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Revisiting productivity growth accounting decompositions ☆

Filippo Massari

Department of Economics, Dolan School of Business, Fairfield University, 1073 North Benson Road, Fairfield, CT 06824, United States of America

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ABSTRACT

This paper proposes a modification to popular productivity growth accounting decompositions useful for calibrating endogenous growth models. Specifically, the within-firm component is further decomposed to show the covariance of firms' productivity growth rates and relative levels. This moment provides information about the systematic churning within the relative productivity distribution that, in endogenous growth models, stems from firms' investment behavior, thus affecting aggregate income growth. This decomposition allows assessing modeling assumptions and quantifying parameters that introduce or affect differential incentives to grow across firms.

1. Introduction

What explains changes in aggregate productivity? Economists and practitioners employ productivity growth accounting techniques to decompose aggregate productivity as a first diagnostic tool for further analysis. These decompositions illustrate how much of aggregate productivity growth is associated with improved firm-level productivity or reallocation of resources across incumbents, entering, and exiting firms.[1] Furthermore, these decompositions allow determining moments from the data that are helpful in calibrating or selecting the most appropriate models (Bartelsman et al., 2013).

The most widely used decompositions are Foster et al. (2001), and the dynamic Olley–Pakes presented in Melitz and Polanec (2015). They adopt an arbitrary definition of average productivity as the weighted geometric average of firms' productivity levels (alternatively expressed as the arithmetic average of firms' productivity log-levels), with market or labor shares as weights.[2] They then decompose average productivity growth into the various components. However, the definition of average productivity may be questioned due to the sensitivity of results under alternative definitions. For example, the Melitz and Polanec (2015) appendix provides different results for their exercise when defining average productivity as the arithmetic average of productivity levels. Dias and Marques (2021) and Bruhn et al. (2023) point out the sources of this discrepancy.

This paper approaches the topic from the point of view of theorists who use the results coming from these decompositions. After showing that standard theoretical assumptions within different streams of literature favor a definition of average productivity as

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E-mail address: fmassari@fairfield.edu.
URL: http://filippomassari.com/.

[1] Some recent and valuable examples of how these decompositions are employed include an assessment of productivity dynamics during the Covid pandemic (Bloom et al., 2023), making sense of sluggish Italian productivity growth (Bugamelli et al., 2018), understanding the nature of Chinese productivity growth (Gao et al., 2023), or tracking productivity developments as in the OECD MultiProd project (Berlingieri et al., 2017).

[2] Although in this stream of literature the term "aggregate" refers to average productivity, for the remainder of the paper I will use the term "average", in line with the criticism levied, among others, by Osotimehin (2019) and Baqaee and Farhi (2020). In the paper, I show that aggregate productivity can be decomposed into average productivity and an aggregation term, thus justifying formally my nomenclature.

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arithmetic instead of geometric, this paper proposes a modification to these decompositions.[3] Specifically, it points out that when average productivity is defined as an arithmetic average, the within-firm growth component can be decomposed further to show explicitly a covariance between firms' productivity growth rates and relative levels that is of interest for endogenous growth models with firm dynamics. The sign of this covariance determines which class of models better describes the data, and its magnitude offers a useful target for calibration.

The object of this paper is relevant primarily for one reason. The theoretical growth literature includes models that align with Gibrat Law (Klette and Kortum, 2004), and models that deviate from it (Thompson, 2001; Akcigit and Kerr, 2018) or can deviate from it under specific parametrizations (Laincz, 2009; Acemoglu et al., 2018; Massari, 2023).[4] They all have reasons to exist, as the former group presents cleaner and less mathematically challenging models. In contrast, the latter introduces models potentially more in line with the empirical evidence but are harder to handle. Therefore, a theorist is left wondering whether and for what purposes introducing this complication is worth it. Additionally, in the case of adopting models that deviate from Gibrat Law, knowing the correlation between firm growth rates and levels would provide a useful data moment to target when calibrating the model. As economy-wide data to perform these decompositions are not publicly available, economists implementing them would offer a valuable service to applied theorists if they adopted the modification proposed in this paper.

The paper proceeds as follows: in Section 2, I introduce a standard theoretical framework to derive the models-consistent definitions of aggregate and average productivity; in Section 3, I introduce the modification to the Dynamic Olley–Pakes decomposition and explain its use for applied theorists; and in Section 4, I conclude.

2. Defining aggregate and average productivity

This section shows how to derive the object usually studied in productivity growth accounting decompositions from widely used definitions of aggregate productivity in theoretical models. The purpose of this endeavor is to show that standard theoretical assumptions are not irreconcilable with the study of average productivity dynamics. On the contrary, these models nest an arithmetic average of individual firms' productivities and aggregation terms. Because these aggregation terms are stationary, these models predict that steady-state growth in aggregate productivity is driven by average productivity growth. Importantly, the decomposition provides an argument for decomposing the arithmetic average of individual firms' productivities instead of the more popular geometric average. The arithmetic average is more appropriate because the purpose of these decompositions is to inform theory.

Productivity growth accounting relies on methodologies like Foster et al. (2001) or Melitz and Polanec (2015)[5] that start from an arbitrary definition of aggregate productivity. The most widely used definition, as it yields the cleanest decompositions, is the weighted sum of firms' log productivity levels, with employment or market shares as exogenous weights, which implies a Cobb–Douglas aggregator where average output is the geometric mean of individual firms' output. However, because of this assumption, an aggregator of this type is rarely used in theoretical models.

Instead, at least three streams of literature on aggregate productivity favor a different definition. The first is the literature that studies aggregate productivity differences across countries that result from obstacles to an optimal allocation of resources. A good review of this literature is by Restuccia and Rogerson (2017), and a forceful argument for departing from a Cobb–Douglas specification is made by Bartelsman et al. (2013), which documents a strong positive correlation between firm sizes and productivity levels. That paper rationalizes that correlation through a model with a CES aggregator of goods to an optimal expansion in firm size to higher productivity.

A second stream of literature, which is the main focus of this paper, is endogenous growth theory. Monopolistic competition with a CES aggregator has been a staple in this literature ever since Romer (1990), as also illustrated in Romer (1994), because it grants market power that allows recouping the innovation cost. Furthermore, as well articulated in Peretto (1999), this specification gives rise to incentives to conduct R&D investment to steal market share from rival firms.

A final stream of literature (Osotimehin, 2019; Baqaee and Farhi, 2020) concerns the quantitative relevance for aggregate productivity of factors' misallocation due to various frictions. Those papers provide sufficient statistics to assess the contribution of factor reallocation in response to microeconomic shocks. Although these papers' purpose differs from productivity growth accounting, their proposed structure imposes more general and standard theoretical assumptions. In their simplest specification, the one of a horizontal economy, the aggregator is CES.

Having established that the theoretical literature favors a CES aggregator over a Cobb–Douglas, I show that an arithmetic weighted average of individual productivities is nested within the CES specification, thus providing partial insights about aggregate productivity dynamics.[6] Furthermore, arithmetic average productivity growth captures all of the long-run growth dynamics, while changes in other components that affect aggregate productivity must be temporary.

[3] I focus exclusively on the dynamic Olley–Pakes decomposition because the result is more readily visible. The procedure to modify the Foster et al. (2001) decomposition is the same, but that decomposition features a more complex interaction between firms' productivities and their labor or market shares.

[4] Gibrat Law postulates that firms' employment or sales growth rates and their levels are uncorrelated. Empirical studies have repeatedly rejected it, documenting a negative correlation between the two, and a firm-size distribution that is consistent with a firm growth process consistent with negative scale dependence (Sutton, 1997; Caves, 1998; Audretsch et al., 2004; Rossi-Hansberg and Wright, 2007). Meanwhile, there is evidence of a positive correlation between firms' size and their productivity level (Bartelsman et al., 2013). These two pieces of evidence suggest that firms' productivity growth and levels should be negatively correlated.

[5] See Balk (2021), especially chapter 5, for a comprehensive review.

[6] I could make the same arguments while working with any additive aggregator that is homogeneous of degree one in individual goods. The CES is just an example of the aggregators that are widely used and conform to this property. I restrict my attention to this case given how widespread this specification is relative to alternative additive specifications.

Therefore, :

$$Y_t = \left[\int_0^{N_t} y_{i,t}^{\frac{\epsilon-1}{\epsilon}} di\right]^{\frac{\epsilon}{\epsilon-1}}, \tag{1}$$

with N_t firms and firms' production function with only one input, labor:

$$y_{i,t} = A_{i,t} L_{i,t}^{\alpha}, \tag{2}$$

where $A_{i,t}$ is firm-level productivity.

Using Eqs. (1) and (2) and multiplying and dividing by average productivity $A_t = \int_0^{N_t} S_{i,t} A_{i,t} di$, average labor L_t/N_t, and the love of variety term, I obtain the following decomposition of aggregate labor productivity into average productivity and aggregation terms:

$$\frac{Y_t}{L_t} = \underbrace{A_t}_{\text{Average productivity}} \underbrace{\underbrace{N_t^{\frac{1}{\epsilon-1}}}_{\text{Love of variety}} \underbrace{\left\{\frac{1}{N_t}\int_0^{N_t} \left((S_{i,t}N_t)^{\alpha} a_{i,t}\right)^{\frac{\epsilon-1}{\epsilon}} di\right\}^{\frac{\epsilon}{\epsilon-1}}}_{\text{Allocation}} \underbrace{\left(\frac{L_t}{N_t}\right)^{\alpha-1}}_{\text{Diminishing returns}}}_{\text{Aggregation}}, \tag{3}$$

where $S_{i,t}$ is firm i's employment share, and $a_{i,t} = A_{i,t}/A_t$ is relative productivity.

The aggregation component collapses to 1 when the aggregator and production function are linear. Hence, these aggregation terms allow for the measurement of the direct effect on aggregate productivity that arises due to the presence of non-linearities. This pursuit is valuable as quantifying the magnitude of the aggregation component provides information regarding the benefit of introducing non-linearities in theoretical models.

When nonlinearities are quantitatively important, the aggregation component is sizeable. Consequently, it can be a relevant source of cross-sectional productivity differences across industries or countries. However, aggregate productivity growth decompositions are concerned with the dynamic aspect. Average productivity and the love of variety component — which depends on the number of goods produced — grow over time in the data, and according to theories where both vertical and horizontal innovation are modeled endogenously, such as Peretto and Connolly (2007). The other two components, instead, would change only following changes in the distribution of input shares, relative productivity, or average firm size. These changes could characterize transitional periods but not the long-run or steady-state.[7]

Therefore, as this paper aims to illustrate the relevance of productivity growth decompositions for endogenous growth theory, the focus of aggregate productivity can shift to the dynamics of average productivity. In those models, average productivity growth would capture all of the aggregate productivity growth after accounting for the effect of product variety expansion, which can be studied separately.

Although commonly labeled aggregate productivity, average productivity is the standard object of growth accounting. However, in Eq. (3), average productivity is the average of productivity levels instead of the productivity log-levels (or, equivalently, geometric average of productivity levels) common in the productivity growth accounting literature. Other studies (Dias and Marques, 2021; Bruhn et al., 2023) have shown that choosing geometric or arithmetic averages leads to results that differ widely, a point that will also become clear in the next section. For the moment, I note that standard theoretical assumption lead to a natural decomposition of aggregate productivity as aggregation terms of stationary firm-level variables, number of varieties, and arithmetic weighted average of firm-level productivity.

3. A productivity growth decomposition: The role of mean reversion

The previous section makes two arguments. First, weighted average labor productivity, the object of analysis of productivity growth accounting decompositions, offers insights into understanding aggregate productivity. Second, the arithmetic weighted average of labor productivity ought to be preferred to the geometric weighted average if the purpose of productivity growth accounting exercises is to inform theory. This section, instead, focuses on productivity growth. It shows that when average productivity is defined as an arithmetic weighted average, popular decompositions can be decomposed further to show explicitly a covariance between productivity growth and levels, which is an informative moment for endogenous growth models. I then discuss its relevance to theory.

To illustrate my point, I rely on the dynamic Olley–Pakes decomposition proposed by Melitz and Polanec (2015). Although the component of interest is more visible and easily derived in this decomposition, the procedure shown below allows it to be isolated in any other decomposition.

[7] It is standard in theoretical models to deliver a steady-state with stationary distributions of all variables, because tendencies to monopoly/monopsony or to a perfectly even distribution are counterfactual in most industries. Moreover, the stationarity of firm size is a key feature of many theoretical models (Bond-Smith, 2019), which has been repeatedly tested empirically; see for example Laincz and Peretto (2006) and Ha and Howitt (2007).

The dynamic Olley–Pakes decomposition decomposes average productivity change into an unweighted average change (within component), a change in covariance between employment shares and firm-level productivity (between component), and entry/exit:

$$A_t - A_{t-1} = \underbrace{\int_0^{N_{c_{t-1}}} \frac{A_{i,t} - A_{i,t-1}}{N_{c_{t-1}}} di}_{\text{Within}} + \underbrace{\Delta cov_{c_t}}_{\text{Between}}$$
$$+ \underbrace{S_{E_t}\left(A_{E_t} - A_{c_t}\right)}_{\text{Entry}} + \underbrace{S_{X_t}\left(A_{c_{t-1}} - A_{X_{t-1}}\right)}_{\text{Exit}}, \tag{4}$$

where

$$\Delta cov_{c_t} = \int_0^{N_{c_{t-1}}} \left(\frac{S_{i,t}}{S_{c_t}} - \frac{1}{N_{c_{t-1}}}\right)\left(A_{i,t} - A_{c_t}\right) di$$
$$- \int_0^{N_{c_{t-1}}} \left(\frac{S_{i,t-1}}{S_{c_{t-1}}} - \frac{1}{N_{c_{t-1}}}\right)\left(A_{i,t-1} - A_{c_{t-1}}\right) di. \tag{5}$$

Dividing both sides by A_{t-1} yields:

$$g_t^A = \underbrace{\int_0^{N_{c_{t-1}}} \frac{1}{N_{c_{t-1}}} a_{i,t-1}\, g_t^{A_i}}_{\text{Within}} + \underbrace{\frac{\Delta cov_{c_t}}{A_t}}_{\text{Between}}$$
$$+ \underbrace{S_{E_t} \frac{A_t}{A_{t-1}} \left(a_{E_t} - a_{c_t}\right)}_{\text{Entry}} + \underbrace{S_{X_{t-1}}\left(a_{c_{t-1}} - a_{X_{t-1}}\right)}_{\text{Exit}}, \tag{6}$$

where $a_{c_t} = \frac{A_{c_t}}{A_t}$, $a_{E_t} = \frac{A_{E_t}}{A_t}$, $a_{X_t} = \frac{A_{X_t}}{A_t}$.

Notice the difference in the within component of Eqs. (4) and (6). When average productivity is a geometric mean, productivity in Eq. (4) is in log levels. Thus, the equation decomposes the growth rate of average productivity. In that case, the within component is an unweighted arithmetic average of firms' productivity growth rates. Instead, when average productivity is an arithmetic mean, the relevant decomposition is Eq. (6), where the within component is a weighted average of firms' growth rates, with the relative productivity level as the weight.

To see the key result of this paper, I decompose the within component further by dividing it in two parts:

$$g_t^A = \underbrace{\underbrace{\bar{g}_t^{A_i}}_{\text{Average growth}} + \underbrace{\int_0^{N_{c_{t-1}}} \frac{a_{i,t-1} - 1}{N_{c_{t-1}}} g_t^{A_i} di}_{\text{Heterogeneity}}}_{\text{Within}} \tag{7}$$

where $\bar{g}_t^{A_i} = \int_0^{N_{c_{t-1}}} \frac{1}{N_{c_{t-1}}} g_t^{A_i} di$ represents the unweighted average of the productivity growth rates of individual continuing firms.

Using the fact that $\int_0^{N_{c_{t-1}}} \frac{1}{N_{c_{t-1}}} \left(\bar{a}_{i,t-1} - \bar{a}_{c_{t-1}}\right) di = 0$, where $\bar{a}_{c_t} = \frac{\bar{A}_{c_t}}{\bar{A}_t}$, and $\bar{A}_{i,t} = \int_0^{N_t} \frac{A_{i,t}}{N_t} di$, the heterogeneity component is:

$$g_t^{HETEROGENEITY} = \underbrace{\left(\bar{a}_{c_{t-1}} - 1\right) \bar{g}_t^{A_i}}_{\text{Survival selection}} + \underbrace{cov\left(g_t^{A_i}, \bar{a}_{i,t-1}\right)}_{\text{Churning}}. \tag{8}$$

Survival selection is a correction term. It depends on the relative productivity level of surviving firms and whether surviving firms are, on average, more or less productive than exiting firms. The higher the relative productivity of survivors, the higher the contribution to aggregate growth from this channel. Models that assume an exogenous exit shock that hits all firms symmetrically would miss this. Hence, the size of this sub-component can inform theorists about the benefit of modeling exit endogenously.

This paper's key argument is that the sub-component *Churning* should be explicitly shown in decompositions because of its relevance to theory. It describes the nature of firms' mobility within the relative productivity distribution. In the firm dynamics literature, firm-level productivity evolves exogenously; thus, the sub-component could be directly used to calibrate the distribution of the productivity shocks.

This sub-component also offers valuable information for growth theorists, with the caveat that these models have so far focused exclusively on the steady-state, which is not directly observable. Growth models that deliver Gibrat Law, like Klette and Kortum (2004) and its derivatives, predict that this sub-component is 0. The result of these models could, therefore, be tested directly from here. Additionally, because delivering Gibrat Law simplifies the model's structure, a value for the churning sub-component close to 0 would indicate that these models deliver an approximation of the firms' growth process that could be satisfactory for some purposes.

Instead, several models predict that this sub-component differs from 0. Models like Laincz (2009) deliver a dynamic tendency to monopoly, countered by entry that adds a degree of competition within the industry. Therefore, the prediction in this model is that the sign is positive. Additionally, its magnitude provides information about the degree of increasing returns or the innovative ability of industry leaders relative to competitors. One of the parameters that determines these forces could be calibrated using this covariance as a target.

Finally, models like Thompson (2001) and Akcigit and Kerr (2018) produce industry dynamics that deviate from Gibrat Law because more productive firms have lower productivity growth than less productive firms. Acemoglu et al. (2018) and Massari (2023) deliver the same outcome under some parametrizations. If the churning component is, on average, negative, the data would suggest that one of these models is the right one to adopt. Furthermore, its magnitude is helpful for calibration. The Thompson (2001) model delivers this outcome exclusively because of knowledge spillovers. Hence, this moment provides information about their strength. The Acemoglu et al. (2018) model delivers a negative sign when young firms start with low productivity but have a higher ability to innovate. Hence, this moment provides information about the correlation between the model's parameters. Massari (2023) includes both these aspects, but it also includes endogenous diminishing returns in relative terms as firm growth depend on vertical innovation, whose returns depends on the firm's market share. Therefore, this moment is important to capture the balance of the various forces of divergence and convergence in productivity levels. Finally, in Akcigit and Kerr (2018), the negative correlation between productivity growth rates and levels comes from diminishing returns to horizontal innovation (expanding the number of products produced) within the firm. The churning sub-component here could be useful in determining the importance of firms' horizontal relative to vertical innovation.

4. Conclusion

This paper proposes a modification to productivity growth accounting decompositions. The modification is possible when average productivity is defined as the weighted arithmetic average of individual firms' productivity levels. It consists in further decomposing the within-firm component to show the covariance between firms' productivity growth rates and levels. This covariance is particularly important for endogenous growth models with firm dynamics. First, different models predict different steady-state signs for this covariance. Second, in models that predict a non-zero covariance, its magnitude could be employed to determine the value of a parameter.

The paper first shows how the weighted arithmetic average relates to standard definitions of aggregate productivity in the theoretical literature. It then explains that aggregate productivity growth, after accounting for variety expansion, is driven exclusively by arithmetic average productivity growth in steady-state. Finally, it derives the decomposition and explains its relevance for theory.

Based on this paper's arguments, I encourage analysts with access to private, economy-wide data on firms' productivities and factor shares to adopt a definition of average productivity as the weighted arithmetic average of individual productivities. Moreover, I encourage them to decompose the within component further and report the covariance between productivity growth rates and levels.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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