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Aggregate productivity slowdown in Europe: New evidence from corporate balance sheets

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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 not be 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 2014-17.

1 Introduction

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. To the contrary, 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). The degree to which market activity is driven by highly productive firms is often recognized as allocative efficiency, and it has been a focal point of the policy debate throughout the recent decades (Banerjee and Duflo, 2019; Gopinath et al., 2017; Barbiero et al., 2020).

In their seminal paper, Olley and Pakes (1996) (hereafter OP) propose an elegant way to express such-defined allocative efficiency, as a cross-sectional covariance-like term between the firms' market shares and respective productivity levels. Should highly-productive firms enjoy large market shares, firms' distribution would contribute positively to aggregate productivity compared to a uniform distribution. Alternatively, should the market be dominated by low-productivity entities, one can think of such an outcome as inefficient.

The OP framework has become an industry benchmark in empirical studies, as it offers a simple, yet powerful, tool to analyse the micro-macro links in productivity. For instance,

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on the example of the US telecommunications equipment industry, OP show that deregulation might have increased the covariance term by increasing the allocation of resources to the most productive entities. More recently, Bartelsman et al. (2013) deliver evidence that variation in the covariance term is a significant predictor of the cross-country differences in aggregate productivity levels. On the European level, Eurostat (2016) estimates that if the OP allocative efficiency among the EU manufacturing firms remained at the level from 2003 throughout the following years, the production in that sector would have been by 6 per cent higher in 2014, ceteris paribus. When taking into account market service firms, the gains would have been around 24 per cent over the same period.

We take the OP framework as a starting point in our analysis. In particular, we propose new methodology to estimate the OP covariance term 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 aggregate sector-specific OP results across various data partitions. We further support the inference with bootstrap confidence intervals, hence allowing for more meaningful comparison of productivity metrics across the literature.

While the idea of estimating OP components on re-scaled variables is not a novelty (see, for instance, Hyytinen et al. (2016)), we take it one step further and, still in the OLS framework, we propose a formal approach to estimate the conditional OP covariance term. In particular, under standard regularity conditions, our method allows to capture the distributional contribution of firm-specific factors to the within-sector covariance productivity component. This constitutes a major improvement over cross-sector or cross-country regressions, whereby the within-group firms' distributions are collapsed to the first moments only. Our method allows also to include other firm-specific controls, reducing thereby the omitted variables bias.

We test our framework on a sample of EU manufacturing firms. We focus on labour productivity metric, expressed as output per person employed, as it appears to suffer more from the hysteresis effect than the Total Factor Productivity (TFP).[1] Our main research question concerns the degree to which the capital structure of the corporate ecosystem affected the allocative efficiency component, and consequently the aggregate productivity growth, in years 2004-17.

On this background, our study falls in the scope of the finance-productivity nexus. Access to external finance is one of the key factors which allow innovative companies to enter the markets and grow (Aghion et al., 2004; Gorodnichenko and Schnitzer, 2013). Similarly, properly functioning financial markets should allow for orderly exit of less productive incumbents, and smoothly reallocate resources to their most productive use (Aghion et al., 2019). The creative destruction process may take longer than desired, from a welfare perspective, if it is blurred by market frictions.

Agency problems, linked for instance to the corporate capital structure, are a point in case. At excessive debt levels, managers can be discouraged from pursuing the most productive investment projects and instead they can lock in the resources in less profitable endeavours

[1]It should be flagged, however, that our methodology can be applied to any input- or output-based productivity metric, available at firm level.

(Jensen and Meckling, 1976). On the other hand, problems with access to finance can also lead firms to shift investment away from the most productive projects (Banerjee and Duflo, 2005). While our identification strategy cannot unambiguously answer whether the allocative inefficiencies are related to too much or too little debt, we shed more light on the problem by studying the relation between distribution of firms' debt and the OP covariance component over time, controlling for proxies of debt overhang and financial constraints.

Our results reveal a number of interesting patterns. Firstly, we confirm 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 argue that corporate indebtedness could have a non-negligible effect on the OP covariance productivity component. At the EU level, financial leverage contributed some 27% 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 2014-17, it never really recovered to the pre-crisis levels with the contribution being nearly twice smaller at 14%. To put it in perspective, should the financial leverage component in years 2014-17 grow at the pre-crisis levels, the covariance productivity component in 2017 could have been higher by 0.76 per cent in Central-Eastern and South-Eastern Europe, by 1.75 per cent in Southern Europe and by 6.67 per cent in Western and Northern Europe.

Finally, we elaborate on the reasons for which the after-crisis covariance productivity growth has been subdued. 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 2014-17.

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 access to finance is investigated in Section 5. Section 6 concludes.

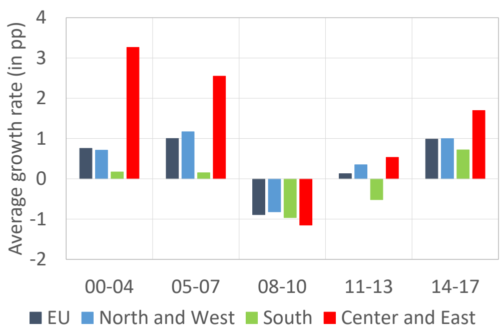
2 Motivation

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.[2]

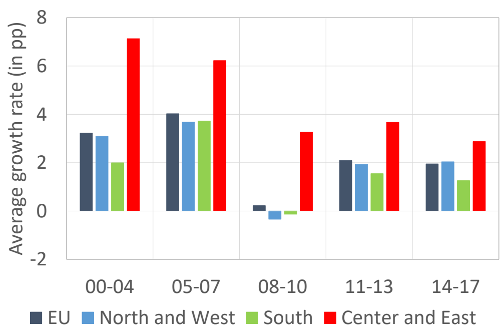
In Europe, even though the TFP has been on a trend decline since the late 90s is some countries, the slowdown in productivity growth is predominantly visible in terms of labour output (see Figure 1). On aggregate level, the TFP growth between 2014 and 2017 bounced back to its pre-crisis years, amounting to an average 1 per cent per year. To the contrary, labour productivity growth halved throughout the same period from 4 per cent per year in 2005-07 to around 2 per cent in 2014-17.[3]

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, as along the convergence with the rest of EU, the productivity gap diminishes and productivity growth slows down. However, given the relatively small GDP share of the region (of around 8%), the overall impact on the EU remains contained. Figure 1(b) confirms that the drop in labour productivity growth rates is consistently observed throughout the EU regions.

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]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).

[3]On this background, labour productivity becomes our key variable of interest throughout the empirical part of this study.

2.1 Productivity and misallocation

A strand of research claims that resource misallocation is responsible for the disappointing overall post-crisis economic performance. The OP decomposition is one of the key frameworks to support the policy debate in this respect. In essence, OP measures the gains or losses in aggregate productivity relative to a situation where market shares are distributed randomly across firms within a certain sector. A positive OP covariance-like term, suggests that the resources are being allocated efficiently, as firms with relatively high productivity levels have also higher market shares.

On the basis of the OP metric, a large-scale study requested by the European Commission and delivered by the National Institute of Economic and Social Research, the Valencian Institute of Economic Research, and the Austrian Institute of Economic Research, reveals that that reallocation of resources plays an important part in explaining cross-country differences in the levels of productivity on a sample of 21 EU countries (Eurostat, 2016). The report finds that, on average, allocative efficiency has seen a small decrease in the post-crisis years. Yet, there are substantial differences between industries, with manufacturing characterized by lower levels of allocative efficiency than, for instance, the services sector.

An alternative measure of allocative efficiency 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 it is an implication of 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. (2015) 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.[4]

The OP framework, and the marginal product dispersion, are effectively two sides of the same coin and describe the static case of within-sector distribution of resources. The most recent literature proposes that a part, at least, 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.

Even though the above methods do not account for the dynamic process of entry and exit of firms, but treat all firms as incumbents instead, 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

[4] This is sometimes referred to as the hysteresis effect.

deterioration in the two fundamental microeconomic forces, i.e. (i) a noticeable decline in the pace the laggard firms catch up with the global productivity frontier, and (ii) a reduction in the extent of corporate exit-entry dynamism and its productivity-enhancing effect. More recently, Melitz and Polanec (2015) extend the OP decomposition for the entry-exit dynamics, which constitutes a major step to better understand the reasons behind the slowdown in the allocative efficiency growth. For instance, on the example of Slovenian manufacturing firms, they estimate that the measurement bias associated with entry and exit accounts for up to 10 percentage points of aggregate productivity growth.

2.2 The role of exit and entry in the corporate ecosystem

New firms offer an important way for new products and new production methods to be introduced into markets and can drive out less efficient production techniques. New firms can also spur incumbent firms to improve productivity, in an attempt to survive (Aghion et al., 2004).

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 per cent.[5] 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 as it appears that exits have not increased significantly during the crisis.

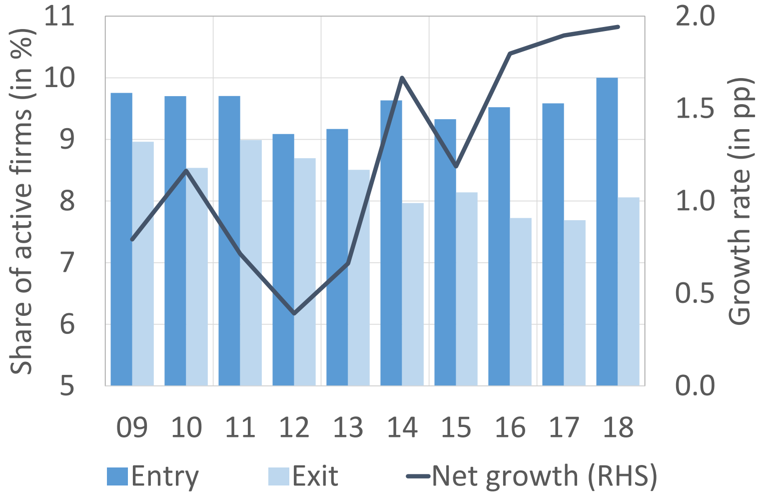
The absence of a cyclical pattern in the exit rate may suggest that that firms which could have exited the market, received an extra lifeline at the expense of lower aggregate productivity levels. Such a lifeline has been visible, for instance, through the roll-over of bank loans, even for incumbent firms without bright market prospects. This phenomenon is often dubbed as ever-greening (Peek and Rosengren, 2005).[6]

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).

[5] To avoid confusion, unless stated otherwise, throughout the text we use % symbol to describe shares, and 'per cent' formulation to describe changes like, for instance, growth rates.

[6] We borrow this term from Peek and Rosengren (2005), even though it was originally coined to describe the situation among Japanese banks.

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



Notes: Authors' computations based on Eurostat.

2.3 Access to finance as an indirect contributor

A vast body of literature point to the conclusion that better access to credit should have an unambiguously positive effect on productivity and 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.

Access to finance matters for innovation too. Gorodnichenko and Schnitzer (2013) show that a firm's decision to invest into innovative activities is sensitive to financial frictions, which can prevent firms from adopting better technologies. On a sample of firms from Eastern Europe and Commonwealth of Independent States, they find evidence that costly external funding may significantly hamper convergence to the technological frontier.

The recent studies show, however, that the link between credit access and productivity growth may be non-monotonic. Aghion et al. (2019) show the existence of two counteracting effects of access to credit on productivity growth. On the one hand, better access to credit makes it easier for entrepreneurs to innovate. On the other hand, 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. Overall, the link between credit access and productivity growth may look like an inverted U-shape. Productivity is an increasing function of credit conditions when credit is rationed. Beyond a certain threshold, however, the relationship becomes inverted, as access to credit becomes too loose and it becomes associated with ever-greening or 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 productivity 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 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, limits their ability to compete in the product market and consequently the low-productivity firms rip of the excess returns on their products, weighing down on the aggregate productivity.

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 Borio et al. (2015), who decompose sector-wide productivity into an OP-like common and an allocation component. The authors show that while allocation element does not explain much of the variation in the overall 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 investment decisions and by extrapolation can influence the productivity levels. 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 our study reach back to the arguments proposed by Jensen and Meckling (1976), Fuchs et al. (2016) and Barbiero et al. (2020), whereby agency problems between managers and shareholders, and between firms and investors, can lead firms to shift investment away from the most productive projects available and therefore reduce the aggregate productivity levels over time. More precisely, we measure to what extent the relation between firm-level capital structure, and the OP allocative efficiency component, changed over the first two decades of this century in the EU.

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.[7] 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 a multi-sector economy (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.

Our procedure relies on the analogy principle, whereby population conditional covariance parameters can be estimated by the corresponding sample statistics. As we operate in the OLS world, the framework requires that all Gauss-Markov assumptions hold. In this respect, the strict exogeneity assumption is particularly relevant for proper identification of the contribution to the covariance term, as it guarantees its unbiasedness. Importantly, we propose to control for other observable firm-specific factors when estimating the contribution, which should reduce the omitted variable bias and soften the identification assumption to conditional strict exogeneity.

3.1 A one-sector approach

Let us denote the aggregate productivity level in industry s by Ψ_s. The specific productivity metric depends on the application, and it can represent either an industry level index of TFP or labour productivity, in levels or in log-units, computed by using either input or output shares. The 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.[8] Within-sector number of firms is given by n_s, and we consider only meaningful cases where $n_s \geq 2$. Firm-level productivity is represented by ψ_{is}.

The OP covariance-like term indicates by how much productivity is modified compared to uniform distribution where each firm has the same market share (a benchmark 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,

[7] 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 in the on-line Appendix.

[8] 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.

the efficiency component can be re-written as:[9]

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

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, the basic OLS transformation identifies 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 its standard score $\tilde{w}$, with $\mathrm{var}(\tilde{w}) = 1$. 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.

It should be noted that there are multiple ways to re-scale the variables and still get the same regression results. Hyytinen et al. (2016), for instance, propose a GMM estimation framework where they re-scale the market share variable only as $(w_i - \bar{w})/\sigma_w^2 n$. The re-scaling methods are clearly interchangeable, and our further arguments can be aligned to match the one of Hyytinen et al. (2016). Ultimately, the choice of the re-scaling method depends on individual preferences. In our case, the $\tilde{w}$ variable is a standard score, which is often an already implemented transformation in statistical software and thereby remains our preferred specification.

3.2 Generalisation to several sectors

Let us assume that the economy consist of S sectors, indexed as $s = 1, ..., S$ with $S \geq 2$.[10] 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 calculating their weighted average. The procedure is formalized in Proposition 2 in the on-line Appendix.

[9] 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.

[10] 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.

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 $\hat{\beta}_1$ OLS-weighted 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.[11]

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

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

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 sample fitted values, by the analogy principle. 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 $\mathrm{cov}(\hat{\psi}_s, \hat{w}_s) = \hat{\alpha}_1 \hat{\beta}_1 \mathrm{var}(Z_s)$. We propose the following estimation framework to match the desired magnitude of the coefficients:

[11] 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.

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

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, $(n_s - 1)\text{cov}(\hat{\psi}_s, \hat{w}_s) = \hat{\alpha}_1\hat{\beta}_1$. For correct magnitude identification, we require that the strict exogeneity assumption holds for both regressions, such that $\mathbb{E}[\nu|\tilde{Z}] = 0$ and $\mathbb{E}[\varepsilon|\tilde{Z}] = 0$, making $\hat{\alpha}$ and $\hat{\beta}$ estimates unbiased.

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:

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

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 $(n_s - 1)\text{cov}(\hat{\psi}_s|Q = q, \hat{w}_s|Q = q) = \hat{\alpha}_1\hat{\beta}_1$. This specification allows to weaken the strict exogeneity condition to $\mathbb{E}[\nu|\tilde{Z}, \tilde{Q}] = 0$ and $\mathbb{E}[\varepsilon|\tilde{Z}, \tilde{Q}] = 0$.

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 a 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).[12] 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 the Appendix.

Last but not least, we estimate the role of capital structure 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 capital composition. 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). We don't put any ex-ante size thresholds on the firms in the sample.

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

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

country-sector level, we focus only on sectors which have at least 30 firms in every year from 2004 until 2017 at the country 4-digit level. 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 2004-17, 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. Firstly, 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.

Secondly, 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 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.

Thirdly, 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.

Fourthly, 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%. CESEE 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

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. CESEE 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.

CESEE 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, CESEE 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.

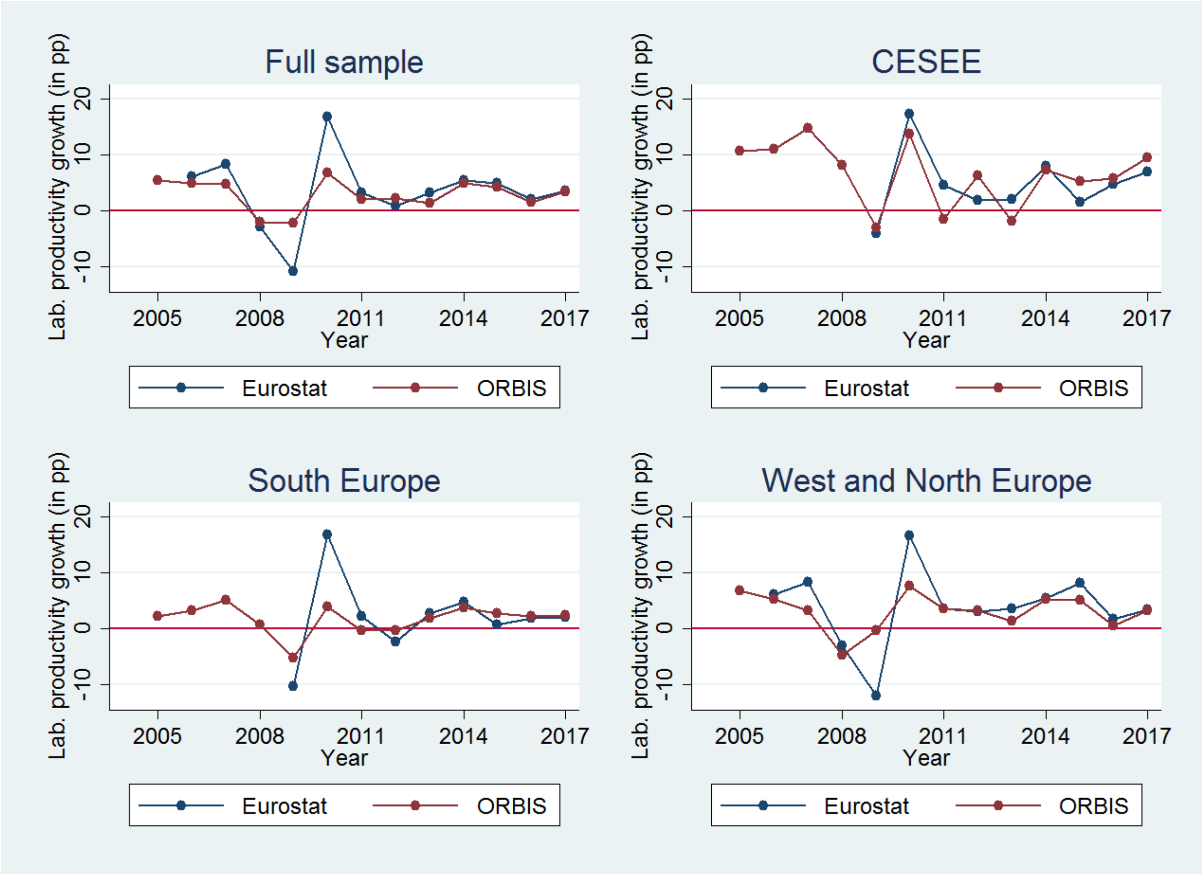
It is widely acknowledged that ORBIS data set, while not offering an unbiased sample of European corporates (Gopinath et al., 2017), provide the most comprehensive and homogeneous data set of firm levels data on which conduct analysis (Kalemli-Özcan et al., 2015). The records happen to be gathered from 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.[13] 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 data set, CESEE, Southern Europe and Western and Northern Europe, respectively.

[13] 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 2005-17.



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

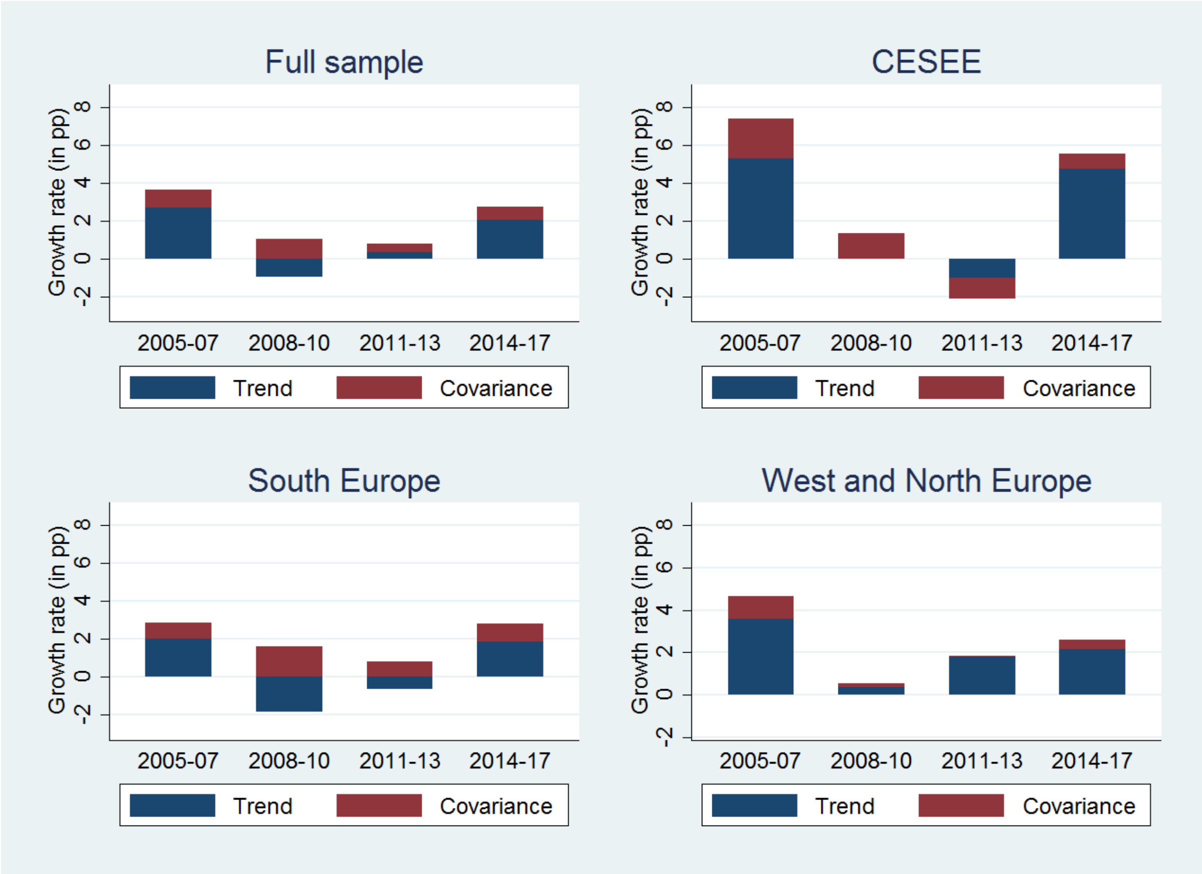
Firstly, we estimate the OP decomposition in the OLS framework, according to Eq. (3). In particular, we estimate an equation:

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

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 the 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 per cent on average between 2005 and 2007. It then collapsed to 0.1 per cent during the crisis years, with very muted recovery at 0.8 per cent in years 2011-13. Productivity growth converged but did not reach pre-crisis levels throughout 2014-17, averaging to around 2.8 per cent 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, the European corporate ecosystem seemed to have allocated resources more efficiently, with more productive corporates absorbing more resources. The allocative efficiency contribution was strongest during the period of the global financial crisis, which 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 the

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 rates. In fact, while the overall growth rate post 2014 was lower by a quarter compared to the years 2005-07, the growth rate of covariance productivity component itself more than halved throughout the period, from 5.6 per cent in 2005-07 to 2.7 per cent in 2014-17.

Beyond aggregate dynamics, the analysis also brings interesting insights regarding regional differences. The CESEE region enjoyed the highest productivity growth throughout 2005-07 and 2014-17, reaching 7.4 per cent and 5.6 per cent, respectively. The crisis years took, however, their toll. Productivity growth slowed down to 1.3 per cent in 2008-10, being exclusively supported by the allocative efficiency component. Productivity then receded by 2.1 per cent during the period of the sovereign debt crisis, in 2011-13, as trend component and allocation efficiency declined. It is indeed the only occurrence in our study over which the allocative efficiency contributed negatively to the overall productivity growth. While productivity growth bounced back over the years 2014-17, 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.

For the Southern Europe, at around 2.9 per cent per year, the pre-crisis productivity growth was below the EU benchmark. It 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, also during the crises. In fact, the allocative efficiency played a substantial positive role throughout the crisis. Despite the supportive role of the allocation efficiency, the overall productivity growth stalled during the sovereign debt crisis. Over the most recent period, productivity growth has rebounded however, slightly exceeding the pre-crisis pace.

Annual productivity growth, in the pre-crisis years, in West and North Europe reached on average 4.7 per cent, with the covariance component accounting for 23% of this increase. While productivity growth substantially slowed down during the crisis years, to 0.5 per cent a year, and accelerated thereafter, it remains more than 1 percentage point below the pre-crisis levels in the more recent period. The allocative efficiency component did not substantially contribute to productivity growth during the period of the global financial crisis, nor during the sovereign debt turbulence. It picked up marginally only in the most recent period. However, less than one-fifth of the total level of labour productivity can be attributed to the covariance component, which is 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 20%, on average, its supportive role during the recovery should not be underestimated, especially in the CESEE and Southern European regions. Should the allocative efficiency component grow at its pre-crisis pace in years 2014-17, the overall productivity would grow faster by nearly 0.7 percentage points (3.4 per cent against actual of 2.7 per cent). To put it in level terms, should the covariance component in years 2014-17 grow at the 2005-07, in 2017 labour productivity would have been higher by EUR 1,141 in the CESEE region and by EUR 1,979 in Southern Europe.[14]

[14] The allocative productivity growth in 2014-17 in Western and Northern Europe was in this respect higher than in pre-crisis years.

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 in standard scores). The independent variables are taken in the first lags to alleviate at least some of the endogeneity concerns. Variables ε and ν are the i.i.d error terms. Dimensions i, s, c and t correspond to the firm, sector, country and year, respectively. 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, under exogeneity of ε and ν, 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 in the Appendix.[15]

Firstly, the results confirm the previous section observation that the covariance productivity growth more than halved in the EU17 from 2005-07 to 2014-17.

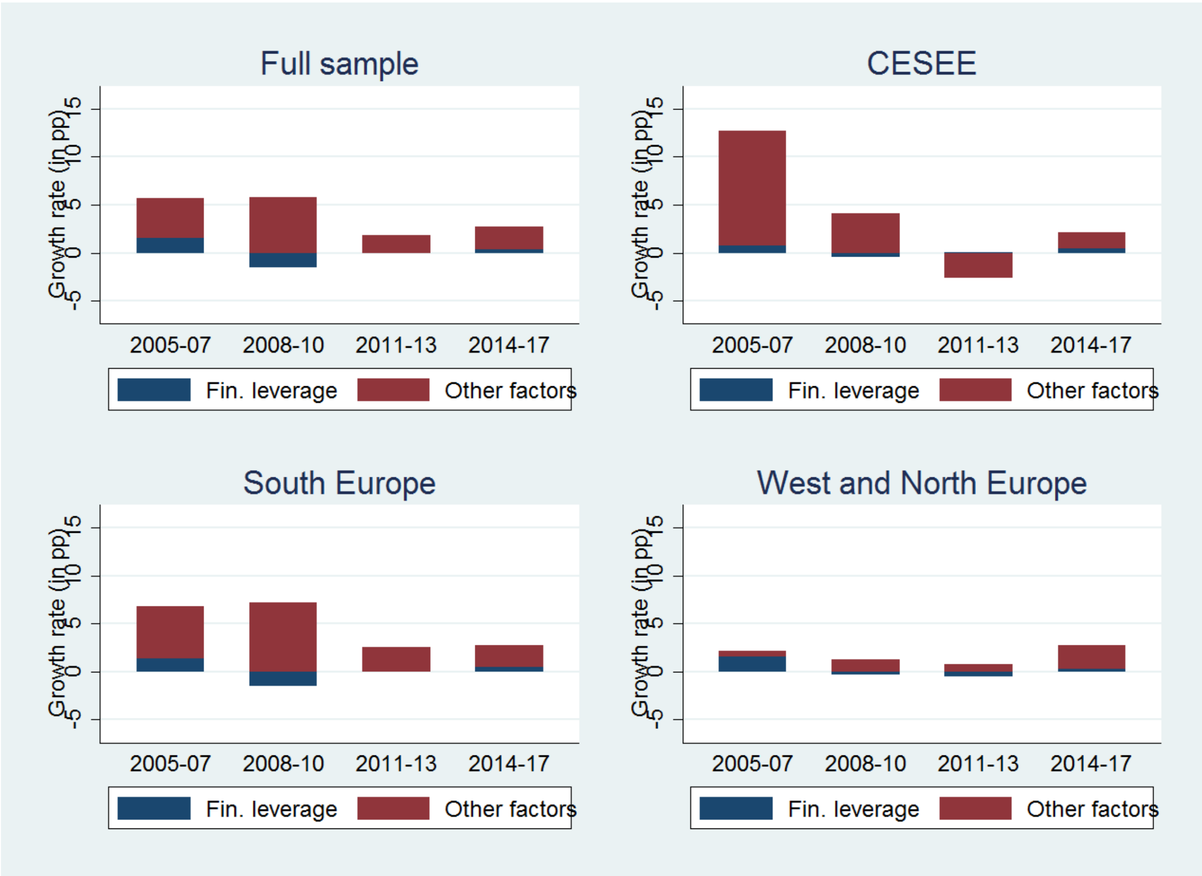
Secondly, and more importantly, the role of firm-level financial leverage also evolved. Looking at the EU17, access to finance contributed some 27% of the allocative productivity growth before the crisis. During the financial crises, when banks were short on capital and rationed credit, dependence on external finance was weighing on the within-sector resource allocation. That could have been attributed to both productive firms being strapped of external finance, but also to sustaining credit lines to less productive incumbent firms. In the after-crisis years, the finance-driven allocative efficiency growth was muted. While it picked up marginally between in 2014-17, 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 a key driver for allocative efficiency growth in the CESEE region. For South Europe, the benefits of the financial leverage on allocative efficiency growth in pre-crisis years were completely offset during the subsequent crisis phase. It remained muted afterwards.

However, finance played a more nuanced role for the productivity growth in West and North Europe. While the region actually observed a small improvement in allocative productivity growth from 2.2 per cent in 2005-07 to 2.7 per cent in 2014-17, there role played by financial leverage flipped. In the pre-crisis period, financial leverage was contributing 71% to the overall

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

efficiency growth. This contribution almost vanished during the two crisis episodes. 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 2014-17, the contribution from financial leverage to allocative efficiency growth was below 10%.

Should the financial leverage component in years 2014-17 grow at the pre-crisis levels, the allocative efficiency could have grown by 0.67 percentage points, 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.[16]

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, however, we shed more light on this phenomenon on the example of Western and Northern Europe, as a 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 does 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 (Aghion et al., 2004). 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 (Jensen and Meckling, 1976). 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 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

[16]We arrive at these numbers by calculating the 2017 financial leverage component with a growth rate in each of the years between 2014-17 replaced by the 2005-07 average. For the CESEE region, for instance, the average growth rate in financial component was 9.7 per cent 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).

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, rather stylized, 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 channel(s) that alter the contribution of financial leverage to the allocative efficiency growth. However, we can approximate them through stylized what-if scenarios, by estimating the model in Eq. (9) controlling for the firm-level 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, yet they are still present on the market. While we cannot directly account for the bank-firm relation in this respect, this proxy may be associated with a degree of firm's zombiefication and therefore it indirectly suggests that some of firm's bad debt may be rolled over (Bank of England, 2013). Lastly, we consider firms' development to be hampered by financial constraints if they have a low collateralization index, defined as the share of tangible to total assets being in the first quartile of the within-sector distribution.[17] 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 choreography. In particular, the interest coverage problems escalated throughout 2008-10 and

[17]It should be noted that one firm can belong to several groups. For instance, for the years 2011-13 about a third of credit-constrained firms are also tagged as suffering from debt overhang and ever-greening. While it blurs the lines between the channels, the general results still hold for firms which belong to one category only.

remained 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 2011-13, highlighting the difficulties among firms to boost profitability metrics even after the crisis. Broadly-speaking, however, the post-2014 shares largely match the pre-crisis patterns.

We re-estimate Eq. (9) by adding an extra interaction variable, to the set of control variables $\tilde{Q}$, for each of the three channels listed above. This extra control accounts for distributional impact of financial leverage onto the allocative efficiency component, which can be attributed to either debt overhang, ever-greening or financial constraints.[18]

The results are presented in Table 4 in columns (2), (3) and (4), respectively. Additionally, the overall growth rate financial leverage contribution is presented for comparison in column (1).[19] The table should be read by comparing the numbers in columns (2)-(4) to the numbers in column (1), such that higher numbers in columns (2)-(4) reflect that the presence of firms, associated with a specific channel in the overall distribution of firms, hampered the covariance productivity growth attributed to financial leverage.

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

Years	(1) Fin. leverage	(2) No debt overhang	(3) No ever-greening	(4) No credit constraints
2005-2007	1.55%			
2008-2010	-0.34%	0.79%	0.14%	-1.60%
2011-2013	-0.56%	-1.80%	-1.26%	0.25%
2014-2017	0.26%	0.02%	-0.02%	0.62%

Notes: Growth in financial leverage component of covariance productivity, estimated by controlling for distributional impact associated with debt overhang (column 2), ever-greening (3) and credit constrains (4). See the main text for the proxies used to classify firms across the three potentially overlapping groups. The numbers reflect the average annual growth rates in respective periods.

It can be readily observed that during the crisis years between 2008-10 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 excessive debt levels, the growth contribution would have jumped from -0.34 per cent to 0.79 per cent.

After the crisis, credit constraints become more visible. While the covariance productivity growth linked to financial leverage between 2011 and 2013 was -0.56 per cent, it would have been 0.25 per cent (so even above the overall covariance productivity growth) if we control for the distributional effects generated by firms with low collateral level.

This pattern is exacerbated in years 2014-17. Excluding the effects spanned by low-collateral companies, the covariance productivity growth generated by financial leverage would have been 0.62 per cent, compared to 0.26 per cent when calculated over the entire distribution of firms. In other words, should the distribution of firm-level productivity be independent from collateral

[18] For instance, for the debt overhang dummy D, the extra control is $\tilde{Lev}_{isct-1} \times D_{isct-1}$.

[19] The numbers reported under the column (1) correspond to the blue bar, i.e. the growth in contribution of financial leverage in Figure 5.

levels, debt could have been more than twice more effective in spurring allocative efficiency growth across West and North Europe between 2014-17.[20]

6 Concluding remarks

The goal of the paper is threefold. 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. The first one describes the productivity level common across all the firms in a sector. The second one is a covariance-like term, often associated with allocative efficiency, which describes to what extent highly productive firms dominate in a particular sector.

Our OLS framework is 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 the EU17 countries, using a comprehensive unbalanced data set of around 672,000 firms, over the years 2004-17. We find that the allocative efficiency component contributed positively to the overall labour productivity growth throughout the years. This 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 CESEE and Southern European regions. Should it had grown at its pre-crisis pace in years 2014-17, the 2017 level of labour productivity would have been higher by EUR 1,141 in the 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 2014-17, it never really recovered to the pre-crisis levels with the contribution being nearly twice smaller at 14%.

We further measure to what extent firm-level debt metrics contributed to the evolution of the allocative efficiency over time. We find that Western and Northern Europe experienced a major change in how the within-sector distribution of debt was associated with the allocative efficiency growth after the financial crisis. Specifically, 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 2014-17, on average.

[20] 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 rather viewed through a prism the within-sector distribution of productivity, but these factors could have still hampered sector-wide trend productivity growth, for instance.

In the last step of the analysis, we try to explain this change. In particular, we estimate 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 our index of collateral availability. 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 2014-17.

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 certainly desirable directions.

Secondly, the findings indicate that productive efficiency growth could have been muted, in the recent years, by firms having problems with access to 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 more efficient allocation of resources and, by extrapolation, can spur the overall productivity growth.

This study has a natural continuation in the dynamic OP decomposition, as proposed by Melitz and Polanec (2015). While there is no clear-cut way to embed our OLS framework in the dynamic OP specification, controlling for exit-entry rates could have offered more precise estimates on the role of finance in the aggregate productivity growth. Similarly, to better track the role of the financial sector, conditional on data availability, a possible extension could 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

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

Suppose we take the standard score $\tilde{x}$ of the x covariate, such that $\bar{\tilde{x}} = 0$ and $\mathrm{var}(\tilde{x}) = 1$. 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

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

□

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

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

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. $\square$

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*

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

where $\psi''_i = \psi_i \sqrt{n-1}$, $w''_i = w_i \sqrt{n-1}$, $\tilde{z}_i^r$ is a standard score of z_i^r, $r = 1, ..., d_Z$, 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

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

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

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

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

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

In continuous setup the second term becomes

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

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

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

□

Proposition 4 (General Covariance Decomposition)**.** *Suppose the data consist of n observations split into S partitions as* $\{\psi_{is}, w_{is}, z_{is}^1, ..., z_{is}^{d_Z}\}_{i=1}^{n_s}$ *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*

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

where $\psi_{is}'' = \psi_{is}\sqrt{n_s - 1}$, $w_{is}'' = w_{is}\sqrt{n_s - 1}$, $\tilde{z}_{is}^r$ *is a standard score of* z_i^r*, with* $r = 1, ..., d_Z$*, 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 decomposition in Eq. (4) can be rewritten as*

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

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 $n/(n_s - 1)$. □

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*

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

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, $\tilde{z}_{is}^r$ *is a standard score of* z_i^r, *with* $r = 1, ..., d_Z$ *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, trade payables to total assets and firms' age (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, trade payables to total assets and firms' age (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).

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