0121	-0.0266	0.124
		[0.0402]	[0.0584]	[0.0103]	[0.0177]	[0.0950]
	below - above	0.126	-0.197	0.00992	-0.00190	-0.0596
	pval H0: below=above	0.0833	0.0911	0.603	0.956	0.686

Source: Own elaborations from ASIA dataset.

Notes: Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01. All regressions are weighted by the number of employees in each LLM; year and region (NUTS2) fixed effects included. For each LLM, specialization is proxied by the Herfindahl index computed over total employees at the sector 2-digit level. Export openness computed as the share of revenues from exporting activities. Banks computed as the ratio between the number of banks localized in the LLM and the population of the LLM in 2001.

Table 16: Robustness check: different definitions of credit supply shocks

	Industry-level regressions			LLM-level regressions		
	Baseline	Fixed weights	Variable weights	Baseline	Fixed weights	Variable weights
Average productivity	1.244***	1.302***	1.437***	0.177***	0.183***	0.151***
	[0.300]	[0.287]	[0.407]	[0.0416]	[0.0681]	[0.0387]
Reallocation	-0.842**	-0.806**	-0.0309	-0.107*	-0.112*	-0.0888
	[0.366]	[0.348]	[0.344]	[0.0545]	[0.0689]	[0.0555]
Entry	0.0723	0.0283	0.122*	0.0152	0.0265*	0.0186*
	[0.0676]	[0.0609]	[0.0729]	[0.00982]	[0.0145]	[0.0112]
Exit	-0.0982	-0.0552	-0.0602	-0.0240	-0.0220	-0.0123
	[0.104]	[0.0854]	[0.0987]	[0.0173]	[0.0233]	[0.0166]
Aggregate productivity	0.423	0.265	1.629***	0.0918	0.0507	0.0825
	[0.429]	[0.375]	[0.509]	[0.0724]	[0.0890]	[0.0690]
Year FE	Y	Y	Y	Y	Y	Y
Nace 2-digit FE	Y	Y	Y	N	N	N
Region FE	N	N	N	Y	Y	Y
Observations	1,416	1,416	1,416	4,865	4,865	4,865

Source: Own elaborations from ASIA dataset.

Notes: All regressions are weighted by the number of employees in each LLM. Standard errors clustered at the Nace 2-digit or at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01. The baseline regressions (columns 1 and 4) use the definition of credit supply shock in equation 6; the fixed-weights columns (2 and 5) use a credit supply shock that aggregates the individual bank shocks according to the average market shares in years 2005–2007; the variable-weights columns (3 and 6) use a credit supply shock that aggregates the individual bank shocks according to market shares varying year by year.