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Allocative Efficiency and Finance

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Abstract

In this paper, we study the relationship between aggregate productivity growth and finance; importantly, we go beyond the study of the impact of credit supply shocks on firm productivity, stemming from the reduction in firms' investment, as we also estimate its effect through the reallocation of labor across firms, and through the exit and entry margin. We are in a ideal position to address this question because we have access to a unique dataset that cover the universe of Italian manufacturing firms in Italy between 2000 and 2015. Our findings show that bank shocks affect the average firm productivity, reallocation, and the entry and exit margins only in the crisis period (post 2008). A negative credit supply shock reduces aggregate productivity, since it lowers firm average productivity and the contribution of entering firms to aggregate productivity. However, these effects are counterbalanced, as negative credit shocks improve the allocation of resources (as measured by the Olley-Pakes covariance) and force the least productive firms to exit the market. As a consequence, the overall effect of credit shocks on aggregate productivity is negligible. However, the cleansing effects of negative credit shocks are sizable and mostly work through a reallocation of workers from the least productive to the most productive firms.

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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 affect aggregate productivity. Negative credit shocks can impact aggregate productivity through several channels. First, they can lower firm-level productivity, as they exacerbate credit constraints preventing firms from investing, hiring workers and innovating. Second, credit shocks could increase firm exit, which may benefit aggregate productivity, to the extent that low productivity firms are forced to leave the market. Third, negative credit supply shocks 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 finance on aggregate productivity, which may also go 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.

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 (BdI-ISTAT). This is crucial to obtain a complete picture of the reallocation process and of the entry and exit of firms. Our empirical approach is guided by 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 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 2-digit industry. As a consequence we estimate the credit supply shocks at the sector (2-digit) level using the procedure proposed in Greenstone et al. (2014). In a nutshell, we regress the growth rate of credit by each bank in each sector controlling for a full set of sector-time and bank-time fixed effects. The latter represent the credit supply shocks, which we then aggregate at the sector level, using the share of credit of each bank in each sector. 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. We apply the same approach also when working at the firm-level, to estimate whether the credit shocks affect more strongly low or high productivity firms. We do so both for consistency, but also because we cannot match the firm level data with the credit registry due to confidentiality issues. In addition, the Italian credit register does not cover the universe of bank-firm lending relationships and the reporting threshold, set at 75,000 Euros until 2008, and at 30,000 Euros afterwards, would exclude several small firms, which would prevent us from exploiting a key unique feature of our data: the availability of the universe of Italian firms, which is key to fully gauge the entry and exit margins and the reallocation of workers.

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 (2012–2014). 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. Moreover, it gives us the chance to roughly quantify the overall impact of the credit crunch on aggregate productivity, distinguishing the various channels through which its effects unfolded.

Our findings show that credit shocks affect all the four margins of aggregate productivity growth. Negative credit shocks 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. Finally, weaker credit supply growth has significant but modest effects in terms of the net demography margin: on the one hand, it increases the positive contribution of exit to aggregate productivity; on the other hand, it further lowers the negative contribution of entry, since entrants in a period of worse credit supply availability are on average less productive relative to the incumbents.

The effects we estimate are sizable. In crisis times negative credit supply shocks contributed for a quarter of the drop in the contribution of average productivity to total productivity, and for more than half of the increase in the contribution of reallocation. Overall, during the crisis, idiosyncratic credit shocks had a significant *direct* impact on the average productivity of firms and on the reallocation of resources. However, the total direct effect of credit shocks on aggregate productivity are small, as a consequence of the opposing forces they exert through average productivity and firm entry on the one hand, and through the reallocation and exit processes on the other.

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 identify 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) finds 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, lead to a significant decline in sectoral total factor productivity as capital inflows are misallocated toward firms that have higher net worth but are not necessarily more productive. This effect has been especially pronounced in Spain.

Two recent works focusing in 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 ar e 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 affects productivity. Second, we use a unique dataset covering the universe of Italian firms, which allows us to fully gauge reallocation and the entry and exit of 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. (2016)).

The paper is organized as follows. Section 2 presents the data used in this paper. 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 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. In section 5 we detail our empirical strategy, while section 6 illustrates the main results and quantifies the aggregate effects. Section 7 provides supporting evidence on the results on reallocation by looking at firm-level data. Finally, section 8 concludes.

2 Data

The paper relies on two different data sources. The first is a firm-level dataset that covers the universe of manufacturing firms that were active for at least 6 months in a given business year from 2000 to 2015. The construction of the dataset is the result of a joint collaboration between 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.[1] We deflate the data on sales to 2010 prices, using sector-level price indexes for sales. In the spirit of Geurts and Van Biesebroeck (2014), we exploit administrative information to obtain a measure of entry and exit of firms purged from errors.

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

The quality of this 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.[2] The two series are very similar over the entire period of observation. 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, that 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 second data source is the comprehensive Italian Credit Register, a database owned by the Bank of Italy, which contains data on all individual bank-borrower relationships 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.

Despite the quality and the richness of our data we cannot match the firm level data with the credit registry, due to confidentiality issues. As a consequence, we will aggregate both firm and credit registry data to perform our empirical analysis at the industry-level (2-digit) also when we will estimate the effects of credit shocks on individual firms.

During our sample period (2000-2015), Italian manufacturing shrunk significantly. Table 1 reports descriptive statistics of the firms in our sample. Starting in 2003, the number of firms declined almost every year: in 2015 there were about 110,000 firms less than in 2002. As a consequence, the number of employees dropped by more than 800,000 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 were already dropping somewhat even before the crisis.

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

[2] 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.

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 offered 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 recession in half of the observed years, while not attaining a consistently fast-paced growth in the remaining years. 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 (2007–09), and a more moderate contraction during the sovereign debt crisis (2012–13).

The dynamics of manufacturing value added should be read in parallel to the chart displayed in panel (b), depicting the evolution of the aggregate credit supply shock. This has been obtained as an average of the credit supply shocks in equation 6, weighted by the share of loans granted in each sector. Credit supply has grown at rates above the mean until the global financial crisis: during the 2001–2003 recession, which didn't have a financial nature, the growth of credit supply declined only slightly, 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 supply growth; 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 partial recovery emerged from 2013 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 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.

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

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

How did these components evolve in our reference period? Going back to Figure 2, the dynamics of aggregate productivity —depicted in panel (a)— has been substantially similar to that of manufacturing value added, with wider fluctuations especially at the beginning of the sample. Reallocation —displayed in panel (c)— has always provided a positive contribution to aggregate labor productivity, partially offsetting the consistently negative contribution of average firm productivity (not reported in the figure, but available in 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 two jumps in the reallocation component seem to mirror the troughs experienced by credit supply.

Panel (d) displays the contribution of entry and exit. The contribution of exiting (entering) firms is always positive (negative), since their aggregate productivity is always lower than the one of incumbents. The entry component fluctuates in a narrow band, around the -2 percentage points, slightly declining over the entire period. The exit component remains quite 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 jumped up by roughly 1 percentage point; it then appeared to converge back to its before-crisis values, but experienced another increase after the burst of the sovereign debt crisis. Like in the case of reallocation, the contribution of exiting firms displays remarkable variations only in periods of substantial credit supply shrinkage.

Overall, this broad picture of the productivity dynamics in Italian manufacturing provides some suggestive evidence of a link between the evolution of credit supply and certain components of aggregate labor productivity, most notably the reallocation and the exit terms. In the remainder of this paper, we exploit our firm-level data to provide some evidence in favor of this hypothesis, and to explore what are the mechanisms that give rise to the fluctuations we observe in the aggregate.

The Melitz and Polanec (2015) decomposition can be applied at any level of aggregation of firms. So far we have discussed in detail the decomposition applied to the whole manufacturing sector, but the components of the such decomposition can be also expressed in terms of the components at a more granular level. We applied the decomposition at the 2-digit Nace sector level. Even under the assumption that firms do not change sector over time,[3] the overall contribution of reallocation (the one in panel (d)) 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. The last column reports the share of within sectoral reallocation.

All in all, the table suggests that within sector components are significantly larger than the between components. With the notable exception of 2008, the within component accounts on average for more than 85% of the reallocation. These results are consistent with previous findings of a remarkable role of within industry reallocation in shaping aggregate productivity growth.

Finally, Table 4 reports the aggregate productivity decomposition and its component at the sector level by sub-period. 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 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. Overall, the contribution of net demography is positive in almost all sectors, but its magnitude increases after 2008.

4 The credit supply shock: estimation and basic facts

we aim at studying the impact of credit supply shocks on the 4 components of aggregate productivity as in Melitz and Polanec (2015). To identifiy bank-specific credit shocks, we apply the methodology of Greenstone et al. (2014) on loan-level microdata from the Italian Credit Register data. Since three of the components of Melitz-Polanec decomposition, reallocation,

[3]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, i.e. 2-digit Nace sector, between to adjacent years is relatively small, therefore such assumption despite simplifying the analysis does not introduce systematic bias in the results.

entry and exit need to be studied at the industry-level, we aggregate credit granted by each bank at the sector-time level, and we estimate the following model:

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

where $\Delta \ln(L_{bst})$ is the log change in credit granted by bank b to sector s (which is 2-digit) at time t. $\alpha_{b,t}$ are a set of bank*time fixed effects and γ_{st} are a set of unit of sector*time fixed effects. In practice, model 5 compares the growth of credit from different banks lending to the same sector in any year. The sector*time fixed effects control for changes in demand and economic conditions at the sector 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.[4] The set of bank-time fixed effects, $\alpha_{b,t}$, identifies a supply-induced change in credit under the assumption that the at the sector-time level there is no bank-specific demand for credit, so that the set of sector-time fixed effects fully control for changes in demand and in the riskiness and economic prospects of the sectors. Under this condition, these shocks are uncorrelated with with any characteristics of the firms and of the markets in which the banks operate. This assumption could be violated if a bank specialized in financing a certain industry. Even in this case, though, the set of bank*time effects can still be interpreted as a supply-side shock (Amiti and Weinstein (2013), Greenstone et al. (2014)).

We then aggregate these bank-specific shocks to obtain a measure of the evolution of credit supply at the sector level. 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 sector s in year t. These shares are computed aggregating the loans in the Credit Register at the sector 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.[5] 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,

[4]This approach to identify the bank-lending channel at the firm-level has been first proposed by Khwaja and Mian (2008).

[5]We have checked the robustness of the estimates presented in section 5 by using a credit supply shock obtained both by fixing weights as of 1999 and by letting weights vary across years. Results are basically unchanged. In the former case, the magnitude of the estimated coefficients is slightly attenuated, while in the latter it is slightly inflated.

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 we have a sector for which we estimate a credit supply shock of 5 and -5 at 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.

Table 5 shows the distribution of the credit supply shocks obtained as shown in equation 6, across industries 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.[6] 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*.[7] 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)).

[6] 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.

[7] 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.

5 Empirical strategy

In this section we investigate the effect of credit supply on sector-level productivity performance, 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, adopting regression models that speak as much as possible to the components of the aggregate productivity breakdown.

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 sector level (2-digit); $CSS_{s,t}$ 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 the one attached to 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 2, we claim this to be the case: on one side, the bank-specific shocks are by construction uncorrelated with any characteristics of the firms and the markets in which the bank 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.

In the next section, we will separately analyze the effect of credit supply at the sector level. We will focus on the effects on three different margin: the intensive margin (incumbent firms) the exit margin, and the entry margin. Finally, we will assess the effects on aggregate productivity.

6 Main results: Industry-level analysis

We test how credit shocks affect each of the 4 component of the Melitz-Polanec decomposition at the 2-digit industry level. Table 7, top panel, displays the results. Column 2 shows the impact on average productivity and column 3 the one on the OP covariance component. 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 average productivity of firms in the sector grows. This result is in line with intuition and with other empirical findings for the case of Italy Manaresi and Pierri (2016). The contribution of the OP covariance component to productivity growth is lower when industry s is hit by an idiosyncratic increase in credit supply. This result suggests that —when credit expands— the allocation of resources worsens, as smaller/less productive firms are able to acquire market shares. On the contrary, when credit contracts, resources are reallocated to the firms with higher market shares (the larger/more productive ones) in the same industry.

Column 4 displays the effect of credit shocks on the contribution of entrants, computed as described in equation 4. The estimated coefficient is positive, as expected, and statistically significant. Finally, column 5 shows the effect on the contribution of exiting firms. Results show that positive idiosyncratic shocks to credit in an industry decrease the contribution of exiting firms in the industry. Again, this is consistent with expectations.

The middle and bottom panels of Table 7 split the sample into pre-crisis (2000–2007) and crisis years (2008–2015). Results show that credit shocks affect the different components of productivity only during periods of financial crisis. This is reasonable, suggesting that when credit is abundant, idiosyncratic shocks can be easily absorbed, leading to limited effects on the firms' ability to grow, on the way resources are allocated, and on the decision of entering and exiting the market. When instead credit is overall scarce, idiosyncratic credit supply shocks can have large effects on these different margins.

Interestingly, the effect on total productivity is largely not significant. This suggests that the the different margins end up offsetting each other and having a small overall effect on aggregate productivity growth.

These findings suggest that —despite having no effect on aggregate productivity growth— idiosyncratic credit supply shocks trigger important within-industry dynamics. The effects on average firm productivity, on the OP covariance term, and —to a lesser extent— on the entry and exit margins are in fact sizable. During the crisis, credit supply changes contributed for a quarter of the drop in the contribution of average productivity to total productivity, and for more than half of the increase in the contribution of (within-industry) reallocation.

Therefore, idiosyncratic credit shocks had a significant *direct* impact on the average productivity of firms and on the reallocation of resources, especially during the crisis. Yet, the total effects of credit shocks may be larger. First, the identification of the supply-side component of the credit shock forces us to focus on relative idiosyncratic shocks. Our approach fails to detect the effects of aggregate, economy-wide credit shocks. For example an aggregate credit crunch may increase, say, uncertainty, and in this way depress firm investment and hiring decisions, and in this way productivity (due for example to lower R&D expenditure, or the lack of purchase of capital of newer vintage, or because of a worse match with workers; see de Ridder (2016) on the long-run impact of financial crises on output). Similarly, an aggregate credit crunch may reduce demand and in this way have an impact on firm productivity, again through lower investment and hiring decisions. Therefore, our findings can be regarded as a lower bound of the overall impact of credit shocks on aggregate productivity.

In the following section we exploit firm-level data to provide further evidence supporting the main results, in particular the ones hinting at potential cleansing effects of negative credit shocks.

7 Firm-level evidence

7.1 Employment growth at the firm level

Having established the relationship between bank supply shocks and the components of aggregate productivity growth, in this section we use the richness of our firm level data to provide some micro evidence on the reallocation mechanism described above. In doing so, it is worth stressing that —while in many models size and productivity are two perfectly-correlated features— in reality there are many large and unproductive firms, as well as many small and high productive firms. This heterogeneity turns out to be crucial to understand the underlying forces contributing to aggregate productivity growth via reallocation. Suppose, for example, that size and productivity correlate perfectly; then, an increase in allocative efficiency could stem from a shift of resources (employees) from the least to the most productive firms (that is, large firms get bigger and small ones shrink). When size and productivity are not perfectly correlated, however, this simple relationship does not hold anymore.

For this reason, we start by dividing firms according to the quintiles of the within-industry size and productivity distributions they belong to. As displayed in Table 8, between 25 and 40% of the firms belong to the main diagonal (firms that display roughly a one-to-one correlation between productivity and size), and therefore there are many firms lying off the main diagonal. Because of this, using either size or productivity to characterize the heterogeneous effects of the bank shocks could be misleading. As a consequence, we classify firms assigning them to one of the following three groups. The first contains all firms that are relatively less productive than their size would predict (that is, they belong to an employment quintile larger than the productivity one); we label these firms as "Under-performers" (U). The second group contains all the firms lying on the main diagonal (that is, firms that are either small and unproductive or large and very productive); we label these firms as "Balanced" (B). Finally, the third group contains all the firms that are relatively less productive than their size would predict; we label these firms as "Over-performers" (O). With this categorization of firms in hand, we study if the bank supply shock has heterogeneously affected employment growth at the firm level.

We estimate the effect of credit supply shock on employment growth using the following equation:

$$\Delta y_{ist} = \beta CSS_{s,t} + \delta_t + \delta_s + \delta_i + X_{it-1} + \varepsilon_{ist} \tag{8}$$

where y_{ist} is the growth rate of employment at firm level (log differences); $CSS_{s,t}$ is the credit supply shock, as defined in equation 6; δ_t are year fixed effects; δ_s are a set of sector fixed effects and δ_i are firm fixed effects. The vector X_{it-1} include the lagged level of employment and productivity to account for firm heterogeneity. ε_{ist} is an error term. Standard errors are double clustered at the sector and firm level to account for serial correlation.

Table 9 displays the results on employment growth at the firm level. The first column reports the results for the full sample, while the second and the third columns show the sample split before and after 2008, respectively. The top panel shows a positive and significant coefficient, once more driven by the years during the crisis (p-value 0.12). This tells us that —while in good times credit shocks do not on average induce firms to grow in size— during credit restrictions firm release some of their employees.

This effect is not uniform across firms: in the bottom panel of the table, we allow the effect of credit supply to be heterogeneous across different groups of firms. Results show that the positive effect of the credit supply shock is concentrated group of Under-performers, while it doesn't have a significant impact on Balanced and Over-performers. This effect is entirely driven by the observations belonging to the period during the crisis: when a negative credit shock hits the economy, under-performing firms on average reduce their employment, while the others ones do not modify their scale.

This evidence, which is consistent with a more selective economic environment arising as a consequence of a credit crunch, suggests that the credit restrictions experienced by Italian firms during the recessions of 2009 and 2012–2014 have had a "cleansing effect" on manufacturing. This has implied a redistribution of employment shares in favour of relatively more productive firms, and is therefore in line with a more prominent role of reallocation on the dynamics of aggregate productivity during a credit restriction.

7.2 Productivity dynamics at the firm level

We now turn to the analysis of the impact of credit supply shock on firms' productivity at the firm level. We estimate equation 8 using the growth rate of productivity at the firm level as a dependent variable. In table 10, the credit supply shock has a positive and significant coefficient (top panel, column 1); as columns (2) and (3) show, the result is entirely driven by the years during the crisis, mostly characterized by negative supply shocks. The sign of this relationship may reflect both managerial choices at the firm level (for example, through the dynamics of investments) and short-run adjustments in sales that are not accompanied by contemporaneous adjustments in terms of employees.

When we allow the effect of the credit supply shock to be heterogeneous across firms, in the set of results in the bottom panel of the table, we find the credit supply to be heterogeneous across different types of firms defined again in terms of the productivity and size distribution. Results show that the positive effect of the credit supply shock is concentrated in the balanced and over-performing firms, while it doesn't have a significant impact on under-performing firms. This effect is entirely driven by the observations belonging to the period during the crisis (although not precisely estimated): when a negative credit shock hits the economy, balanced and over-performing firms will on average reduce their productivity, while the Under-performing ones will not modify their productivity. This finding is consistent with the effects on employment growth: because output falls for all firms during recessions, productivity falls relatively more among firms that do not adjust employment (see table 9).

8 Conclusions

In this paper we study if and to what extent credit supply shocks can 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 detailed 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. 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 other channels, such as the within-firm productivity (because of the lower productivity growth of the incumbents).

Finally, our findings indicate that most of the gains come from the reallocation of employment shares to more efficient firms. However, the relevance of this channel could be especially large in a country like Italy, which is characterized by a high level of misallocation (Calligaris et al., 2016; Gamberoni et al., 2016) and therefore present a greater scope for reallocation. The positive effects of the credit restriction on reallocation may be smaller in other countries.

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Tables

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

	# firms	# employees	avg. size	sales	sales p.w.
			Levels		
2000	502,102	4,460,597	8.88	915,418	205,223
2001	502,706	4,481,840	8.92	961,250	214,477
2002	508,245	4,531,410	8.92	917,462	202,467
2003	497,751	4,551,915	9.14	898,515	197,393
2004	487,815	4,466,044	9.16	936,484	209,690
2005	482,369	4,411,785	9.15	927,168	210,157
2006	477,894	4,395,526	9.20	974,697	221,748
2007	473,469	4,432,864	9.36	1,014,716	228,908
2008	459,217	4,388,661	9.56	984,992	224,440
2009	438,678	4,153,744	9.47	822,789	198,084
2010	426,504	4,001,394	9.38	869,212	217,227
2011	425,312	3,982,285	9.36	898,559	225,639
2012	417,228	3,897,932	9.34	871,785	223,653
2013	407,307	3,782,829	9.29	831,344	219,768
2014	396,401	3,704,193	9.34	849,658	229,377
2015	389,346	3,627,960	9.32	855,010	235,672
			Growth rates		
2001	0.12	0.48	0.36	5.01	4.51
2002	1.10	1.11	0.00	-4.56	-5.60
2003	-2.06	0.45	2.57	-2.07	-2.51
2004	-2.00	-1.89	0.11	4.23	6.23
2005	-1.12	-1.21	-0.10	-0.99	0.22
2006	-0.93	-0.37	0.56	5.13	5.52
2007	-0.93	0.85	1.79	4.11	3.23
2008	-3.01	-1.00	2.08	-2.93	-1.95
2009	-4.47	-5.35	-0.92	-16.47	-11.74
2010	-2.78	-3.67	-0.92	5.64	9.66
2011	-0.28	-0.48	-0.20	3.38	3.87
2012	-1.90	-2.12	-0.22	-2.98	-0.88
2013	-2.38	-2.95	-0.59	-4.64	-1.74
2014	-2.68	-2.08	0.62	2.20	4.37
2015	-1.78	-2.04	-0.27	2.83	4.98

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 Italian aggregate manufacturing productivity

	Avg. prod.	Reallocation	Entry	Exit	Total
2001	-1,27	2,20	-1,86	1,89	0,96
2002	-2,59	2,54	-2,10	1,54	-0,61
2003	-3,92	0,88	-1,36	2,37	-2,04
2004	-0,21	3,02	-1,45	2,59	3,95
2005	-2,82	2,95	-1,54	2,17	0,76
2006	1,26	3,87	-1,95	2,44	5,62
2007	-0,41	3,06	-2,20	2,65	3,10
2008	-3,82	0,41	-2,39	3,14	-2,66
2009	-18,04	2,08	-1,75	3,74	-13,98
2010	1,02	7,93	-2,61	4,06	10,40
2011	-3,23	4,95	-2,24	2,65	2,12
2012	-7,59	1,80	-1,92	3,14	-4,57
2013	-5,61	5,88	-2,29	3,44	1,41
2014	-2,11	5,29	-2,16	3,57	4,59
2015	0,40	3,98	-2,29	3,59	5,68

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 single components may not add up to the total variation, since entry and exit from the manufacturing sector are not accounted for; their impact on the dynamics of aggregate productivity is negligible.

Table 3: Within and Between components of reallocation

	Total	Within	Between	% within
2001	2,20	2,30	-0,10	104,6
2002	2,54	1,90	0,64	74,7
2003	0,88	0,93	-0,06	106,4
2004	3,02	2,36	0,66	78,0
2005	2,95	2,32	0,63	78,5
2006	3,87	3,04	0,83	78,5
2007	3,06	2,80	0,26	91,6
2008	0,41	0,21	0,20	50,8
2009	2,08	3,26	-1,18	157,0
2010	7,93	5,77	2,16	72,7
2011	4,95	4,21	0,74	85,0
2012	1,80	1,62	0,18	90,1
2013	5,88	4,96	0,92	84,4
2014	5,29	4,39	0,90	83,0
2015	3,98	2,85	1,14	71,5
	Sub-period simple means			
2000–2007	2,65	2,23	0,41	87,46
2008–2015	4,04	3,41	0,63	86,81
2000–2015	3,39	2,86	0,53	87,11

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 Sectors

Sector	Avg. prod.	Reallocation	Entry	Exit	Total
		Period 2000–2007			
10	-1.53	1.00	-2.63	2.29	-0.87
11	-0.74	1.54	-1.51	0.77	0.07
13	-3.71	2.31	-1.22	1.90	-0.71
14	-2.48	4.09	-3.19	4.14	2.56
15	-4.20	4.45	-2.11	2.86	1.00
16	-0.00	1.14	-1.97	2.86	2.03
17	-3.65	6.31	-0.07	2.95	5.53
18	-2.85	3.98	-1.41	5.87	5.60
20	-2.61	3.37	-0.54	2.79	3.01
21	1.09	2.24	-0.22	0.19	3.30
22	-2.18	4.16	-0.92	1.55	2.62
23	-0.26	1.25	-1.68	1.46	0.76
24	-2.00	5.04	-0.54	0.73	3.23
25	-0.18	1.97	-1.70	1.64	1.73
26	-1.46	0.18	-0.24	1.90	0.38
27	-1.79	4.79	-1.28	1.14	2.86
28	-1.91	4.69	-0.85	1.82	3.76
29	-5.16	7.10	-1.60	2.27	2.61
30	-0.32	-0.45	-1.17	1.30	-0.63
31	-1.74	1.88	-2.42	2.73	0.46
32	-0.00	-0.85	-2.19	2.97	-0.07
33	1.02	-0.11	-1.98	0.41	-0.66
		Period 2008–2015			
10	-2.57	2.12	-3.56	4.60	0.58
11	-1.73	2.20	-3.35	3.06	0.18
13	-6.13	5.26	-1.86	3.81	1.07
14	-6.20	3.78	-4.69	6.95	-0.15
15	-5.65	4.70	-3.47	4.75	0.32
16	-5.84	1.93	-1.45	4.50	-0.86
17	-4.75	4.91	-1.01	1.68	0.83
18	-5.32	3.28	-1.52	3.60	0.04
20	-3.29	2.88	-1.19	1.16	-0.44
21	0.36	2.84	-0.84	-0.37	2.00
22	-4.68	3.99	-1.03	2.04	0.31
23	-6.09	3.52	-1.11	2.54	-1.13
24	-4.48	2.71	-0.66	0.89	-1.53
25	-4.71	3.59	-1.35	2.55	0.08
26	-4.31	6.19	-0.31	0.18	1.75
27	-4.99	3.69	-0.80	3.01	0.91
28	-4.50	4.09	-0.51	0.93	0.01
29	-5.69	6.63	-0.82	0.90	1.03
30	-7.12	7.86	-1.88	3.12	1.98
31	-6.65	3.96	-1.83	3.95	-0.57
32	-3.84	1.89	-2.20	3.09	-1.05
33	-4.44	3.53	-2.70	2.90	-0.70

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 single components may not add up to the total variation, since entry and exit from the manufacturing sector are not accounted for; their impact on the dynamics of aggregate productivity is negligible. Simple averages across year on year decomposition

Table 5: Summary statistics for the credit supply shock

2-digit Nace	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
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

	Total	Avg. Prod.	Reallocation	Entry	Exit
$CSS_{i,t}$	-0.254	0.407***	-0.594**	0.0828*	-0.151***
	(0.176)	(0.0986)	(0.239)	(0.0463)	(0.0532)
Sample Split: 2000–2007					
$CSS_{i,t}$	-0.300	-0.0323	-0.171	-0.0502	-0.0465
	(0.450)	(0.373)	(0.479)	(0.0958)	(0.218)
Sample Split: 2008–2015					
$CSS_{i,t}$	-0.194	0.325**	-0.566***	0.121***	-0.0731*
	(0.141)	(0.131)	(0.200)	(0.0203)	(0.0376)

Source: Own elaborations from ASIA dataset.
Notes: Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 8: Firm distribution by size and productivity

Size	Quintiles of Productivity				
	1	2	3	4	5
1	38.78	21.82	15.32	12.40	11.69
2	26.54	24.94	20.29	16.41	11.81
3	17.90	24.15	23.86	19.95	14.14
4	11.41	19.30	24.27	24.38	20.65
5	5.36	9.80	16.27	26.86	41.71
Firms classification into group					
1	B	O	O	O	O
2	U	B	O	O	O
3	U	U	B	O	O
4	U	U	U	B	O
5	U	U	U	U	B

Source: Own elaborations from ASIA dataset.
Notes:

Table 9: Growth rate of employees

	full sample	Sample Split 2000-2007	2008-2015
$CSS_{i,t}$	0.147*	0.108	0.131
	[0.0807]	[0.123]	[0.0974]
Heterogenous effects			
$CSS_{i,t}$ *			
Under-performer	0.233***	0.0575	0.220**
	[0.0786]	[0.129]	[0.102]
Balanced	0.140	0.146	0.123
	[0.0839]	[0.120]	[0.0979]
Over-performer	0.0838	0.152	0.0353
	[0.0823]	[0.120]	[0.0942]
N	3664477	1815960	1801220

Source: Own elaborations from ASIA dataset.
Notes: Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01

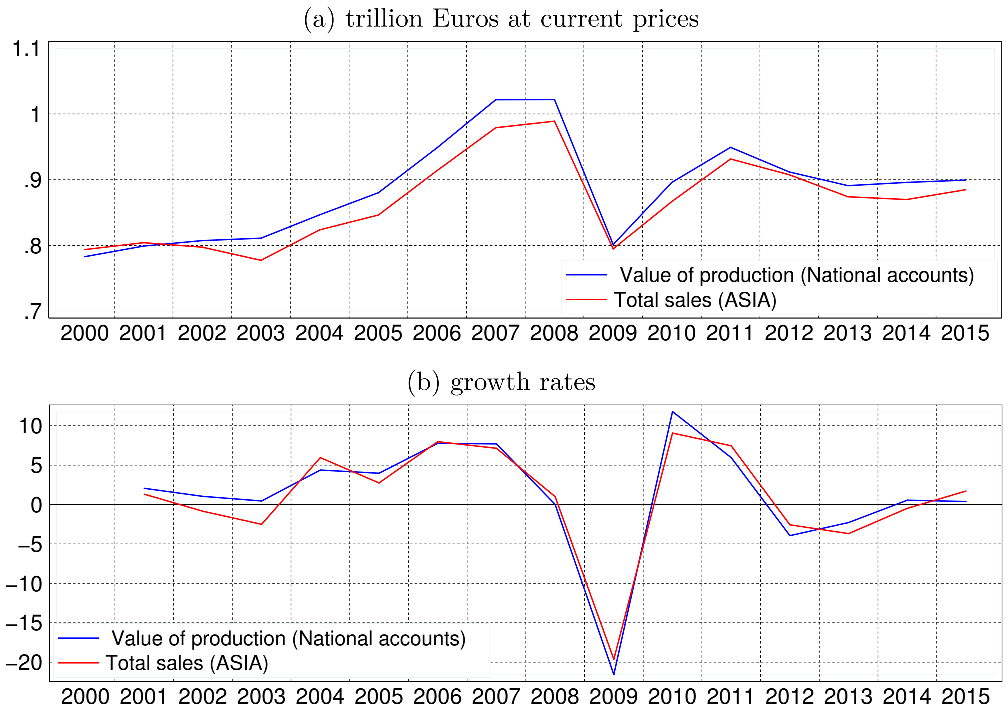
Table 10: Growth rate of productivity

		Sample Split	
	full sample	2000-2007	2008-2015
$CSS_{i,t}$	0.274**	-0.0000986	0.267
	[0.127]	[0.174]	[0.235]
Heterogeneous effects			
$CSS_{i,t}$ *			
Under-performer	0.205	-0.0213	0.171
	[0.129]	[0.170]	[0.233]
Balanced	0.274**	-0.0282	0.266
	[0.126]	[0.170]	[0.232]
Over-performer	0.359**	0.00446	0.390
	[0.129]	[0.174]	[0.237]
N	3664477	1815960	1801220

Source: Own elaborations from ASIA dataset.
Notes: Standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01

Figures

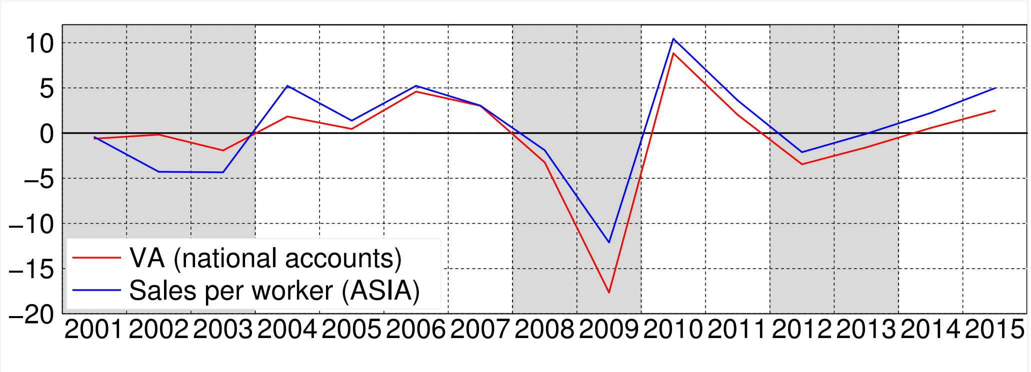
Figure 1: Comparison between National Accounts and ASIA dataset



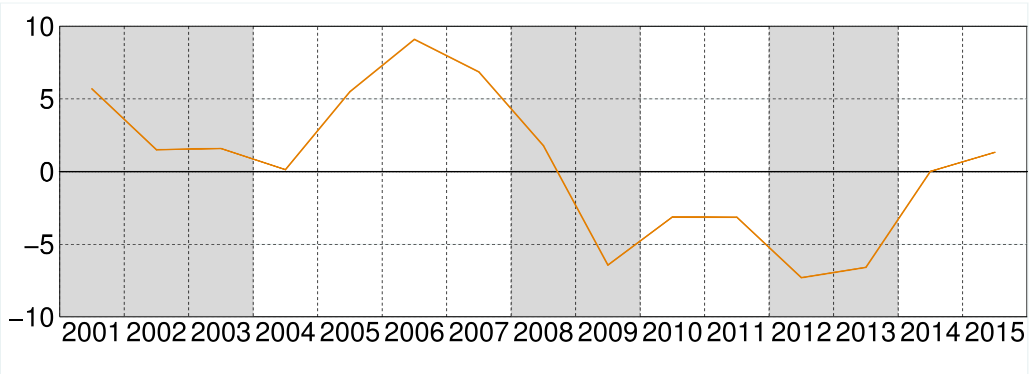
Source: National accounts and ASIA database.

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

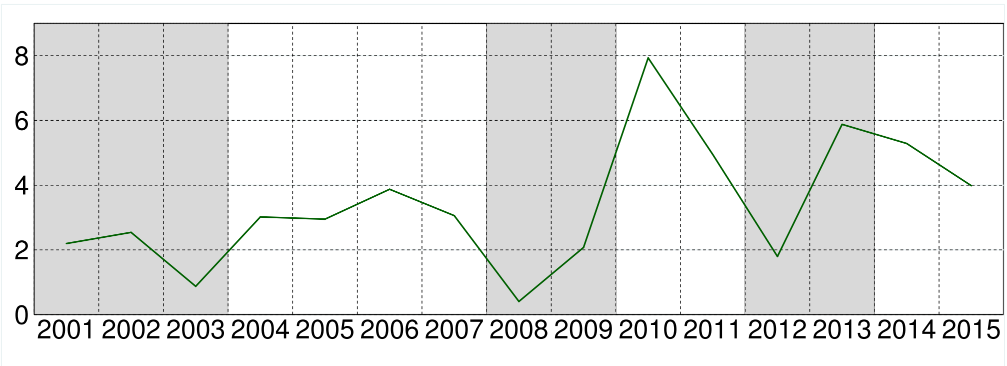
(a) aggregate VA and productivity (sales per worker)



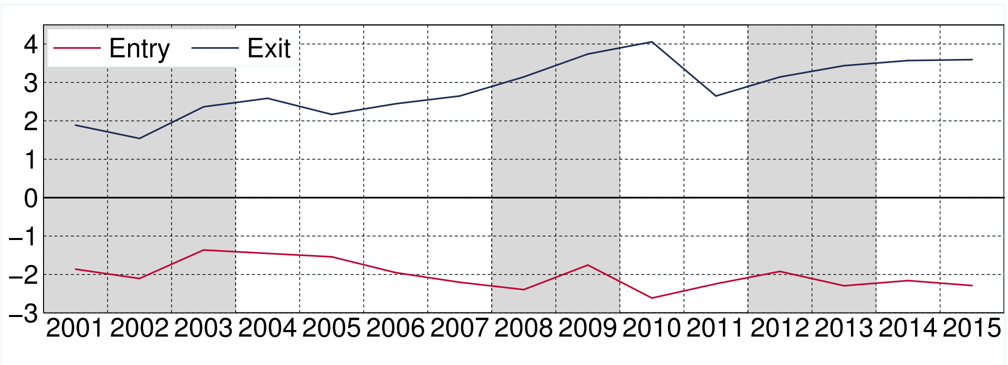
(b) total credit granted to manufacturing firms



(c) contribution of reallocation to aggregate productivity growth



(d) contribution of entry & exit to aggregate productivity growth



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.