Aggregate productivity slowdown in Europe through the prism of corporate balance sheets

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This version: Early March 2021

Abstract

Capitalising on the productivity decomposition proposed by Olley and Pakes (1996), we analyse the role of financial factors behind the relatively muted post-crisis rebound in productivity compared to previous upturns in Europe. Firstly, we provide an OLS-consistent framework to decompose sector-level productivity into trend and allocative efficiency components. We then extend our approach to estimate the contribution of firm-level confounders to the sector-level allocative component. Secondly, we find that financial leverage played an important role in explaining the change in aggregate productivity growth in Europe between 2004 and 2017. Thirdly, focusing on Northern and Western Europe, we show that the productivity potential could have not been fully exploited due to access to credit conditions. Specifically, reducing collateral bottlenecks could more than double the effectiveness of financial leverage in spurring productivity growth in this region between 2014-2017.

1 Introduction

Slowdown in the aggregate productivity in the early years of the XXI century has attracted a lot of attention in the literature (Banerjee and Duflo, 2019). While a number of theories have been put forward, pinning down several mechanisms, one of the key ones is the problem of resource misallocation (Gopinath et al., 2017; Barbiero et al., 2020).

From the perspective of aggregate production, it matters greatly whether the available resources are employed in the firms that make the best use of them. Indeed, longer-term economic growth can be reduced when less productive firms lock in production factors which could have been better deployed elsewhere (Banerjee and Duflo, 2005; Peek and Rosengren, 2005). While the creative destruction theory predicts that inefficient firms should be replaced by more productive ones, the process may take longer than desired from a welfare perspective owing to market frictions, bank forbearance, or side-effects of regulation. In fact, Eurostat (2016) estimates that if allocative efficiency among the EU manufacturing firms remained at the level from 2003 throughout the following years, the production in that sector would have

*Views presented in the paper are those of the authors only and do not necessarily represent the views of the European Investment Bank (EIB).

been by 6 per cent higher in 2014, ceteris paribus. When taking into account the market service firms, the gains would have been around 24 per cent over the same period.

Several approaches have been developed to estimate resource misallocation and its macroeconomic implications. On the one hand, Hsieh and Klenow (2009) and Gopinath et al. (2017) consider that the dispersion of the marginal revenue product of production factor within sector is indicative of ressource misallocation. Under efficient allocation, companies shouldn't be able to extract rents from production factors and marginal revenues should be equal for firms producing the same good. On the other hand, Olley and Pakes (1996) (hereafter OP) propose to decompose aggregate productivity as a sum of trend and covariance component (the latter one is often dubbed as allocative efficiency). The proposed methodology relies on the idea that more productive firms should have a higher market share, such that if low-productivity firms dominate certain market segments one can denote such an outcome as inefficient. More recently, Melitz and Polanec (2015) extend the OP decomposition for the entry-exit dynamics of firms.

We take the Olley and Pakes (1996) as a starting point in our study. Firstly, we propose a new methodology to estimate the OP components of aggregate productivity within an Ordinary Least Square (OLS) framework. We formally show that, after re-scaling the relevant variables, a re-weighted OLS regression offers an simple and convenient technique to provide an aggregation of sector-specific OP results across various data partitions. Secondly, we offer an extension of the OLS framework to estimate the contribution of firm-specific factors to the sector-wide covariance productivity component. In particular, we show that this contribution can be represented as a product of relevant coefficients from the regressions on productivity and market shares metrics. Interestingly, the method allows to control for other firm-specific factors, reducing thereby the omitted variables bias.

We take this novel methodology to the data and assess the contribution of financial variables, in particular the debt-related ones, to the OP covariance productivity dynamics across selected EU Member States. Firstly, we find that the allocative efficiency component contributed positively to the overall labour productivity growth throughout the years. The contribution was the strongest during the crisis years, which could be attributed to the cleansing effect of the recession (Duval et al., 2019), and the smallest in the years following the crisis, as the firms took their time to adjust the production processes.

Secondly, we estimate the contribution of firm-level financial leverage to the growth in covariance productivity component. At the EU level, access to finance contributed some 27 per cent of the allocative productivity growth before the crisis and then collapsed during the crisis period. In the after-crisis years the finance-driven allocative effiency growth was muted. While it picked up marginally between in 2014-2017, it never really recovered to the pre-crisis levels with the contribution being nearly twice smaller at 14 per cent. To put it in perspective, should the financial leverage component in years 2014-2017 grow at the pre-crisis levels, the covariance labour productivity component in 2017 could have been higher by 0.76% in Central-Eastern and South-Eastern Europe, by 1.75% in Southern Europe and by 6.67% in Western and Northern Europe, or respectively by EUR 87, EUR 512 and EUR 967.

Finally, we elaborate on the reasons for which the after-crisis covariance productivity growth has been subdued. In particular, we calculate the contribution of financial leverage to the allocative efficiency component, controlling for the distributional effects generated by the firms susceptible to either debt overhang, ever-greening or financial constraints problems. It seems that during the crisis years, the allocative productivity growth was mostly hampered by the debt overhang problem, and after the crisis the productivity gains were locked in by financial constraints, linked to the availability of collateral. For instance, should the distribution of firm-level productivity be independent from collateral levels, debt could have been more than twice more effective in spurring allocative efficiency growth across West and North Europe between 2014-2017.

The reminder of the paper consists of 5 sections. Section 2 motivates the study with a brief overview of the recent literature. Section 3 offers an introduction to our methodological approach with the main details and derivations laid out in the on-line Appendix. The empirical design, focusing on the estimation of allocative efficiency, is depicted in Section 4. The role of external finance access is investigated in Section 5. Section 6 concludes.

2 Motivation

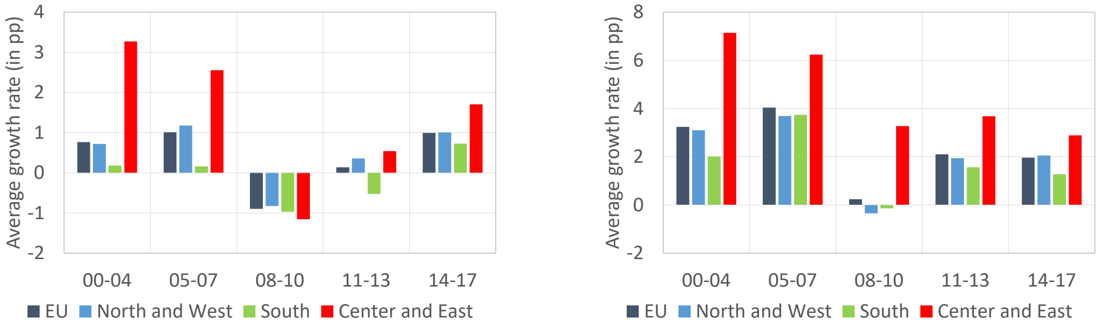
Long-run productivity growth has not been stable across developed economies. After the golden years of solid growth in Total Factor Productivity (TFP), from the beginning of the twentieth century to the end of the sixties, came almost 3 decades of stagnation (Gordon, 2016). In particular, between 1920 and 1970 the annualized TFP growth in the US reached 1.89 per cent per year, while between 1970 and 1995 it averaged to about a third of that, leveling at 0.57 per cent per year. After a couple of better-than-average years of TFP growth leading to the new millennium, the productivity again substantially reduced its dynamism in the recent years. According to Gordon (2016), from 2004 until 2014 the productivity growth in the US average to a mere 0.4 per cent per year. While the rates of growth picked up recently, they are still substantially below the hefty years of the XX century.[1] In Europe also, productivity growth is on a trend decline since the late 90s. Figure 1 compares the evolution of TFP growth and labour productivity growth in the first early 2000s years.[2] For the EU and the three subregions, the two measures have decreased over time, with the decline exacerbated during the crisis period. In the current upturn, a partial reversion is observed, but growth rates remain below pre-crisis average - particularly so when it comes to the labour productivity measure (Figure 1 (b)).

Productivity deceleration is much pronounced in the Central Eastern and Southern-Eastern Europe (CESEE). To a large extent, it can be explained by the gradual catching-up process of the region - along the convergence with the rest of EU, the productivity gap diminishes and productivity slows down. However, given the relatively small GDP share of the region (of around 8%), the overall impact on the EU remains contained. At best, the catching-up process of CESEE contributes little to the overall EU evolution.

[1] Some research suggests that the impact of the digital sector on economic activity is underestimated in national accounts. Some estimates for the US indicate that growth could have been up to 0.15 p.p. each year since 2005 (Nakamura et al., 2017).

[2] It is well known that TFP growth is difficult to measure as it requires estimating production functions at the sectoral level. Therefore, we extend our attention in the paper to a simpler measure - labour productivity - expressed as output per hours worked.

Figure 1: Long-term evolution of productivity measured from macroeconomic series.



(a) Total factor productivity

(b) Labour productivity

Notes: Labour productivity calculated as GDP per person employed. Authors' computations based on European Commission and Eurostat. See notes to Table 1 for the composition of the regions.

As productivity growth raises aggregate production levels, it is no surprise that it has been a focal element of both theoretical and empirical research. While there is no single answer pointing to one specific bottleneck to unlock productivity growth potential, a number of possible explanations have been put forward.

2.1 Productivity and misallocation

A strand of research claims that resource misallocation is responsible for the disappointing overall post-crisis economic performance. Among it, a chunk of the literature draws on the seminal work of Hsieh and Klenow (2009) who take the view that productivity dispersion reflects a deviation from the competitive equilibrium and as such can be associated with resource misallocation. Gorodnichenko et al. (2018) propose a simple theoretical framework, linking the dispersion in marginal products of capital and labour to efficient allocation of resources. Under perfect allocation, the marginal products should be equal across firms operating in the same sectors. High dispersion can be related to distortions to the production sector and whether resources flow to the most productive investment projects. The authors argue that rising misallocation of resources in European countries could be one of the culprits to the productivity slowdown.

Borio et al. (2016) emphasize the role of misallocation of labour during the pre-crisis financial boom and the long shadow it has cast post-crisis. The authors develop an empirical analysis covering more than 20 advanced economies over 40 years. Their analysis suggests that resource misallocation can be a consequence of a major financial boom and bust cycle, and it can be present years after the economy rebounds.

In the most recent literature, several reasons have been advanced to explain why part of the productivity dispersion could also reflect an equilibrium. For example, David et al. (2018) show that dispersion in static marginal products of capital is linked to systematic investment risks. As firms can differ in their exposure to these risks, firm-level risk premia are not identical and productivity is not necessarily equalized within sector.

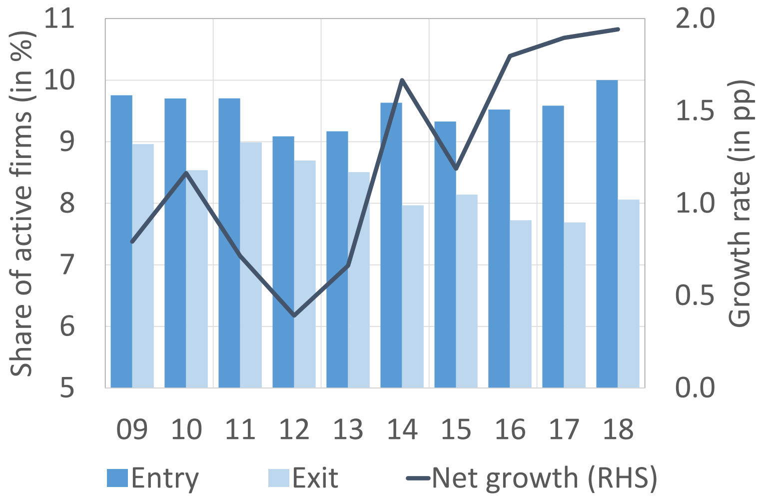
Beyond resource allocation, life in the corporate ecosystem is yet another important contributor to productivity growth. Indeed, building on the work of Foster et al. (2001), Andrews et al. (2016) show that the productivity slowdown results from the deterioration in the two underlying microeconomic forces, a noticeable decline over time in the pace of laggard firm's catch-up to the global productivity frontier, and a reduction in the extent of market dynamism and growth-enhancing reallocation.

2.2 The role of Exit and Entry in the corporate ecosystem

Reflecting the productivity trends cited at the beginning of Section 2, Decker et al. (2014) show that the US economy has recorded a trend towards concentration and less entries in the corporate ecosystem over the last three decades. The percentage of employment at firms with less than 100 employees has fallen from 40 to 35% and the annual rate of enterprise creation has decreased from 13 to less than 8%. In parallel, the share of employment by young firms (less than 5 years) has decreased from 18 to 8%, while that by large large firms has increased, from one-quarter in the 1980s to about one-third in 2010.

Focusing on the EU economy, Figure 2 plots the entry and exit rate in the corporate ecosystem, over the recent years. Net entry follows a cyclical cycle and it has been, on average, positive over the last years. Net entry is observed to be higher during periods of upswing, such as since the beginning of 2013, and lower during downturns, such as during the sovereign debt crisis. This cyclical pattern is mostly driven by changes in entry rates it appears that exits have not increased significantly during the crisis.

Figure 2: Exit and entry in the European corporate ecosystem.



Notes: Authors' computations based on Eurostat.

The absence of a cyclical pattern in the exit rate may suggest that, since the financial crisis in Europe, the roll-over of bank loans has taken place at the expense of exiting the market. This phenomenon is often dubbed as ever-greening (Peek and Rosengren, 2005). This seems at odds with the normal cyclical behaviour of cleansing, whereby recessions enable weaker firms to exit the market, thereby freeing resources for the rest of the economy and enabling these resources to move to the most productive firms. When the banking sector is relatively weak and encumbered with impaired assets, it is slow to recognize the losses. As a consequence, the incentives for ever-greening go up, locking in banking capital which could have been used more productively otherwise (Gropp et al., 2018; Andrews and Petroulakis, 2019).

2.3 Access to finance as an indirect contributor

Access to finance may have important influence how corporates allocate the resources. A vast body of literature point to the conclusion that better access to credit should have an unambiguously positive effect on economic growth (Rajan and Zingales, 1998). Companies which are credit-rationed may not pursue the most productive investment projects if they do not have access to the necessary funding. In parallel, firms with abundant and cheap financing may find it profitable to engage in projects which would have not been profitable otherwise. The ability to channel the resources to highly productive projects may be then distorted by the allocation of corporate credit, financial incentives and ability of financial sector to screen and monitor investment projects. Weak banking sector can exacerbate these elements.

However, the recent studies show that the link between credit access and productivity growth may not be monotonic. Aghion et al. (2019) show the existence of two counteracting effects of access to credit on productivity growth. The authors argue that excessively easy access to credit can be a drag on productivity. This is because better credit access allows less efficient incumbent firms to remain longer on the market, thereby discouraging entry of new and potentially more efficient innovators. On the one hand, better access to credit makes it easier for entrepreneurs to innovate. On the other hand, better credit access allows less efficient incumbent firms to remain longer on the market, thereby discouraging entry of new and potentially more efficient innovators. Overall, the link between credit access and productivity growth may be inverted U-shaped, with productivity increasing as credit conditions relax. Beyond a certain threshold, the relationship becomes inverted, as access to credit becomes too loose and it favours ever-greening, misallocation and becomes detrimental to productivity growth.

Duval et al. (2019) argue that after the global financial crisis, the interplay between tighter credit conditions and weak corporate balance sheets generated a TFP hysteresis effect, playing an important role in the post-crisis productivity slowdown in advanced economies. They further deliver evidence that more restrictive access to credit led more vulnerable firms to cut back on intangible investment expenditure, hence reducing innovation.

Itskhoki and Moll (2019) demonstrate that in the presence of financial frictions, in the form of a collateral constraint, highly productive entrepreneurs cannot expand their capital. This, in fact, locks them out from competing in the product market and consequently the low-productivity firms rip of the excess returns on their products, weighing down on productivity metrics. The authors estimate that the overall welfare gains from optimal labor taxation policies can range from 0.2 to 0.5% in consumption-equivalent units.

Gopinath et al. (2017) find significant trends in the loss in TFP due to misallocation of resources in Italy and Portugal, but do not find such trends in Germany, France, and Norway. This signals that misallocation can be associated with country-wide credit market conditions, as firms in Southern Europe are likely to operate in less-developed financial markets. Having pointed this out, the authors illustrate how the decline in the real interest rate has led to a significant decline in sectoral total factor productivity. This was a consequence of capital inflows being misallocated toward firms that had higher net worth but were not necessarily more productive.

This conclusion is reiterated by Banerjee and Hofmann (2018), who decompose sector-wide productivity into a common component and an allocation component. The authors show that while allocation does not account for much of the evolution in productivity, it is negatively affected by a flattening of the yield curve. It is linked to the fact that investment is financed at long-term rates. Higher rates result in lower investment such that resources are relocated to the higher productivity sectors, improving the overall resource allocation.

Firm-level capital structure may be another important channel through which macro-financial conditions translate into resource decisions. Barbiero et al. (2020) show that at higher levels of indebtedness firms which operate in high-growth sectors invest relatively more than otherwise identical firms with less debt. These positive effects disappear, however if firms' debt is already excessive, if it is dominated by short maturities, and during systemic banking crises.

Theoretical foundations of this study reach back to the arguments proposed by Barbiero et al. (2020) that agency problems between managers and shareholders, and between firms and investors, can lead firms to shift investment away from the most productive projects available (Myers, 1977; Jensen and Meckling, 1976; Fuchs et al., 2016).

More specifically, we focus on the link between corporates' balance sheet and sector-level productivity. We first develop a new approach to implement the Olley-Pakes approach decomposition of labour productivity into the sector-wide trend productivity and firms' allocation efficiency, expressed as a within-sector covariance between firms' market share and productivity. The idea behind the decomposition is that if firms with higher productivity have a higher market share, then firms' distribution contributes positively to productivity compared to a uniform allocation. We then estimate this decomposition on a very large of EU corporates. Finally, we link the allocative efficiency component to the distribution of debt.

3 Analytical framework

Our methodological approach capitalizes on the aggregate productivity decomposition proposed by Olley and Pakes (1996), OP hereafter. It is developed in three steps.[3] In the first step, we consider a very simplified economy consisting only of one sector at a given time (Section 3.1). In the second step, we generalize our methodology to an economy consisting of many sectors (Section 3.2). In the third step, we focus on the drivers of the efficiency component of the OP equation (Section 3.3). More specifically, we propose to estimate the relevance of the confounding variables to the level of efficiency component by using the law of total covariance.

[3]The presentation of the paper is rather simplified to the basic logic behind the mathematical formulas in the main body of the paper, but the formal proofs and generalizations are available on the in-line Appendix.

Importantly, the framework allows to measure the contribution of particular confounders to the OP efficiency component, controlling for firm-specific factors and thereby alleviating, to the extent of observable and measurable factors, the omitted variable bias.

3.1 A one-sector approach

Let us denote the aggregate productivity level in industry s by Ψ_s. OP decomposition rewrites aggregate productivity in terms of the unweighted and weighted components as:

$$\Psi_s = \bar{\psi}_s + \sum_i \left(\psi_{is} - \bar{\psi}_s\right)\left(w_{is} - \bar{w}_s\right), \tag{1}$$

where $\bar{\psi}_s = 1/n_s \sum_{i=1}^{n_s} \psi_{is}$ is the unweighted average productivity level, w_{is} is the within-sector market share of firm i, and $\bar{w}_s$ is the mean market share. By definition, the market shares of each firm operating in a specific sectors are positive and they add up to 1.[4] Within-sector number of firms is given by n_s, and we take only meaningful cases where $n_s \geq 2$. Firm-level productivity is represented by ψ_{is}.

The OP decomposes aggregate productivity into an un-weighted component, sometimes referred to as trend productivity, and a covariance component, representing the allocative efficiency. The latter indicates by how much productivity is modified compared to uniform distribution where each firm has the same market share, a benchamrk case reflected in $\bar{\psi}_s$. The component is positive, raising productivity, when stronger-productivity firms have a higher market share. Conversely, it is negative, reducing the overall productivity in the sector, when low productivity firms tend to have higher market shares.

To build a link to the OLS regression, we observe that, using the sample covariance estimates, the efficiency component can be re-written as:[5]

$$\sum_i \left(\psi_{is} - \bar{\psi}_s\right)\left(w_{is} - \bar{w}_s\right) = (n_s - 1)\mathrm{cov}(\psi_s, w_s), \tag{2}$$

where cov stands for covariance. It follows that the OLS estimate $\hat{\beta}_1$ from a simple linear model $\psi = \beta_0 + \beta_1 w + \varepsilon$, is a re-scaled Right Hand Side (RHS) of Eq. (2). Skipping the subscripts, it is a well known property of OLS that $\hat{\beta}_1 = \mathrm{cov}(\psi, w)/\mathrm{var}(w)$, where $\mathrm{var}(w)$ is the variance of w.

Consequently, the covariance misallocation estimate can be calculated by fitting the OLS regression on re-scaled variables $\psi' \equiv f(\psi)$ and $\tilde{w} \equiv g(w)$. The key transformation is the standarization of w to $\tilde{w}$, where $\mathrm{var}(\tilde{w}) = 1$. To balance the effects on the dependent variable, in the second transformation we set $\psi' = \psi(n-1)\sigma_w$, where σ_w is the standard deviation of w.

Estimating the regression on the re-scaled variables $\psi' = \beta_0 + \beta_1 \tilde{w} + \varepsilon$, one may find that $\hat{\beta}_1 = (n-1)\mathrm{cov}(\psi, w)$, which is equivalent to the RHS of Eq. (2). The formal demonstration of the argument is given in Proposition 1 in the online Appendix.

[4]While the decomposition from Eq. (1) was extended by a time dimension (see, for instance, Melitz and Polanec (2015)), there is no clear-cut regression representation of such dynamic specification. Hence, we focus here on static estimates for time t and leave the dynamic representation for future investigations.

[5]For the population covariance, the multiplier becomes n_s instead of $n_s - 1$. We apply the Bessel's correction in line with the majority of OLS software implementations.

3.2 Generalisation to several sectors

Let us assume that the economy consist of S sectors, indexed as $s = 1, ..., S$ with $S \geq 2$.[6] By the law of total expectations, Eq. (2) can be aggregated at the general economy level as:

$$\mathbb{E}\left[(n_S - 1)\mathrm{cov}(\psi_S, w_S)|S\right] = \sum_s (n_s - 1)\mathrm{cov}(\psi_s, w_s)\pi_s, \tag{3}$$

where π_s determines the across-sector market share weights that add up to 1.

As Eq. (3) is linear between sectors, the OLS strategy developed in Section 3.1 can be extended to cover multiple sectors provided that (i) ψ' and $\tilde{w}$ are standardized by sector and (ii) the regression is re-weighted by a combination of π_s and the inverse sample weights $n/(n_s - 1)$, where n_s is the number of firms in sector s and n is the total number of firms. It can be verified that the estimates from the weighted OLS on the re-scaled variables on the full sample, correspond to the outcome when estimating the covariance productivity by sector and taking the weighted average. The procedure is formalized in Proposition 2 in the on-line Appendix.

Eqs. (2) and (3) offer an elegant and efficient framework to track the OP covariance productivity across multiple sectors. One should note that the original variation for the covariance component comes only from within-sector firm characteristics such that the $\hat{\beta}_1$ estimate is a weighted sum of sector-specific allocative efficiency scores. The population weights can be chosen to correct for under/over-representation of particular sectors in data sets.[7] A direct benefit of applying the OLS framework to the OP decomposition is related to the inference. If the standarization of ψ and w were deterministic, OLS estimates could have been estimated consistently under Gauss–Markov assumptions. In practice, however, both ψ' and $\tilde{w}$ are stochastic as σ_w is itself an estimate. While it is possible to derive a closed-form asymptotics for such a basic example, due to complexities of the next steps, in our applications we will rely on bootstrapped confidence intervals.

Under a reasonable assumption that the variables in question have finite first and second moments, $\hat{\beta}_1$ from the weighted OLS regression is asymptotically tight. We propose a stratified bootstrap approach, where for each bootstrap replica b we re-sample firms (with replacement) per sector and estimate the corresponding $\hat{\beta}_1^b$. Standard errors and confidence intervals are calculated over the bootstrapped results $\hat{\beta}_1^1, ..., \hat{\beta}_1^B$, where B is the total number of replicas.

3.3 Estimating the relevance of confounding factors

For transparency, we revert to a single-sector setup to introduce conditional elements in the OP decomposition. Suppose that there is a confounding variable Z with realizations z, observed at a firm level. For simplicity, take that Z is one dimensional, however Proposition 3 in Appendix

[6] While in our exposition, the decomposition of the economy is based on sectors of activity, it does have not to. A data cut can also reflect a geography, legal type, size, R&D content, etc.

[7] While it is not the direct element of further analysis, the unweighted average component from the OP decomposition in Eq. (1) can also be extracted through the OLS framework but with a modest modification. In particular, the term $\bar{\psi}_s$ is equivalent a constant from a re-weighted regression $\psi_{is} = \beta_0 + \beta_1\tilde{w}_{is} + \varepsilon_{is}$. As the constant term aggregation does not involve the Bessel's correction, the weights in the weighted OLS should equal the product of population weights π_s and uncorrected inverse sample weights n/n_s. Since our primary objective is to study the covariance metric, we leave it out from the proposition.

allows for d_Z-dimensional setups, $d_Z \geq 1$. By the law of total covariance, we arrive at:

$$\operatorname{cov}(\psi_s, w_s) = \mathbb{E}\left[\operatorname{cov}(\psi_s, w_s|Z)\right] + \operatorname{cov}(\mathbb{E}[\psi_s|Z], \mathbb{E}[w_s|Z]). \tag{4}$$

The first element in the decomposition is the average covariance term when controlling for confounder Z at the firm level. It informs what would have been the level of covariance had the within-sector variation in Z been removed. The second term depicts the contribution of confounder Z to the overall covariance level, through relation with both ψ and w variables.

While the first term in Eq. (4) does not have a direct plug-in estimate, under taking the linear representation as the first-best approximation, the second term can be estimated on corresponding fitted values. More precisely, let us take $\mathbb{E}[\psi_i|z_i] \equiv \hat{\psi}_i = \hat{\alpha}_0 + \hat{\alpha}_1 z_i$ and $\mathbb{E}[w_i|z_i] \equiv \hat{w}_i = \hat{\beta}_0 + \hat{\beta}_1 z_i$, where both α and β parameters are fitted on the respective models using the OLS framework. It follows that $\operatorname{cov}(\hat{\psi}_s, \hat{w}_s) = \hat{\alpha}_1 \hat{\beta}_1 \operatorname{var}(Z_s)$. We propose the following estimation framework to match the desired magnitude of the coefficients:

$$\begin{aligned} \psi''_{is} &= \alpha_0 + \alpha_1 \tilde{z}_{is} + \nu_{is}, \\ w''_{is} &= \beta_0 + \beta_1 \tilde{z}_{is} + \varepsilon_{is}, \end{aligned} \tag{5}$$

where $\psi''_{is} = \psi_{is}\sqrt{n_s - 1}$, $w''_{is} = w_{is}\sqrt{n_s - 1}$ and $\tilde{z}_{is}$ is the standard score of Z in sector s. In effect, $(n_s - 1)\operatorname{cov}(\hat{\psi}_s, \hat{w}_s) = \hat{\alpha}_1 \hat{\beta}_1$.

At this stage it is worth noting, that the setup has its identification limits when $d_Z \geq 2$. Even if the confounders were mutually independent, the marginal contribution of confounders $Z^1, ..., Z^{d_Z}$ can only be identified jointly as a sum of product of respective coefficients, i.e. $\hat{\alpha}_1^1 \hat{\beta}_1^1 + ... + \hat{\alpha}_{d_Z}^{d_Z} \hat{\beta}_{d_Z}^{d_Z}$. It is due to the fact that the magnitude of the remainder terms in multivariate extension of Eq. (4) depends on the order of conditioning variables.

Despite the limits when considering a large number of covariates, the setup has an interesting property that allows to single out the effects of specific covariates, controlling for other firm-level characteristics. Let us reformulate the original question in the way that we're interested in measuring the impact of a confounding variable Z on the OP covariance productivity level, controlling for a vector of observable variables Q, $d_Q \geq 1$. This question translates into the conditional covariance decomposition as:

$$\operatorname{cov}(\psi_s, w_s|Q = q) = \mathbb{E}\left[\operatorname{cov}(\psi_s, w_s|Q = q, Z)\right] + \operatorname{cov}(\mathbb{E}[\psi_s|Q = q, Z], \mathbb{E}[w_s|Q = q, Z]). \tag{6}$$

We propose to fit the following linear models:

$$\begin{aligned} \psi''_{is} &= \alpha_0 + \alpha_1 \tilde{z}_{is} + \gamma_1 \tilde{q}_{is}^1 + ... + \gamma_{d_Q} \tilde{q}_{is}^{d_Q} + \nu_{is}, \\ w''_{is} &= \beta_0 + \beta_1 \tilde{z}_{is} + \delta_1 \tilde{q}_{is}^1 + ... + \delta_{d_Q} \tilde{q}_{is}^{d_Q} + \varepsilon_{is}, \end{aligned} \tag{7}$$

where variables ψ''_{is}, w''_{is} and $\tilde{z}_{is}$ are as above, and we use a standard scores for Q variables denoted by $\tilde{q}_{is}^1$ through $\tilde{q}_{is}^{d_Q}$ to match the scale of Z variable. As realizations q enter into Eq. (7) as fixed, it follows that $(n_s - 1)\operatorname{cov}(\hat{\psi}_s|Q = q, \hat{w}_s|Q = q) = \hat{\alpha}_1 \hat{\beta}_1$.

We note that the decompositions in Eq. (4) and in Eq. (6) happen within sector, hence similar aggregation strategy as in Section 3.2 can be applied to cover multiple sectors. The formalization of the procedure can be found in Propositions 4 and 5 in the online Appendix. Similarly, the standard errors for the product of the coefficients can be obtained with stratified bootstrap approach.

4 Estimating allocative efficiency

We now take the proposed methodology to the data. We begin by a brief description of our sample data of European corporates, and comparing them against basic summary statistics officially reported by the Eurostat. In the analysis, we pay particular attention to geographical breakdown, distinguishing between the three main regions, i.e. Western and Northern Europe, Southern Europe and Central, Eastern and Southern Eastern Europe (CESEE).[8] The sectoral granularity covers the representative group of 228 4-digit manufacturing sectors, according to the Nace Rev. 2 classification.

We estimate the OP decomposition, i.e. the trend and covariance productivity components, for each year from 2004 until 2017. Our core metric concerns the labour productivity, defined as value added per person employed. Following the strategy proposed in Section 3, we estimate the OP decomposition on productivity levels. We then compute the growth rates and report the results on them in the main text. Results on the levels are reported in Appendix.

Last but not least, we estimate the contribution of availability of external finance at the firm-level to economy-wide covariance productivity component, controlling for several observable factors. There are multiple potential candidate variables to consider when thinking about access to finance metrics. In the current setup, we follow the strategy proposed by Barbiero et al. (2020), and in the main specification we focus on the financial leverage, defined as a ratio of total debt to total assets. As a robustness check we extend the specification to the net financial leverage, defined as a ratio of total debt minus cash holdings to total assets.

4.1 Data

We use firm-level information included in the ORBIS database provided by Bureau van Dijk (BvD). The database contains firm-level financial statements and ownership data, gathered and standardized to the so-called 'global format', being comparable across jurisdictions. Our database updates come semi-annually in vintages, where each vintage is cleaned up from companies which haven't reported any information for 10 years or more. Therefore, to correct for the survivorship bias, we aggregate the data for all the vintages to obtain a sample covering 14 years, from 2004 until 2017.

We select corporates from all EU28 countries and consider unconsolidated accounts. As the within-sector coverage is key in our identification strategy, we look into the Manufacturing sector only (Section C according to the Nace Rev. 2 classification), as having the most representative coverage (Gopinath et al., 2017). Our main grid of interest is composed of 228 4-digit sectors (from the total pot of 230 4-digit sectors reported by Eurostat).

[8] For exact country coverage please refer to the notes to Table 1.

In the data-cleaning procedure, we exclude observations with odd or inconsistent values in the spirit of Barbiero et al. (2020). We drop firm-year observations in which total assets, fixed assets, intangible fixed assets, sales, long-term debt, loans, creditors, debtors, other current liabilities, or total shareholder funds and liabilities have negative values. We then check for the reporting consistency and drop the firm-year financial statements which violate the basic balance-sheet equivalences by more than 10%. Specifically, we impose that (i) total assets match total liabilities, (ii) total assets match the sum of fixed assets and current assets, and (iii) current liabilities match the sum of loans, trade credit and other current liabilities. We also deflate variables using the country-specific Harmonised Index of Consumer Prices (HICP) deflators. All data are winsorized at 1% level.

To limit potential composition bias and to guarantee sufficient statistical power at the sectoral level, we focus only on sectors which have at least 30 firms in every year from 2004 until 2017 at the 4-digit. While this step results in a dropout of around 18% of all observations (20% of firms), it improves the comparability of the results across years and it is less susceptible to sudden swings in the reported number of firms per sector.

Our main variables of interest include the Value Added (VA) market share and labour productivity. The former is calculated based on the reported added value in the corporate accounts. If it is not given explicitly, we fit it either by the sum of employee cost and EBITDA, or by the difference between turnover/sales and material costs. To reflect the sectoral grid, the VA market shares are calculated based on 4-digit sector codes. Labour productivity is obtained as the ratio between value added and the number of people employed in a firm.

Finally, to improve the representativeness of the sample, we exclude the countries for which the average sector coverage is below 10% of the active population of enterprises as reported by the Structural Business Statistics in Eurostat. While this leaves out Poland and Germany, for instance, the data attrition is small (around 1% in terms of number of observations, and roughly 2% in terms of the number of firms).

Overall, we work with a data set covering 17 EU countries: Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Hungary, Italy, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and the United Kingdom. We work with an unbalanced panel of 671,818 unique firms over the years 2004-2017, which gives a total of 4,397,353 firm-year observations. Using a 4-digit decomposition of manufacturing, we cover 228 sectors. The basic summary statistics for the manufacturing sector for the whole area considered and the three main regions is given in Table 1.

Several stylised facts appear. First, more than half of the observations in the analysis come from South European countries. This is not a surprise given a relatively broader ORBIS coverage for these countries (Barbiero et al., 2020). Nevertheless, the number of observations in the CESEE region, as well as in Western and Northern Europe, reaches nearly 1 million in each case. We believe this is enough to provide a meaningful comparison benchmarks for the analysis, yet we take a closer look at the data representativeness later in this section.

Second, labour productivity appears to be the highest in Western and Northern Europe at around 60,000 euros per year, followed by the Southern Europe with almost 41,000 euros and finally the CESEE region with around 13,000 euros. These patterns are fully consistent with

Table 1: Basic summary statistics.

	Obs.	Mean	Median	St. dev.	Min.	Max.
			Full sample			
Lab. productivity	4,397,353	39,647.77	32,484.50	35,077.79	609.00	245,167.00
Employment	4,397,353	23.95	7.00	52.14	1.00	375.00
Total assets (log)	4,393,137	13.22	13.17	1.99	6.69	19.01
Debt/Assets	3,500,531	0.66	0.64	0.37	0.00	4.07
Long debt/Assets	3,605,938	0.12	0.03	0.19	0.00	0.95
Sales/Assets	4,186,967	1.51	1.23	1.25	0.03	13.00
Cash/Assets	4,229,482	0.14	0.06	0.18	0.00	0.99
Fixed assets/Assets	4,390,817	0.31	0.26	0.25	0.00	0.97
Tan. assets/Assets	4,336,089	0.26	0.19	0.23	0.00	0.97
			CESEE			
	Obs.	Mean	Median	St. dev.	Min.	Max.
Lab. productivity	853,723	12,541.61	7,511.00	14,812.29	609.00	91,103.29
Employment	853,723	26.85	6.00	60.57	1.00	375.00
Total assets (log)	850,040	11.79	11.76	2.12	6.69	17.07
Debt/Assets	482,937	0.62	0.53	0.58	0.00	4.07
Long debt/Assets	567,100	0.06	0.00	0.14	0.00	0.72
Sales/Assets	849,617	1.87	1.34	1.96	0.03	13.00
Cash/Assets	820,521	0.17	0.07	0.23	0.00	0.99
Fixed assets/Assets	849,194	0.35	0.31	0.28	0.00	0.97
Tan. assets/Assets	844,151	0.33	0.29	0.28	0.00	0.97
			Southern Europe			
	Obs.	Mean	Median	St. dev.	Min.	Max.
Lab. productivity	2,547,468	40,961.91	33,357.90	33,135.47	1,695.50	204,981.17
Employment	2,547,468	19.20	8.00	37.71	1.00	271.00
Total assets (log)	2,547,022	13.56	13.47	1.73	9.70	18.13
Debt/Assets	2,119,092	0.68	0.68	0.33	0.08	2.24
Long debt/Assets	2,132,542	0.14	0.06	0.20	0.00	0.95
Sales/Assets	2,540,088	1.27	1.10	0.89	0.06	5.32
Cash/Assets	2,463,793	0.11	0.05	0.15	0.00	0.73
Fixed assets/Assets	2,546,151	0.30	0.26	0.23	0.00	0.91
Tan. assets/Assets	2,507,850	0.25	0.19	0.22	0.00	0.86
			West and North Europe			
	Obs.	Mean	Median	St. dev.	Min.	Max.
Lab. productivity	996,162	59,517.45	50,885.00	37,507.98	7,899.00	245,167.00
Employment	996,162	33.64	7.00	71.13	1.00	375.00
Total assets (log)	996,075	13.59	13.31	1.93	9.88	19.01
Debt/Assets	898,502	0.62	0.60	0.31	0.08	1.97
Long debt/Assets	906,296	0.13	0.04	0.19	0.00	0.81
Sales/Assets	797,262	1.86	1.66	1.08	0.17	6.30
Cash/Assets	945,168	0.18	0.11	0.19	0.00	0.81
Fixed assets/Assets	995,472	0.32	0.25	0.25	0.00	0.93
Tan. assets/Assets	984,088	0.22	0.16	0.20	0.00	0.84

Notes: Lab. productivity is measured as a ratio of firm-level value added and number of employees. Employment is measured as number of employees. Debt represents total debt of a company, including current and non-current liabilities. Full sample covers 17 EU economies. CESSE includes Bulgaria, Croatia, Czechia, Estonia, Hungary, Romania, Slovakia and Slovenia. South Europe includes Italy, Portugal and Spain. West and North Europe includes Belgium, Denmark, Finland, France, Sweden and the United Kingdom.

the productivity metrics reported throughout the literature and measured from macroeconomics aggregates (Eurostat, 2016). Importantly, labour productivity shows a fair degree of variation for each of the regions.

Third, firms located in Western and Northern Europe tend to be bigger on average, both in terms of total assets and the number of employees. Firms with the lowest average number of employees are located in Southern Europe, while the CESEE region is relatively more populated with the smallest firms in terms of asset size.

Fourth, there are important differences related to firms' indebtedness. The highest debt to assets ratio can be found in Southern Europe at the average level of 68%. CESSEE countries, as well as Western and Northern European countries have lower leverage ratios, each reaching 62%. Looking at the maturity composition of debt, short-term debt rather dominates in the CESSEE region, with long-term debt reaching only 6% of total assets, on average in this region. This proportion is more twice higher in the two other regions.

Finally, the asset composition also reveals interesting differences. Southern European companies appear to be a bit shorter on cash, with cash to assets ratio at 11%. The two other regions have stronger cash ratios between 17% and 18% of total assets, on average. While the proportion of fixed assets seems to be rather consistent between regions, at around one-third of total assets, CESSEE corporate fixed assets consist predominantly of tangible assets. For reference, as much as one-third of fixed assets in Western and Northern Europe can be attributed to intangible assets.

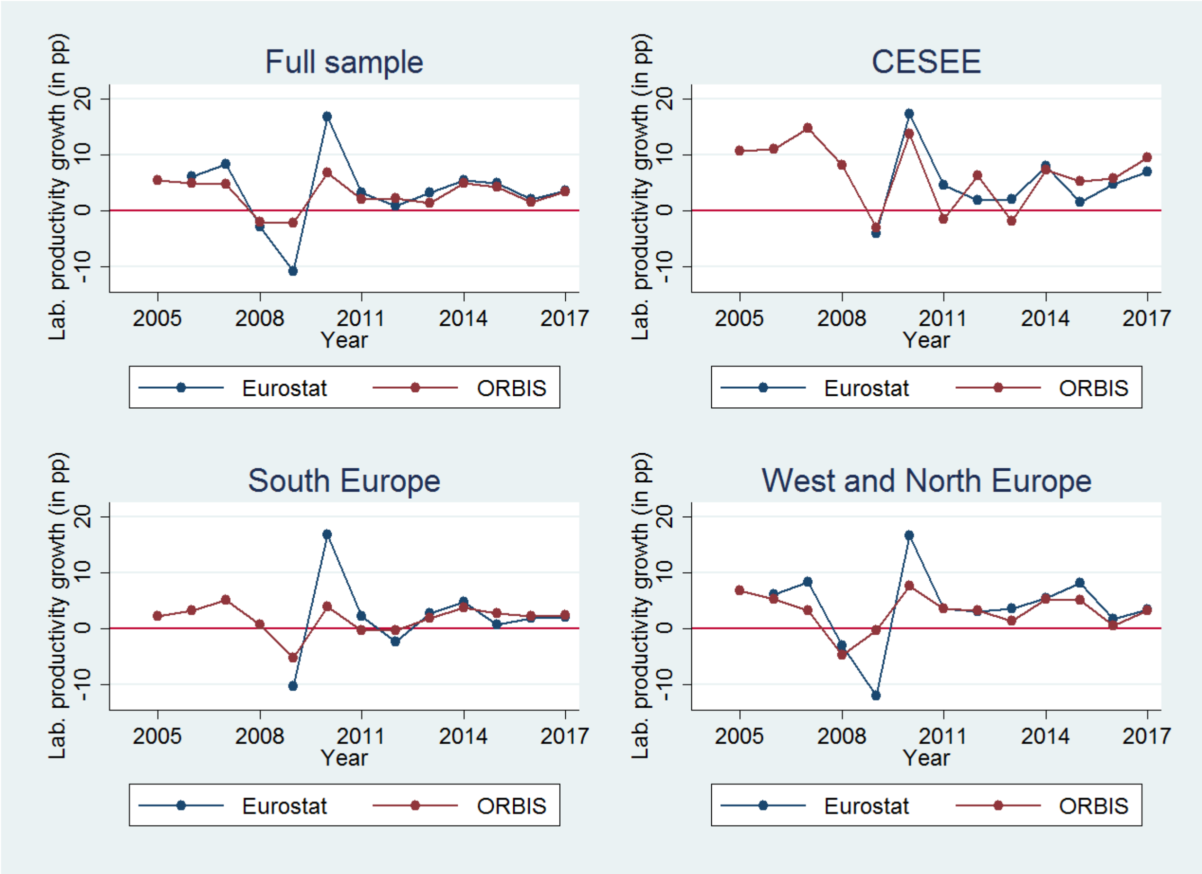
It is widely acknowledged that ORBIS dataset, while not offering an unbiased sample of European corporates (Gopinath et al., 2017), provide the most comprehensive and homogeneous dataset of firm levels data on which conduct analysis (Kalemli-Özcan et al., 2015). The records happen to be gathered from somewhat larger firms, and there are coverage differences across sectors and jurisdictions. To some extent, these characteristics are already reflected in Table 1.

While we recognize the ORBIS drawbacks, we believe that the data set we craft for the analysis reproduces more than a fair degree of patterns in labour productivity dynamics. Figure 3 compares the annual labour productivity growth calculated using our dataset, and puts it against the economy-wide benchmarks, as reported in Structural Business Statistics in Eurostat. More specifically, firm-level data are aggregated at 2-digit Nace Rev. 2 level and compared against the same sectors in Eurostat.[9] Sector level data are aggregated with time-invariant VA weights, also taken from Eurostat.

While the amplitude of the annual changes is somewhat smaller in the sample than in the economy-wide data (in particular after the crisis years 2009 and 2010 in Southern Europe and Western-Northern Europe), clear patterns are visible. The correlation coefficients are 91%, 79%, 81% and 77%, for the entire dataset, CESEE, Southern Europe and Western and Northern Europe, respectively.

[9] Due to data availability in Eurostat, we are able to make this comparison on 2-digit level only. In the sample, there are 33 2-digit manufacturing sectors, across EU17 countries.

Figure 3: Annual labour productivity growth in broad regions over 2005-2017.



Notes: Firm-level data are aggregated at 2-digit Nace Rev. 2 level and compared against the same sectors in Eurostat. Sector level data are aggregated with time-invariant value added weights taken from Eurostat. See notes to Table 1 for the composition of the regions.

4.2 Results of the OP decomposition

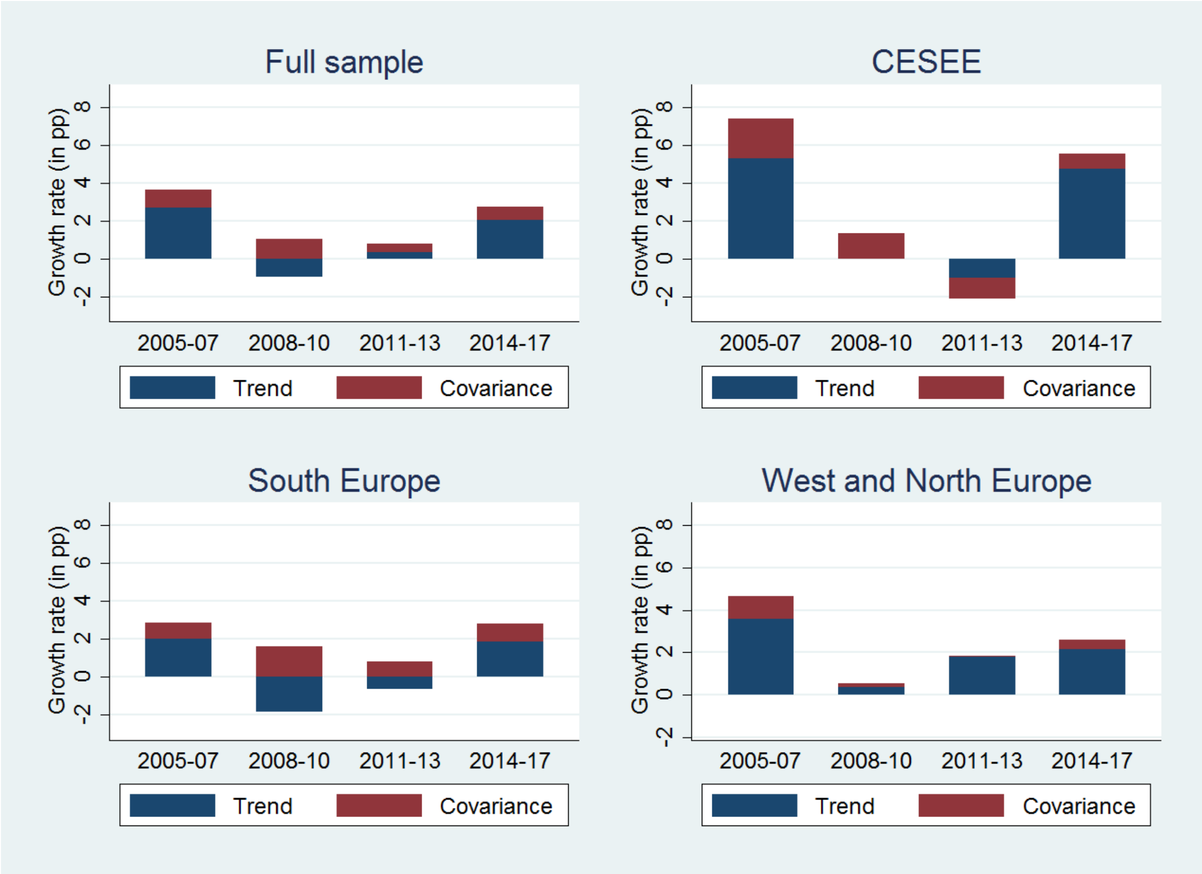
Firstly, we estimate the OP decomposition in the OLS framework, according to Eq. (3). In particular, we estimate an equation:

$$\psi'_{isct} = \beta_0 + \beta_1 \tilde{w}_{isct} + \varepsilon_{isct}, \tag{8}$$

where ψ' is the re-scaled labour productivity, $\tilde{w}$ is the standardized market share and ε is an i.i.d error term. Dimensions i, s, c and t correspond to the firm, sector, country and year, respectively. We use weighted Least squares estimation, with weights π_s determined by the product of inverse sample weights $n/(n_s - 1)$ and sector-specific VA weights taken from Eurostat. We aggregate the results by regions, according to dimension c.

Following Section 3, the covariance component of the OP productivity decomposition is equivalent to the coefficient $\hat{\beta}_1$, whereas the trend productivity is a sector-rescaled coefficient $\hat{\beta}_0$. While the results are estimated in levels, for better tractability we reformulate them in the growth rates in Figure 4. The raw level results are given in Table B1 in Appendix.

Figure 4: Drivers of aggregate productivity according to Olley-Pakes decomposition.



Notes: Sector grid corresponds to 4-digit Nace Rev. 2 classification. Sector-level results are aggregated with time-invariant value added weights taken from Eurostat. Yearly level estimates are converted into annual growth rates and averaged over respective time frames. See notes to Table 1 for the composition of the regions.

Several stylised facts emerge from the analysis.

Firstly, looking at the overall sample, annual productivity grew by 3.7% on average between 2005 and 2007. It then collapsed to 0.1% during the crisis years, with very muted recovery at 0.8% in years 2011-2013. Productivity growth converged but did not reach pre-crisis levels throughout 2014-2017, averaging to around 2.8% annually in this period.

Secondly, and interestingly, the allocative efficiency component contributed positively to overall labour productivity growth throughout the entire period. Hence, over time, reorganisation within the European corporate ecosystem tend to allocate resources more efficiently, with more productive corporates absorbing more resources. The allocative efficiency contribution was strongest during the period of the global financial crisis, a finding that can be attributed to the cleansing effect of recessions (Caballero and Hammour, 1994; Duval et al., 2019). Conversely, the contribution of allocative efficiency to productivity growth was smallest in the following years, during the sovereign debt crisis. The allocative component accounted for 26-27% of total productivity growth, both in the years before the crisis and after 2014. Thirdly, it must be pointed out that the crisis changed the composition of overall labour productivity in terms of trend and covariance components. In level terms, 22% of labour productivity in 2004 could have been attributed to allocative efficiency (see Table B1 in Appendix). In 2017 it was already

26%. This change is important to keep in mind, as with larger shares lower growth rates in covariance component can be overrepresented in the overall growth. In fact, while the overall growth rate post 2014 was lower by a quarter compared to the years 2005-2007, the growth rate of covariance productivity component itself more than halved throughout the period, from 5.6% in 2005-2007 to 2.7% in 2014-2017.

Behind aggregate dynamics, the analysis also bring interesting insights regarding regional differences.

Regarding CESEE region. The region enjoyed the highest productivity growth throughout 2005-2007 and 2014-2017, reaching 7.4% and 5.6%, respectively. The crisis years took, however, their toll. Productivity growth slowed down to 1.3% in 2008-2010, being exclusively supported by the allocative efficiency component. Productivity then receded by 2.1% during the period of the sovereign debt crisis, in 2011-2013, as trend component and allocation efficiency declined. It is indeed the only occurrence in our study over which the allocative efficiency contributed negatively to overall productivity growth.[10] While productivity growth bounced back over the years 2014-2017, it did not reach the pre-crisis levels. CESEE is also a region where the role of allocative efficiency in the levels of labour productivity diminished from 40% in 2004, to 34% in 2017.

Regarding Southern Europe. At the level of around 2.9%, pre-crisis productivity growth was below the average for the entire EU. It then further collapsed during the crisis years, as the trend component fell sharply and became negative. However, the allocative efficiency remained positive during the entire period, including during the crises. The allocative efficiency played a substantial positive role throughout the crisis, an observation that suggest that the cleansing effect was dominating the ever greening effect. Despite the supportive role of the allocation efficiency, productivity growth did not raise during the sovereign debt crisis as southern economies where most affected. Over the most recent period, productivity growth has rebounded, growing at a pace sightly above that before the global financial crisis.

regarding Western and Northern Europe, in pre-crisis years, annual productivity growth in West and North Europe reached 4.7%, with the covariance component accounting for 23% of this increase. While productivity growth substantially slowed down during the crisis years, to 0.5% a year, and accelerated thereafter, it remains more than 1% below pre-crisis levels in the last period. Differently from the two other regions, the allocative efficiency component did not contribute to productivity growth during the period of the great financial crisis. It did not contribute also during the period of the sovereign debt crisis and started contributing positively only during the last period, over 2014-2017, by only 17%. Hence, over the last period, only less than one-fifth of the total level of labour productivity is attributed to the covariance component, less than in the two other regions.

While the share of allocative efficiency component in overall labour productivity level before the crisis was limited to around one-fifth, on average, its supportive role during the recovery should not be underestimated, especially in the CESSE and Southern European regions. Should the allocative efficiency component grow at its pre-crisis pace in years 2014-2017, the overall

[10]we show below that there is no evidence that the negative contribution of allocative efficiency to productivity growth over this period can be attributed to credit flows being allocated to less-productive companies.

productivity would grow faster by nearly 0.7 percentage points (3.4% against actual of 2.7%). To put it in level terms, should the covariance component in years 2014-2017 grow at the 2005-2007, in 2017 labour productivity would have been higher by EUR 1,141 in CESEE region and by EUR 1,979 in Southern Europe.[11] In the next section, we analyse whether the availability of external finance can contribute to explain the variations in the contribution of the allocative efficiency component to productivity growth over time and regions.

5 Access to finance

5.1 Distribution of debt and allocative efficiency

We measure the contribution of firms' indebtedness to the OP covariance productivity, conditional on a set of observed characteristics, according to Eq. (6). Specifically, we estimate the following two equations

$$\begin{aligned} \psi''_{isct} &= \alpha_0 + \alpha_1 \tilde{Lev}_{isct-1} + \Gamma \tilde{Q}_{isct-1} + \varepsilon_{isct}, \\ w''_{isct} &= \beta_0 + \beta_1 \tilde{Lev}_{isct-1} + \Delta \tilde{Q}_{isct-1} + \nu_{isct}, \end{aligned} \tag{9}$$

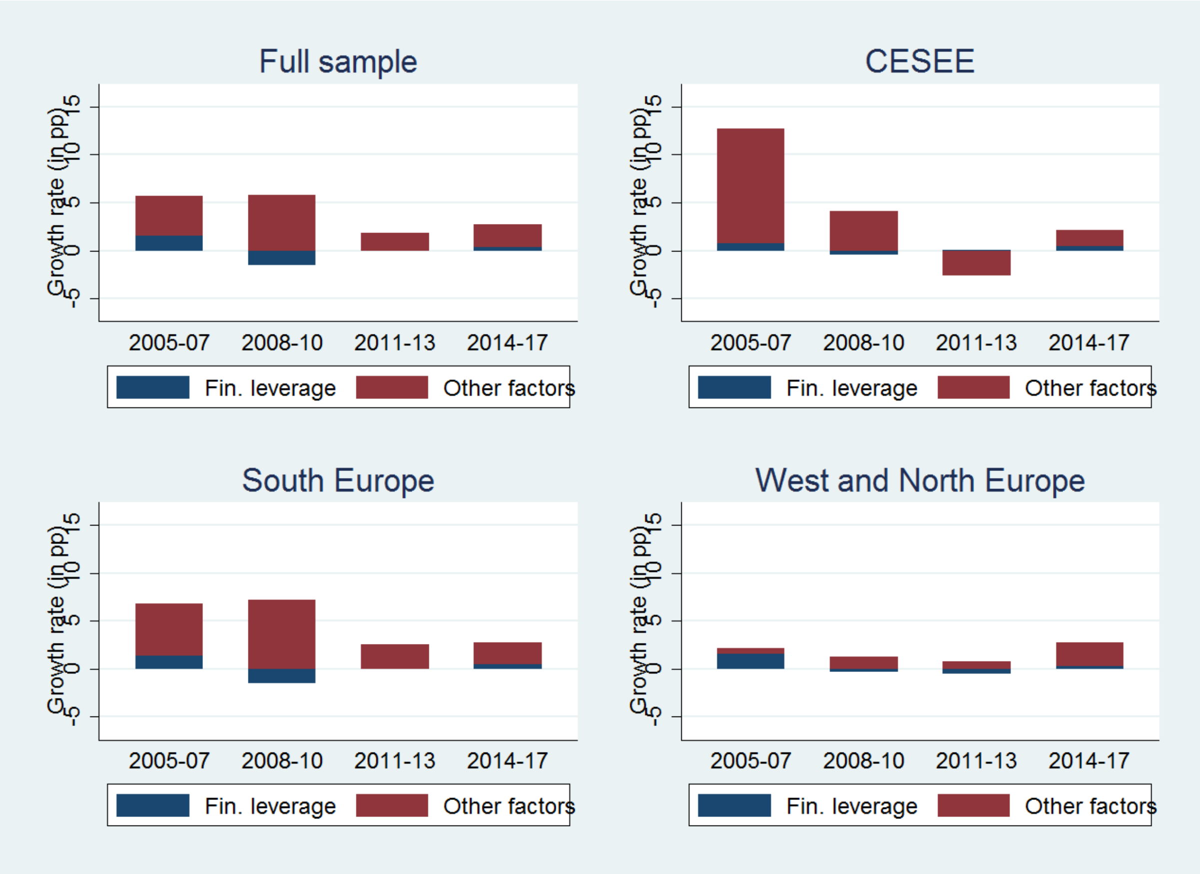
where ψ'' is the re-scaled labour productivity, w'' is the re-scaled market share, $\tilde{Lev}$ is the standardized indebtedness metrics (debt to asset ratio), and matrix $\tilde{Q}$ consists of control variables including cash to asset ratio, sales to asset ratio, accounts payable to assets ratio and company's age (all standardized). The independent variables are taken in first lags to alleviate at least some of the endogeneity concerns. Variables ε and ν are i.i.d error terms. Dimensions i, s, c and t correspond to the firm, sector, country and year, respectively. The same as above, we use the WLS estimation, with weights π_s determined by the product of inverse sample weights $n/(n_s - 1)$ and sector specific value added weights taken from Eurostat.

According to Section 3, the conditional contribution of leverage to the component of the covariance productivity component is equivalent to the product of coefficients $\hat{\alpha}_1 \times \hat{\beta}_1$. The results are estimated in levels, but for better tractability we plot them in the growth rates in Figure 5. The raw level results are given in Table B2 Appendix.[12]

[11] The allocative productivity growth in 2014-2017 in Western and Northern Europe was in this respect higher than in pre-crisis years.

[12] We also rerun the analysis on financial leverage net of cash holdings. As all the main conclusions still hold, we skipe their description in the text, however, the level results are presented in Table B3 in Appendix.

Figure 5: Contribution of financial leverage to covariance productivity growth.



Notes: Control variables include lagged sales over total assets, cash over total assets, accounts payable over total assets and company's age. Leverage is calculated as total debt over total assets and taken in period $t-1$. Sector-level results are aggregated with time-invariant value added weights taken from Eurostat. Yearly level estimates are converted into annual growth rates and averaged over respective time frames. See notes to Table 1 for the composition of the regions.

Firstly, the results confirm the previous section observation that the covariance productivity growth more than halved in the EU17 from 2005-2007 to 2014-2017.

Secondly, and more importantly, the role of firm-level financial leverage also evolved. Looking at the EU17, access to finance contributed some 27% of the allocative productivity growth before the crisis. During the financial crises, as bank were short on capital and rationed credit, dependence on external finance was weighing on within-sector resource allocation. That could have been attributed to both productive firms being strapped for finance, but also ever-greening of loans (Peek and Rosengren, 2005). In the after-crisis years, the finance-driven allocative efficiency growth was muted. While it picked up marginally between in 2014-2017, it never really recovered to the pre-crisis levels with the contribution being nearly twice smaller at 14%.

Thirdly, the geographical breakdown reveals interesting patterns. Financial leverage has never been an important driver for allocative efficiency growth. While the time patterns correspond to the ones observed in the full sample, the contribution of firm-level debt to asset ratio to the sector-wide productivity composition was small.

Growth rates in South Europe track the general patterns to a great extent, which is not surprising given that the region constitutes more than a half of the whole sample of firms. West and North Europe is somewhat more interesting. While the region actually observed a small improvement in allocative productivity growth from 2.2% in 2005-2007 to 2.7% in 2014-2017, there role played by financial leverage flipped. In the pre-crisis period, financial leverage was contributing by 71% to the overall efficiency growth, a contribution that almost vanished during the two crisis periods years. The acceleration in the allocative efficiency in this region after 2014 was not resulting from a pronounced rise in the contribution from the allocation of debt. Indeed, between 2014-2017, the contribution from financial leverage to allocative efficiency growth was below 10%.

Should the financial leverage component in years 2014-2017 grow at the pre-crisis levels, the allocative efficiency could have grown by 0.67 percentage points more, and the overall labour productivity by 0.18 percentage points faster. In level terms, labour productivity could have been higher by roughly EUR 87 in CESEE, by EUR 512 in South Europe and by EUR 967 in West and North Europe.[13]

The method does not allow us to adequately identify the within-sector relation between debt and productivity. In other words, we can't say if the problems associated with firm-level external finance are related to too much or too little debt. In the next section, we try to shed more light on this phenomenon, focusing on Western and Northern Europe, region that recorded the larger change in the contribution of financial factors to allocative efficiency after the crises.

5.2 Debt and within-sector productivity

Under perfect allocative efficiency, few most productive firms would supply the market. This dos not materialise because (i) productive firms cannot expand and raise enough their market share, or because (ii) less-productive firms manage to keep a market share well above its optimal value. Access to finance can play a role in both cases.

In the first example, productive firms can be at unsustainable levels of debt. It is often referred to as a debt overhang problem, whereby excessive debt levels alter investment incentives at the firm managerial level. In particular, managers may forego some profitable investment projects, if they need to share a big portion of returns with debt holders (Myers, 1977). Should this happen among productive firms, the foregone opportunities may result in lower growth prospects, and hence it can impede the aggregate productivity.

The second possibility is that productivity laggards receive extra life support from higher-than-optimal debt levels. While it can happen for a variety of possibly non-financial reasons, including state ownership for instance, we will put them in a joint category of ever-greening. Ever-greening corresponds to a situation where a financial institution sustains credit lines to firms without sufficient profit generating capacity (Peek and Rosengren, 2005). It happens typically in a heavily stressed or undercapitalized banking sector, where the short-term provisioning costs exceed the long-term costs of ever-greening.

Last but not least, it can be that productive firms cannot get sufficient financing for their

[13]We arrive at these numbers by calculating the 2017 financial leverage component with a growth rate in each of the years between 2014-2017 replaced by the 2005-2007 average. For CESEE region, for instance, the average growth rate in financial component was 9.7% between 2005 and 2007, which gives is $0.659 \times (1 + 0.097)^4 - 0.868 = 0.086$ (with more digit precision it is 0.087).

investment projects. This problem, generally known as credit constraints, has been vastly studied throughout the literature. It is generally attributed to information asymmetries, which can make private sector financial institutions unwilling to extend credit, especially uncollateralised credit, to SMEs and mid-caps even at high interest rates (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981). The result is credit rationing, i.e. an equilibrium where banks decide to keep the supply of credit below demand, rather than to provide the extra loan demand at higher interest rates. These three cases are summarised in Table 2.

Table 2: High/low debt as a drag on productivity growth.

	Most productive firms	Least productive firms
"Over" indebtedness	Debt overhang	Ever-greening
"Under" indebtedness	Credit constraints	-

In our methodology, we cannot uniquely identify the key channels that altered the contribution of financial leverage to the allocative efficiency growth. However, we can proxy them in our setup by estimating the model in Eq. (9), after controlling for the proxies of (i) debt overhang, (ii) ever-greening and (iii) credit constraints. While we recognize that sole measuring of these factors can contribute a paper of its own, we focus on three rule-of-thumb indicators which can be derived from firm-level financial statements.

More specifically, we tag firms as suffering from debt overhang problem if the interest coverage ratio was below 1 for three consecutive years (Ferrando and Wolski, 2018). We classify firms as potentially benefiting from ever-greening if they had negative profits for three consecutive years. Lastly, we consider firms' development to be hampered by financial constraints if they have a low collateralization index, if its share of tangible to total assets belongs to the first quartile of the within-sector distribution.[14] The evolution of each of the groups over time is presented in Table 3.

Table 3: Corporate ecosystem composition in West and North Europe.

	Debt overhang	Ever-greening	Credit constraints
2005-2007	15%	5%	25%
2008-2010	22%	7%	25%
2011-2013	23%	10%	24%
2014-2017	15%	7%	24%

Notes: Shares correspond to the average proportion of firms tagged as suffering from debt overhang problems, benefiting from ever-greening and under credit constrains.

It can be readily observed that the firms assigned to either of the groups, do not constitute more than a quarter of all firms, yet the proportions are comfortably above zero level to provide meaningful interpretation. While, by construction, the share of credit constrained firms is set at one quarter, the debt overhang and ever-greening categories closely track the crisis period. In particular, the interest coverage problems escalated throughout 2008-2010 and remained

[14] It should be noted that the same firm can belong to several groups.

elevated in the subsequent years, to then decrease to the pre-crisis levels after 2014. The problems of profitability tracked this trend, with a clear peak in years 2011-2013, highlighting the difficulties for the firms to boost profitability metrics even after the crisis. Broadly-speaking, however, the post-2014 shares largely match the pre-crisis patterns.

In the next step, we re-estimate Eq. (9) separately on each of the three group. First, only considering firms with debt overhang, then firms benefiting from ever-greening and finally firms suffering from credit constrains. The results are presented in Table 4.

Table 4: Financial leverage and covariance productivity growth in West and North Europe.

Years		Financial leverage contribution excluding firms with			Overall
	Entire	Debt overhang	Ever-greening	Credit constraints	
2005-2007	1.55%				2.17%
2008-2010	-0.34%	0.79%	0.14%	-1.60%	0.93%
2011-2013	-0.56%	-1.80%	-1.26%	0.25%	0.23%
2014-2017	0.26%	0.02%	-0.02%	0.62%	2.74%

Notes: The results of Eq. (9) are reported in the columns two to four, by excluding firms with debt overhang problems, benefiting from ever-greening and under credit constrains respectively. See the main text for the proxies used to classify firms across the three potentially overlapping groups.

For the group of western and northern economies in respective periods, Table 4 depicts the growth rate for the overall covariance productivity component in the column 'Overall'. The contribution of financial leverage is measured for the entire distribution of firms in column 'Total'.[15]. The contributions controlling for the effects generated by firms susceptible either to debt overhang, ever-greening or credit constraints problems can be deducted from the middle three columns. The table reports the average growth rate of covariance productivity component (column 'Overall'), and the contribution of financial leverage, as proposed in Section 4.2, for the entire sample of firms, and when controlling for the distributional effects generated by the firms susceptible to either debt overhang, ever-greening or financial constraints problems. The table should be read by comparing the numbers in the middle three columns to the numbers in column 'Total', i.e. higher numbers in the middle reflect that the specific channel hampers the covariance productivity growth attributed to financial leverage channel.

It can be readily observed that during the crisis years between 2008-2010 the substantial slowdown in allocative productivity growth could have been linked to the debt overhang problem. In other words, if we take away from the overall covariance productivity the effects generated by firms with insufficient coverage levels, the growth would contribution would have jumped from -0.3% to 0.8%.

After the crisis, credit constraints become more visible. While the covariance productivity growth linked to financial leverage between 2011 and 2013 was -0.6%, it would have been 0.3% (so even above the overall covariance productivity growth) if we control for the distributional effects generated by firms with low collateral level.

[15]The numbers reported under the column 'Entire' correspond to the sum of the two bars in the bottom-right corner of Figure 5, while those reported under 'Overall' correspond to the blue bar, i.e. the contribution of financial leverage in the same figure.

This pattern is exacerbated in years 2014-2017. Excluding the effects spanned by low-collateral companies, the covariance productivity growth generated by financial leverage would have been 0.6%, compared to 0.3% when calculated over the entire distribution of firms. In other words, should the distribution of firm-level productivity be independent from collateral levels, debt could have been more than twice more effective in spurring allocative efficiency growth across West and North Europe between 2014-2017.[16]

6 Concluding remarks

The goal of the paper is twofold. Firstly, we develop a formal framework to estimate the OP productivity decomposition through a linear regression. The decomposition splits the sector-wide productivity into two components, i.e. the one attributed to the productivity level common across all the firms in a sector, and allocative efficiency component, which describes to what extent highly productive firms dominate in a particular sector. The latter is mathematically expressed as a scaled covariance between firms' productivity levels and market shares.

We propose an OLS framework as a one-equation elegant solution to estimate and aggregate the OP decomposition for multiple-sectors economies. Our main attention is paid to the allocative efficiency, for which we develop a formal approach to estimate the contribution of firm-level confounding variables to the sector-wide aggregates.

Secondly, we take the methodology to the data and estimate the OP productivity decomposition on a sample of manufacturing firms in EU countries using a comprehensive unbalanced dataset of around 672 thousands firms over the years 2004-2017. We find that the allocative efficiency component contributed positively to the overall labour productivity growth throughout the years. These contribution was strongest during the crisis years, which could be attributed to the cleansing effect of the recession (Duval et al., 2019), and the smallest in the years following the crisis.

While the contribution of allocative efficiency component to overall labour productivity level before-crisis was limited to around one-fifth, on average, its role in the recovery should not be underestimated, especially in the CESSE and Southern European regions. Should it had grown at its pre-crisis pace in years 2014-2017, the 2017 level of labour productivity would have been higher by EUR 1,141 in CESEE region and by EUR 1,979 in Southern Europe.

We then estimate the contribution of firm-level financial leverage to the growth in covariance productivity component. On the EU sample, access to finance contributed some 27% to the allocative productivity growth before the crisis and then collapsed during the crisis period. In the after-crisis years the finance-driven allocative efficiency growth was muted. While it picked up marginally between in 2014-2017, it never really recovered to the pre-crisis levels with the contribution being nearly twice smaller at 14 per cent.

We then assess the drivers behind the declining contribution of allocative efficiency, whether most productive firms had too little debt or least productive ones to much. We focus on Western and Northern Europe where the results suggest a major change in the within-sector distribution

[16]It needs to be pointed out that the fact that we don't find similarly strong evidence in favour of debt overhang or ever-greening problems, does not mean that they are insignificant factors for firm-level productivity. The exercise should be taken through a prism the within-sector distribution of productivity.

of debt in a direction less favourable to allocative efficiency growth since the financial crisis. The share of leverage contribution to the covariance productivity growth dropped from more than 70% in pre-crisis years to less than 10% in years 2014-2017, on average.

We identify the financial channels altering the contribution of the financial leverage to allocative efficiency by splitting the dataset and estimating the contribution of financial leverage to the allocative efficiency component, controlling for the distributional effects generated by the firms susceptible to either debt overhang, ever-greening or financial constraints problems. We find that while during the crisis years, the allocative productivity growth was mostly hampered by the debt overhang problem, after the crisis, the productivity gains were locked in by financial constraints, as exemplified by availability of collateral. Should the distribution of firm-level productivity be independent from collateral levels, debt could have been more than twice more effective in spurring allocative efficiency growth across West and North Europe between 2014-2017.

The results offer interesting policy guidance. Firstly, we underline the relevance of distributional aspects of aggregate productivity levels. While the sector-wide technology is, without doubt, the dominant force behind production capacity, the role of allocative efficiency in the growth rate should not be neglected. Policies which aim at improving the entry-exit processes, like lower barriers to entry or more efficient bankruptcy regimes, are desirable directions.

Secondly, the findings indicate that aggregate productivity growth is muted by difficulties faced by firms to access finance. The evidence points to a conclusion that highly productive but low-collateral firms do not make sufficient use of available external resources to increase their market shares. With this in mind, public intervention to alleviate collateral-related financial constraints can bring impetus to productivity growth.

This study has a natural continuation to test the relevance of other confounding variables to the allocative efficiency levels. To better track the role of the financial sector for instance, conditional on data availability, a natural extension of the setup could be to include banking indicators, like capital or liquidity metrics.

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A Technical appendix

Proposition 1 (Sectoral Productivity Estimation)**.** *Suppose the data consist of* n *observations* $\{\psi_i, w_i\}_{i=1}^{n}$*. Given the linear model specification of the form*

$$\psi_i' = \beta_0 + \beta_1 \tilde{w}_i + \varepsilon_i,$$

where $\psi_i' = \psi_i(n-1)\sigma_w$*,* σ_w *is the standard deviation of* w*,* $\tilde{w}_i$ *is a standard score of* w_i *and* ε_i *is the i.i.d. disturbance, the decomposition in Eq. (1) can be rewritten in terms of Ordinary Least Squares estimates as*

$$\Psi = \frac{\hat{\beta}_0/\sigma_w}{(n-1)} + \hat{\beta}_1.$$

Proof of Proposition 1. Consider the simple linear model of the form

$$y_i = \alpha_0 + \alpha_1 x_i + \varepsilon_i,$$

where $\{y_i, x_i\}_{i=1}^{n}$ is the data sample and ε_i is the unobserved error component. The Ordinary Least Squares (OLS) estimates minimize the sum of squared residuals $\hat{\varepsilon}_i$, where

$$\hat{\varepsilon}_i = y_i - \alpha_0 - \alpha_1 x_i.$$

It is well known that the procedure offers a solution

$$\hat{\alpha}_0 = \bar{y} - \hat{\alpha}_1 \bar{x}, \quad \text{and} \quad \hat{\alpha}_1 = \frac{\sum_{i=1}^{n} (y_i - \bar{y})(x_i - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} = \frac{\operatorname{cov}(y, x)}{\operatorname{var}(x)}.$$

Suppose we take the standard score $\tilde{x}$ of the x covariate, such that $\bar{\tilde{x}} = 0$ and $\operatorname{var}(\tilde{x}) = 1$. Suppose also that we set $y_i' \equiv y_i \times \sigma_x$. It follows that for the model

$$y_i' = \beta_0 + \beta_1 \tilde{x}_i + \varepsilon_i,$$

we get

$$\hat{\beta}_0 = \bar{y}\sigma_x, \quad \text{and} \quad \hat{\beta}_1 = \operatorname{cov}\left(y', \frac{x - \bar{x}}{\sigma_x}\right) = \operatorname{cov}(y, x).$$

□

Proposition 2 (General Productivity Estimation)**.** *Suppose the data consist of* n *observations split into* S *partitions as* $\{\psi_{is}, w_{is}\}_{i=1}^{n_s}$ *with* $n_s \geq 1$ *and* $\{s = 1, ..., S\}$*. Given the linear model specification of the form*

$$\psi_{is}' = \beta_0 + \beta_1 \tilde{w}_{is} + \varepsilon_{is},$$

where $\psi_{is}' = \psi_{is}(n_s - 1)\sigma_{w_s}$*,* σ_{w_s} *is the standard deviation of* w *within partition* s*,* $\tilde{w}_{is}$ *is a standard score of* w_i *within partition* s *and* ε_{is} *is the i.i.d. disturbance, the decomposition in Eq. (3) can be rewritten in terms of Weighted Least Squares estimates as*

$$\Psi = \frac{\hat{\beta}_0 \, \mathbb{E}\left[\bar{\psi}_S \mid S\right]}{\mathbb{E}\left[\bar{\psi}_S' \mid S\right]} + \hat{\beta}_1,$$

where weights are determined by the product of population weights π_s and inverse sample weights $n/(n_s - 1)$.

Proof of Proposition 2. Given the population is partitioned according to an operator $\mathcal{Z}$ with partitions given by $\mathcal{Z}_1, ..., \mathcal{Z}_S$, the population shares are given by

$$\pi_s = \mathbb{P}((y,x) \in \mathcal{Z}_s), \quad s = 1, ..., S,$$

while the sample weights are given by

$$h_s = (n_s - 1)/n, \quad s = 1, ..., S, \quad \text{and} \quad n_s \geq 2,$$

and the weight for unit i is given by

$$v_{is} = \pi_{is}/h_{is}, \quad i = 1, ..., n.$$

Consider the simple linear model of the form

$$y_i = \alpha_0 + \alpha_1 x_i + \varepsilon_i,$$

where $\{y_i, x_i\}_{i=1}^n = \{\{y_{is}, x_{is}\}_{i=1}^{n_s}\}_{s=1}^S$ is the data sample and ε_{is} is the unobserved error component. The Weighted Least Squares (WLS) estimates minimize the sum of squared residuals $\hat{\varepsilon}_{is}$, i.e.

$$\min_{\alpha_0,\alpha_1} \sum_i v_i \hat{\varepsilon}_i^2 = \sum_i (\sqrt{v_i} y_i - \alpha_0 \sqrt{v_i} - \alpha_1 \sqrt{v_i} x_i)^2.$$

It can be verified that

$$\hat{\alpha}_0 = \bar{y}_v - \hat{\alpha}_1 \bar{x}_v, \quad \text{and} \quad \hat{\alpha}_1 = \frac{\sum_{i=1}^n v_i \left(y_i - \bar{y}_v\right)\left(x_i - \bar{x}_v\right)}{\sum_{i=1}^n v_i \left(x_i - \bar{x}_v\right)^2}$$

where the subscript v denotes the weighted mean.

Suppose we take the standard score $\tilde{x}$ of the x covariate for each partition, such that $\bar{\tilde{x}}_s = 0$ and $\text{var}(\tilde{x}_s) = 1$ for $s = 1, ..., S$. Suppose also that we set $y'_{is} \equiv y_{is} \times \sigma_{x_s}$. It follows that for the model

$$y'_{is} = \beta_0 + \beta_1 \tilde{x}_{is} + \varepsilon_{is},$$

we get

$$\hat{\beta}_0 = \bar{y}'_v = \frac{\sum_s \sum_i v_{is} y'_{is}}{\sum_s \sum_i v_{is}} = \frac{\sum_s v_s \sum_i y'_{is}}{\sum_s v_s n_s} = \frac{\sum_s v_s n_s \bar{y}'_s}{\sum_s v_s n_s} = \frac{\sum_s \pi_s^b \bar{y}'_s}{\sum_s \pi_s^b} = \mathbb{E}[\bar{y}_S \sigma_{x_S} \mid S],$$

where superscript b stands for Bessel-corrected weight $\pi_s^b = \pi_s(n_s - 1)/n_s$ and we exploited the fact that the weights are equal for units in the same sector $v_{is} \equiv v_s$.

Similarly,

$$
\begin{aligned}
\hat{\beta}_1 &= \frac{\sum_s \sum_i v_{is} \left(y'_{is} - \bar{y}'_v\right) \left(\tilde{x}_{is} - \bar{\tilde{x}}_v\right)}{\sum_s \sum_i v_{is} \left(\tilde{x}_{is} - \bar{\tilde{x}}_v\right)^2} \\
&= \frac{\sum_s v_s \sum_i \left(y'_{is} - \bar{y}'_s\right) \left(\tilde{x}_{is} - \bar{\tilde{x}}_s\right)}{\sum_s v_s n_s} \\
&= \frac{\sum_s v_s (n_s - 1) \mathrm{cov}\left(y'_s, \tilde{x}_s\right)}{\sum_s v_s n_s} \\
&= \frac{\sum_s \pi_s / \sigma_{x_s} \mathrm{cov}\left(y'_s, x_s\right)}{\sum_s \pi_s} = \mathbb{E}[\mathrm{cov}\left(y_S, x_S\right) |S],
\end{aligned} \tag{A1}
$$

where we note that $\bar{\tilde{x}}_v = \bar{\tilde{x}}_s = 0$, and we exploited that if $\mathbb{E}[x] = 0$ then $\mathbb{E}[y]$ doesn't directly affect the covariance level. □

Proposition 3 (Sectoral Covariance Decomposition)**.** *Suppose the data consist of n observations $\{\psi_i, w_i, z_i^1, ..., z_i^{d_Z}\}$. Suppose there are $d_Z \times 2$ linear regression equations indexed by $r = 1, ..., d_Z$ as*

$$
\begin{aligned}
\psi''_i &= \alpha_0^{r=1} + \alpha_1^{r=1} \tilde{z}_i^1 + \varepsilon_i^{r=1}, \\
w''_i &= \beta_0^{r=1} + \beta_1^{r=1} \tilde{z}_i^1 + \varepsilon_i^{r=1}, \\
&\cdots \\
\psi''_i &= \alpha_0^m + \alpha_1^m \tilde{z}_i^1 + ... + \alpha_{d_Z}^m \tilde{z}_i^{d_Z} + \varepsilon_i^m, \\
w''_i &= \beta_0^m + \beta_1^m \tilde{z}_i^1 + ... + \beta_{d_Z}^m \tilde{z}_i^{d_Z} + \varepsilon_i^m,
\end{aligned}
$$

where $\psi''_i = \psi_i \sqrt{n-1}$, $w''_i = w_i \sqrt{n-1}$, $\tilde{z}_i^j$ is a standard score of z_i^j, $j = 1, ..., d_Z$, and ε_i^r is the i.i.d. disturbance for r-th set of equations. Then, the covariance decomposition in Eq. (4) can be rewritten as

$$
(n-1)\mathrm{cov}(\psi, w) = (n-1)\, \mathbb{E}\left[\mathrm{cov}(\psi, w | Z^1, ..., Z^{d_Z})\right] + \sum_{r=1}^{d_Z} \alpha_r^r \beta_r^r.
$$

Proof of Proposition 3. Before turning to the proof it is useful to remind the multivariate covariance decomposition. We take that Z is a d_Z-dimensional vector of confounders, with $d_Z > 0$ and $r = 1, ..., d_Z$. By the law of total covariance we get that

$$
\begin{aligned}
\mathrm{cov}(\psi, w) = \mathbb{E}&\left[\mathrm{cov}(\psi, w | Z^1, ..., Z^{d_Z})\right] \\
&+ \sum_{j=2}^{d_Z} \mathbb{E}\left[\mathrm{cov}(\mathbb{E}[\psi | Z^1, ..., Z^j], \mathbb{E}[w | Z^1, ..., Z^j] \mid Z^1, ..., Z^{j-1})\right] \\
&+ \mathrm{cov}(\mathbb{E}[\psi | Z^1], \mathbb{E}[w | Z^1]).
\end{aligned} \tag{A2}
$$

In the proof we apply mathematical induction and switch to continuous domain for brevity. Let's take $r = 1$, and substitute the conditional expectations by the linear regressions $\mathbb{E}[\psi | \tilde{Z}^1] =$

$\hat{\psi}^1$ and $\mathbb{E}[w|\tilde{Z}^1] = \hat{w}^1$.

$$\begin{aligned}
\text{cov}(\psi, w) &= \mathbb{E}\left[\text{cov}(\psi, w|\tilde{Z}^1)\right] + \text{cov}(\mathbb{E}[\psi|\tilde{Z}^1], \mathbb{E}[w|\tilde{Z}^1]) \\
&= \int \text{cov}(\psi, w|\tilde{Z}^1 = \tilde{z}^1) \mathrm{d}\,\mathbb{P}(\tilde{Z} \leq \tilde{z}) + \text{cov}(\alpha_0^1 + \alpha_1^1 \tilde{Z}^1, \beta_0^1 + \beta_1^1 \tilde{Z}^1) \\
&= \int \text{cov}(\psi, w|Z^1 = z^1) \mathrm{d}\,\mathbb{P}(Z \leq z) + \alpha_1^1 \beta_1^1 \text{var}(\tilde{Z}^1) \\
&= \mathbb{E}\left[\text{cov}(\psi, w|Z^1)\right] + \alpha_1^1 \beta_1^1,
\end{aligned}$$

where we exploited that by design $\mathbb{P}(\tilde{Z} \leq \tilde{z}) = \mathbb{P}(Z \leq z)$.

Let's take $r = 2$ and apply similar strategy

$$\text{cov}(\psi, w) = \mathbb{E}\left[\text{cov}(\psi, w|\tilde{Z}^1, \tilde{Z}^2)\right] + \mathbb{E}\left[\text{cov}(\mathbb{E}[\psi|\tilde{Z}^1, \tilde{Z}^2], \mathbb{E}[w|\tilde{Z}^1, \tilde{Z}^2] \mid \tilde{Z}^1)\right] + \alpha_1^1 \beta_1^1.$$

In continuous setup the second term becomes

$$\int \text{cov}(\mathbb{E}[\psi|\tilde{Z}^1 = \tilde{z}^1, \tilde{Z}^2], \mathbb{E}[w|\tilde{Z}^1 = \tilde{z}^1, \tilde{Z}^2]) f(\tilde{z}^1) \mathrm{d}\tilde{z}^1 =$$
$$\int \text{cov}(\alpha_0^2 + \alpha_1^2 \tilde{z}^1 + \alpha_2^2 \tilde{Z}^2, \beta_0^2 + \beta_1^2 \tilde{z}^1 + \beta_2^2 \tilde{Z}^2) f(\tilde{z}^1) \mathrm{d}\tilde{z}^1 = \alpha_2^2 \beta_2^2.$$

For the second term of $r = m \leq d_Z$ expansion we get

$$\begin{aligned}
\int \ldots \int \text{cov}(\,&\mathbb{E}[\psi|Z^1 = z^1, \ldots, Z^{m-1} = z^{m-1}, Z^m], \\
&\mathbb{E}[w|Z^1 = z^1, \ldots, Z^{m-1} = z^{m-1}, Z^m]) f(\tilde{z}^1, \ldots, \tilde{z}^{m-1}) \mathrm{d}\tilde{z}^1 \ldots \mathrm{d}\tilde{z}^{m-1} = \alpha_m^m \beta_m^m.
\end{aligned}$$

□

Proposition 4 (General Covariance Decomposition)**.** *Suppose the data consist of n observations split into S partitions as* $\{\psi_{is}, w_{is}, z_{is}^1, \ldots, z_{is}^{d_Z}\}_{i=1}^{n_s}$ *with* $n_s \geq 1$ *and* $\{s = 1, \ldots, S\}$*. Suppose there are* $d_Z \times 2$ *linear regression equations indexed by* $r = 1, \ldots, d_Z$ *as*

$$\begin{aligned}
\psi_{is}'' &= \alpha_0^{r=1} + \alpha_1^{r=1} \tilde{z}_{is}^1 + \varepsilon_{is}^{r=1}, \\
w_{is}'' &= \beta_0^{r=1} + \beta_1^{r=1} \tilde{z}_{is}^1 + \varepsilon_{is}^{r=1}, \\
&\cdots \\
\psi_{is}'' &= \alpha_0^m + \alpha_1^m \tilde{z}_{is}^1 + \ldots + \alpha_{d_Z}^m \tilde{z}_{is}^{d_Z} + \varepsilon_{is}^m, \\
w_{is}'' &= \beta_0^m + \beta_1^m \tilde{z}_{is}^1 + \ldots + \beta_{d_Z}^m \tilde{z}_{is}^{d_Z} + \varepsilon_{is}^m,
\end{aligned}$$

where $\psi_{is}'' = \psi_{is}\sqrt{n_s - 1}$*,* $w_{is}'' = w_{is}\sqrt{n_s - 1}$*,* $\tilde{z}_i^j$*,* $\tilde{z}_{is}^j$ *is a standard score of* z_i^j*, with* $j = 1, \ldots, d_Z$*, within partition s, and* ε_{is}^r *is the i.i.d. disturbance for r-th set of equations. Then, the partition-wise aggregation of decomposition in Eq. (4) can be rewritten as*

$$\begin{aligned}
\mathbb{E}[(n_s - 1)\text{cov}(\psi_S, w_S) \mid S] &= \mathbb{E}\left[(n_s - 1)\,\mathbb{E}\left[\text{cov}(\psi, w|Z^1, \ldots, Z^{d_Z})\right] \mid S\right] \\
&+ \sum_{r=1}^{d_Z} \text{cov}\left(\mathbb{E}\left[\alpha_0^{rS} \mid S\right], \mathbb{E}\left[\beta_0^{rS} \mid S\right]\right) + \sum_{r=1}^{d_Z} \mathbb{E}\left[\alpha_r^{rS} \mid S\right] \mathbb{E}\left[\beta_r^{rS} \mid S\right].
\end{aligned}$$

Proof of Proposition 4. Let's start with the aggregate

$$\operatorname{cov}(\psi, w) = \mathbb{E}\left[\operatorname{cov}\left(\psi, w|\tilde{Z}^1\right)\right] + \operatorname{cov}\left(\mathbb{E}[\psi|\tilde{Z}^1], \mathbb{E}[w|\tilde{Z}^1]\right) = A + B. \tag{A3}$$

Firstly, we consider term A

$$\begin{aligned}
A &= \mathbb{E}\left[\int \operatorname{cov}(\psi_S, w_S|\tilde{Z}_S^1 = \tilde{z}_S^1)\mathrm{d}\,\mathbb{P}(\tilde{Z}_S \leq \tilde{z}_S) \mid S\right] \\
&= \mathbb{E}\left[\int \operatorname{cov}(\psi_S, w_S|Z_S^1 = z_S^1)\mathrm{d}\,\mathbb{P}(Z_S \leq z_S) \mid S\right] \\
&= \mathbb{E}\left[\mathbb{E}\left[\operatorname{cov}(\psi_S, w_S|Z_S^1)\right] \mid S\right],
\end{aligned}$$

where we exploited that by design $\mathbb{P}(\tilde{Z}_s \leq \tilde{z}_s) = \mathbb{P}(Z_s \leq z_s)$ for $s = 1, ..., S$.

Secondly, we take term B

$$\begin{aligned}
B &= \operatorname{cov}\left(\alpha_0^1 + \alpha_1^1\tilde{Z}^1, \beta_0^1 + \beta_1^1\tilde{Z}^1\right) \\
&= \mathbb{E}\left[\operatorname{cov}\left(\alpha_1^1\tilde{Z}^1, \beta_1^1\tilde{Z}^1 \mid S\right)\right] + \operatorname{cov}\left(\mathbb{E}\left[\alpha_0^1 + \alpha_1^1\tilde{Z}^1 \mid S\right], \mathbb{E}\left[\beta_0^1 + \beta_1^1\tilde{Z}^1 \mid S\right]\right) \\
&= \mathbb{E}\left[\operatorname{cov}\left(\mathbb{E}\left[\alpha_1^{1S} \mid S\right]\tilde{Z}^1, \mathbb{E}\left[\beta_1^{1S} \mid S\right]\tilde{Z}^1 \mid S\right)\right] \\
&+ \operatorname{cov}\left(\mathbb{E}\left[\alpha_0^{1S} \mid S\right] + \mathbb{E}\left[\alpha_1^{1S}\tilde{Z}^1 \mid S\right], \mathbb{E}\left[\beta_0^{1S} \mid S\right] + \mathbb{E}\left[\beta_1^{1S}\tilde{Z}^1 \mid S\right]\right) \\
&= \mathbb{E}\left[\alpha_1^{1S}|S\right]\mathbb{E}\left[\beta_1^{1S}|S\right] + \operatorname{cov}\left(\mathbb{E}\left[\alpha_0^{1S} \mid S\right], \mathbb{E}\left[\beta_0^{1S} \mid S\right]\right).
\end{aligned}$$

By the steps proposed in the proof of Proposition 3 the setup can be extended to multivariate $\tilde{Z}$ variable.

Note that the first term in the expansion of B is not weight invariant due to the different weighting of in the covariance, i.e.

$$\mathbb{E}\left[\alpha_1^{1S}|S\right]\mathbb{E}\left[\beta_1^{1S}|S\right] = \underbrace{\mathbb{E}\left[\alpha_1^{1S}\beta_1^{1S}|S\right]}_{\text{Weight invariant}} - \underbrace{\operatorname{cov}\left(\alpha_1^{1S}, \beta_1^{1S} \mid S\right)}_{\text{Not weight invariant}}$$

To balance the relative importance between the α_1^{1s} and β_1^{1s}, when calculating the scaled version of the Olley and Pakes (1996) allocative efficiency, we weight both components symmetrically by $\sqrt{n_s - 1}$.

Following Proposition 2, the regression equations can be estimated by the Weighted Least Squares, where weights are determined by the product of population weights π_s and inverse sample weights $n/(n_s - 1)$. $\square$

Proposition 5 (Conditional General Covariance Decomposition)**.** *Suppose the data consist of n observations split into S partitions as $\{\psi_{is}, w_{is}, q_{is}^1, ..., q_{is}^{d_Q}, z_{is}^1, ..., z_{is}^{d_Z}\}_{i=1}^{n_s}$ with $n_s \geq 1$ and*

$\{s = 1, ..., S\}$. *Suppose there are* $d_Z \times 2$ *linear regression equations indexed by* $r = 1, ..., d_Z$ *as*

$$
\begin{aligned}
\psi''_{is} &= \alpha_0^{r=1} + \alpha_1^{r=1}\tilde{z}_{is}^1 + \gamma_1^{r=1}\tilde{q}_{is}^1 + ... + \gamma_{d_Q}^{r=1}\tilde{q}_{is}^{d_Q} + \varepsilon_{is}^{r=1},\\
w''_{is} &= \beta_0^{r=1} + \beta_1^{r=1}\tilde{z}_{is}^1 + \delta_1^{r=1}\tilde{q}_{is}^1 + ... + \delta_{d_Q}^{r=1}\tilde{q}_{is}^{d_Q} + \varepsilon_{is}^{r=1},\\
&\dots\\
\psi''_{is} &= \alpha_0^{m} + \alpha_1^{m}\tilde{z}_{is}^1 + ... + \alpha_{d_Z}^{m}\tilde{z}_{is}^{d_Z} + \gamma_1^{r=1}\tilde{q}_{is}^1 + ... + \gamma_{d_Q}^{r=1}\tilde{q}_{is}^{d_Q} + \varepsilon_{is}^{m},\\
w''_{is} &= \beta_0^{m} + \beta_1^{m}\tilde{z}_{is}^1 + ... + \beta_{d_Z}^{m}\tilde{z}_{is}^{d_Z} + \delta_1^{r=1}\tilde{q}_{is}^1 + ... + \delta_{d_Q}^{r=1}\tilde{q}_{is}^{d_Q} + \varepsilon_{is}^{m},
\end{aligned}
$$

where $\psi''_{is} = \psi_{is}\sqrt{n_s - 1}$, $w''_{is} = w_{is}\sqrt{n_s - 1}$, $\tilde{q}_{is}^j$ *is a standard score of* q_i^j, *with* $j = 1, ..., d_Q$ *within partition* s, $\tilde{z}_{is}^j$ *is a standard score of* z_i^j, *with* $j = 1, ..., d_Z$ *within partition* s, *and* ε_{is}^r *is the i.i.d. disturbance for* r*-th set of equations. Then, the partition-wise aggregation of conditional covariance decomposition in Eq. (6) can be rewritten as*

$$
\begin{aligned}
\mathbb{E}[(n_s - 1)\mathrm{cov}(\psi_S, w_S) \mid Q = q, S] = \mathbb{E}\left[(n_s - 1)\,\mathbb{E}\left[\mathrm{cov}(\psi, w | Z^1, ..., Z^{d_Z})\right] \mid Q = q, S\right]\\
+ \sum_{r=1}^{d_Z} \mathrm{cov}\left(\mathbb{E}\left[\alpha_0^{rS} \mid Q = q, S\right], \mathbb{E}\left[\beta_0^{rS} \mid Q = q, S\right]\right)\\
+ \sum_{r=1}^{d_Z} \mathbb{E}\left[\alpha_r^{rS} \mid Q = q, S\right]\mathbb{E}\left[\beta_r^{rS} \mid Q = q, S\right].
\end{aligned}
$$

Proof of Proposition 5. Proof follows from steps outlined in the proof of Proposition 4. □

B Detailed results

Table B1: Olley-Pakes productivity decomposition.

	Full Sample		CESEE		South Europe		West-North Europe	
Year	Trend	Covariance	Trend	Covariance	Trend	Covariance	Trend	Covariance
2004	52.49	15.02	13.77	9.04	53.38	18.75	55.71	10.57
	(0.197)	(0.418)	(0.199)	(0.808)	(0.261)	(0.684)	(0.262)	(0.653)
2005	54.08	15.33	14.54	8.35	54.34	18.17	58.26	12.23
	(0.175)	(0.399)	(0.206)	(0.564)	(0.275)	(0.623)	(0.28)	(0.677)
2006	55.49	16.72	16.10	10.15	54.81	19.64	60.99	13.33
	(0.187)	(0.43)	(0.231)	(0.669)	(0.203)	(0.543)	(0.324)	(0.871)
2007	58.10	17.10	17.59	10.53	57.74	20.71	63.26	12.71
	(0.173)	(0.393)	(0.202)	(0.892)	(0.232)	(0.52)	(0.302)	(0.666)
2008	56.56	18.21	17.80	11.14	56.21	22.99	61.52	12.21
	(0.176)	(0.472)	(0.213)	(1.062)	(0.211)	(0.651)	(0.319)	(0.743)
2009	53.10	18.57	16.60	9.99	51.16	23.75	60.05	12.19
	(0.163)	(0.535)	(0.184)	(0.56)	(0.206)	(0.759)	(0.272)	(0.717)
2010	55.83	19.36	17.47	11.53	53.24	24.45	63.93	13.03
	(0.186)	(0.52)	(0.195)	(0.809)	(0.22)	(0.678)	(0.317)	(0.719)
2011	56.02	19.55	16.94	9.95	52.16	25.43	66.00	12.28
	(0.173)	(0.424)	(0.198)	(0.565)	(0.198)	(0.626)	(0.33)	(0.651)
2012	55.94	20.41	17.45	10.67	50.95	26.47	67.45	12.91
	(0.189)	(0.386)	(0.196)	(0.616)	(0.185)	(0.555)	(0.381)	(0.765)
2013	56.60	20.39	16.57	10.53	51.76	26.32	68.10	13.08
	(0.171)	(0.413)	(0.153)	(0.557)	(0.18)	(0.577)	(0.316)	(0.846)
2014	58.58	21.35	17.62	11.10	53.42	27.76	70.63	13.41
	(0.188)	(0.408)	(0.159)	(0.637)	(0.223)	(0.609)	(0.33)	(0.669)
2015	60.42	22.62	19.39	11.32	54.15	29.19	74.05	14.58
	(0.198)	(0.45)	(0.185)	(0.74)	(0.193)	(0.605)	(0.37)	(0.759)
2016	61.41	22.38	20.58	11.17	55.94	29.31	73.90	13.81
	(0.195)	(0.446)	(0.18)	(0.674)	(0.201)	(0.549)	(0.416)	(0.678)
2017	63.13	22.67	22.18	11.45	57.89	29.32	75.30	14.50
	(0.196)	(0.431)	(0.227)	(0.739)	(0.202)	(0.677)	(0.433)	(0.696)

Notes: Numbers are calculated for each NACE 4-digit sector and aggregated according to time-invariant value added weights for specific country groups. Bootstrapped standard errors from 100 replicas are given in parentheses (significance codes skipped for transparency, all values significant at 0.001 level).

Table B2: Financial leverage and allocative efficiency.

	Full Sample		CESEE		South Europe		West-North Europe	
Year	Leverage	Total	Leverage	Total	Leverage	Total	Leverage	Total
2005	1.31	15.33	0.67	8.35	1.20	18.17	0.72	12.23
	(0.11)	(0.439)	(0.099)	(0.585)	(0.154)	(0.744)	(0.14)	(0.788)
2006	1.89	16.72	0.86	10.15	2.05	19.64	1.01	13.33
	(0.143)	(0.543)	(0.098)	(0.73)	(0.208)	(0.619)	(0.163)	(0.968)
2007	1.77	17.10	0.77	10.53	1.68	20.71	1.11	12.71
	(0.121)	(0.446)	(0.09)	(0.797)	(0.14)	(0.577)	(0.165)	(0.714)
2008	1.56	18.21	0.99	11.14	1.52	22.99	1.02	12.21
	(0.109)	(0.515)	(0.127)	(1.038)	(0.167)	(0.687)	(0.157)	(0.881)
2009	0.65	18.57	0.61	9.99	0.41	23.75	0.82	12.19
	(0.073)	(0.524)	(0.118)	(0.794)	(0.079)	(0.646)	(0.168)	(0.85)
2010	0.95	19.36	0.62	11.53	0.69	24.45	0.98	13.03
	(0.093)	(0.485)	(0.138)	(1.171)	(0.096)	(0.554)	(0.193)	(0.813)
2011	1.01	19.55	0.79	9.95	0.67	25.43	0.97	12.28
	(0.091)	(0.444)	(0.154)	(0.453)	(0.102)	(0.644)	(0.171)	(0.915)
2012	0.99	20.41	0.65	10.67	0.63	26.47	0.83	12.91
	(0.087)	(0.419)	(0.129)	(0.6)	(0.097)	(0.566)	(0.177)	(0.946)
2013	0.93	20.39	0.66	10.53	0.65	26.32	0.77	13.08
	(0.093)	(0.508)	(0.135)	(0.549)	(0.092)	(0.607)	(0.153)	(0.776)
2014	1.02	21.35	0.66	11.10	0.74	27.76	0.79	13.41
	(0.096)	(0.462)	(0.152)	(0.553)	(0.123)	(0.656)	(0.17)	(0.69)
2015	1.14	22.62	0.78	11.32	0.94	29.19	0.80	14.58
	(0.112)	(0.515)	(0.178)	(0.759)	(0.121)	(0.608)	(0.203)	(0.903)
2016	1.12	22.38	1.03	11.17	0.93	29.31	0.66	13.81
	(0.113)	(0.496)	(0.144)	(0.6)	(0.129)	(0.572)	(0.165)	(0.844)
2017	1.25	22.67	0.87	11.45	1.13	29.32	0.91	14.50
	(0.116)	(0.451)	(0.174)	(0.608)	(0.119)	(0.629)	(0.174)	(0.862)

Notes: Contribution of financial leverage to covariance productivity component (Column Leverage), conditional on the level of cash to total assets, sales to total assets and trade payables to total assets (all in $t-1$). Financial leverage is calculated as a sum of current and non-current liabilities to total assets and taken in $t-1$. For comparison, the total covariance component is given according to Olley and Pakes (1996). Numbers are calculated for each NACE 4-digit sector and aggregated according to time-invariant value added weights for specific country groups. Bootstrapped standard errors from 100 replicas are given in parentheses (significance codes skipped for transparency, all values significant at 0.001 level).

Table B3: Net financial leverage and allocative efficiency.

	Full Sample		CESEE		South Europe		West-North Europe	
Year	Net Lev.	Total	Net Lev.	Total	Net Lev.	Total	Net Lev.	Total
2005	1.88	15.33	0.80	8.35	1.70	18.17	1.27	12.23
	(0.154)	(0.499)	(0.121)	(0.605)	(0.19)	(0.838)	(0.257)	(0.833)
2006	2.77	16.72	1.03	10.15	2.88	19.64	1.63	13.33
	(0.225)	(0.52)	(0.113)	(0.701)	(0.299)	(0.649)	(0.223)	(1.132)
2007	2.58	17.10	0.95	10.53	2.37	20.71	1.87	12.71
	(0.189)	(0.438)	(0.118)	(0.851)	(0.209)	(0.546)	(0.231)	(0.695)
2008	2.31	18.21	1.35	11.14	2.14	22.99	1.74	12.21
	(0.173)	(0.518)	(0.193)	(1.184)	(0.237)	(0.691)	(0.243)	(0.814)
2009	0.92	18.57	0.86	9.99	0.59	23.75	1.50	12.19
	(0.109)	(0.601)	(0.129)	(0.746)	(0.116)	(0.742)	(0.307)	(0.842)
2010	1.31	19.36	0.92	11.53	0.97	24.45	1.68	13.03
	(0.128)	(0.512)	(0.202)	(1.069)	(0.136)	(0.665)	(0.325)	(0.873)
2011	1.40	19.55	1.19	9.95	0.95	25.43	1.48	12.28
	(0.128)	(0.419)	(0.203)	(0.486)	(0.138)	(0.585)	(0.288)	(0.736)
2012	1.40	20.41	1.06	10.67	0.92	26.47	1.31	12.91
	(0.132)	(0.495)	(0.183)	(0.58)	(0.123)	(0.693)	(0.351)	(0.876)
2013	1.31	20.39	1.05	10.53	0.95	26.32	1.20	13.08
	(0.141)	(0.412)	(0.175)	(0.571)	(0.139)	(0.586)	(0.285)	(0.819)
2014	1.52	21.35	1.09	11.10	1.11	27.76	1.38	13.41
	(0.125)	(0.479)	(0.221)	(0.515)	(0.154)	(0.647)	(0.277)	(0.768)
2015	1.69	22.62	1.27	11.32	1.39	29.19	1.29	14.58
	(0.14)	(0.549)	(0.21)	(0.707)	(0.162)	(0.584)	(0.338)	(0.835)
2016	1.76	22.38	1.71	11.17	1.46	29.31	1.15	13.81
	(0.141)	(0.47)	(0.209)	(0.582)	(0.188)	(0.711)	(0.234)	(0.885)
2017	2.00	22.67	1.54	11.45	1.77	29.32	1.49	14.50
	(0.171)	(0.499)	(0.264)	(0.722)	(0.207)	(0.631)	(0.273)	(0.77)

Notes: Contribution of net financial leverage to covariance productivity component (Column Net Lev.), conditional on the level of cash to total assets, sales to total assets and trade payables to total assets (all in $t-1$). Net financial leverage is calculated as a sum of current and non-current liabilities, minus the cash holdings, to total assets and taken in $t-1$. For comparison, the total covariance component is given according to Olley and Pakes (1996). Numbers are calculated for each NACE 4-digit sector and aggregated according to time-invariant value added weights for specific country groups. Bootstrapped standard errors from 100 replicas are given in parentheses (significance codes skipped for transparency, all values significant at 0.001 level).