Productivity and Organization in Portuguese Firms*

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Abstract

The productivity of firms is, at least partly, determined by a firm's actions and decisions. One of these decisions involves the organization of production in terms of the number of layers of management the firm decides to employ. Using detailed employer-employee matched data and firm production quantity and input data for Portuguese firms, we study the endogenous response of revenue-based and quantity-based productivity to a change in layers: a firm reorganization. We show that as a result of an exogenous demand or productivity shock that makes the firm reorganize and add a management layer, quantity-based productivity increases by about 8%, while revenue-based productivity drops by around 7%. Such a reorganization makes the firm more productive, but also increases the quantity produced to an extent that lowers the price charged by the firm and, as a result, its revenue-based productivity.

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1 Introduction

A firm's productivity depends on the way it organizes production. The decisions of its owners and managers on how to combine different inputs and factors of production with particular technologies given demand for their product determine the production efficiency of a firm. Clearly, these decision makers face many constraints and random disturbances. Random innovations or disruptions, regulatory uncertainties, changes in tastes and fads, among many other idiosyncratic shocks, are undoubtedly partly responsible for fluctuations in firm productivity. However, these random –and perhaps exogenous– productivity or demand fluctuations, result in firm responses that change the way production is organized, thereby affecting its measured productivity. For example, a sudden increase in demand due to a product becoming fashionable can lead a firm to expand and add either a plant, a more complex management structure, a new division, or a new building. These investments are lumpy and, as such, will change the firm's production efficiency and prices discontinuously as well.

In this paper we study the changes in productivity observed in Portuguese firms when they reorganize their management structure by adding or dropping layers of management. Consider a firm that wants to expand as a result of a positive demand shock and decides to add a layer of management (say add another division with a CEO that manages the whole firm). The new organization is suitable for a larger firm and lowers the average cost of the firm thereby increasing its quantity-based productivity. Moreover, the switch to an organizational structure fitted for a larger firm also reduces the marginal cost of the firm leading to higher quantities and lower prices. That is, at the moment of the switch, the firm is using a technology that is still a bit big for the size of its market, which reduces revenue-based productivity. The reason for this is that the organizational decision is lumpy. So a change in organization that adds organizational capacity in the form of a new management layer, leads to increases in quantity-based productivity, but reductions in revenue-based productivity through reductions in prices (due to reduction in the marginal cost, and, perhaps also due to reductions in mark-ups). In that sense, the endogenous response of firm productivity to exogenous shocks can be complex and differ depending on the measure of productivity used. Using a recently developed measure of changes in organization we show that these patterns are very much present in the Portuguese data.

Although the logic above applies to many types of organizational changes and other lumpy investments, we explain it in more detail using a knowledge-based hierarchy model that can guide us in our empirical implementation. Furthermore, this model provides an easy way to identify the changes in organization as we explain below. The theory of knowledge-based hierarchies was developed in Rosen (1982), Garicano (2000) and in an equilibrium context with heterogeneous firms in Garicano and Rossi-Hansberg (2006) and Caliendo and Rossi-Hansberg (2012, from now on CRH). In particular, we use the model in CRH since it provides an application of this theory to an economy with firms that face heterogeneous demands for their products. In the context of CRH, we provide novel theoretical results that characterize the pattern of quantity-based and revenue-based productivity as firms reorganize as a result of exogenous demand or productivity shocks.

The basic technology is one that requires time and knowledge. Workers use their time to produce and generate 'problems' or production possibilities. Output requires solving this problems. Workers have knowledge that they use to try to solve these problems. If they know how to solve them, they do, and output is realized. Otherwise they can redirect the problem to a manager one layer above. Such a manager tries to solve the problem and, if it cannot, can redirect the problem to an even higher-level manager. The organizational problem of the firm is to determine, how much does each employee know, how many of them to employ, and how many layers of management to use in production.

Using matched employer-employee data for the French manufacturing sector, Caliendo, Monte and Rossi-Hansberg (2015), from now on CMRH, show how to use occupation data to identify the layers of management in a firm.[1] They show that the theory of knowledge-based hierarchies can rationalize the layer-level changes in the number of employees and wages as firms grow either with or without changing layers. For example, as implied by the theory, a reorganization that adds a layer of management leads to increases in the number of hours employed in each layer but to a *reduction* in the average wage in each preexisting layer. In contrast, when firms grow without reorganizing they add hours of work to each layer and they *increase* the wages of each worker. This evidence shows that when firms expand and contract they actively manage their organization by hiring workers with different characteristics. The Portuguese data exhibits the same patterns that CMRH found for France. Importantly, the detailed input, revenue and quantity data for Portugal allows us to go a step further and measure the productivity implications of changes in organization.

Measuring productivity well is notoriously complicated and the industrial organization literature has proposed a variety of techniques to do so (see Berry, Levinsohn and Pakes (1995), Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009), and De Loecker and Warzinsky (2012), among others). The first issue is whether we want to measure quantity-based or revenue-based productivity. The distinction is crucial since the first measures how effective is a firm in transforming inputs and factors into output, while the other also measure any price variation, perhaps related to markups, that result from market power. The ability of firms to determine prices due to some level of market power is a reality that is hard to abstract from. Particularly when considering changes in scale that make firms move along their demand curve and change their desired prices. We find that using a host of different measures of revenue productivity (from value-added per worker to Olley and Pakes, 1996, Wooldridge, 2009, and De Loecker and Warzinsky 2012), adding layers is related to *decreases* in revenue-based productivity. As explained above, our theory suggests that this should be the case since firms reduce prices when they expand. However, since firms also received a variety of idiosyncratic demand, markup, and productivity shocks every period it is hard to just directly look at prices to measure this effect.

To measure the effect of organizational change on quantity-based productivity we need a methodology that can account for demand, markup, and productivity shocks over time and across firms.[2] We use the

[1] Following CMRH several studies have shown that occupational categories identify layers of management in other datasets. For example, Tåg (2013) for the Swedish data and Friedrich (2015) for the Danish data.

[2] See Marschak and Andrews (1944) and Klette and Griliches (1996) for a discussion of the output price bias when calculating

methodology proposed by Forlani et al., (2015), which from now on we refer to as MULAMA. This method uses the same cost minimization assumptions as previous methodologies, like De Loecker and Warzinsky (2012), but makes some relatively strong assumptions on the way demand differs across firms in order to allow for correlated demand and productivity disturbances. Furthermore, it is amenable to introducing the organizational structure we described above. Note also that since we focus on changes in quantity-based productivity as a result of a firm reorganization we can sidestep the difficulties in comparing quantity-based productivity across horizontally differentiated products. Using this methodology, and quantity data available in the Portuguese data, we find that adding (dropping) layers is associated with increases (decreases) in quantity-based productivity. The finding survives a variety of robustness checks and alternative formulations of the productivity process. For example, we can allow for changes in organization to have a permanent or only a contemporaneous impact on quantity-based productivity as well as for various fixed effects. This is our main finding: we link a careful measure of productive efficiency (quantity-based productivity as measured by MULAMA) with an increase in the management capacity of a firm (as measured by the number of layers)[3].

Up to this point we have not addressed the issue of causality. The results above only state that adding layers coincides with declines in revenue-based productivity and increases in quantity-based productivity. To the extent that organization, like capital infrastructure, cannot adjust much in the short run in the wake of current period shocks the above results can be interpreted as causal. We relax this assumption by using a set of instruments represented by demand and cost shocks predicting organizational changes but uncorrelated with current productivity shocks. In this respect, the MULAMA model allows quantifying past productivity, demand and markups shocks pushing firms to expand or contract production scale while being uncorrelated with current shocks. In addition to these set of instruments suggested by our theory, we make use of a more traditional set of instruments based on real exchange rates and a firm's export and import patterns. We show that our results on both revenue-based and quantity-based productivity do seem to be causal. In our preferred specification, with instrumental variables, we also show that the effect of changes in the number of layers on productivity remains significant even when we introduce quantity directly into the productivity process as a proxy for shocks affecting productivity beyond the organization channel.

In sum, in this paper we show that the organizational structure of firms, as measured by their hierarchical occupational composition, has direct implications on the productivity of firms. As they add organizational layers, their quantity-based productivity increases, although the corresponding expansion decreases their revenue productivity as they reduce prices. This endogenous component of productivity determines, in part, the observed heterogeneity in both revenue and quantity-based productivity across firms. Failure to reorganize in order to grow can, therefore, result in an inability to exploit available productivity improvements. This would imply that firms remain inefficiently small, as has been documented in some developing countries (Hsieh and Klenow, 2014).

productivity.

[3]In a related result, Garcia and Voigtländer (2014) find among new Chilean exporters a reduction in revenue-based productivity and an increase in quantity-based productivity. The mechanism and findings in our paper can be used directly to rationalize their findings since exporting amounts to a firm revenue shock.

The rest of this paper is organized as follows. In Section 2 we provide a short recap of the knowledge-hierarchy theory that we use to guide our empirical exploration and describe its implications for productivity. Section 3 discusses the Portuguese manufacturing data set we use in the paper. Section 4 presents the basic characteristics of Portuguese production hierarchies. In particular, we show that firms with different numbers of layers are in fact different and that changes in the number of layers are associated with the expected changes in the number of workers and wages at each layer. Section 5 presents our main results on revenue-based productivity, as well as the methodology we use to measure quantity-based productivity and our main empirical results on this measure. It also presents a variety of robustness results as well as our results for revenue-based and quantity-based productivity using instrumental variables. Section 6 concludes. The appendix includes more details on our data set, a description of all Tables and Figures, as well as additional derivations and robustness tests of the results in the main text.

2 A Sketch of a Theory of Organization and its Empirical Implications

The theory of knowledge-based hierarchies, initially proposed by Garicano (2000), has been developed using a variety of alternative assumptions (see Garicano and Rossi-Hansberg, 2015, for a review). Here we discuss the version of the technology with homogenous agents and heterogeneous demand developed in CRH.

So consider firm i in period t that faces a Cobb-Douglas technology

$$Q_{it}\left(O_{it}, M_{it}, K_{it}\right) = a_{it} O_{it}^{\alpha_O} M_{it}^{\alpha_M} K_{it}^{\gamma-\alpha_M-\alpha_H} \tag{1}$$

with quantity-based productivity a_{it}, returns to scale given by γ and where O_{it} denotes the labor input, M_{it} material inputs and K_{it} capital. The parameter $\alpha_O \geq 0$ represents the expenditure share on the labor input, $\alpha_M \geq 0$ on materials and $\gamma - \alpha_M - \alpha_O$ on physical capital. The labor input is produced using the output of a variety of different workers with particular levels of knowledge. The organizational problem is embedded in this input. That is, we interpret the output of the knowledge hierarchy as generating the labor input of the firm. Hence, in the rest of this section we focus on the organizational problem of labor and abstract from capital and materials. We return to the other factors in our estimation of productivity below.

Production of the labor input requires time and knowledge. Agents employed as workers specialize in production, use their unit of time working in the production floor and use their knowledge to deal with any problems they face in production. Each unit of time generates a problem, that, if solved yields one unit of output. Agents employed as managers specialize in problem solving, use h units of time to familiarize themselves with each problem brought by a subordinate, and solve the problems using their available knowledge. Problems are drawn from a distribution $F\left(z\right)$ with $F''\left(z\right) < 0$. Workers in a firm know how to solve problems in an interval of knowledge $[0, z_L^0]$, where the superindex 0 denotes the layer (0 for workers) and the subindex the total number of management layers in the firm, L. Problems outside this interval, are passed on to managers of layer 1. Hence, if there are n_L^0 workers in the firm, $n_L^1 =$

$hn_L^0\left(1-F\left(z_L^0\right)\right)$, managers of layer one are needed. In general, managers in layer ℓ learn $\left[Z_L^{\ell-1}, Z_L^\ell\right]$ and there are $n_L^\ell = hn_L^0(1-F(Z_L^{\ell-1}))$ of them, where $Z_L^\ell = \sum_{l=0}^{\ell} z_L^l$. Problems that are not solved by anyone in the firm are discarded. Agents with knowledge z_L^ℓ obtain a wage $w\left(z_L^\ell\right)$ where $w'\left(z_L^\ell\right) > 0$ and $w''\left(z_L^\ell\right) \geq 0$. Market wages simply compensate agents for their cost of acquiring knowledge.

The organizational problem of the firm is to choose the number of workers in each layer, their knowledge and therefore their wages, and the number of layers. Hence, consider a firm that produces a quantity O of the labor input. $C_L(O;w)$ is the minimum cost of producing a labor input O with an organization with L layers[4] at a prevailing wage schedule $w(\cdot)$, namely,

$$C_L(O;w) = \min_{\{n_L^\ell, z_L^\ell\}_{l=0}^L \geq 0} \sum\nolimits_{\ell=0}^{L} n_L^\ell w\left(z_L^\ell\right) \tag{2}$$

subject to

$$\begin{aligned} O &\leq F(Z_L^L)n_L^0, & (3)\\ n_L^\ell &= hn_L^0[1-F(Z_L^{\ell-1})] \text{ for } L \geq \ell > 0, & (4)\\ n_L^L &= 1. & (5) \end{aligned}$$

The first constraint just states that total production of the labor input should be larger or equal than O, the second is the time constraint explained above, and the third states that all firms need to be headed by one CEO. The last constraint is important since it implies that small firms cannot have a small fraction of the complex organization of a large firm. We discuss bellow the implications of partially relaxing this constraint. The *variable* cost function is given by

$$C(O;w) = \min_{L\geq 0} \{C_L(O;w)\}.$$

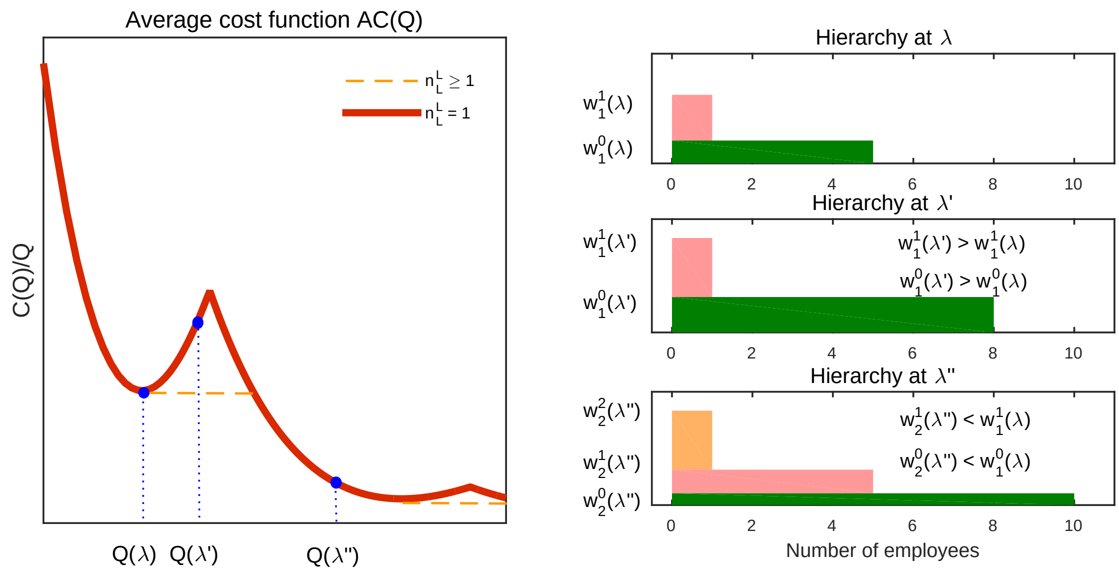
CRH show that the average cost function ($AC(O;w) = C(O;w)/O$) that results from this problem exhibits the properties depicted in Figure 1 (which we reproduce from CMRH). Namely, it is U-shaped given the number of layers, with the average cost associated to the minimum efficient scale that declines as the firm adds layers. Each point in the average cost curve in the figure correspond to a particular organizational design. Note that the average cost curve faced by the firm is the lower-envelope of the average cost curves for a given number of layers. The crossings of these curves determine a set of output thresholds (or correspondingly demand thresholds[5]) at which the firms decides to reorganize by changing the number of layers. The overall average cost, including materials and capital, of a firm that is an input price taker will have exactly the same shape (given our specification of the production function in equation (1) under $\gamma = 1$).

[4]Throughout we refer to the number of layers of the firm by the number of management layers. So firms with only workers have zero layers, firms with workers and managers have 1 layer, etc.

[5]Note that since output increases (decreases) discontinuously when the firm adds (drops) layers, the average cost curve is discontinuous as a function of the level of demand λ.

Consider the three dots in the figure, which correspond to firms that face different levels of demand as parametrized by λ.[6] Suppose that after solving the corresponding profit maximization using the cost function above, a firm that faces a demand level of λ decides to produce $Q(\lambda)$ (or $q(\lambda)$ in logs). The top panel on the right-hand-side of Figure 1 tells us that it will have one layer with 5 workers and one layer with one manager above them. The figure also indicates the wages of each of them (the height of each bar), which is increasing in their knowledge. Now consider a firm that as a result of a demand shock expands to $Q(\lambda')$ without reorganizing, that is, keeping the same number of layers. The firm expands the number of workers and it increases their knowledge and wages. The reason is that the one manager needs to hire more knowledgeable workers, who ask less often, in order to increase her span of control. In contrast, consider a firm that expands to $Q(\lambda'')$. This firm reorganizes by adding a layer. It also hires more workers at all preexisting layers. However, it hires less knowledgeable workers, at lower wages, in all preexisting layers. The reason is that by adding a new layer the firm can avoid paying multiple times for knowledge that is rarely used by the bottom ranks in the hierarchy. In the next section we show that all these predictions are confirmed by the data.

Figure 1: Average Cost and Organization



We can also use Figure 1 to show how the organizational structure changes as we relax the integer constraint of the top manager, in (5). First, note that at the minimum efficient scale (MES), which is given by the minimum of the average cost, having one manager at the top is optimal for the firm. So the constraint in (5) is not binding. Hence, relaxing the constraint can affect the shape of the average cost function on segments to the right and to the left of the MES. The reason why average costs rise for quantities other

[6] In our examples here we focus on changes in the level of demand. Later on we will further consider changes in the exogenous component of productivity and changes in markups. Indeed, whatever pushes the firm to change its desired output can affect a firm's organizational structure.

than MES is that firms are restricted to have one manager at the top. Otherwise, the firm could expand the optimal organizational structure at the MES by just replicating the hierarchy proportionally as it adds or reduces managers at the top.

For instance, suppose we allow organizations to have more than one manager at the top, namely $n_L^L \geq 1$. Figure 1 presents dashed lines that depict the shape of the average cost for this case. As we can see, the average cost is flat for segments to the right of the MES up to the point in which the firm decides to add a new layer. At the moment of the switch, the average cost starts falling until it reaches the MES and then it becomes flat again. All the predictions that we discussed before still hold for this case. The only difference is the way in which firms expand after they reach their MES up to the point in which they reorganize. We allow for this extra degree of flexibility when we use the structure of the model and take it to the data.[7]

2.1 Productivity Implications

In the following section we show that firms that grow or shrink substantially do so by adding or dropping management layers. These reorganizations also have consequences on the measured productivity of firms. In the model above quantity-based productivity of a firm in producing the labor input can be measured as the inverse of the average cost at constant factor prices; namely, $Q(\lambda)/\bar{C}(Q(\lambda); C(\cdot;1), 1, 1)$ where $\bar{C}(Q(\lambda); C(\cdot; w), P_m, r)$ denotes the overall cost function of the firm and P_m and r the price of materials and capital. Note that $Q(\lambda)$ denotes quantity produced and not revenue. Revenue-based productivity is instead given by $P(\lambda)Q(\lambda)/\bar{C}(Q(\lambda); C(\cdot;1), 1, 1)$ where $P(\lambda)$ denotes the firm's output price.

Quantity-based productivity increases with an increase in λ when the firm adds layers. The reason is simply that any voluntary increase in layers is accompanied by an increase in the quantity produced, which results in a lower average costs for the firm when using the new organizational structure. The firm is only willing to add an extra layer of management, and hire more managers that do not generate production possibilities at a higher cost, if it can use the new organization to produce more at a lower average and marginal cost. Of course, under standard assumptions that lead to a downward sloping demand, the increase in quantity will also decrease the price that consumers are willing to pay for the good. Note that, since the firm is choosing the level of λ at which it switches layers, we know that profits will be continuous in λ. This implies that the increase in revenue has to be identical to the increase in variable costs. Given that, in the presence of fixed production costs, total revenue has to be larger that variable costs in order for profits to be non-negative, the proportional increase in revenue will be smaller than the proportional increase in costs. The result is a decline in revenue-based productivity.

The logic above uses the following assumptions which are necessary for the proof of Proposition 1 below.

[7] Alternatively, one could also relax the integer constraint by letting $n_L^L \geq \epsilon$, where $1 > \epsilon > 0$. Following the discussion in the main body, in this case, the average cost also has flat segments to the left of the MES up to the point in which it reaches $n_L^L = \epsilon$. At this point the average cost jumps to the level of the MES of the new optimal (and lower) number of layers. Depending on the value of ϵ this will imply that the firm might decide to drop more than one layer. If ϵ is low enough, the average cost curve will be a step function with no smoothing declining segments. The lower is ϵ, the easier it is for the firm to produce less quantity with more layers, and in the limit, as $\epsilon \to 0$, firms converge to $L = \infty$. This case is counterfactual since we observe that in most cases firms expand by adding one layer at the time (see Section 4).

Assumption 1: *Firms face fixed production costs and their chosen price is an increasing function of their marginal cost.*

Proposition 1 *Given Assumption 1, a) Quantity-based productivity* ***increases*** *with a marginal increase in λ when the firm adds layers; b) Revenue-based productivity* ***decreases*** *with a marginal increase in λ when the firm adds layers.*

Proof. Without loss of generality we fix factor prices and focus on the problem of one firm. Denote the profits of a firm with demand draw λ producing with L layers by $\pi(\lambda, L) = P(\lambda, L) Q(\lambda, L) - \bar{C}(Q(\lambda, L); C_L(\cdot; 1), 1, 1) - F$, where we denote by $P(\lambda, L)$, and $Q(\lambda, L)$ the price and the quantity produced, respectively, given λ and L, and by F the fixed production costs. To ease notation we let $\bar{C}(Q(\lambda, L); C_L) \equiv \bar{C}(Q(\lambda, L); C_L(\cdot; 1), 1, 1)$. Denote by $\bar{\lambda}$ the level of demand at which the firm is indifferent between producing with L and $L+1$ layers; namely, $\pi(\bar{\lambda}, L) = \pi(\bar{\lambda}, L+1) \geq 0$.

We prove part a) of the proposition by contradiction. Consider first how quantity-based productivity changes when a firm at $\bar{\lambda}$ experiences demand $\bar{\lambda} + \varepsilon$, for $\varepsilon > 0$ infinitesimally small, and optimally decides to add a layer.[8] Toward a contradiction, suppose that quantity-based productivity is lower when the firm adds a layer, i.e.

$$\frac{Q(\bar{\lambda}, L+1)}{\bar{C}(Q(\bar{\lambda}, L+1); C_{L+1})} \leq \frac{Q(\bar{\lambda}, L)}{\bar{C}(Q(\bar{\lambda}, L); C_L)}.$$

In the remainder of the proof we show that there exists an alternative feasible choice of quantity, $Q'(\bar{\lambda}, L+1)$, that attains higher profits than $Q(\bar{\lambda}, L+1)$, therefore contradicting the optimality of $Q(\bar{\lambda}, L+1)$. First, note that—as shown in Proposition 2 of CRH—since the minimum average cost for a given number of layers decreases with the number of layers, i.e.

$$Q_L^* \equiv \min_Q \frac{\bar{C}(Q; C_L)}{Q} \geq Q_{L+1}^* \equiv \min_Q \frac{\bar{C}(Q; C_{L+1})}{Q},$$

and the level of output that achieves this minimum increases with the number of layers, there exists a quantity $Q'(\bar{\lambda}, L+1) > Q(\bar{\lambda}, L)$ such that

$$\frac{Q(\bar{\lambda}, L+1)}{\bar{C}(Q(\bar{\lambda}, L+1); C_{L+1})} \leq \frac{Q(\bar{\lambda}, L)}{\bar{C}(Q(\bar{\lambda}, L); C_L)} \leq \frac{Q'(\bar{\lambda}, L+1)}{\bar{C}(Q'(\bar{\lambda}, L+1); C_{L+1})}. \tag{6}$$

Note that $Q'(\bar{\lambda}, L+1) > Q(\bar{\lambda}, L+1)$ always since $Q(\bar{\lambda}, L+1)$ is in the decreasing segment of the average cost curve, i.e. $Q(\bar{\lambda}, L+1) \leq Q_{L+1}^*$. To see this, note that if the firm had choosen a quantity level associated with the same average cost but on the increasing segment of the average cost curve, i.e.

[8] To ease notation we drop from the proof, from now on, ε.

$Q''\left(\bar{\lambda}, L+1\right) \geq Q^*_{L+1}$ such that

$$\frac{Q''\left(\bar{\lambda}, L+1\right)}{\bar{C}(Q''\left(\bar{\lambda}, L+1\right); C_{L+1})} = \frac{Q\left(\bar{\lambda}, L+1\right)}{\bar{C}\left(Q\left(\bar{\lambda}, L+1\right); C_{L+1}\right)},$$

the firm would have set lower prices and obtained lower profits. Therefore, $Q'\left(\bar{\lambda}, L+1\right) > Q\left(\bar{\lambda}, L+1\right)$.

Since the marginal cost is increasing in quantity—as shown in Proposition 1 of CRH—if prices are increasing in the marginal cost then $P(Q'\left(\bar{\lambda}, L+1\right)) \geq P(Q\left(\bar{\lambda}, L+1\right))$. Combined with inequality (6), the latter implies that

$$\frac{P(Q'\left(\bar{\lambda}, L+1\right))Q'\left(\bar{\lambda}, L+1\right)}{\bar{C}\left(Q'\left(\bar{\lambda}, L+1\right); C_{L+1}\right)} \geq \frac{P(Q\left(\bar{\lambda}, L+1\right))Q\left(\bar{\lambda}, L+1\right)}{\bar{C}\left(Q\left(\bar{\lambda}, L+1\right); C_{L+1}\right)}.$$

Since the cost function—as shown in Proposition 1 of CRH—is strictly increasing in quantity, *a fortiori*

$$P(Q'\left(\bar{\lambda}, L+1\right))Q'\left(\bar{\lambda}, L+1\right) - \bar{C}\left(Q'\left(\bar{\lambda}, L+1\right); C_{L+1}\right) \geq$$

$$\geq P(Q\left(\bar{\lambda}, L+1\right))Q\left(\bar{\lambda}, L+1\right) - \bar{C}\left(Q\left(\bar{\lambda}, L+1\right); C_{L+1}\right),$$

i.e. the profits associated with $Q'\left(\bar{\lambda}, L+1\right)$ are higher than those associated with $Q\left(\bar{\lambda}, L+1\right)$. This is a contradiction. Hence, quantity-based productivity is strictly higher after adding layers at $\bar{\lambda}$. So we have proven part a), namely, that quantity-based productivity **increases** with a marginal increase in λ when the firm adds layers.

We prove part b) of the proposition directly. Consider how revenue-based productivity changes when the firm with demand level $\bar{\lambda}$ adds a layer. Since $\pi\left(\bar{\lambda}, L\right) = \pi\left(\bar{\lambda}, L+1\right)$,

$$P\left(\bar{\lambda}, L+1\right) Q\left(\bar{\lambda}, L+1\right) - P\left(\bar{\lambda}, L\right) Q\left(\bar{\lambda}, L\right) = \bar{C}\left(Q\left(\bar{\lambda}, L+1\right); C_{L+1}\right) - \bar{C}\left(Q\left(\bar{\lambda}, L\right); C_L\right).$$

Since $\pi\left(\bar{\lambda}, L+1\right) \geq 0$ and $F > 0$, $P\left(\bar{\lambda}, L+1\right) Q\left(\bar{\lambda}, L+1\right) > \bar{C}\left(Q\left(\bar{\lambda}, L+1\right); C_{L+1}\right)$ which implies that

$$\frac{P\left(\bar{\lambda}, L+1\right) Q\left(\bar{\lambda}, L+1\right) - P\left(\bar{\lambda}, L\right) Q\left(\bar{\lambda}, L\right)}{P\left(\bar{\lambda}, L+1\right) Q\left(\bar{\lambda}, L+1\right)} < \frac{\bar{C}\left(Q\left(\bar{\lambda}, L+1\right); C_{L+1}\right) - \bar{C}\left(Q\left(\bar{\lambda}, L\right); C_L\right)}{\bar{C}\left(Q\left(\bar{\lambda}, L+1\right); C_{L+1}\right)},$$

or

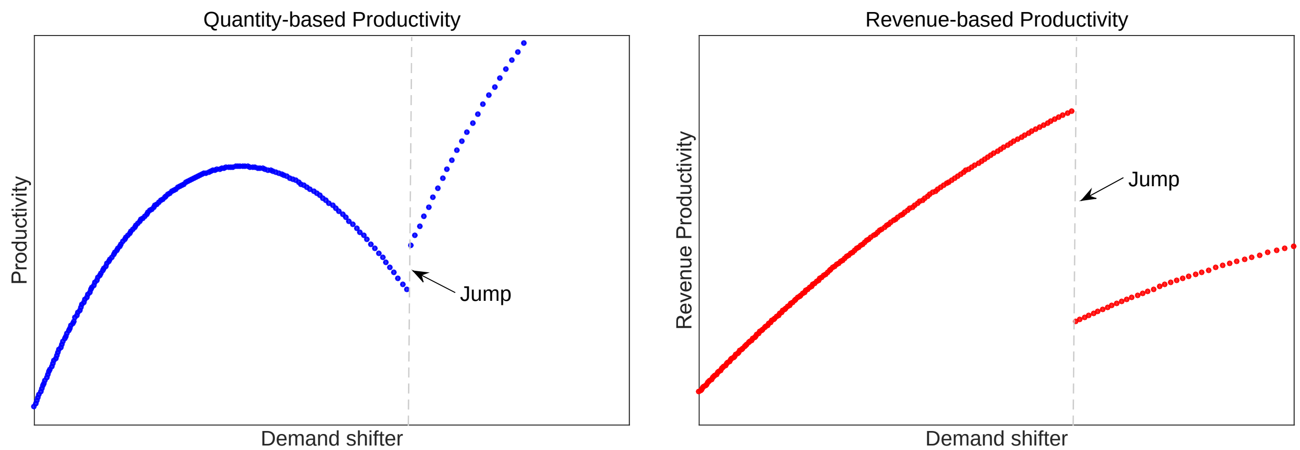
$$\frac{P\left(\bar{\lambda}, L\right) Q\left(\bar{\lambda}, L\right)}{\bar{C}\left(Q\left(\bar{\lambda}, L\right); C_L\right)} > \frac{P\left(\bar{\lambda}, L+1\right) Q\left(\bar{\lambda}, L+1\right)}{\bar{C}\left(Q\left(\bar{\lambda}, L+1\right); C_{L+1}\right)}.$$

Hence, we have proven part b), namely, that revenue-based productivity decreases with a marginal increase in λ when the firm adds layers. ■

This effect in both types of productivity is illustrated in Figure 2 where we consider the effect of a shock in λ that leads to a reorganization that adds one layer of management.

In sum, firms that add layers as a result of a marginal revenue shock increase their quantity discontinuously. The new organization is more productive at the new scale, resulting in an increase in quantity-based productivity, but the quantity expansion decreases price and revenue-based productivity. When firms face negative shocks that make them drop layers we expect the opposite effects.

Figure 2: Quantity and Revenue Productivity Changes as a Firm Adds Layers



2.1.1 An example

To illustrate the mechanism described above we can use the example of a single-product firm producing aluminium cookware (anonymous given confidentiality requirements). It increased its workforce over time and, in particular, by 27 percent between 1996 and 1998. In the same period exports increased by 170%, and went from representing 10% of the firms sales in 1996 to 16% in 1998. Between 1997 and 1998 the firm reorganized and added a layer of management.

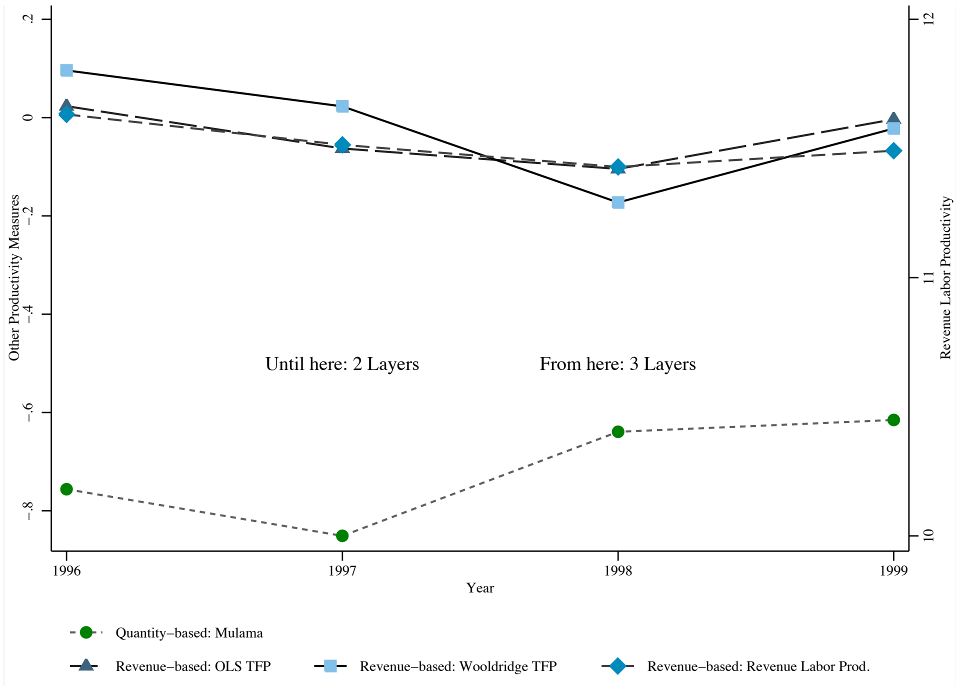
Our firm had a layer of workers and a layer of managers until 1997 and it added a new layer of management in 1998 (so it went from 1 layer to 2 layers of management). Figure 3 plots its quantity-based and revenue-based productivity around the reorganization (we plot 3 alternative measures of revenue-based productivity).[9] The pattern in the figure is typical in our data. The year in which the firm reorganizes its quantity-based productivity clearly jumps up and its revenue-based productivity declines. In contrast, it is hard to see any significant pattern in the changes in these measures of productivity for the year before or the year after adding the extra layer.

Figure 4 shows the corresponding levels of output, prices and revenue for the same firm and time period. The graph shows how, in fact, the increase in quantity-based productivity is accompanied by an increase in quantity, a fairly large decrease in price, and a small increase in revenue. These changes align exactly with our story in which the increase in quantity-based productivity generated by the reorganization (that adds a layer of management) leads to an increase in quantity, a lower marginal cost that leads to a decline in price, and a correspondingly muted increase in revenue and decline in revenue-based productivity. Note

[9]We describe the precise methodology and data used to measure both types of productivity in detail in Section 4.

that quantity in this firms grows not only at the time of the reorganization but before and after it as well. This is consistent with a firm that is progressively moving toward the quantity threshold in which it decides to reorganize. In these other years, demand and productivity shocks do not trigger a reorganization and so we do not see the corresponding decline in price.

Figure 3: An Example of a Firm that Adds Layers: Productivity Measures (logs)



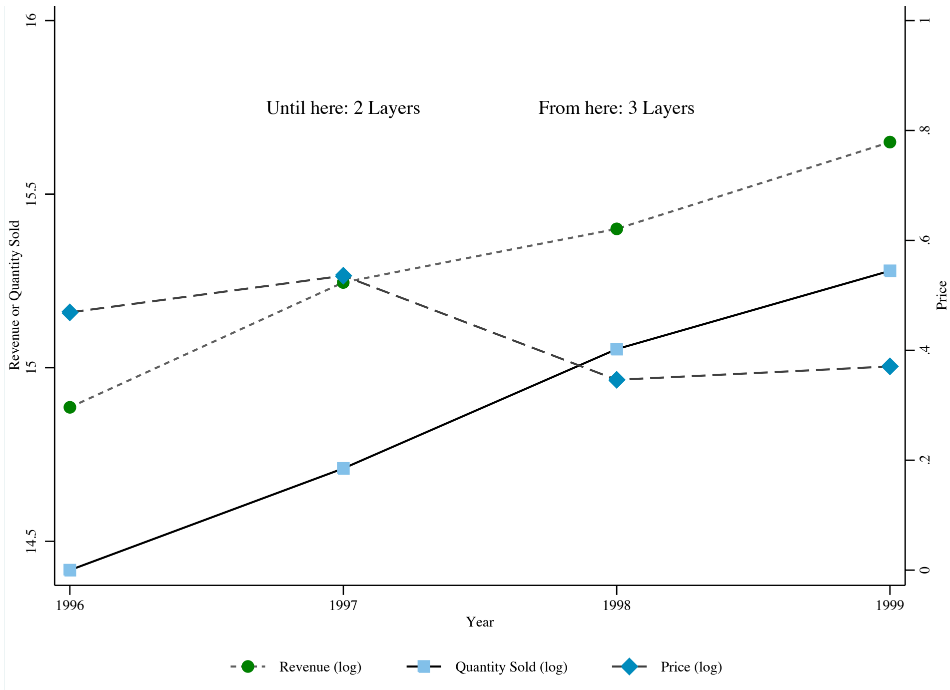
Of course, the case of this firm could be an isolated event in which all these variables happen to align in a way consistent with our interpretation. The rest of the paper is dedicated to present systematic evidence of the ubiquitousness of these exact patterns for quantity and revenue-based productivity as firms reorganize.

3 Data Description and Processing

Our data set is built from three data sources: a matched employer-employee panel data set, a firm-level balance sheet data set, and a firm-product-level data set containing information on the production of manufactured goods. Our data covers the manufacturing sector of continental Portugal for the years 1995-2005.[10] As explained below in detail, the matched employer-employee data virtually covers the universe of firms, while both the balance sheet data set and the production data set only cover a sample of firms. We build two nested samples. The largest of them sources information from the matched employer-employee data

[10] Information for the year 2001 for the matched employer-employee dataset was not collected. Hence, our sample excludes the year 2001 (see Appendix A).

Figure 4: An Example of a Firm that Adds Layers: Output, Price, and Revenue



set for the subset of firms for which we also have balance sheet data. We refer to this sample as Sample 1. It contains enough information to calculate measures of revenue-based productivity at the firm-year-level. The second sample covers a further subset of firms for which we also have production data. This data is necessary to calculate quantity-based productivity at the firm-product-year-level. We refer to this sample as Sample 2. All our revenue-based productivity results below hold similarly well for both samples, although we only present results using Sample 2 for brevity.

Employer-employee data come from *Quadros de Pessoal* (henceforth, QP), a data set made available by the Ministry of Employment of Portugal, drawing on a compulsory annual census of all firms in Portugal that employ at least one worker.[11] Currently, the data set collects data on about 350,000 firms and 3 million employees. Reported data cover the firm itself, each of its plants, and each of its workers. Each firm and each worker entering the database are assigned a unique, time-invariant identifying number which we use to follow firms and workers over time. Variables available in the data set include the firm's location, industry, total employment, and sales. The worker-level data cover information on all personnel working for the reporting firms in a reference week in October of each year. They include information on occupation, earnings, and

[11] Public administration and non-market services are excluded. *Quadros de Pessoal* has been used by, amongst others, Blanchard and Portugal (2001) to compare the U.S. and Portuguese labor markets in terms of unemployment duration and worker flows; by Cabral and Mata (2003) to study the evolution of the firm size distribution; by Mion and Opromolla (2014) to show that the export experience acquired by managers in previous firms leads their current firm towards higher export performance, and commands a sizeable wage premium for the manager.

hours worked (normal and overtime). The information on earnings includes the base wage (gross pay for normal hours of work), seniority-indexed components of pay, other regularly paid components, overtime work, and irregularly paid components. It does not include employers' contributions to social security.[12]

The second data set is *Central de Balanços* (henceforth, CB), a repository of yearly balance sheet data for non financial firms in Portugal. Prior to 2005 the sample was biased towards large firms. However, the value added and sales coverage rate was high. For instance, in 2003 firms in the CB data set accounted for 88.8 percent of the national accounts total of non-financial firms' sales. Information available in the data set includes a firm sales, material assets, costs of materials, and third-party supplies and services.

The third data set is the *Inquérito Anual à Produção Industrial* (henceforth, PC), a data set made available by Statistics Portugal (INE), containing information on sales and volume sold for each firm-product pair for a sample of firms with at least 20 employees covering at least 90 percent of the value of aggregate production. From PC we use information on the volume and value of a firm's production. The volume is recorded in units of measurement (number of items, kilograms, liters) that are product-specific while the value is recorded in current euros. From the raw data it is possible to construct different measures of the volume and value of a firm's production. For the sake of this project we use the volume and value corresponding to a firm's sales of its products. This means that we exclude products produced internally and to be used in other production processes within the firm as well as products produced for other firms, using inputs provided by these other firms. The advantage of using this definition is that it nicely corresponds to the cost of materials coming from the balance sheet data. For example, the value of products produced internally and to be used in other production processes within the firm is part of the cost of materials while products produced for other firms, using inputs provided by these other firms, is neither part of the cost of materials nor part of a firm's sales from the PC data. We aggregate products at the 2-digits-unit of measurement pairs and split multi-products firms into several single-product firms using products revenue shares as weights (see Appendix A).[13]

3.1 Occupational structure

To recover the occupational structure at the firm level we exploit information from the matched employer-employee data set. Each worker, in each year, has to be assigned to a category following a (compulsory) classification of workers defined by the Portuguese law.[14] Classification is based on the tasks performed

[12] The Ministry of Employment implements several checks to ensure that a firm that has already reported to the database is not assigned a different identification number. Similarly, each worker also has a unique identifier, based on a worker's social security number. The administrative nature of the data and their public availability at the workplace—as required by the law—imply a high degree of coverage and reliability. It is well known that employer-reported wage information is subject to less measurement error than worker-reported data. The public availability requirement facilitates the work of the services of the Ministry of Employment that monitor the compliance of firms with the law.

[13] In our analysis, we also experimented with using the sample of single-product firms only. Results, available upon request, are qualitatively identical and quantitatively very similar.

[14] Following CMRH we use occupational categories to identify layers of management. In the case of French firms, CMRH use the PCS classification. In this study we use the Portuguese classification (Decreto Lei 121/78 of July 2^{nd} 1978) which is not the ISCO.

and skill requirements, and each category can be considered as a level in a hierarchy defined in terms of increasing responsibility and task complexity. Table A.1 in Appendix A contains more detail about the exact construction of these categories.

On the basis of the hierarchical classification and taking into consideration the actual wage distribution, we partition the available categories into management layers. We assign "Top executives (top management)" to occupation 3; "Intermediary executives (middle management)" and "Supervisors, team leaders" to occupation 2; "Higher-skilled professionals" and some "Skilled professionals" to occupation 1; and the remaining employees, including "Skilled professionals", "Semi-skilled professionals", "Non-skilled professionals", and "Apprenticeship" to occupation 0.

We then translate the number of different occupations present in a firm into layers of management. A firm reporting c occupational categories will be said to have $L = c - 1$ layers of management: hence, in our data we will have firms spanning from 0 to 3 layers of management (as in CMRH). In terms of layers within a firm we do not keep track of the specific occupational categories but simply rank them. Hence a firm with occupational categories 2 and 0 will have 1 layer of management, and its organization will consist of a layer 0 corresponding to some skilled and non-skilled professionals, and a layer 1 corresponding to intermediary executives and supervisors.[15]

Table 1 presents some basic statistics for Sample 1 for the ten years spanned by our data. The data exhibits some clear trends over time. In particular, the number of firms declines and firms tend to become larger. In all our regressions we control for time and industry fixed effects.

Table 1: Firm-level data description by year

		Mean			
Year	Firms	Value Added	Hours	Wage	# of layers
1996	8,061	1,278	102,766	4.37	1.25
1997	8,797	1,227	91,849	4.48	1.20
1998	7,884	1,397	96,463	4.81	1.28
1999	7,053	1,598	105,003	4.93	1.31
2000	4,875	2,326	139,351	5.13	1.62
2002	4,594	2,490	125,392	5.63	1.62
2003	4,539	2,363	124,271	5.65	1.70
2004	4,610	2,389	124,580	5.82	1.74
2005	3,962	2,637	129,868	6.01	1.76

Notes: Value added in 2005 euros. Wage is average hourly wage in 2005 euros.

[15] One potential concern with this methodology to measure the number of layers is that many firms will have layers with occupations that are not adjacent in the rank. This does not seem to be a large problem. More than 75% of firms have adjacent layers.

4 Portuguese Production Hierarchies: Basic Facts

In this section we reproduce some of the main results in CMRH for France using our data for Portugal in Sample 1. These results underscore our claim that the concept of layers we use is meaningful. We show this by presenting evidence that shows, first, that firms with different numbers of layers are systematically different in a variety of dimensions; second, that firms change layers in a systematic and expected way; third, that the workforce within a layer responds as expected as firms add or subtract layers. This evidence makes us confident that interpreting the adding and dropping of layers in data as a firm reorganization is warranted by the evidence.

Table 2: Firm-level data description by number of layers

		Mean			Median
# of layers	Firm-years	Value added	Hours	Wage	Wage
0	14,594	267.2	12,120.7	3.55	3.16
1	14,619	648.4	31,532.0	4.03	3.64
2	12,144	2,022.7	96,605.2	4.51	4.11
3	13,018	10,286.2	327,166.8	5.73	5.20

Notes: Value added in 000s of 2005 euros. Wage is either average or median hourly wage in 2005 euros. Hours are yearly.

Table 2 presents the number of firm-year observations by number of management layers as well as average value added, hours, and wages. It also presents the median wage given that the wage distribution can be sometimes very skewed. The evidence clearly shows that firms with more layers are larger in terms of value added and hours. It also shows that firms with more layers pay on average higher wages.

Figures 5 to 7 present the distributions of value added, employment and the hourly wage by layer. The distributions are clearly ordered. The distributions for firms with more layers are shifted to the right and exhibit higher variance. In Figure 6 the modes in the distribution of hours corresponds to the number of hours of one full-time employee, two full-time employees, etc. The figures show that firms with different numbers of layers are in fact very different. The notion of layers seems to be capturing a stark distinction among firms.

Our definition of layers of management is supposed to capture the hierarchical structure of the firm. So it is important to verify that the implied hierarchies are pyramidal in the sense that lower layers employ more hours and pay lower hourly wages. Table 3 shows that the implied hierarchical structure of firms is hierarchical in the majority of cases. Furthermore, the implied ranking holds for 76% of the cases when comparing any individual pair of layers. Similarly, Table 4 shows that lower layers command lower wages in the vast majority of cases. We conclude that, although perhaps with some imprecision, our definition of layers does a good job in capturing the hierarchical structure of firms.

Our primary goal is to study the endogenous productivity responses of firm that reorganize. So it is important to establish how often they do so. Table 5 presents a transition matrix across layers. In a given

Figure 5: Value Added Density

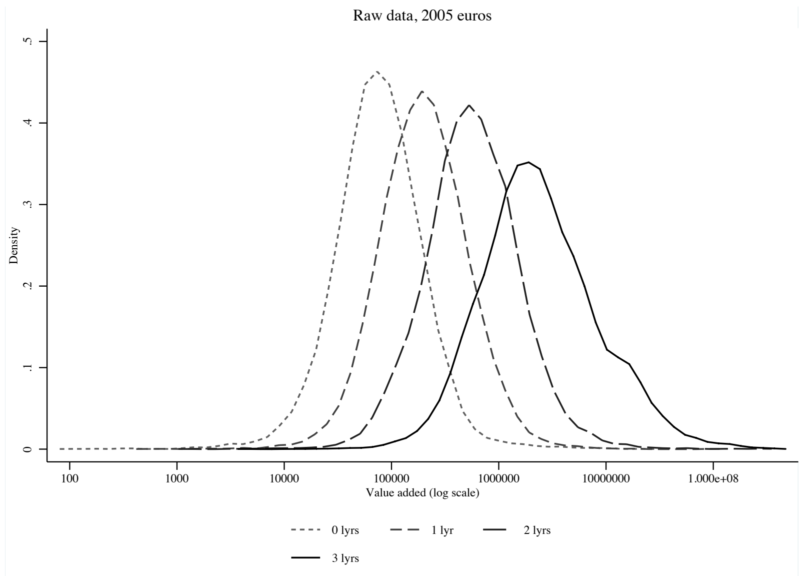
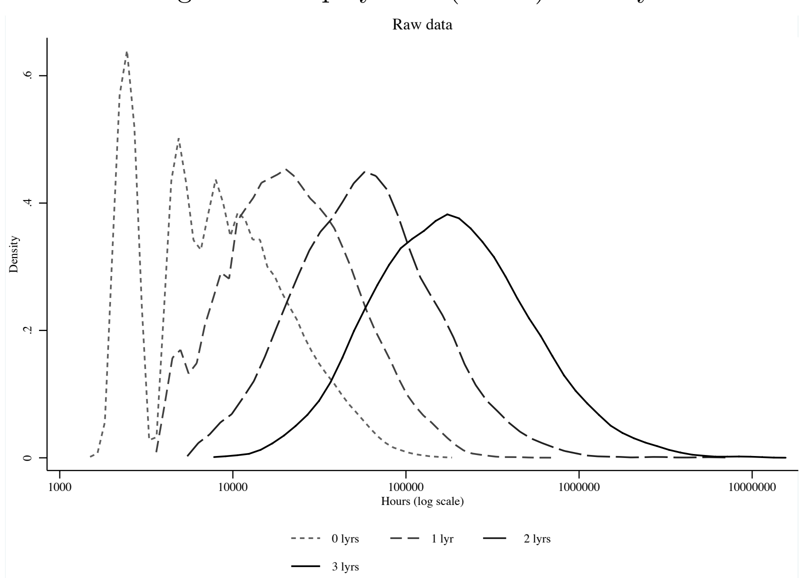


Figure 6: Employment (Hours) Density



year about half the total number of firms keep the same number of layers, with the number increasing to 70% for firms with 4 layers (3 layers of management). Most of the firms that do not reorganize just exit, with the percentage of exiting firms declining with the number of layers. About 12% of firms in a layer reorganize by adding a layer, and about the same number downscale and drop one. Overall, as in France, there seem to be many reorganizations in the data. Every year around 20% of firms add and drop occupations, and

Figure 7: Hourly Wage Density

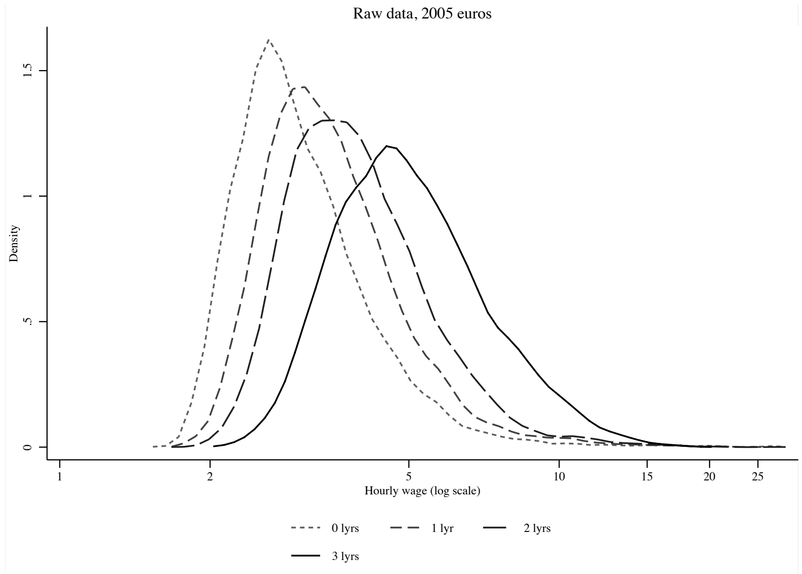


Table 3: Percentage of firms that satisfy a hierarchy in hours

# of layers	$N_L^l \geq N_L^{l+1}$ all l	$N_L^0 \geq N_L^1$	$N_L^1 \geq N_L^2$	$N_L^2 \geq N_L^3$
1	91.64	91.64	–	–
2	69.62	92.07	77.35	–
3	50.51	88.70	74.34	83.65

N_L^l = hours at layer l of a firm with L layers.

therefore restructure their labor force (the number is lower for firms with 3 layers of management since, given that the maximum number of management layers is 3, they can only drop layers).

A reorganization is accompanied with many other firm-level changes. In Table 6 we divide firms depending on whether they add, do not change, or drop layers, and present measured changes in the total number of hours, number of hours normalized by the number of hours in the top layer, value added, and average wages. For all these measures we present changes after de-trending in order to control for the time trends in the data that we highlighted before. First, note that firms that either expand or contract substantially tend

Table 4: Percentage of firms that satisfy a hierarchy in wages

# of layers	$w_L^l \leq w_L^{l+1}$ all l	$w_L^0 \leq w_L^1$	$w_L^1 \leq w_L^2$	$w_L^2 \leq w_L^3$
1	75.87	75.87	–	–
2	65.66	85.21	79.57	–
3	67.11	92.36	84.62	87.82

Table 5: Distribution of layers at $t+1$ conditional on layers at t

		# of layers at $t+1$					
		Exit	0	1	2	3	Total
# of layers at t	0	31.19	54.29	12.54	1.69	0.29	100.00
	1	25.75	10.26	51.12	11.35	1.51	100.00
	2	21.73	1.49	12.06	49.62	15.09	100.00
	3	15.68	0.37	1.46	12.90	69.59	100.00
	New	85.08	5.31	3.77	3.01	2.83	100.00

to reorganize. This is the case both in terms of hours or in terms of value added. Furthermore, changes in either hours or value added seem to be symmetric, but with opposite sign, for firms that add and drop layers. Finally, firms that add layers tend to pay higher wages. However, once we de-trend, it is clear that wages in the preexisting layers decline. So average wages increase because the agents in the new layer earn more than the average but workers in preexisting layers earn less as their knowledge is now less useful (as found for France in CMRH).

Table 6: Changes in firm-level outcomes

# of layers	All	Increase L	No Change in L	Decrease L
dln total hours	-0.0068^a	0.2419^a	-0.0080^a	-0.2992^a
- detrended		0.2472^a	-0.0011	-0.2911^a
dln normalized hours	0.0099^b	1.0890^a	-0.0204^a	-1.1043^a
- detrended		1.0761^a	-0.0299^a	-1.1128^a
dlnVA	0.0173^a	0.0509^a	0.0155^a	-0.0126^a
- detrended		0.0323^a	-0.0013	-0.0307^a
dln avg. wage	0.0369^a	0.0683^a	0.0348^a	0.0122^a
- detrended		0.0303^a	-0.0018^c	-0.0253^a
common layers	0.0356^a	0.0068^b	0.0348^a	0.0750^a
- detrended		-0.0295^a	-0.0005	0.0387^a

Notes: ^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1.

The results above can be further refined by looking at layer-level outcomes for firms that expand without reorganizing and firms that expand as a result of a reorganization. The theory predicts that firms that expand but keep the same number of layers will increase employment and wages in all layers. In contrast, firms that expand and add layers, will increase employment in all layers but will decrease wages (and according to the theory, knowledge) in all preexisting layers. That is, adding a layer allows the firm to economize on the knowledge of all the preexisting layers. Tables 7 and 8 present the elasticity of normalized hours (hours at each layer relative to the top layer) and wages, respectively, to value added for firms that do not add layers. The first column indicates the number of layers in the firm, and the second the particular layer for which the elasticity is calculated. The theory predicts that all elasticities should be positive. This prediction is confirmed for all elasticities except for one case where the estimate is not significant. Hence, we conclude that firms that grow without reorganizing increase employment and wages in all layers.

Table 7: Elasticity of n_L^ℓ with respect to value added for firms that do not change L

# of layers	Layer	Elasticity	# observations
1	0	0.1155^a	6,351
2	0	0.1146^a	4,998
2	1	-0.0147	4,998
3	0	0.1760^a	7,079
3	1	0.0847^a	7,079
3	2	0.0987^a	7,079

Notes: Robust standard errors in parentheses: ^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1.

Table 8: Elasticity of w_L^ℓ with respect to value added for firms that do not change L

# of layers	Layer	Elasticity	# observations
0	0	0.0056	6,987
1	0	0.0216^a	6,351
1	1	0.0283^a	6,351
2	0	0.0150^b	4,998
2	1	0.0229^b	4,998
2	2	0.0303^b	4,998
3	0	0.0225^a	7,079
3	1	0.0201^a	7,079
3	2	0.0298^a	7,079
3	3	0.0199^b	7,079

Notes: Robust standard errors in parentheses: ^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1.

Tables 9 and 10 show changes in normalized hours and wages when firms reorganize. The tables show the total number of layers before and after the reorganization, as well as the layer for which the log-change is computed. As emphasized before, adding layers should lead to increases in employment but declines in wages in all preexisting layers. These implications are verified for all transitions in all layers except for two non-significant results for firms that start with zero layers of management. Similar to the results in CMRH for France, our estimates for Portugal show that firms that add layers in fact concentrate workers' knowledge, as proxied by their wages, on the top layers. This is one of the consequences of a firm reorganization and supports empirically the underlying mechanism that, we hypothesize, leads to an increase (decrease) in quantity-based productivity as a result of a reorganization that adds (drops) layers.

Table 9: $d\ln n^{\ell}_{Lit}$ for firms that transition

# of layers before	# of layers after	Layer	$d\ln n^{\ell}_{Lit}$	# observations
0	1	0	1.2777^{a}	1,614
0	2	0	1.6705^{a}	218
0	3	0	2.3055^{a}	37
1	0	0	-1.2304^{a}	1,275
1	2	0	0.5178^{a}	1,410
1	2	1	0.4920^{a}	1,410
1	3	0	0.9402^{a}	188
1	3	1	0.8367^{a}	188
2	0	0	-1.6449^{a}	150
2	1	0	-0.5645^{a}	1,215
2	1	1	-0.5060^{a}	1,215
2	3	0	0.6806^{a}	1,520
2	3	1	0.7098^{a}	1,520
2	3	2	0.6340^{a}	1,520
3	0	0	-2.5187^{a}	38
3	1	0	-0.9772^{a}	149
3	1	1	-0.8636^{a}	149
3	2	0	-0.7977^{a}	1,312
3	2	1	-0.7532^{a}	1,312
3	2	2	-0.6465^{a}	1,312

Notes: Robust standard errors in parentheses: ^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1.

5 Changes in Productivity

We now present our methodology to measure changes in revenue-based and quantity-based productivity induced by firm reorganization. The measurement of revenue productivity has received a lot of attention in the industrial organization literature, and so we expand standard methodologies to account for the role of layers. Measuring quantity-based productivity is more involved and requires more detailed data. We address each measurement exercise in turn.

In both cases, once recovered productivity, we analyze the link between productivity (outcome variable) and changes in layers (explanatory variable). In doing so we always control for lagged productivity because it is well known that productivity is highly persistent over time. We use sequences of firm-years with either one or zero changes in layers. The underlying idea is to compare the productivity of firms that are, for example, increasing the number of layers both among them as well as with firms that are not changing the number of layers. In the former case, we obtain identification of the impact on productivity via comparing firms increasing the number of layers before and after the change. In the latter case we also get identification from comparing the productivity of firms changing layers with those that do not. To better isolate reorganization events and ease comparability of an otherwise complex structure we break firms

Table 10: $d \ln w^{\ell}_{Lit}$ for firms that transition

# of layers before	# of layers after	Layer	$d \ln w^{\ell}_{Lit}$	# observations
0	1	0	0.0062	1,614
0	2	0	0.0207	218
0	3	0	-.1878^{a}	37
1	0	0	0.0557^{a}	1,275
1	2	0	0.0038	1,410
1	2	1	-0.0624^{a}	1,410
1	3	0	-0.0230^{a}	188
1	3	1	-0.1710^{a}	188
2	0	0	0.0692^{a}	150
2	1	0	0.0373^{a}	1,215
2	1	1	0.1192^{a}	1,215
2	3	0	-0.0015	1,520
2	3	1	-0.0113^{b}	1,520
2	3	2	-0.0676^{a}	1,520
3	0	0	0.2673^{a}	38
3	1	0	0.0691^{a}	149
3	1	1	0.1672^{a}	149
3	2	0	0.0313^{a}	1,312
3	2	1	0.0467^{a}	1,312
3	2	2	0.1114^{a}	1,312

Notes: Robust standard errors in parentheses: ^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1.

into sequences that correspond to at most one change in the hierarchical structure. More specifically, we define a sequence of type $L - L'$ as the series of years in which a firm has the same consecutively observed number of management layers L plus the adjacent series of years in which a firm has the same consecutively observed number of management layers L'. For example, a firm that we observed all years between 1996 and 2000 and that has zero layers in 1996, 1997, and 2000 and one layer in 1998 and 1999 would have two sequences: A 0-1 sequence (1996 to 1999) as well as a 1-0 sequence (1998 to 2000). Firms that never change layers in our sample form a constant-layer sequence. We then separately analyze sequences characterized by an increasing, decreasing or constant number of layers as well as all sequences together. In particular, we use the productivity corresponding to such sequences as dependent variable and run both basic OLS and firm-product-sequence fixed effects regressions.[16] When considering fixed effects, we provide below results based on the within estimator as well as on the dynamic panel data system GMM estimator developed in Arellano and Bover (1995).[17] In Appendix F, we revisit all our results using an alternative grouping of firms

[16] To be more specific, if a firm sells two products and its time hierarchy profile is characterized by two types of increasing sequences we break—as indicated in Section 3—the firm into two single-product firms and assign to each of these two firms a specific identifier. At the same time within each firm-product identifier we distinguish sequences depending on their $L - L'$ type by allowing for firm-product-sequence type fixed effects. In our analysis, we also experimented with using the sample of single-product firms only. Results, available upon request, are qualitatively identical and quantitatively very similar.

[17] More specifically, we implement this with the xtabond2 command in Stata.

based on their number of layers the first time we see them reorganize in the data.[18]

In all OLS specifications we use a battery of time-varying industry/product affiliation dummies as well as time dummies. We use time dummies in fixed effects specifications. Throughout, standard errors are clustered at the firm-level. Bootstrapped standard errors are virtually identical to firm-clustered ones.

5.1 Revenue-based Productivity

There are two problems related to explicitly accounting for the choice of organization into productivity estimations. The first one is endogeneity: the firm chooses the optimal organizational structure also based on productivity shocks. The second one is measurement: the number of workers in a firm and the total wage bill are observables in standard datasets but the amount of problem-solving managerial knowledge leveraging production capacity (our labor input O) is typically not observable. Furthermore, two firms with identical total wage bill and number of workers will have different labor inputs O depending on their organizational structure (number of layers and knowledge within each layer). In what follows we show how to solve these two problems in the context of revenue productivity estimations.

The Cobb-Douglas production function for firm i in period t introduced in equation (1) can be expressed in logs as

$$q_{it} = a_{it} + \alpha_O o_{it} + \alpha_M m_{it} + (\gamma - \alpha_M - \alpha_O) k_{it} \tag{7}$$

where a_{it} denotes productivity, o_{it} the log of the labor input, m_{it} the log of materials, and k_{it} the log of capital.

The labor input O_{it} is not directly observable, but we can use the fact that

$$O_{it} = \frac{C\left(O_{it}; w\right)}{C\left(O_{it}; w\right)} O_{it} = \frac{C\left(O_{it}; w\right)}{AC\left(O_{it}; w\right)}. \tag{8}$$

The numerator of this expression, $C\left(O_{it}; w\right)$, is the total expenditure on the labor input, i.e., the total wage bill of the firm (which is observable in standard data) while the denominator, $AC\left(O_{it}; w\right) = C\left(O_{it}; w\right)/O_{it}$, is the unit cost of the labor input (which is, by contrast, unobservable). Indeed, while average wages per worker are observable in standard data, $C\left(O_{it}; w\right)/O_{it}$ is not because the labor input O_{it} does not correspond to the number of workers in a firm but rather to the amount of problem-solving managerial knowledge leveraging production capacity. Substituting (8) into the production function and multiplying

[18] The second approach groups firms according to the number of layers (0, 1, 2 or 3) the firm has in the year of the first observed reorganization. We then follow firms over time and relate changes in the hierarchical structure to the evolution of firm productivity. Appendix F presents results for each of these groups using either OLS or firm-product fixed effects. Again, for the latter case we provide both within and dynamic panel system GMM results. Crucially, both approaches lead to very similar conclusions and magnitudes. One issue with this second approach is that firms within each of the four groups might be both increasing and decreasing the number of layers several times over the observed time span. In contrast, in the first approach, that we present in the main text, we focus on single events and distinguish more explicitly reorganizations leading to an increase or decrease in the number of layers.

by the price leads to an equation for revenue given by

$$r_{it} = \bar{a}_{it} + \alpha_O \ln C\left(O_{it}; w\right) + \alpha_M m_{it} + (\gamma - \alpha_M - \alpha_O) k_{it}, \tag{9}$$

where $\bar{a}_{it} \equiv p_{it} + a_{it} - \alpha_O \ln AC\left(O_{it}; w\right)$ denotes revenue-based productivity. In what follows we assume $-\alpha_O \ln AC\left(O_{it}; w\right) = \beta L_{it}$ which implies $\bar{a}_{it} = p_{it} + a_{it} + \beta L_{it}$. Note that $-\alpha_O \ln AC\left(O_{it}; w\right) = \beta L_{it}$ is what is implied by the CRH model if we substitute the constraint (5) in the organizational problem with $n_L^L \geq \epsilon$, for small enough $\epsilon > 0$. In such a case we thus only need to keep track of the number of management layers (L_{it}) rather than both the number of layers and the average knowledge within each layer ℓ (z_L^ℓ).

Turning to the time evolution of productivity we follow the literature and impose productivity follows an autoregressive process. In particular we assume productivity in t ($\bar{a}_{it}$) depends upon productivity at time t-1 ($\bar{a}_{it-1}$) with the latter incorporating the effect of organization in t-1 (L_{it-1}). If the firm does not change the number of layers in t we assume $\bar{a}_{it} = \phi_a \bar{a}_{it-1} + \nu_{ait}$. However, if the firm changes the number of layers in t we need to consider the extra term $\Delta L_{it} \equiv L_{it} - L_{it-1}$:

$$\bar{a}_{it} = \phi_a \bar{a}_{it-1} + \beta \Delta L_{it} + \nu_{ait}, \tag{10}$$

where ν_{ait} is a productivity shock that is i.i.d. across firms and time. We follow again the literature and assume ν_{ait} is uncorrelated with all past values of $\bar{a}_{it}$. As far as the correlation between ν_{ait} and ΔL_{it} is concerned we could in principle make two different hypothesis. On the one hand, we could assimilate organization to capital investments and assume the number of layers is predetermined in the short-run, i.e., the current organizational structure has been chosen in the past and cannot immediately adjust to current period shocks. In this case ΔL_{it} would not be, very much like capital k_{it}, correlated with ν_{ait}. On the other hand, one might argue that contemporaneous shocks could be big enough to trigger an organizational change and in this respect it is important to note that cumulated shocks are those who matter, i.e., the current shock might be in itself small but just enough to pass the threshold making a reorganization profitable. In this scenario ν_{ait} would be uncorrelated with past values of L_{it} but correlated with ΔL_{it} in (10). Both arguments have some merits and in what follows we explore both. More specifically, we estimate revenue-based TFP $\bar{a}_{it}$ under the weaker assumption that ΔL_{it} and ν_{ait} are correlated. We accomplish this by using the lag of ΔL_{it} as well as L_{it-2} as instruments for ΔL_{it}. This provides estimates that are consistent under both scenarios. When subsequently regressing our measure of revenue-based productivity on changes in the organizational structure as described above we provide in this Section results based on the predetermined hypothesis (ν_{ait} not correlated with ΔL_{it}) while leaving to Section 5.3 the discussion of results based on the endogeneity assumption.

As far as firm choices are concerned we assume, in line with the literature, that capital is predetermined in t. We further allow firms to optimally choose materials in order to minimize short-run costs. As for the labor input, we follow Ackerberg et al. (2015) and assume it is somewhere in between capital and materials in terms of its capacity to adapt to contemporaneous shocks. The cost of materials is common across firms but can vary over time while the unit cost of the labor input $AC(O_{it};w)$ varies across firms and time. From first-order cost minimization conditions we have that materials' choice m_{it} is a function of k_{it} and $\bar{a}_{it}$. Indeed, whatever the structure of organization chosen by the firm (L_{it}), it will ultimately pin down $\bar{a}_{it}$ which in turn, together with capital k_{it}, determines the optimal materials' expenditure. After inverting the first-order conditions of the firm, we can express $\bar{a}_{it}$ as a function of capital and materials, namely, $\bar{a}_{it} = g(k_{it}, m_{it})$.

From now onwards we follow Wooldridge (2009) and consider the value-added form of the revenue function (9) which is known in the literature to perform better in terms of identification.[19] In particular, using (10) as well as the inverted input demand equation of the firm, $\bar{a}_{it-1} = g(k_{it-1}, m_{it-1})$, we obtain

$$va_{it} = \alpha_O^{'} \ln C(O_{it};w) + \alpha_K^{'} k_{it} + \phi_a^{'} g(k_{it-1}, m_{it-1}) + \beta^{'} \Delta L_{it} + \nu_{ait}. \tag{11}$$

where va_{it} is value added and, for example, the coefficient $\alpha_O^{'}$ equals α_O times a scaling factor common to all other coefficients. As shown in, for example, Bilir and Morales (2016) going from (9) to (11) simply requires the optimal materials expenditure to be a constant fraction of the revenue (which is true in our Cobb-Douglas production function framework) and a CES demand (which is the specification used in CRH).

The error term ν_{ait} in (10) is uncorrelated with k_{it} and m_{it-1}. Hence, $g(k_{it-1}, m_{it-1})$ is also uncorrelated with ν_{ait} in (11). The wage bill $C(O_{it};w)$ and the change in the number of layers at t, ΔL_{it}, are instead endogenous and we instrument them with the wage bill at $t-1$, the change in the number of layers at $t-1$, and the number of layers in $t-2$. As for the term $\phi_a^{'} g(k_{it-1}, m_{it-1})$ we use a second order polynomial approximation in k_{it-1} and m_{it-1}. We finally estimate (11) by IV and ultimately get an estimate of revenue TFP as

$$\widehat{\bar{a}}_{it} = va_{it} - \hat{\alpha}_O^{'} \ln C(O_{it};w) - \hat{\alpha}_K^{'} k_{it}.$$

Equipped with $\widehat{\bar{a}}_{it}$ we can now comprehensively estimate the impact of changes in organization on revenue productivity by following the two approaches outlined at the beginning of Section 5 and using both OLS and fixed effects. In this respect $\widehat{\bar{a}}_{it}$ is a measure of revenue productivity that, while accounting for the standard problem of inputs endogeneity, explicitly incorporates the choice of organization. Yet, one might wonder to what extent our findings rely on the particular revenue productivity measure we propose. The literature has proposed several ways to estimate revenue productivity and we have actually experimented with several estimation techniques including standard Olley and Pakes (1996), Levinsohn and Petrin (2003) and De Loecker and Warzynski (2012). We provide in Appendix C and D many of the results obtained with these alternative techniques. We also provide in Appendix C findings obtained with simpler approaches like OLS and value added per worker and show below results referring to the most basic measure of revenue-based productivity one could think of: revenue per worker. All of these results point to a coherent picture in

[19] Wooldridge (2009) builds on Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015) and shows how to obtain consistent estimates of input elasticities with a one-step GMM procedure. The results are qualitatively and quantitatively very similar if we simply implement the methodology in Olley and Pakes (1996).

Table 11: Wooldridge Revenue TFP. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.741^a	0.769^a	0.805^a	0.785^a
	(0.030)	(0.032)	(0.021)	(0.017)
Change in layers	-0.068^a	-0.108^a		-0.079^a
	(0.011)	(0.016)		(0.008)
Constant	-0.006	-0.028	-0.018	-0.010
	(0.018)	(0.036)	(0.026)	(0.014)
Observations	4,127	2,708	2,989	9,824
Adjusted R^2	0.622	0.520	0.642	0.598

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

which an increase (decrease) in the number of layers decreases (increases) revenue productivity. However, we believe the numbers we obtain below with the modified Wooldridge (2009) procedure explicitly incorporating the choice of organization are to be preferred.

Table 11 provides our baseline results. The dependent variable is productivity at time t ($\widehat{a}_{it}$) while the main control variable is lagged productivity and the key covariate is the change in the number of management layers in t. Table 11 reports coefficients referring to sequences corresponding to an increasing (column 1), decreasing (column 2) or constant (column 3) number of layers while column 4 groups all sequences together.

Table 11 shows that adding a layer (column 1) reduces revenue-based productivity by 6.8%, while dropping one (column 2) increases it by slightly less than 11%. The overall effect (column 4) of changing a layer is about 8% and coefficients are highly significant in all cases.

The OLS estimations in Table 11 closely matches our assumption about the productivity process (10) in that—besides the issue of endogeneity we deal with in Section 5.3—there is no space for unobserved heterogeneity correlated with lagged TFP and/or the change in layers. We extend our framework to the presence of time-invariant unobserved heterogeneity, to be dealt with either time differencing (dynamic panel) or a within transformation (within estimator). More specifically, given the simultaneous presence of a lagged dependent variable and fixed effects, we employ in Table 12 the system GMM estimator proposed by Arellano and Bover (1995) within the context of dynamic panel data with endogenous regressors. We also present more standard results obtained by means of the within estimator in Appendix C and D. The two sets of results are qualitatively identical and quantitatively very similar.

Table 12 portraits a picture very similar to the one emerging from Table 11.[20] While the effect of changing layers is now a bit smaller across the board, it is negative and significant in all specifications. At the same time Table 12 indicates that decreasing the number of layers has a bigger impact on productivity

[20]As far as test diagnostic is concerned, system GMM estimations in Table 12 are characterized by small and often not significant AR(2) tests on residuals suggesting the way we model the dynamics captures well the persistency features of the data.

Table 12: Wooldridge Revenue TFP. Firm-product-sequence FE. Dynamic panel

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.373^a	0.436^a	0.518^a	0.462^a
	(0.061)	(0.085)	(0.072)	(0.045)
Change in layers	-0.036^a	-0.087^a		-0.056^a
	(0.009)	(0.012)		(0.006)
Constant	0.049	-0.016	0.012	0.019
	(0.032)	(0.034)	(0.034)	(0.016)
Observations	4,127	2,708	2,989	9,824
Number of fixed effects	1,655	1,268	1,276	4,199
AR(2) Test Stat	1.837	1.254	1.204	2.331
P-value AR(2)	0.066	0.210	0.229	0.020

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table 13: Revenue Labor Productivity. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.772^a	0.898^a	0.914^a	0.855^a
	(0.020)	(0.014)	(0.014)	(0.011)
Change in layers	-0.118^a	-0.181^a		-0.132^a
	(0.015)	(0.024)		(0.012)
Constant	2.717^a	1.185^a	0.971^a	1.705^a
	(0.240)	(0.165)	(0.157)	(0.126)
Observations	4,206	2,750	3,090	10,046
Adjusted R^2	0.768	0.749	0.854	0.792

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

than adding layers. The overall effect of changing layers is now down to 5-6% as compared to roughly 8% in specifications without fixed effects. This might be due to unobservables being positive correlated with the change in layers and/or with the lag of productivity so warranting the use of fixed effects. However, this might as well be driven by standard measurement error, and related attenuation bias, being more pronounced when taking first differences to eliminate fixed effects. For both reasons we do not necessarily consider the numbers in Table 12 as being more accurate than those in Table 11.

Last but not least we present in Table 13 the results based on the simplest measure of revenue productivity one could think of: log revenue per worker. We present here simple OLS regressions and report in Appendix C and D the corresponding within and system GMM estimates along with those of the other measures of revenue productivity we consider like De Loecker and Warzynski (2012). Looking at Table 13 the same consistent patterns emerges. Interestingly enough, impacts are considerably larger in this case with an average decrease (increase) in revenue productivity of about 13% upon an increase (decrease) in the number of management layers. This is consistent with a scenario in which firms who, for example, reorganize by increasing the number of layers also adjust capital and materials in such a way that TFP changes translate into amplified changes of the revenue to labor ratio.

Overall these results paint a very consistent portrait. Revenue-based productivity decreases (increases) with a reorganization that adds (cuts) layers by between 4 and 8%. The result varies somewhat, depending on whether one controls or not for the presence of unobserved heterogeneity correlated with organizational changes. Furthermore, taking care of multiple inputs and adjusting for the endogenous choice of materials and labor is important as well, and reduces the absolute magnitude of the estimated effect of a reorganization. Nevertheless, the main result that revenue productivity jumps in the opposite direction as the number of layers is very robust across specifications and exercises. Clearly, revenue productivity can jump down either because firms reduce their prices or, perhaps, because quantity-based productivity goes down (a result that would contradict our hypothesis). Thus, we now proceed to estimate the effect of a reorganization on quantity-based productivity.

5.2 Quantity-based Productivity

Measuring quantity-based productivity is harder than measuring revenue-based productivity partly because we need information about quantities, which is rarely available, and partly because we need to account more explicitly for differences in demand across firms. Two firms producing similar products might be characterized by the same quantity productivity but face rather different demands. They will thus end up charging different prices and making different input choices so complicating the estimation of the production function. Furthermore, the empirical implications derived from the theory that we outlined in Section 2 crucially depend on accounting for heterogeneity and shocks in demand and their potential correlation with productivity shocks. Indeed, whatever the nature of the shock pushing a firm to change its optimal quantity, it will impact firm organizational structure because the latter is optimally designed to fit a given production scale.

This means we require a methodology explicitly allowing for different types of shocks while at the same time not restricting a priori the correlation among these shocks. We actually need more than that. We need to measure all of these shocks if we want to draw a causal relationship going from these shocks, to a change in the optimal production scale triggering a change of the the organizational structure and the latter ultimately impacting on firm productivity. To do so we follow Forlani et al. (2015) who allow computing quantity-based productivity in the presence of potentially correlated productivity, demand and markup shocks. Forlani et al. (2015) also provide a way to quantify these shocks that will be needed to strengthen the causal interpretation of our findings. As discussed in the previous Section, if organization is allowed to change in the short run in the wake of contemporaneous shocks we need some instruments to get causal identification. In this respect, we will use in Section 5.3 information on productivity, demand and markups shocks computed from this Section, as well as other demand and cost shifters, to draw a more causal link between reorganization and productivity: both revenue-based and quantity-based.

In what follows we start with a description of the baseline MULAMA methodology and subsequently expand on its application by explicitly considering the role of organization in producing the labor input. We then draw a link between reorganization and firm quantity-based productivity using several specifications and econometric models under the assumption that organization, like capital infrastructure, cannot adjust much in the short run. We relax this assumption in Section 5.3. Before moving forward it is important to highlight that, for the the purpose of our analysis, neither the methodology developed in De Loecker et al. (2016) nor the one described in Foster et al. (2008) fit our requirements exactly. De Loecker et al (2016) allows recovering quantity productivity while having some demand and markups shocks in the background. However, demand shocks cannot be quantified in their framework. Foster et al. (2008) allow measuring quantity-based productivity and demand shocks but impose a zero correlation between the two shocks as well as a constant markup across firms.

5.2.1 Baseline MULAMA

Following Forlani et al. (2015) we use a two-stage estimation procedure to obtain quantity-based productivity. This approach allows us to explicitly take into account the presence of demand shocks and markup heterogeneity across firms and quantify them. We do this by both assuming costs minimization, which provides a useful way of computing markups as in De Loecker and Warzynski (2012), and by imposing some restrictions on the way demand shocks enter utility. From standard profit maximization conditions the elasticity of revenue with respect to quantity is one over the markup μ_{it}. We assume the elasticity of revenue with respect to demand shocks λ_{it} is also $1/\mu_{it}$. Therefore, $r_{it} = p_{it} + q_{it} = \frac{1}{\mu_{it}}(\lambda_{it} + q_{it})$. Forlani et al. (2015) show how this holds as a first-order linear approximation in a variety of circumstances and in particular when a representative consumer pays p_{it} to get q_{it} but the latter enters utility as $\tilde{q}_{it} = q_{it} + \lambda_{it}$. In this light λ_{it} is a demand shock than can be interpreted as a measure of quality.

Recall the production function in equation (7) and assume the following standard AR(1) quantity-based productivity process: $a_{it} = \phi_a a_{it-1} + \nu_{ait}$. Capital is predetermined in t meaning that k_{it} is uncorrelated with contemporaneous shocks ν_{ait}. Labor and materials are instead optimally chosen with respect to, among others, a_{it} and so they are correlated with ν_{ait}. Furthermore, assume that demand for the product of firm i at time t, in logs, is given by

$$p_{it} = \left(1 - \frac{1}{\eta_{it}}\right)\lambda_{it} - \frac{1}{\eta_{it}}q_{it}$$

where λ_{it} denotes our demand shifters and η_{it} the elasticity of demand. Multiplying both side by q_{it} we have

$$r_{it} = \left(1 - \frac{1}{\eta_{it}}\right)(\lambda_{it} + q_{it}) = \frac{1}{\mu_{it}}(\lambda_{it} + q_{it})$$

where the last equality comes from the assumption of monopolistic competition and the markup is given by

$$\mu_{it} = \frac{\eta_{it}}{\eta_{it} - 1}.$$

Thus, heterogeneity or shocks in the elasticity of demand will result in variation in markups across firms and time. In terms of the time evolution of λ_{it} we assume that

$$\lambda_{it} = \phi_\lambda \lambda_{it-1} + \nu_{\lambda it},$$

where $\nu_{\lambda it}$ is an idiosyncratic demand shock that can be correlated with the idiosyncratic productivity shock ν_{ait}. In doing so we allow more broadly λ_{it} and a_{it} to be correlated with each other. We do not need to make specific assumptions about the time evolution of markups μ_{it}. Indeed, cost minimization implies, for the flexible inputs (which in our model are the labor input and materials), that there is direct link between the ratio of the elasticity of output to the markup and the share of inputs expenditure in firm revenue

$$\frac{\alpha_O}{\mu_{it}} = \frac{O_{it} MC\left(O_{it}; w\right)}{P_{it} Q_{it}},$$

and

$$\frac{\alpha_M}{\mu_{it}} = \frac{M_{it} P_{Mt}}{P_{it} Q_{it}},$$

where $MC\left(O_{it}; w\right)$ is the marginal cost of the labor input and P_{Mt} denotes the price of materials. Note that $M_{it} P_{Mt}$ is the total expenditure on materials, and $O_{it} MC\left(O_{it}; w\right)$ is the total expenditure on the labor input when we allow $n_L^L \geq \epsilon$, for $\epsilon > 0$ (since the unit and marginal cost coincide at the MES).

With this structure in hand, we can proceed to measure quantity-based productivity using data on quantities, revenue, labor, capital, material and inputs expenditure shares. The key insight of our approach is that, by having being explicit about demand, we can explicitly write down the revenue function in terms of demand, productivity and markups and use both the revenue and quantity equations to estimate parameters. This is why there are two steps in our estimation procedure. In doing so we depart from the more standard approach of focusing on the quantity equation only.

We start from the revenue equation. Denote

$$LHS_{it} = \frac{r_{it} - s_{Oit}\left(o_{it} - k_{it}\right) - s_{Mit}\left(m_{it} - k_{it}\right)}{s_{Mit}},$$

where s_{xit} is the share in expenditure of input x. After some manipulations of the revenue equation we can obtain an expression for LHS_{it} that we can estimate in the first stage. Namely,

$$LHS_{it} = b_1 z_{1it} + b_2 z_{2it} + b_3 z_{3it} + b_4 z_{4it} + b_5 z_{5it} + u_{it}, \tag{12}$$

where $z_{1it} = k_{it}$, $z_{2it} = LHS_{it-1}$, $z_{3it} = k_{it-1}$, $z_{4it} = \frac{r_{it-1}}{s_{Mit-1}}$, $z_{5it} = q_{it-1}$, $u_{it} = \left(\nu_{ait} + \nu_{\lambda it}\right)/\alpha_M$. Appendix

B presents a detailed derivation of equation (12). Note that we can simply use OLS to estimate equation (12) since u_{it}, the combined contemporaneous demand and productivity shocks, is not correlated with the covariates. This equation allows us to identify several reduced-form parameters of the model: $\hat{b}_1 = \frac{\gamma}{\alpha_M}$, $\hat{b}_2 = \phi_a$, $\hat{b}_3 = -\phi_a \frac{\gamma}{\alpha_M}$, $\hat{b}_4 = \phi_\lambda - \phi_a$, and $\hat{b}_5 = \frac{-\phi_\lambda + \phi_a}{\alpha_M}$.

Using $\hat{b}_1$ and $\hat{b}_2$ we can implement a second stage to separately identify γ where we use the productivity process and the production function (quantity equation) to obtain

$$q_{it} - \hat{b}_2 q_{it-1} = b_6 z_{6it} + \nu_{ait}$$

where

$$z_{6it} = \frac{o_{it} - k_{it}}{\hat{b}_1} \frac{s_{Oit}}{s_{Mit}} + \frac{m_{it} - k_{it}}{\hat{b}_1} + k_{it} + \frac{\hat{b}_2}{\hat{b}_1} LHS_{it-1} - \hat{b}_2 k_{it-1} - \frac{r_{it-1}\hat{b}_2}{\hat{b}_1 s_{Mit-1}},$$

with $b_6 = \gamma$.[21] Note that since k_{it} is predetermined in t we can instrument for z_{6it} with k_{it}. This is what we do using the instrumental variables (IV) estimator.

Then, our estimate of productivity is given by

$$\hat{a}_{it} = q_{it} - \frac{\hat{b}_6}{\hat{b}_1} \frac{s_{Oit}}{s_{Mit}} (o_{it} - k_{it}) - \frac{\hat{b}_6}{\hat{b}_1} (m_{it} - k_{it}) - \hat{b}_6 k_{it},$$

our estimate of demand shocks by

$$\hat{\lambda}_{it} = \frac{\hat{b}_6}{\hat{b}_1 s_{Mit}} r_{it} - q_{it},$$

and our estimate of markups by

$$\hat{\mu}_{it} = \frac{\hat{b}_6}{\hat{b}_1 s_{Mit}}.$$

The basic estimation methodology that we just described is amenable to various generalizations. In particular we can allow for a translog production function and can allow for a quadratic rather than the linear dependence of the productivity process on past productivity. We can also allow for labor to be somewhere in between materials and capital in terms of its responsiveness to contemporaneous shocks.

5.2.2 Changes in layers in MULAMA

The methodology to estimate quantity productivity introduced above does not incorporate the effect of changes in organization in the labor input. To do so we parallel what we did in Section 5.1, while further experimenting in Sections 5.2.3 and 5.2.4 with other approaches, in order to solve the two very same

[21] Note that, alternatively, we could have used a combination of the estimates in the first stage to obtain an estimate of γ, instead of using a second stage. This alternative methodology is in general not as robust and precise, since it involves multiplications and divisions of estimated coefficients as well as a difference between ϕ_λ and ϕ_a that is significantly different from zero. In any case, identification of γ in the first stage still requires information on quantity because quantity is among the right-hand side variables.

Table 14: Quantity TFP. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.892^a	0.875^a	0.905^a	0.895^a
	(0.014)	(0.015)	(0.013)	(0.008)
Change in layers	0.029^a	0.033^a		0.026^a
	(0.011)	(0.012)		(0.007)
Constant	0.926^a	0.113^a	0.320^b	0.093^a
	(0.048)	(0.035)	(0.131)	(0.035)
Observations	4,171	2,840	3,055	10,066
Adjusted R^2	0.781	0.753	0.804	0.783

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

problems: (i) the potential endogeneity of the organizational structure with respect to contemporaneous shocks; (ii) the fact that knowledge embedded in the labor input is not directly observable and neither the number of workers not the total wage bill of the firm are sufficient statistics for it.

To address these issues we substitute O_{it} in the production function for $C(O_{it}; w) / AC(O_{it}; w)$ (as we did for the case of revenue-based productivity, see Equation 8) and assume the process for quantity-based productivity to be

$$\tilde{a}_{it} = \phi_a \tilde{a}_{it-1} + \beta \Delta L_{it} + \nu_{ait}, \tag{13}$$

where, as before, we adjust the process for quantity-based productivity to take into account the dependence on layers and modify the MULAMA procedure to incorporate this endogeneity; see Appendix B for further details. As we mentioned above, a change in the average cost of the organization $AC(O_{it}; w)$ corresponds to $\beta \Delta L_{it}$ if we replace constraint (5) by $n_L^L \geq \epsilon > 0$, since in this case the average cost function is a step function where the steps correspond to changes in layers.

Once quantified $\tilde{a}_{it}$ we can comprehensively estimate the impact of changes in organization on quantity productivity by following the two approaches outlined at the beginning of Section 5 and using both OLS and fixed effects. We deal with endogeneity in Section 5.3. Table 14 provides OLS estimation results. All of the 3 estimates of β in Table 14 are positive and significant and point to an impact of about 3%: reorganizations leading to an increase (decrease) in the number of layers increase (decrease) quantity TFP by around 3%. Interestingly enough, and parallel to the revenue TFP analysis, downward transitions seem to be characterized by somewhat larger effects than upward transitions. Though, differences are less stark here.

In Table 15 we further allow for the presence of time-invariant unobservables correlated with changes in organization. In particular, we allow for firm-product-sequence fixed effects in Table 15. We report below estimates obtained with the dynamic panel data system GMM estimator[22] and show in Appendix E almost

[22] Note that the same observation we made in Footnote 19 applies for the case of Table 15.

Table 15: Quantity TFP. Firm-product-sequence FE. Dynamic panel data

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.622^a	0.713^a	0.641^a	0.678^a
	(0.090)	(0.083)	(0.065)	(0.045)
Change in layers	0.029^a	0.020^c		0.019^a
	(0.011)	(0.011)		(0.007)
Constant	0.019	0.141	0.409	0.433^a
	(0.222)	(0.090)	(0.274)	(0.080)
Observations	4,171	2,840	3,055	10,066
Number of fixed effects	1,673	1,280	1,298	4,251
Adjusted R^2				
AR(2) Test Stat	1.101	-0.0738	2.372	2.110
P-value AR(2)	0.271	0.941	0.0177	0.0348

Firm-level clustered standard errors in parentheses

^{a} $p<0.01$, ^{b} $p<0.05$, ^{c} $p<0.1$

identical results obtained with the within estimator. Estimates in Table 15 are in line with OLS results in Table 14. Point estimates are somewhat smaller now suggesting an impact of reorganization on quantity productivity in between 2 and 3% on average. The slight drop in magnitude when using fixed effects is in line with what we observed for revenue productivity and it might signal some moderate issue of unobserved heterogeneity or be the result of some measurement error magnified when first-differencing the data.

5.2.3 Level Effects

The previous formulations restrict the impact of organizational changes on productivity to be fully contemporaneous. In particular, a change in organization, whether measured as a change in the number of layers or as a change in quantity, affects productivity in t but, conditional on productivity in t, does not affect productivity in $t+1$. However, one could think of an alternative scenario in which an organizational change takes more than a year to fully impact on productivity. One way of incorporating a slow adjustment of productivity to organizational changes is to assume that the level of, as opposed to the change in, the number of layers or quantity should enter the random processes of revenue and quantity productivity. More specifically, one could assume for quantity productivity:

$$\tilde{a}_{it} = \phi_a \tilde{a}_{it-1} + \beta L_{it} + \nu_{ait}, \tag{14}$$

and for revenue productivity

$$\bar{a}_{it} = \phi_a \bar{a}_{it-1} + \beta L_{it} + \nu_{ait}. \tag{15}$$

We provide in Appendices C (for revenue productivity) and E (for quantity productivity) selected estimation results obtained using processes 14 and 15 to compute productivity and draw a link with organization.

These results point to qualitatively identical findings with respect to what provided above. In terms of quantitative implications, coefficients corresponding to the layer level variable are in general larger than those obtained above with the change in layers variable suggesting that, if anything, estimates provided so far are to be considered as conservative. Such a pattern is consistent with a scenario in which a change in organization takes some time to fully impact on productivity. By focusing on changes in t rather than levels, the formulations above allow capturing most but not all of this slow adjustment. Yet, we prefer the more demanding specifications using ΔL_{it} and Δq_{it} because the level of layers or quantity is more likely to be correlated with unobservables affecting productivity.

Given that the main difference between the impact of a reorganization on revenue-based and quantity-based productivity is its effect on prices, one obvious reaction is to try to look directly at the effect of reorganizations on prices. So it is important to note that we do not actually observe prices in our data. We have information on quantities sold and related revenues. Thus, we can construct unit values (revenue over quantity) rather than actual prices. There are several problems related to using unit values. First, any measurement errors in quantity and/or revenue will add up into this residual measure of prices. Second, prices could change as a consequence of supply side shifters, like costs, as well as other demand side shifters, like markups and taste shocks. As a result, price changes might be a noisy measure of firms' quantity-based and revenu-based productivity changes. Yet, in Appendix H we present the results of a reorganization on our measure of prices. We find that the results using prices are consistent with our main results but are, in general, more noisy.

5.3 Endogeneity of Organization

The results so far have shown, we believe, that a set of detailed and specific predictions on revenue-based and quantity-based productivity changes as a result of a firm's reorganization are robustly present in the data. The fact that when we see firms adding layers revenue-based productivity declines but quantity-based productivity increases, and that this is significantly the case even after including a large battery of fixed effects and using different measures and specifications, lends credibility to the causal interpretation that our theory provides for these facts.

Still, in drawing a link between productivity and organization, we have not yet accounted for the endogeneity of organization to contemporaneous productivity shocks. To be more precise, we have allowed for such endogeneity in estimating revenue-based and quantity-based productivity but we have subsequently treated reorganization as a predetermined variable when regressing productivity on changes in organization. To the extent that organization, like capital infrastructure, cannot adjust much to current period shocks the number of layers is a predetermined variable and so results above are to be interpreted as causal. In what follows we relax this assumption and use a number of demand and cost shifters that can predict a reorganization but are not correlated with current period productivity shocks.

In this respect, the MULAMA model allows quantifying past productivity, demand and markups shocks pushing firms to expand or contract production scale while being uncorrelated with current shocks. For example, a_{it-2}, λ_{it-1} and μ_{it-1} are all uncorrelated with ν_{ait}. At the same time, cumulated past productivity, demand and markups shocks affect optimal production scale and contribute determining the timing of a reorganization. For example, a series of positive shocks would increase the quantity produced by a firm and get the firm closer to the threshold beyond which a reorganization becomes profitable. In sum, past productivity, demand and markups shocks meet the requirements of good instruments for organizational changes and we use them below to establish a more causal link between organization and both revenue-based and quantity-based productivity.[23]

In addition to these instrumental variables we use more traditional (and external to the model) demand and cost shocks (see Bertrand, 2004, Park et al., 2010, and Revenga, 1992, for examples).[24] Concretely, with information on nominal exchange rates, consumer price indexes, and firm-level information on exports and imports across countries, we aggregate real exchange rate changes across destination/origins using lagged exports/imports country shares as weights and construct firm-time specific real exchange rate shocks.[25] An appreciation of the average real exchange rate across the destination served by a firm represents a positive demand shock while an appreciation of the average real exchange rate across the sourcing origins of a firm represents a negative cost shock.

As shown by first stage F-statistics below our set of instruments has a good predictive power with respect to changes in organization. However, we cannot rule out that the demand and cost shocks we use as instruments affect productivity via channels other than organization. For example, an appreciation of the exports real exchange rate could push a firm to quality-upgrade its products and change the skill composition of its workforce. Within our framework, we already account for the changes in prices and employment costs stemming from this shock. However, it might be that such a shock directly impacts productivity and that it does it in a way that is not fully captures by organizational changes. In order to address this problem, we incorporate organization into productivity using the number of layers while at the same time allowing productivity to depend on production scale via channels other than organization. More specifically, we assume for revenue productivity

$$\bar{a}_{it} = \phi_a \bar{a}_{it-1} + \beta \Delta L_{it} + \phi_q \Delta q_{it} + \nu_{ait}, \tag{16}$$

and for quantity productivity

$$\tilde{a}_{it} = \phi_a \tilde{a}_{it-1} + \beta \Delta L_{it} + \phi_q \Delta q_{it} + \nu_{ait}. \tag{17}$$

[23] More specifically, we use as instruments demand and markups at time $t-1$, productivity at time $t-2$, capital at time t, number of layers in $t-1$, revenue in $t-1$ as well as all of these variables lagged to the first available year. All of these variables meet the requirements of goods instruments under the assumptions of our model.

[24] In Appendix A we describe in greater detail how we follow the literature to construct these instruments.

[25] Of course, not all firms are subject to exchange rate shocks. But it turns out that for a small open economy like Portugal, 46% of the firms in our sample either export or import in a way that makes the construction of this additional instrumental variable possible. Our weights are time-varying so increasing identification power. However, they are more prone to endogeneity issues. We provide in Appendix E complementary results obtained using initial period fixed weights. Results are qualitatively identical and quantitatively very similar.

Table 16: Wooldridge Revenue TFP. Instrumental Variable. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.921^a	0.917^a	0.912^a	0.920^a
	(0.013)	(0.021)	(0.016)	(0.009)
Change in layers	-0.070^a	-0.082^a		-0.072^a
	(0.021)	(0.028)		(0.017)
Change in quantity	0.765^b	0.792^b	-0.230	0.395
	(0.374)	(0.343)	(0.255)	(0.269)
Observations	4,057	2,686	2,934	9,677
Kleibergen-Paap stat.	12.73	10.48	11.83	18.34
Adjusted R^2	0.725	0.674	0.848	0.806

Firm-level clustered standard errors in parentheses

^{a} $p<0.01$, ^{b} $p<0.05$, ^{c} $p<0.1$

We show in Appendix B how to modify the Wooldrige (2009) revenue productivity model as well as MULAMA to account for (16) and (17). Once recovered estimates of $\bar{a}_{it}$ and $\tilde{a}_{it}$ we subsequently regress them on both changes in layers and changes in quantity using our set of instruments to account for the endogeneity of both regressors.[26] These specifications allow us to test for the causal impact of a change in layers while allowing for alternative mechanisms—working through quantity changes—to also impact productivity. Coming back to the example of an appreciation of the exports real exchange rate, we thus allow quality-upgrading and skill composition changes to affect productivity via a change in the quantity produced.

Table 16 presents IV results for revenue productivity. First-stage F statistics (Kleibergen-Paap stat.) are consistently well above 10 across samples and indeed coefficients are quite precisely estimated.[27] In this respect, the results show a negative relationship between changes in layers and revenue-based productivity even when controlling for changes in quantity and allowing both variables to be endogenous. Magnitudes are now a bit larger than before and around 7% across specifications. A similar but positive effect stems from Table 17 for quantity productivity. Coefficients are positive and significant. Point estimates are around 5% independently on whether the firm is adding or dropping layers. Though, we find a larger effect of around 8% when we pull all the observations in column 4. Appendix G presents further results using our IV strategy.

Overall, throughout our investigation we did not find any significant evidence to falsify the hypothesis proposed by the hierarchy model. All the significant evidence was in line with the main implications. Hence,

[26] In all the tables that use instrumental variables we do not present the value of constants since we de-mean all variables. Since we are using a battery of instrumental variables as well as past productivity, the set of fixed effects we used in some of the previous regressions are not obviously necessary. They also reduce the precision of our estimates substantially. So for all results using instrumental variables we do not consider fixed effects, although we keep product group and time dummies in all regressions.

[27] The first stage estimates for tables 16 and 17 are presented in Appendix I.

Table 17: Quantity TFP. Instrumental Variable. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.953[a]	0.905[a]	0.967[a]	0.954[a]
	(0.014)	(0.018)	(0.017)	(0.012)
Change in layers	0.054[b]	0.048[b]		0.079[a]
	(0.021)	(0.022)		(0.020)
Change in quantity	0.035	-0.026	0.139	0.046[a]
	(0.058)	(0.131)	(0.107)	(0.061)
Observations	4,171	2,840	3,055	10,066
Kleibergen-Paap stat.	45.1	289.3	40.6	602.4
Adjusted R^2	0.855	0.741	0.902	0.872

Firm-level clustered standard errors in parentheses

[a] p<0.01, [b] p<0.05, [c] p<0.1

we conclude that when firms receive an exogenous shock that makes them reorganize, both quantity-based and revenue-based productivity are significantly affected. An extra layer increases (decreases) quantity (revenue) productivity by around 8% (7%), and a drop in layers decreases (increases) quantity (revenue) productivity by a similar percentage.

5.4 Aggregate Productivity Effects from Reorganization

The results in the previous Section indicate that reorganizations lead to large changes in quantity-based productivity for a firm. If we want to gauge the importance of organization for aggregate productivity dynamics, we need to understand how important is the effect of reorganizations for the average firm that reorganizes. So, for the firms that reorganize we want to ask how important is the change in productivity that resulted from the reorganization, compared to changes in productivity due to shocks, or the mean reversion implied by the process in (17).

Consider a firm i that we observe from $t-T$ to t. Iterating over equation (17) we obtain that

$$\tilde{a}_{it} - \tilde{a}_{it-T} = \left(\phi_a^T - 1\right)\tilde{a}_{it-T} + \beta \sum_{v=0}^{T-1} \phi_a^v \Delta L_{it-v} + \sum_{v=0}^{T-1} \phi_a^v \left(\phi_q \Delta q_{it-v} + \nu_{ait-v}\right).$$

Hence, the overall change in productivity for a firm, given by $\tilde{a}_{it} - \tilde{a}_{it-T}$, can be decomposed into three components. The first term is a mean reversion component that is negative when $\tilde{a}_{it-T}$ is positive since $\phi_a < 1$. Namely, productivity tends to revert to its long term mean given a number of layers. The cumulative change in productivity due to a reorganization, is given by the second term, namely, $\beta \sum_{v=0}^{T-1} \phi_a^v \Delta L_{it-v}$. The third term is just the accumulated effect of past shocks.

We calculate these terms for firms that increase and decrease the number of layers between $t-T$ and t. Using our results for β, ϕ_q and ϕ_a from the MULAMA specification with both change in layers and quantity

Table 18: Change in Quantity TFP due to Reorganization

	Firms that increase layers		Firms that reduce layers	
Percentiles	Overall change	Due to reorganization	Overall change	Due to reorganization
10%	-0.562	0.024	-0.633	-0.050
25%	-0.193	0.026	-0.304	-0.029
50%	0.057	0.027	-0.021	-0.029
75%	0.342	0.029	0.266	-0.026
90%	0.739	0.052	0.795	-0.025
Mean	0.065	0.031	-0.010	-0.031
Observations	817	817	466	466

in column 4 of Table 17 we calculate each of these terms for the whole distribution of firms. Clearly, the actual change in productivity across firms is very heterogeneous. Some firms that add layers experiment a large decline in productivity, while some experiment a very large increase. Hence, we order firms by their overall change in productivity and in Table 18 present the distribution of the overall changes in productivity and the change in productivity due to changes in layers.[28] Columns two and three present the results for firms that increase layers, while columns four and five present the results for firms that drop layers.

The results are stark. On average, or for the median firm, the increase in productivity due to reorganization explains about half of the increase in overall productivity. This is clearly not the case for all firms, some of them receive large positive or negative productivity shocks that account for most of the changes in productivity, but on average those shocks (and the associated reversion to the mean) contribute to half of the aggregate variation. The result is that reorganization can account for an increase in quantity-based productivity, when firms reorganize by adding layers, of about 3% while the average increase in productivity for these firms was 6.5%. Similarly, when firms reduce the number of layers, reorganization accounts for a 3% decrease in quantity-based productivity while the average decrease in productivity for these firms was about 1%. Reorganization accounts for more than 100% of the overall decrease in productivity of downsizing firms! These results underscore the importance of the reorganization of firms as a source of aggregate productivity gains in the economy.

6 Conclusion

Large firm expansions involve lumpy reorganizations that affect firm productivity. Firms that reorganize and add a layer increase hours of work by 25% and value added by slightly more than 3%, while firms that do not reorganize decrease hours slightly and value added by only 0.1%. Reorganization therefore accompanies firms' expansions. A reorganization that adds layers allows the firm to operate at a larger scale. We have shown that such a reorganization leads to increases in quantity-based productivity of about 8%. Even though the productive efficiency of the firm is enhanced by adding layers, its revenue-based productivity

[28] The unit of observation is actually a firm-product and we allow $t-T$ and T to vary across firm-product pairs.

declines by around 7%. The new organizational structure lowers the marginal cost of the firm and it allows it to increase its scale. This makes firms expand their quantity and move down their demand curves, thereby lowering prices and revenue-based productivity.

We use a detailed data set of Portuguese firms to show that these facts are very robustly present in the data. Our data set is somewhat special in that it not only includes employer-employee matched data, necessary to built a firm's hierarchy, but it also includes information on quantity produced. This allows us to contrast the effect of reorganization, using fairly flexible methodologies, to calculate quantity and revenue-based productivity. Furthermore, given that we have a relatively long panel, we show that the results hold using a large number of fixed effects on top of time and industry dummies. We do not find any case in which the evidence significantly falsifies the main hypothesis of the effect of a reorganization on both types of firm productivity. In contrast, we present significant evidence of a causal effect of an increase in layers on both revenue-based and quantity-based productivity.

Our findings underscore the role that organizational decisions play in determining firm productivity. Our results, however, can be viewed more broadly as measuring the impact of lumpy firm level changes on the endogenous component of firm productivity. Many changes that increase the capacity of the firm to grow (like building a new plant or production line, or creating a new export link with a foreign partner) will probably result in similar effects on quantity and revenue-based productivity. In our view, the advantage of looking at reorganizations using a firm's management layers, as defined by occupational classifications, is that firms change them often and in a very systematic way. Furthermore, this high frequency implies that many of the observed fluctuations in both quantity-based and revenue-based productivity result from these endogenous firm decisions and should not be treated as exogenous shocks to the firm.

Recognizing that part of a firm's productivity changes are endogenous is relevant because the ability of firms to change their organization might depend on the economic environment in which they operate. We have shown that changing the number of management layers is important for firms to realize large productivity gains when they grow. Environments in which building larger hierarchies is hard or costly due, for example, to the inability to monitor managers or to enforce detailed labor contracts prevent firms from obtaining these productivity gains.[29] This, among other factors, could explain why firms in developing countries tend to grow less rapidly (Hsieh and Klenow, 2014).

[29] See Bloom et al. (2013) for some evidence on potential impediments in India.

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Appendix

A Additional Details about Data, Tables and Figures

We start with the matched employer-employee data set, keeping only firms in the manufacturing sector located in mainland Portugal and dropping firms with non-positive sales. Information for the year 2001 for the matched employer-employee data set was only collected at the firm-level. Given that worker-level variables are missing in 2001 we have to drop all firm-level observations for 2001. There are in total 353,311 firm-year observations. We then focus on the worker-level information and drop a minority of workers with an invalid social security number and with multiple jobs in the same year. We further drop worker-year pairs whenever (i) their monthly normal or overtime hours are non-positive or above 480; (ii) the sum of weekly normal and overtime hours is below 25 and above 80; (iii) their age is below 16 and above 65 years; (iv) they are not full-time employees of the firm. Based on the resulting sample, we trim worker-year pairs whose monthly wage is outside a range defined by the corresponding year bottom and top 0.5 percentiles. This leaves us with 321,719 firm-year and 5,174,324 worker-year observations. In the analysis, we focus on manufacturing firms belonging to industries (NACE rev.1 2-digits between 15 and 37) excluding 16 "Manufacture of tobacco products", 23 "Manufacture of coke, refined petroleum products and nuclear fuel", 30 "Manufacture of office machinery and computers", and 37 "Recycling", due to confidentiality reasons.

We then turn to the balance sheet data set and recover information on firms' operating revenues, material assets, costs of materials, and third-party supplies and services. We compute value-added as operating revenues minus costs of materials and third-party supplies and services. We drop firm-year pairs with non-positive value-added, material assets, cost of materials, and size. This reduces the size of the overall sample to 61,872 firm-year observations and 2,849,363 worker-year observations.

Finally, we turn to the production data set and recover information on firm-product sales and volume for each firm-product-year triple in the data set. In the production data set a product is identified by a 10-digits code, plus an extra 2-digits that are used to define different variants of the variable.[30] The first 8 digits correspond to the European PRODCOM classification while the additional two have been added by INE to further refine PRODCOM. The volume is recorded in units of measurement (number of items, kilograms, liters) that are product-specific while the value is recorded in current euros. We drop observations where the quantity produced, quantity sold, and sales are all zero. For each product-firm-year combination, we are able to compute a unit value. We adjust the quantity sold, for each firm-year-product, by multiplying it by the average (across firms) product-year unit value. We then construct a more aggregate partition of products based on the first 2-digits as well as on the unit of measurement. More specifically, we assign

[30] From the raw data it is possible to construct different measures of the volume and value of a firm's' production. For the sake of this project we use the volume and value corresponding to a firms' sales of its products. This means we exclude products produced internally and to be used in other production processes within the firm as well as products produced for other firms, using inputs provided by these other firms. The advantage of using this definition is that it nicely corresponds to the cost of materials coming from the balance sheet data.

10-digits products sharing the same first 2 digits and unit of measurement to the same aggregate product. We keep only manufacturing products, and aggregate quantity sold and sales at the firm-year-product level following the new definition of a product. We restrict the analysis to products with at least 50 firm-year observations. Finally, we merge the production data with the matched employer-employee and firm balance sheet data.

Given that we restricted the set of products considered in the analysis, we compute the ratio between total firm-year sales in the sample coming from the production data set and firm-year sales in the firm balance sheet sample and drop firm-year pairs we extreme values of the ratio (below 25 percent and above 105 percent). We then adjust firm sales (from the balance sheet data), cost of materials, material assets, wage bill, size, value-added, wage bill of layer zero, and number of employees in layer zero using the above sales ratio. We then split the same set of variables into parts associated with each product, using the product sales in the production data set. We trim firm-year-product triples that do not satisfy one or more of the following constraints: the sum of cost of materials and wages, as a share of sales, below one; unit value between the 1st and 99th percentiles; cost of materials as a share of sales between the 1st and 99th percentiles; ratio of material assets to size between the 1st and 99th percentiles. The size of the sample is now 19,031 firm-year observations and 1,593,294 worker-year observations.

Table A.1: Classification of Workers According to Hierarchical Levels

Level	Tasks	Skills
1. Top executives (top management)	Definition of the firm general policy or consulting on the organization of the firm; strategic planning; creation or adaptation of technical, scientific and administrative methods or processes	Knowledge of management and coordination of firms fundamental activities; knowledge of management and coordination of the fundamental activities in the field to which the individual is assigned and that requires the study and research of high responsibility and technical level problems
2. Intermediary executives (middle management)	Organization and adaptation of the guidelines established by the superiors and directly linked with the executive work	Technical and professional qualifications directed to executive, research, and management work
3. Supervisors, team leaders	Orientation of teams, as directed by the superiors, but requiring the knowledge of action processes	Complete professional qualification with a specialization
4. Higher-skilled professionals	Tasks requiring a high technical value and defined in general terms by the superiors	Complete professional qualification with a specialization adding to theoretical and applied knowledge
5. Skilled professionals	Complex or delicate tasks, usually not repetitive, and defined by the superiors	Complete professional qualification implying theoretical and applied knowledge
6. Semi-skilled professionals	Well defined tasks, mainly manual or mechanical (no intellectual work) with low complexity, usually routine and sometimes repetitive	Professional qualification in a limited field or practical and elementary professional knowledge
7. Non-skilled professionals	Simple tasks and totally determined	Practical knowledge and easily acquired in a short time
8. Apprentices, interns, trainees	Apprenticeship	

Notes: Hierarchical levels defined according to Decreto Lei 121/78 of July 2nd (Lima and Pereira, 2003).

All monetary values are deflated to 2005 euros using the monthly (aggregated to annual) Consumer Price Index (CPI - Base 2008) by Special Aggregates from Statistics Portugal. Monthly wages are converted to annual by multiplying by 14.

In order to construct our firm level exchange rate shock, we follow Bertrand (2004), Park et al. (2010) and Revenga (1992). Nominal exchange rates and consumer price indexes data come from the International Financial Statistics (IFS) dataset provided by the International Monetary fund and refer to the period 1995-2005. Using this data along with firm-level information on exports and imports across countries we construct two firm-time specific instruments; one based on firm-exports and one based on firm-imports.

We start by computing the log real exchange rate between Portugal (h) and any other country (k) at time t using the formula:

$$\log(RER_{kt}) = \log\left(\frac{e_{hkt}}{CPI_{ht}/CPI_{kt}}\right)$$

where the nominal exchange rate (e_{hkt}) is defined as units of home currency per unit of k currency at time t while CPI_{ht} and CPI_{kt} are the consumer price indexes of Portugal and country k respectively.

In the case of the export IV we look at the portfolio of destinations k served by firm i at time $t-1$ and compute export shares for each destination k: EX_s_{ikt-1}. We then use such shares to aggregate $\log(RER_{kt})$ at time t across countries to obtain a firm-time specific log real exchange rate:

$$\log(EX\_RER_{it}) = \sum_k EX\_s_{ikt-1} \log(RER_{kt})$$

We construct a similar instrument using information on import origins shares: $\log(IM\_RER_{it})$. Note that the level of $\log(EX\_RER_{it})$ and $\log(IM\_RER_{it})$ does not mean much per se. What does have a precise meaning is the time change within a firm which indicates whether there has been an overall appreciation or a depreciation of the real exchange rate faced by a particular firm on the export and import markets. Consequently, we use the change between $t-1$ and t of $\log(EX\_RER_{it})$ and $\log(IM\_RER_{it})$ as instruments in t. To be precise, we use the product of these change and the export or import intensity of the firm (exports over turnover or imports over inputs expenditure) in $t-1$ as an instrument. The export-based appreciation or depreciation is meant to capture shocks to a firm's demand while import-based appreciation or depreciation proxies for cost shocks.

Some concepts are recurring in the explanation of a majority of the tables and figures. We define them here and consider them understood main text:

- **Layer number.** In the matched employer-employee data set, each worker, in each year, has to be assigned to a category following a (compulsory) classification of workers defined by the Portuguese law (see Table A.1 and Mion and Opromolla, 2014). Classification is based on the tasks performed and skill requirements, and each category can be considered as a level in a hierarchy defined in terms of increasing responsibility and task complexity. On the basis of the hierarchical classification and taking into consideration the actual wage distribution, we partition the available categories into occupations. We assign "Top executives (top management)" to occupation 3; "Intermediary executives (middle management)" and "Supervisors, team leaders" to occupation 2; "Higher-skilled professionals" and some "Skilled professionals" to occupation 1; and the remaining employees, including "Skilled professionals", "Semi-skilled professionals", "Non-skilled professionals", and "Apprenticeship" to occupation 0. The position of the workers in the hierarchy of the firm, starting from 0 (lowest layer, present in all firms) to 3 (highest layer, only present in firms with 3 layers of management).

- **Number of layers of management.** A firm reporting c occupational categories will be said to have $L = c - 1$ layers of management: hence, in our data we will have firms spanning from 0 to 3 layers of management (as in CMRH). In terms of layers within a firm we do not keep track of the specific occupational categories but simply rank them. Hence a firm with occupational categories 2 and 0 will have 1 layer of management, and its organization will consist of a layer 0 corresponding to some skilled and non-skilled professionals, and a layer 1 corresponding to intermediary executives and supervisors.

- **Reorganization in year t.** A firm reorganizes in year t when it changes the number of management layers with respect to those observed in the most recent prior available year (year $t-1$ in most cases).

- **Year of the first observed reorganization for a firm.** The earliest reorganization year observed (for those firms first appearing in the data prior to 1997) or the first year in which a firm appears in the data (for those firms first appearing in the data in 1997 or later).

- **Firm industry.** The industry of the firm is measured according to the NACE rev.1 2-digits disaggregation. This includes 19 divisions, from division 15 (Manufacture of food products and beverages) to division 36 (Manufacture of furniture; manufacturing n.e.c.). We drop division 16 (Manufacture of tobacco products), 23 (Manufacture of coke, refined petroleum products and nuclear fuel), and 30 (Manufacture of office machinery and computers) because they comprise very few observations.

- **Wage bill.** A worker annual wage is computed adding the monthly base and overtime wages plus regular benefits and multiplying by 14. We apply a trimming of the top and bottom 0.5 per cent within each year. A firm wage bill is the sum of the annual wages of all its workers that satisfy the criteria listed above.

- **Value added.** Value added is computed, from the balance sheet data set, as operating revenues minus costs of materials and third-party supplies and services.

- **Revenue productivity.** The log of the ratio between firm sales and employment.

- **Value added productivity.** The log of the ratio between firm value added and employment.

- **OLS TFP.** Log total factor productivity computed from a standard three factors (labor, capital and materials) Cobb-Douglas production function model where output is measured by firm sales and the model is estimated via OLS. Separate estimations have been carried for each industry.

- **Olley and Pakes revenue-based TFP.** Log total factor productivity computed from a standard two factors (labor and capital) Cobb-Douglas production function model where output is measured by firm value-added. Productivity shocks are modeled as in Olley and Pakes (1996) while being further enriched with layers along the lines presented in Section 5.1. We use the lagged number of management layers to instrument L_{it} in the second stage of the OP procedure. Separate estimations have been carried for each industry.

- **Wooldridge revenue-based productivity.** Log total factor productivity computed from a standard two factors (labor and capital) Cobb-Douglas production function model where output is measured by firm value-added. Productivity shocks are modeled as in Wooldridge (2009) while being further enriched with layers as described in Section 5.1. Separate estimations have been carried for each industry.

- **Quantity-based TFP.** We run separate quantity-based productivity estimations for each of the aggregate products using variations of the MULAMA methodology. See the next Appendix for a detailed explanation of the estimation methodologies.

Tables and Figures Description

Table 1: This table reports, for each year, the number of firms in Sample 1 and corresponding averages across all firms for selected variables. Value added, hours, and wage are defined above. Value added is in 2005 euros. Wage is average hourly wage in 2005 euros. Hours are yearly. # of layers is the average number of layers of management across firms in each year.

Table 2: Table 2 reports summary statistics on firm-level outcomes, grouping firm-year observations according to the number of layers of management reported (# of layers). Firm-years is the number of firm-years observations in the data with the given number of layers of management. Value added, hours, and wage are defined above. Value added in 000s of 2005 euros. Wage is either average or median hourly wage in 2005 euros. Both value added and wages are detrended. Hours are yearly.

Table 3 and 4: Table 3 reports the fraction of firms that satisfy a hierarchy in hours, grouping firms by their number of layers of management (# number of layers). Hours N_L^l is the number of hours reported in layer l in an L layers of management firm. For $L = 1, 2, 3$, and $l = 0, ..., L-1$ we say that a firm satisfies a hierarchy in hours between layers number l and $l+1$ in a given year if $N_L^l \geq N_L^{l+1}$, i.e. if the number of hours worked in layer l is at least as large as the number of hours worked in layer $l+1$; moreover, we say that a firm satisfies a hierarchy at all layers if $N_L^l \geq N_L^{l+1} \quad \forall l = 0, ..., L-1$, i.e. if the number of hours worked in layer l is at least as large as the number of hours in layer $l+1$, for all layers in the firm. Following these definitions, the top panel reports, among all firms with $L = 1, 2, 3$ layers of management, the fraction of those that satisfy a hierarchy in hours at all layers (first column), and the fraction of those that satisfy a hierarchy in hours between layer l and $l+1$, with $l = 0, ..., L-1$ (second to fourth column).

Table 4 is the same as Table 3 for the case of wages, where w_L^l is the average hourly wage in layer l in an L layers of management firm.

Table 5: Table 5 reports the distribution of the number of layers of management at time $t+1$, grouping firms according to the number of layers of management at time t. Among all firms with L layers of management ($L = 0, ..., 3$) in any year from 1996 to 2004, the columns report the fraction of firms that have layers $0, ..., 3$ the following year (from 1997 to 2005), or are not present in the dataset, Exit. The table also reports, in the bottom row, the distribution of the new firms by their initial number of layers. The elements in the table sum to 100% by row.

Table 6: This table shows changes in firm-level outcomes between adjacent years for all firms (All), and for the subsets of those that increase (Increase L), don't change (No change in L) and decrease (Decrease L) layers. It reports changes in log hours, log normalized hours, log value added, log average wage, and log average wage in common layers for the whole sample. The change in average wage for common layers in a firm that transitions from L to L' layers is the change in the average wage computed using only the $min\{L, L'\}$ layers before and after the transition. To detrend a variable, we subtract from all the log changes in a given year the average change during the year across all firms.

Table 7: This table reports the results of regressions of log change in normalized hours by layer on log change in value added for firms that do not change their number of layers of management L across two adjacent periods. Specifically, we run a regression of log change in normalized hours at layer l (layer) in a firm with L (# of layers in the firm) layers of management on a constant and log change in value added across all the firms that stay at L layers of management across two adjacent years. Robust standard errors are in parentheses.

Table 8: This table reports the results of regressions of log change in hourly wage by layer on log change in value added for firms that do not change their number of layers of management L across two adjacent periods. Specifically, we run a regression of log change in average hourly wage at layer l (layer) in a firm with L (# of layers in the firm) layers of management on a constant and log change in value added across all the firms that stay at L layers of management across two adjacent years. Robust standard errors are in parentheses.

Table 9: This table shows estimates of the average log change in normalized hours at each layer l (Layer) among firms that transition from L (# of layers before) to L' layers (# of layers after), with $L \neq L'$: for a transition from L to L', we can only evaluate changes for layer number $l = 0, ..., \min\{L, L'\}$. $d \ln n^l_{Lit}$ is the average log change in the transition, estimated as a regression of the log change in the number of normalized hours in layer l in two adjacent years on a constant. Robust standard errors are in parentheses.

Table 10: This table shows estimates of the average log change in hourly wage at each layer l (Layer) among firms that transition from L (# of layers before) to L' layers (# of layers after), with $L \neq L'$: for a transition from L to L', we can only evaluate changes for layer number $l = 0, ..., \min\{L, L'\}$. $d \ln w^l_{Lit}$ is the average log change in the transition, estimated as a regression of the log change in the average hourly wage in layer l in two adjacent years on a constant. Robust standard errors are in parentheses.

Table 11: The data underlying Table 11 is composed of sequences of firm-product-years with either

one or zero changes in layers. For a given product, we define a firm sequence of type $L - L'$ as the series of years in which a firm sells the corresponding product and has the same consecutively observed number of management layers L plus the adjacent series of years in which a firm sells the product and has the same consecutively observed number of management layers L'. For example, a firm that we observed selling the product all years between 1996 and 2000 and that has zero layers in 1996, 1997, and 2000 and one layer in 1998 and 1999 would have two sequences: An (increasing) 0-1 sequence (1996 to 1999) as well as a (decreasing) 1-0 sequence (1998 to 2000). Firms that never change layers in our sample form a constant-layer sequence. We group firm-product sequences into "Increasing", "Decreasing", and "Constant" sequence types.

For each type of sequence, Table 11 shows estimates of regressions where the dependent variable is Wooldridge revenue TFP in a given year. The key regressor is the change in the number of management layers in the firm in year t. We control for the Wooldridge revenue TFP in the previous year, and include a set of of year and industry dummies. Firm-level clustered standard errors are in parentheses. The last column of Table 11 shows estimates of a regression that pools all types of sequences.

Table 12: Table 12 shows estimates of the same type of regressions described for Tables 11 while allowing for firm-product-sequence fixed effects. Instead of OLS we employ the system GMM estimator proposed by Arellano and Bover (1995) within the context of dynamic panel data with endogenous regressors.

Table 13: Table 13 shows estimates of the same type of regressions described for Table 11 and 12. The only difference being that the dependent variable is (log) revenue labor productivity.

Table 14 and Table 15: This set of Tables show estimates of the same type of regressions described for Tables 11 and 12. The dependent variable is (log) quantity-based productivity computed according to the MULAMA methodology extended for incorporating changes in the organization of the labor input as described in Section 5.2.2. In this case the key regressor is the change in the number of management layers of the firm in t. We employ product-group dummies instead of industry dummies while always using year dummies.

Table 16 and Table 17: In this set of Tables we instrument both for the change in quantity and for the change in the number of layers using our export- and import-based real exchange rate changes, the number of layers in $t-1$, revenue, demand shocks and markups at time $t-1$, capital at time t, productivity at time $t-2$ as well as all of these variables lagged to the first available year. We employ both product-group dummies and year dummies. In all Tables we report the Kleibergen Paap weak instrument statistic.

Figure 5, 6, and 7: These figures report kernel density estimates of the distribution of log value added (Figure 5), log hours worked (Figure 6) and log hourly wage (Figure 7) by number of layers in the firm. One density is estimated for each group of firms with the same number of layers.

B MULAMA and Wooldridge (2009) Estimation Details and Extensions

In this appendix we show how to derive the first and second stage estimating equations for the baseline MULAMA procedure (Appendix B.1), for the MULAMA procedure with change in layers (Appendix B.2), and for the MULAMA procedure with change in layers and quantity (Appendix B.3). In Appendix B.4 we also provide an extension of the Wooldridge (2009) revenue productivity methodology to account for changes in layers and quantities.

B.1 Baseline MULAMA

Demand in log is given by

$$p_{it} = \left(1 - \frac{1}{\eta_{it}}\right)\lambda_{it} - \frac{1}{\eta_{it}} q_{it}, \tag{B-1}$$

the markup then is

$$\mu_{it} = \frac{\eta_{it}}{\eta_{it} - 1}. \tag{B-2}$$

The production function in log is

$$q_{it} = a_{it} + \alpha_O o_{it} + \alpha_M m_{it} + (\gamma - \alpha_M - \alpha_O) k_{it}, \tag{B-3}$$

and the assumptions over processes for productivity and demand are given by

$$a_{it} = \phi_a \, a_{it-1} + \nu_{ait}, \tag{B-4}$$

$$\lambda_{it} = \phi_\lambda \lambda_{it-1} + \nu_{\lambda it}. \tag{B-5}$$

From cost minimization one obtains that the marginal cost is given by

$$\frac{\partial C_i}{\partial Q_i} = \frac{1}{\alpha_O + \alpha_M} \frac{C_i}{Q_i} \tag{B-6}$$

Using $(B-1)$ and $(B-2)$, revenue can be expressed in the following way

$$r_{it} = \frac{1}{\mu_{it}} \left(q_{it} + \lambda_{it}\right). \tag{B-7}$$

Using $(B-6)$ note that expenditure shares are related to markups in the following way

$$\frac{1}{\mu_{it}} = \frac{s_{Oit}}{\alpha_O} = \frac{s_{Mit}}{\alpha_L}. \tag{B-8}$$

First stage

In order to derive the estimating equation start from $(B-3)$ and $(B-4)$ to obtain

$$q_{it} = \alpha_O \left(o_{it} - k_{it}\right) + \alpha_M \left(m_{it} - k_{it}\right) + \gamma k_{it} + \phi_a \; a_{it-1} + \nu_{ait}, \tag{B-9}$$

then substituting this expression into $(B-7)$

$$r_{it} = \frac{\alpha_O}{\mu_{it}} \left(o_{it} - k_{it}\right) + \frac{\alpha_M}{\mu_{it}} \left(m_{it} - k_{it}\right) + \frac{\gamma}{\mu_{it}} k_{it} + \frac{\phi_a}{\mu_{it}} \; a_{it-1} + \frac{1}{\mu_{it}} \nu_{ait} + \frac{1}{\mu_{it}} \lambda_{it},$$

rearranging and using $(B-8)$ we define as in the main body of the text

$$LHS_{it} = \frac{r_{it} - s_{Oit} \left(o_{it} - k_{it}\right) - s_{Mit} \left(m_{it} - k_{it}\right)}{s_{Mit}}, \tag{B-10}$$

or written differently

$$LHS_{it} = \frac{\gamma}{\alpha_M} k_{it} + \frac{\phi_a}{\alpha_M} a_{it-1} + \frac{1}{\alpha_M} \lambda_{it} + \frac{1}{\alpha_M} \nu_{ait}.$$

We need to find expressions for a_{it-2} and λ_{it-1}.

From $(B-7)$ note that

$$\lambda_{it-1} = \mu_{it-1} r_{it-1} - q_{it-1}, \tag{B-11}$$

then using this expression into $(B-5)$ we obtain

$$\lambda_{it} = \phi_\lambda \left(\mu_{it-1} r_{it-1} - q_{it-1}\right) + \nu_{\lambda it}. \tag{B-12}$$

Now from $(B-10)$ we can obtain

$$a_{it-2} = \frac{\alpha_M}{\phi_a} LHS_{it-1} - \frac{\gamma}{\phi_a} k_{it-1} - \frac{1}{\phi_a} \lambda_{it-1} - \frac{1}{\phi_a} \nu_{ait-1},$$

using $(B-11)$ we get

$$a_{it-2} = \frac{\alpha_M}{\phi_a} LHS_{it-1} - \frac{\gamma}{\phi_a} k_{it-1} - \frac{1}{\phi_a} \left(\mu_{it-1} r_{it-1} - q_{it-1}\right) - \frac{1}{\phi_a} \nu_{ait-1},$$

and after substituting this expression in $(B-4)$,

$$a_{it-1} = \alpha_M LHS_{it-1} - \gamma k_{it-1} - \left(\mu_{it-1} r_{it-1} - q_{it-1}\right). \tag{B-13}$$

Using $(B-13)$ and $(B-12)$ into $(B-10)$ we obtain,

$$\begin{aligned} LHS_{it} &= \frac{\gamma}{\alpha_M}k_{it} + \phi_a LHS_{it-1} - \gamma\frac{\phi_a}{\alpha_M}k_{it-1} \\ &+ (\phi_\lambda - \phi_a)\frac{r_{it-1}}{s_{Mit-1}} \\ &+ (\phi_a - \phi_\lambda)\frac{1}{\alpha_M}q_{it-1} \\ &+ \frac{1}{\alpha_M}(\nu_{ait} + \nu_{\lambda it}). \end{aligned}$$

More compactly, we end up with (12)

$$LHS_{it} = b_1 z_{1it} + b_2 z_{2it} + b_3 z_{3it} + b_4 z_{4it} + b_5 z_{5it} + u_{it}.$$

Second stage

Using (B-8) firm log output q_{it} can be written as

$$q_{it} = \mu_{it} s_{Oit}(o_{it} - k_{it}) + \mu_{it} s_{Mit}(m_{it} - k_{it}) + \gamma k_{it} + a_{it}.$$

Further exploiting (B-4) and (B-13), as well as $\hat{b}_1 = \frac{\gamma}{\alpha_M} = \frac{\gamma}{s_{Mit}\mu_{it}}$ and $\hat{b}_2 = \phi_a$, we get

$$q_{it} = \gamma\frac{o_{it} - k_{it}}{\hat{b}_1}\frac{s_{Oit}}{s_{Mit}} + \gamma\frac{m_{it} - k_{it}}{\hat{b}_1} + \gamma k_{it} + \gamma\frac{\hat{b}_2}{\hat{b}_1}LHS_{it-1} - \gamma\hat{b}_2 k_{it-1} - \gamma\frac{r_{it-1}\hat{b}_2}{\hat{b}_1 s_{Mit-1}} + \hat{b}_2 q_{it-1} + \nu_{ait}$$

and so

$$q_{it} - \hat{b}_2 q_{it-1} = b_6 z_{6it} + \nu_{ait}$$

where

$$z_{6it} = \frac{o_{it} - k_{it}}{\hat{b}_1}\frac{s_{Oit}}{s_{Mit}} + \frac{m_{it} - k_{it}}{\hat{b}_1} + k_{it} + \frac{\hat{b}_2}{\hat{b}_1}LHS_{it-1} - \hat{b}_2 k_{it-1} - \frac{r_{it-1}\hat{b}_2}{\hat{b}_1 s_{Mit-1}},$$

and $b_6 = \gamma$.

B.2 MULAMA with Change in Layers

In this case, the production function in logs can be written as

$$q_{it} = \tilde{a}_{it} + \alpha_O \ln WB_{it} + \alpha_M m_{it} + (\gamma - \alpha_M - \alpha_O)k_{it}, \tag{B-14}$$

where WB_{it} is the wage bill at time t of firm i.

The processes for productivity and demand shocks are

$$\tilde{a}_{it} = \phi_a \, \tilde{a}_{it-1} + \phi_L \Delta L_{it} + \nu_{ait}, \tag{B-15}$$

$$\lambda_{it} = \phi_\lambda \lambda_{it-1} + \nu_{\lambda it}, \tag{B-16}$$

where ν_{ait} and $\nu_{\lambda it}$ can be correlated with each other.

Note that small changes in quantity have no impact on marginal costs through a change in organization ($\frac{\partial \tilde{a}_{it}}{\partial q_{it}} = \frac{\partial \Delta L_{it}}{\partial q_{it}} = 0$). Therefore, the short-run marginal cost still satisfies

$$\frac{\partial C_{it}}{\partial Q_{it}} = \frac{1}{\alpha_O + \alpha_M} \frac{C_{it}}{Q_{it}}. \tag{B-17}$$

Using $(B-1)$ and $(B-2)$, log revenue can be expressed in the following way:

$$r_{it} = \frac{1}{\mu_{it}} \left(q_{it} + \lambda_{it} \right). \tag{B-18}$$

Using $(B-6)$ note that expenditure shares are related to markups in the following way

$$\frac{1}{\mu_{it}} = \frac{s_{Mit}}{\alpha_M} = \frac{s_{Oit}}{\alpha_O}. \tag{B-19}$$

where s_{Oit} here represents the share of total labor expenditure in total revenue.

Using $(B-14)$ and $(B-15)$ one obtains:

$$q_{it} = \alpha_O \left(\ln WB_{it} - k_{it} \right) + \alpha_M \left(m_{it} - k_{it} \right) + \gamma k_{it} + \phi_a \tilde{a}_{it-1} + \phi_L \Delta L_{it} + \nu_{ait}, \tag{B-20}$$

then substituting this expression into $(B-18)$:

$$\begin{aligned} r_{it} &= \frac{\alpha_O}{\mu_{it}} \left(\ln WB_{it} - k_{it} \right) + \frac{\alpha_M}{\mu_{it}} \left(m_{it} - k_{it} \right) \\ &\quad + \frac{\gamma}{\mu_{it}} k_{it} + \frac{\phi_a}{\mu_{it}} \, \tilde{a}_{it-1} + \frac{\phi_L}{\mu_{it}} \Delta L_{it} + \frac{1}{\mu_{it}} \nu_{ait} + \frac{1}{\mu_{it}} \lambda_{it}. \end{aligned}$$

First stage

Rearranging and using $(B-19)$ we define LHS_{it} and get:

$$\begin{aligned} LHS_{it} &\equiv \frac{r_{it} - s_{Oit} \left(\ln WB_{it} - k_{it} \right) - s_{Mit} \left(m_{it} - k_{it} \right)}{s_{Mit}} \\ &= \frac{\gamma}{\alpha_M} k_{it} + \frac{\phi_a}{\alpha_M} \tilde{a}_{it-1} + \frac{1}{\alpha_M} \lambda_{it} + \frac{\phi_L}{\alpha_M} \Delta L_{it} + \frac{1}{\alpha_M} \nu_{ait}. \end{aligned} \tag{B-21}$$

We need to find expressions for $\tilde{a}_{it-2}$ and λ_{it-1}. From $(B-7)$ note that:

$$\lambda_{it-1} = \mu_{it-1} r_{it-1} - q_{it-1}, \tag{B-22}$$

then using this expression into $(B-16)$ we obtain:

$$\lambda_{it} = \phi_\lambda \left(\mu_{it-1} r_{it-1} - q_{it-1} \right) + \nu_{\lambda it}. \tag{B-23}$$

Now from $(B-21)$ we can obtain:

$$\tilde{a}_{it-2} = \frac{\alpha_M}{\phi_a} LHS_{it-1} - \frac{\gamma}{\phi_a} k_{it-1} - \frac{1}{\phi_a} \lambda_{it-1} - \frac{\phi_L}{\phi_a} \Delta L_{it-1} - \frac{1}{\phi_a} \nu_{ait-1},$$

while using $(B-22)$ we get:

$$\tilde{a}_{it-2} = \frac{\alpha_M}{\phi_a} LHS_{it-1} - \frac{\gamma}{\phi_a} k_{it-1} - \frac{1}{\phi_a} \left(\mu_{it-1} r_{it-1} - q_{it-1} \right) - \frac{\phi_L}{\phi_a} \Delta L_{it-1} - \frac{1}{\phi_a} \nu_{ait-1},$$

and after substituting this expression in $(B-15)$

$$\tilde{a}_{it-1} = \alpha_M LHS_{it-1} - \gamma k_{it-1} - \left(\mu_{it-1} r_{it-1} - q_{it-1} \right). \tag{B-24}$$

Using $(B-24)$ and $(B-23)$ into $(B-21)$ we obtain:

$$\begin{aligned} LHS_{it} &= \frac{\gamma}{\alpha_M} k_{it} + \phi_a LHS_{it-1} - \gamma \frac{\phi_a}{\alpha_M} k_{it-1} \\ &\quad + \left(\phi_\lambda - \phi_a \right) \frac{r_{it-1}}{s_{Mit-1}} \\ &\quad + \left(\phi_a - \phi_\lambda \right) \frac{1}{\alpha_M} q_{it-1} \\ &\quad + \frac{\phi_L}{\alpha_M} \Delta L_{it} + \frac{1}{\alpha_M} \left(\nu_{ait} + \nu_{\lambda it} \right), \end{aligned} \tag{B-25}$$

that we can rewrite as

$$LHS_{it} = b_1 z_{1it} + b_2 z_{2it} + b_3 z_{3it} + b_4 z_{4it} + b_5 z_{5it} + b_6 z_{6it} + u_{it}, \tag{B-26}$$

where $z_{1it}{=}k_{it}$, $z_{2it}{=}LHS_{it-1}$, $z_{3it}{=}k_{it-1}$, $z_{4it}{=}\frac{r_{it-1}}{s_{Mit-1}}$, $z_{5it}{=}q_{it-1}$, $z_{6it}{=}\Delta L_{it}$, $u_{it}{=}\frac{1}{\alpha_M}\left(\nu_{ait} + \nu_{\lambda it}\right)$ as well as $b_1{=}\frac{\gamma}{\alpha_M}$, $b_2{=}\phi_a$, $b_3{=}-\gamma\frac{\phi_a}{\alpha_M}$, $b_4{=}(\phi_\lambda - \phi_a)$, $b_5{=}\frac{1}{\alpha_M}\left(\phi_a - \phi_\lambda\right)$ and $b_6{=}\frac{\phi_L}{\alpha_M}$. Given our assumptions the error term u_{it} in is uncorrelated with all of the regressors but $z_{6it}{=}\Delta L_{it}$. Coherently with our assumptions we instrument ΔL_{it} with ΔL_{it-1} and L_{it-2} . After doing this we set $\hat{\beta}{=}\hat{b}_1$ and $\hat{\phi}_a{=}\hat{b}_2$ and do not exploit parameters' constraints in the estimation.

Second stage

From $(B-20)$ and $(B-24)$ we have that log output is given by

$$\begin{aligned} q_{it} &= \alpha_O \left(\ln WB_{it} - k_{it}\right) + \alpha_M \left(m_{it} - k_{it}\right) + \gamma k_{it} \\ &\quad + \phi_a \alpha_M LHS_{it-1} - \phi_a \gamma k_{it-1} - \phi_a \left(\frac{\alpha_M}{s_{Mit-1}} r_{it-1} - q_{it-1}\right) + \phi_L \Delta L_{it} + \nu_{ait}. \end{aligned}$$

Substituting $(B-19)$ and known parameters from the first stage, we obtain

$$\begin{aligned} q_{it} &= \gamma \frac{1}{\hat{\beta}} \frac{s_{Oit}}{s_{Mit}} \left(\ln WB_{it} - k_{it}\right) + \gamma \frac{1}{\hat{\beta}} \left(m_{it} - k_{it}\right) + \gamma k_{it} \\ &\quad + \gamma \frac{\hat{\phi}_a}{\hat{\beta}} LHS_{it-1} - \gamma \hat{\phi}_a k_{it-1} - \gamma \frac{1}{\hat{\beta}} \frac{\hat{\phi}_a}{s_{Mit-1}} r_{it-1} + \hat{\phi}_a q_{it-1} + \phi_L \Delta L_{it} + \nu_{ait.} \end{aligned}$$

Note that the only parameters to estimate are γ and ϕ_L. These are identified using a linear model:

$$q_{it} - \hat{\phi}_a q_{it-1} = b_7 z_{7it} + b_8 z_{8it} + \varepsilon_{it}, \tag{B-27}$$

where:

$$\begin{aligned} z_{7it} &= \frac{1}{\hat{\beta}} \frac{s_{Oit}}{s_{Mit}} \left(\ln WB_{it} - k_{it}\right) + \frac{1}{\hat{\beta}} \left(m_{it} - k_{it}\right) + k_{it} + \frac{\hat{\phi}_a}{\hat{\beta}} LHS_{it-1} - \hat{\phi}_a k_{it-1} - \frac{1}{\hat{\beta}} \frac{\hat{\phi}_a}{s_{Mit-1}} r_{it-1}, \\ z_{8it} &= \Delta L_{it}, \text{ and } \varepsilon_{it} = \nu_{ait}, \end{aligned}$$

as well as $b_7 = \gamma$ and $b_8 = \phi_L$. Note that z_{7it} and z_{8it} are endogenous and we instrument them with k_{it}, ΔL_{it-1} and L_{it-2}. We then set $\hat{\gamma} = \hat{b}_7$ and obtain

$$\hat{a}_{it} = q_{it} - \frac{\hat{\gamma}}{\hat{\beta}} \frac{s_{Oit}}{s_{Mit}} \left(\ln WB_{it} - k_{it}\right) - \frac{\hat{\gamma}}{\hat{\beta}} \left(m_{it} - k_{it}\right) - \hat{\gamma} k_{it}$$

$$\hat{\mu}_{it} = \frac{\hat{\gamma}}{\hat{\beta} s_{Mit}} \text{ and } \hat{\lambda}_{it} = \frac{\hat{\gamma}}{\hat{\beta} s_{Mit}} r_{it} - q_{it}.$$

B.3 MULAMA with Change in Layers and Quantity

In order to incorporate organization into productivity we substitute O_{it} in the production function for $C\left(O_{it}; w\right)/AC\left(O_{it}; w\right)$. In this case, the production function is given by

$$q_{it} = \tilde{a}_{it} + \alpha_O \ln WB_{it} + \alpha_M m_{it} + (\gamma - \alpha_M - \alpha_O) k_{it}, \tag{B-28}$$

where WB_{it} is the wage bill at time t of firm i. The processes for productivity and demand shocks are

$$\tilde{a}_{it} = \phi_a \, \tilde{a}_{it-1} + \phi_L \Delta L_{it} + \phi_q \Delta q_{it} + \nu_{ait}, \tag{B-29}$$

$$\lambda_{it} = \phi_\lambda \lambda_{it-1} + \nu_{\lambda it}, \tag{B-30}$$

where ν_{ait} and $\nu_{\lambda it}$ can be correlated with each other.

At any given point in time firms minimize costs for flexible inputs (labor input and materials M_{it}) considering capital, as well as $\tilde{a}_{it-1}$, ν_{ait}, λ_{it} and the price of materials and knowledge as given. Note that small changes in quantity have no impact on marginal costs through a change in organization ($\frac{\partial \Delta L_{it}}{\partial q_{it}} = 0$). However, we allow in (B-29) changes in quantity to impact TFP through other channels ($\frac{\partial \tilde{a}_{it}}{\partial q_{it}} = \phi_q \frac{\partial \Delta q_{it}}{\partial q_{it}} = \phi_q$). Short-run marginal cost thus satisfies

$$\frac{\partial C_{it}}{\partial Q_{it}} = \frac{1-\phi_q}{\alpha_O + \alpha_M} \frac{C_{it}}{Q_{it}}. \tag{B-31}$$

Using $(B-1)$ and $(B-2)$, log revenue can be expressed in the following way:

$$r_{it} = \frac{1}{\mu_{it}} \left(q_{it} + \lambda_{it} \right) \tag{B-32}$$

Using $(B-31)$ note that expenditure shares are related to markups

$$\frac{1}{\mu_{it} \left(1-\phi_q\right)} = \frac{s_{Mit}}{\alpha_M} = \frac{s_{Oit}}{\alpha_O}, \tag{B-33}$$

where s_{Oit} here represents the share of labor expenditure in total revenue.

Using $(B-28)$ and $(B-29)$ one obtains:

$$\begin{aligned} q_{it} = {} & \frac{\alpha_O}{1-\phi_q} \left(\ln WB_{i,t} - k_{it} \right) + \frac{\alpha_M}{1-\phi_q} \left(m_{it} - k_{it} \right) + \frac{\gamma}{1-\phi_q} k_{it} + \frac{\phi_a}{1-\phi_q} \, \tilde{a}_{it-1} \\ & - \frac{\phi_q}{1-\phi_q} \, q_{it-1} + \frac{\phi_L}{1-\phi_q} \Delta L_{it} + \frac{1}{1-\phi_q} \nu_{ait}, \end{aligned} \tag{B-34}$$

then substituting this expression into $(B-32)$

$$\begin{aligned} r_{it} = {} & \frac{\alpha_O}{\left(1-\phi_q\right)\mu_{it}} \left(\ln WB_{i,t} - k_{it} \right) + \frac{\alpha_M}{\left(1-\phi_q\right)\mu_{it}} \left(m_{it} - k_{it} \right) + \frac{\gamma}{\left(1-\phi_q\right)\mu_{it}} k_{it} \\ & + \frac{\phi_a}{\left(1-\phi_q\right)\mu_{it}} \, \tilde{a}_{it-1} - \frac{\phi_q}{\left(1-\phi_q\right)\mu_{it}} \, q_{it-1} + \frac{\phi_L}{\left(1-\phi_q\right)\mu_{it}} \Delta L_{it} + \frac{1}{\left(1-\phi_q\right)\mu_{it}} \nu_{ait} + \frac{1}{\mu_{it}} \lambda_{it}. \end{aligned}$$

First stage

Rearranging and using $(B-33)$ we define LHS_{it} and get:

$$\begin{aligned} LHS_{it} &\equiv \frac{r_{it} - s_{Oit}\left(\ln WB_{i,t} - k_{it}\right) - s_{Mit}\left(m_{it} - k_{it}\right)}{s_{Mit}} \\ &= \frac{\gamma}{\alpha_M}k_{it} + \frac{\phi_a}{\alpha_M}\tilde{a}_{it-1} - \frac{\phi_q}{\alpha_M}q_{it-1} + \frac{1-\phi_q}{\alpha_M}\lambda_{it} + \frac{\phi_L}{\alpha_M}\Delta L_{it} + \frac{1}{\alpha_M}\nu_{ait}. \end{aligned} \tag{B-35}$$

We need to find expressions for $\tilde{a}_{it-2}$ and λ_{it-1}. From $(B-32)$ note that:

$$\lambda_{it-1} = \mu_{it-1}r_{it-1} - q_{it-1}, \tag{B-36}$$

then using this expression into $(B-30)$ we obtain:

$$\lambda_{it} = \phi_\lambda\left(\mu_{it-1}r_{it-1} - q_{it-1}\right) + \nu_{\lambda it}. \tag{B-37}$$

Now from $(B-35)$ we can obtain

$$\tilde{a}_{it-2} = \frac{\alpha_M}{\phi_a}LHS_{it-1} - \frac{\gamma}{\phi_a}k_{it-1} + \frac{\phi_q}{\phi_a}q_{it-2} - \frac{1-\phi_q}{\phi_a}\lambda_{it-1} - \frac{\phi_L}{\phi_a}\Delta L_{it-1} - \frac{1}{\phi_a}\nu_{ait-1},$$

while using $(B-36)$ we get

$$\tilde{a}_{it-2} = \frac{\alpha_M}{\phi_a}LHS_{it-1} - \frac{\gamma}{\phi_a}k_{it-1} + \frac{\phi_q}{\phi_a}q_{it-2} - \frac{1-\phi_q}{\phi_a}\left(\mu_{it-1}r_{it-1} - q_{it-1}\right) - \frac{\phi_L}{\phi_a}\Delta L_{it-1} - \frac{1}{\phi_a}\nu_{ait-1},$$

and after substituting this expression in $(B-29)$

$$\tilde{a}_{it-1} = \alpha_M LHS_{it-1} - \gamma k_{it-1} - \left(1-\phi_q\right)\left(\mu_{it-1}r_{it-1} - q_{it-1}\right) + \phi_q\ q_{it-1}. \tag{B-38}$$

Using $(B-38)$ and $(B-37)$ into $(B-35)$ we obtain

$$\begin{aligned} LHS_{it} &= \frac{\gamma}{\alpha_M}k_{it} + \phi_a LHS_{it-1} - \gamma\frac{\phi_a}{\alpha_M}k_{it-1} \\ &\quad + \left(\phi_\lambda - \phi_a\right)\frac{r_{it-1}}{s_{Mit-1}} \\ &\quad + \left(\phi_a - \phi_\lambda - \phi_q + \phi_q\phi_\lambda\right)\frac{1}{\alpha_M}q_{it-1} \\ &\quad + \frac{\phi_L}{\alpha_M}\Delta L_{it} + \frac{1}{\alpha_M}\left(\nu_{ait} + \left(1-\phi_q\right)\nu_{\lambda it}\right), \end{aligned} \tag{B-39}$$

that we can rewrite as:

$$LHS_{it} = b_1 z_{1it} + b_2 z_{2it} + b_3 z_{3it} + b_4 z_{4it} + b_5 z_{5it} + b_6 z_{6it} + u_{it}, \tag{B-40}$$

where z_{1it}=k_{it}, z_{2it}=LHS_{it-1}, z_{3it}=k_{it-1}, z_{4it}=$\frac{r_{it-1}}{s_{Mit-1}}$, z_{5it}=q_{it-1}, z_{6it}=ΔL_{it}, u_{it}=$\frac{1}{\alpha_M}\left(\nu_{ait}+\left(1-\phi_q\right)\nu_{\lambda it}\right)$ as well as b_1=$\frac{\gamma}{\alpha_M}$, b_2=ϕ_a, b_3=$-\gamma\frac{\phi_a}{\alpha_M}$, b_4=$(\phi_\lambda-\phi_a)$, b_5=$\frac{1}{\alpha_M}\left(\phi_a-\phi_\lambda-\phi_q+\phi_q\phi_\lambda\right)$ and b_6=$\frac{\phi_L}{\alpha_M}$. Given our assumptions the error term u_{it} in is uncorrelated with all of the regressors but z_{6it}=ΔL_{it} that we instruments with ΔL_{it-1} and L_{it-2}. Therefore $(B-40)$ can be estimated via simple OLS. After doing this we set $\hat{\beta}$=$\hat{b}_1$ and $\hat{\phi}_a$=$\hat{b}_2$ and do not exploit parameters' constraints in the estimation.

Second stage

From $(B-34)$ and $(B-38)$ we have that log output is given by:

$$\begin{aligned} q_{it} &= \frac{\alpha_O}{1-\phi_q}\left(\ln WB_{i,t}-k_{it}\right)+\frac{\alpha_M}{1-\phi_q}\left(m_{it}-k_{it}\right)+\frac{\gamma}{1-\phi_q}k_{it}+\frac{\phi_a}{1-\phi_q}\alpha_M LHS_{it-1}-\frac{\phi_a}{1-\phi_q}\gamma k_{it-1} \\ &\quad -\frac{\phi_a}{1-\phi_q}\left(\frac{\alpha_M}{s_{Mit-1}}r_{it-1}-q_{it-1}\right)-\frac{\phi_q}{1-\phi_q}q_{it-1}+\frac{\phi_L}{1-\phi_q}\Delta L_{it}+\frac{1}{1-\phi_q}\nu_{ait}. \end{aligned}$$

Substituting $(B-33)$ and known parameters from the first stage, we obtain

$$\begin{aligned} q_{it} &= \frac{\gamma}{1-\phi_q}\frac{1}{\hat{\beta}}\frac{s_{Oit}}{s_{Mit}}\left(\ln WB_{i,t}-k_{it}\right)+\frac{\gamma}{1-\phi_q}\frac{1}{\hat{\beta}}\left(m_{it}-k_{it}\right)+\frac{\gamma}{1-\phi_q}k_{it}+\frac{\gamma}{1-\phi_q}\frac{\hat{\phi}_a}{\hat{\beta}}LHS_{it-1} \\ &\quad -\frac{\gamma}{1-\phi_q}\hat{\phi}_a k_{it-1}-\frac{\gamma}{1-\phi_q}\frac{1}{\hat{\beta}}\frac{\hat{\phi}_a}{s_{Mit-1}}r_{it-1}+\frac{\phi_a-\phi_q}{1-\phi_q}q_{it-1}+\frac{\phi_L}{1-\phi_q}\Delta L_{it}+\frac{1}{1-\phi_q}\nu_{ait}. \end{aligned}$$

Note that the only parameters to estimate are γ, ϕ_q and ϕ_L. These are identified using a linear model:

$$q_{it}=b_7z_{7it}+b_8z_{8it}+b_9z_{9it}+\varepsilon_{it}, \tag{B-41}$$

where:

$$\begin{aligned} z_{7it} &= \frac{1}{\hat{\beta}}\frac{s_{Oit}}{s_{Mit}}\left(\ln n^0_{iL,t}-k_{it}\right)+\frac{1}{\hat{\beta}}\left(m_{it}-k_{it}\right)+k_{it}+\frac{\hat{\phi}_a}{\hat{\beta}}LHS_{it-1}-\hat{\phi}_a k_{it-1}-\frac{1}{\hat{\beta}}\frac{\hat{\phi}_a}{s_{Mit-1}}r_{it-1}, \\ z_{8it} &= q_{it-1}, \\ z_{9it} &= \Delta L_{it},\ \text{and } \varepsilon_{it}=\frac{1}{1-\phi_q}\nu_{ait}, \end{aligned}$$

as well as

$$b_7=\frac{\gamma}{1-\phi_q}, b_8=\frac{\phi_a-\phi_q}{1-\phi_q}, b_9=\frac{\phi_L}{1-\phi_q}$$

and so

$$\hat{\phi}_q=\frac{\hat{b}_8-\hat{\phi}_a}{\hat{b}_8-1}, \hat{\gamma}=\hat{b}_7(1-\hat{\phi}_q), \hat{\phi}_L=\hat{b}_9(1-\hat{\phi}_q).$$

Note that z_{7it} and z_{9it} are endogenous and we instrument them with k_{it}, ΔL_{it-1} and L_{it-2}. With values of $\hat{\beta}$, $\hat{\phi}_q$ and $\hat{\gamma}$ we finally have

$$\hat{a}_{it} = q_{it} - \frac{\hat{\gamma}}{\hat{\beta}} \frac{s_{Oit}}{s_{Mit}} (\ln WB_{it} - k_{it}) - \frac{\hat{\gamma}}{\hat{\beta}} (m_{it} - k_{it}) - \hat{\gamma} k_{it}$$

$$\hat{\mu}_{it} = \frac{\hat{\gamma}}{\hat{\beta} s_{Mit}(1 - \hat{\phi}_q)} \text{ and } \hat{\lambda}_{it} = \frac{\hat{\gamma}}{\hat{\beta} s_{Mit}(1 - \hat{\phi}_q)} r_{it} - q_{it}.$$

B.4 Wooldridge (2009) Revenue Productivity with Change in Layers and Quantity

The labor input O_{it} is not directly observable, but we can use the fact that

$$O_{it} = \frac{C(O_{it}; w)}{C(O_{it}; w)} O_{it} = \frac{C(O_{it}; w)}{AC(O_{it}; w)}. \tag{B-42}$$

The numerator of this expression, $C(O_{it}; w)$, is the total expenditure on the labor input, i.e., the total wage bill of the firm (which is observable) while the denominator, $AC(O_{it}; w) = C(O_{it}; w) / O_{it}$, is the unit cost of the labor input (which is unobservable). Substituting (B-42) into the production function and multiplying by the price leads to an equation for revenue given by

$$r_{it} = \bar{a}_{it} + \alpha_O \ln C(O_{it}; w) + \alpha_M m_{it} + (\gamma - \alpha_M - \alpha_O) k_{it}, \tag{B-43}$$

where $\bar{a}_{it} \equiv p_{it} + a_{it} - \alpha_O \ln AC(O_{it}; w)$ denotes revenue-based productivity. In what follows we assume $-\alpha_O \ln AC(O_{it}; w) = \beta L_{it}$ which implies $\bar{a}_{it} = p_{it} + a_{it} + \beta L_{it}$. Note that $-\alpha_O \ln AC(O_{it}; w) = \beta L_{it}$ is what is implied by the CRH model if we substitute the constraint (5) in the organizational problem with $n_L^L \geq \epsilon$, for small enough $\epsilon > 0$.

Turning to the time evolution of productivity we follow the literature and impose productivity follows an autoregressive process. We incorporate into such a process both the impact of changes in organization (ΔL_{it}) and other channels affecting productivity via a change in quantity (Δq_{it}):

$$\bar{a}_{it} = \phi_a \bar{a}_{it-1} + \beta \Delta L_{it} + \phi_q \Delta q_{it} + \nu_{ait}, \tag{B-44}$$

where ν_{ait} is a productivity shock that is i.i.d. across firms and time. We follow again the literature and assume ν_{ait} is uncorrelated with all past values of $\bar{a}_{it}$. As far as the correlation between ν_{ait} and ΔL_{it} is concerned we assume this to be nonzero, i.e., the firm can somehow adjust organization in the wake of contemporaneous shocks ν_{ait}. The correlation between ν_{ait} and Δq_{it} is also nonzero.

More specifically we assume, in line with the literature, that capital is predetermined in t. We further allow firms to optimally choose materials in order to minimize short-run costs. As for the labor input, we follow Ackerberg et al. (2015) and assume it is somewhere in between capital and materials in terms of its capacity to adapt to contemporaneous shocks. The cost of materials is common across firms but can vary over time while the unit cost of the labor input $AC(O_{it};w)$ varies across firms and time. From first-order cost minimization conditions we have that materials' choice m_{it} is a function of k_{it} and $\bar{a}_{it}$. Indeed, whatever the structure of organization chosen by the firm (L_{it}) and the optimal production scale (q_{it}), they will ultimately pin down $\bar{a}_{it}$ which in turn, together with capital k_{it}, determines the optimal materials' expenditure. After inverting the first-order conditions of the firm, we can express $\bar{a}_{it}$ as a function of capital and materials, namely, $\bar{a}_{it} = g(k_{it}, m_{it})$.

From now onwards we follow Wooldridge (2009) and consider the value-added form of the revenue function which is known in the literature to perform better in terms of identification. In particular, using (B-44) as well as the inverted input demand equation of the firm, $\bar{a}_{it-1} = g(k_{it-1}, m_{it-1})$, we obtain

$$va_{it} = \alpha_O^{'} \ln C(O_{it};w) + \alpha_K^{'} k_{it} + \phi_a^{'} g(k_{it-1}, m_{it-1}) + \beta^{'} \Delta L_{it} + \phi_q^{'} \Delta q_{it} + \nu_{ait}. \tag{B-45}$$

where va_{it} is value added and, for example, the coefficient $\alpha_O^{'}$ equals α_O times a scaling factor common to all other coefficients. The error term ν_{ait} in (B-44) is uncorrelated with k_{it} and m_{it-1}. Hence, $g(k_{it-1}, m_{it-1})$ is also uncorrelated with ν_{ait} in (B-45). The wage bill $C(O_{it};w)$, the change in the number of layers ΔL_{it} and the change in quantity Δq_{it} are instead endogenous and we instrument them with the wage bill at $t-1$, the change in the number of layers at $t-1$, the number of layers in $t-2$, the change in quantity at $t-1$ and the level of quantity in $t-2$. As for the term $\phi_a^{'} g(k_{it-1}, m_{it-1})$ we use a second order polynomial approximation in k_{it-1} and m_{it-1}. We finally estimate (B-45) by IV and ultimately get an estimate of revenue TFP as

$$\widehat{\bar{a}}_{it} = va_{it} - \hat{\alpha}_O^{'} \ln C(O_{it};w) - \hat{\alpha}_K^{'} k_{it}.$$

C Supplementary Revenue-based Productivity Results

In this Appendix we provide revenue-productivity results—complementing those of Section 5.1—using a number of alternative estimation techniques. We group this set of results into OLS (C-1 to C-4), within estimator (C-5 to C-10), and dynamic panel data (C11-C15).

Table C-1: Value added per worker. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.627^a	0.811^a	0.833^a	0.748^a
	(0.028)	(0.026)	(0.017)	(0.016)
Change in layers	-0.097^a	-0.179^a		-0.124^a
	(0.013)	(0.023)		(0.012)
Constant	3.858^a	1.932^a	1.726^a	2.611^a
	(0.289)	(0.257)	(0.183)	(0.167)
Observations	4,206	2,750	3,090	10,046
Adjusted R^2	0.619	0.581	0.750	0.650

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table C-2: OLS TFP. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.661^a	0.648^a	0.683^a	0.671^a
	(0.024)	(0.025)	(0.021)	(0.015)
Change in layers	-0.012^a	-0.020^a		-0.014^a
	(0.003)	(0.004)		(0.002)
Constant	-0.001	-0.003	0.005	0.001
	(0.006)	(0.008)	(0.007)	(0.004)
Observations	4,171	2,734	3,055	9,960
Adjusted R^2	0.435	0.399	0.485	0.443

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table C-3: Olley and Pakes TFP. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.779^a	0.846^a	0.886^a	0.843^a
	(0.021)	(0.021)	(0.025)	(0.014)
Change in layers	-0.078^a	-0.106^a		-0.082^a
	(0.011)	(0.016)		(0.008)
Constant	-0.015	-0.023	-0.023	0.017
	(0.018)	(0.034)	(0.025)	(0.013)
Observations	4,171	2,734	3,055	9,960
Adjusted R^2	0.632	0.575	0.718	0.649

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table C-4: Levinsohn and Petrin TFP. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.839[a]	0.867[a]	0.855[a]	0.857[a]
	(0.018)	(0.019)	(0.020)	(0.011)
Change in layers	-0.041[a]	-0.062[a]		-0.044[a]
	(0.010)	(0.013)		(0.007)
Constant	0.003	-0.023	-0.018	0.007
	(0.016)	(0.033)	(0.026)	(0.013)
Observations	4,171	2,734	3,055	9,960
Adjusted R^2	0.670	0.629	0.692	0.667

Firm-level clustered standard errors in parentheses

[a] p<0.01, [b] p<0.05, [c] p<0.1

Table C-5: Wooldridge Revenue TFP. Firm-product-sequence FE. Within estimator

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.091[b]	-0.064[c]	0.065	0.053[b]
	(0.038)	(0.038)	(0.041)	(0.0245)
Change in layers	-0.033[a]	-0.074[a]		-0.048[a]
	(0.009)	(0.014)		(0.008)
Constant	-0.084[a]	-0.022	0.050[b]	0.075[a]
	(0.018)	(0.036)	(0.026)	(0.014)
Observations	4,057	2,686	2,934	9,677
Number of fixed effects	1,630	1,258	1,248	4,136
Adjusted R^2	0.053	0.042	0.031	0.027

Firm-level clustered standard errors in parentheses

[a] p<0.01, [b] p<0.05, [c] p<0.1

Table C-6: Revenue labor productivity. Firm-product-sequence FE. Within estimator

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.083[b]	0.020	0.090[c]	0.081[a]
	(0.036)	(0.064)	(0.053)	(0.028)
Change in layers	-0.038[a]	-0.136[a]		-0.074[a]
	(0.011)	(0.022)		(0.012)
Constant	10.439[a]	11.183[a]	10.527[a]	10.509[a]
	(0.414)	(0.718)	(0.617)	(0.319)
Observations	4,206	2,750	3,090	10,046
Number of fixed effects	1,687	1,289	1,310	4,286
Adjusted R^2	0.019	0.112	0.026	0.032

Firm-level clustered standard errors in parentheses

[a] p<0.01, [b] p<0.05, [c] p<0.1

Table C-7: Value added per worker. Firm-product-sequence FE. Within estimator

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.076^{c}	-0.035	0.030	0.050
	(0.039)	(0.078)	(0.051)	(0.031)
Change in layers	-0.037^{a}	-0.138^{a}		-0.074^{a}
	(0.012)	(0.023)		(0.012)
Constant	9.412^{a}	10.611^{a}	10.032^{a}	9.720^{a}
	(0.400)	(0.788)	(0.532)	(0.316)
Observations	4,206	2,750	3,090	10,046
Number of fixed effects	1,687	1,289	1,310	4,286
Adjusted R^2	0.021	0.104	0.017	0.027

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table C-8: OLS TFP. Firm-product-sequence FE. Within estimator

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	-0.048	-0.059	-0.098^{b}	-0.063^{b}
	(0.042)	(0.055)	(0.043)	(0.028)
Change in layers	-0.007^{b}	-0.013^{a}		-0.008^{a}
	(0.003)	(0.004)		(0.002)
Constant	-0.025^{a}	0.003	-0.005	0.020^{a}
	(0.004)	(0.008)	(0.005)	(0.006)
Observations	4,171	2,734	3,055	9,960
Number of fixed effects	1,673	1,280	1,298	4,251
Adjusted R^2	0.027	0.017	0.020	0.013

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table C-9: Olley and Pakes TFP. Firm-product-sequence FE. Within estimator

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.116^{a}	-0.031	0.142^{a}	0.097^{a}
	(0.037)	(0.066)	(0.054)	(0.029)
Change in layers	-0.033^{a}	-0.076^{a}		-0.050^{a}
	(0.009)	(0.013)		(0.008)
Constant	-0.096^{a}	-0.078^{b}	-0.055^{a}	0.100^{a}
	(0.013)	(0.035)	(0.017)	(0.018)
Observations	4,171	2,734	3,055	9,960
Number of fixed effects	1,673	1,280	1,298	4,251
Adjusted R^2	0.063	0.040	0.059	0.041

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table C-10: Levinsohn and Petrin TFP. Firm-product-sequence FE. Within estimator

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.133^a	-0.048	0.124^a	0.089^a
	(0.043)	(0.055)	(0.040)	(0.027)
Change in layers	-0.017^b	-0.047^a		-0.029^a
	(0.008)	(0.010)		(0.007)
Constant	-0.074^a	-0.096^a	-0.013	0.093^a
	(0.012)	(0.037)	(0.016)	(0.018)
Observations	4,171	2,734	3,055	9,960
Number of fixed effects	1,673	1,280	1,298	4,251
Adjusted R^2	0.054	0.023	0.041	0.033

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table C-11: Revenue labor productivity. Firm-product-sequence FE. Dynamic panel

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.391^a	0.548^a	0.641^a	0.505^a
	(0.082)	(0.082)	(0.071)	(0.050)
Change in layers	-0.057^a	-0.154^a		-0.095^a
	(0.014)	(0.019)		(0.010)
Constant	7.234^a	0.000	4.258^a	0.000
	(0.977)	(0.000)	(0.838)	(0.000)
Observations	4,206	2,750	3,090	10,046
Number of fixed effects	1,687	1,289	1,310	4,286
AR(2) Test Stat	1.864	0.082	0.697	1.297
P-value AR(2)	0.062	0.934	0.486	0.195

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table C-12: Value added per worker. Firm-product-sequence FE. Dynamic panel

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.397^a	0.484^a	0.491^a	0.462^a
	(0.064)	(0.086)	(0.072)	(0.043)
Change in layers	-0.059^a	-0.152^a		-0.095^a
	(0.013)	(0.019)		(0.010)
Constant	0.000	5.301^a	5.258^a	5.545^a
	(0.000)	(0.873)	(0.735)	(0.442)
Observations	4,206	2,750	3,090	10,046
Number of fixed effects	1,687	1,289	1,310	4,286
AR(2) Test Stat	1.555	0.355	0.726	1.506
P-value AR(2)	0.120	0.722	0.468	0.132

Firm-level clustered standard errors in parentheses
^{a} $p<0.01$, ^{b} $p<0.05$, ^{c} $p<0.1$

Table C-13: OLS TFP. Firm-product-sequence FE. Dynamic panel

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.255^a	0.314^a	0.179^b	0.265^a
	(0.057)	(0.063)	(0.078)	(0.039)
Change in layers	-0.006^b	-0.016^a		-0.010^a
	(0.003)	(0.003)		(0.002)
Constant	0.002	-0.000	0.013	0.014^b
	(0.009)	(0.009)	(0.012)	(0.007)
Observations	4,171	2,734	3,055	9,960
Number of fixed effects	1,673	1,280	1,298	4,251
AR(2) Test Stat	1.805	-0.277	-1.326	0.526
P-value AR(2)	0.071	0.782	0.185	0.599

Firm-level clustered standard errors in parentheses
^{a} $p<0.01$, ^{b} $p<0.05$, ^{c} $p<0.1$

Table C-14: Olley and Pakes TFP. Firm-product-sequence FE. Dynamic panel

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.439^{a}	0.452^{a}	0.579^{a}	0.499^{a}
	(0.069)	(0.095)	(0.085)	(0.047)
Change in layers	-0.050^{a}	-0.092^{a}		-0.061^{a}
	(0.009)	(0.012)		(0.007)
Constant	0.041	-0.025		0.018
	(0.026)	(0.034)		(0.017)
Observations	4,171	2,734	3,055	9,960
Number of fixed effects	1,673	1,280	1,298	4,251
AR(2) Test Stat	1.459	0.706	-0.233	0.660
P-value AR(2)	0.145	0.480	0.816	0.509

Firm-level clustered standard errors in parentheses

^{a} $p<0.01$, ^{b} $p<0.05$, ^{c} $p<0.1$

Table C-15: Levinsohn and Petrin TFP. Firm-product-sequence FE. Dynamic panel

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.450^{a}	0.517^{a}	0.573^{a}	0.530^{a}
	(0.076)	(0.078)	(0.068)	(0.045)
Change in layers	-0.022^{a}	-0.058^{a}		-0.035^{a}
	(0.008)	(0.011)		(0.006)
Constant	0.017	-0.002		0.027
	(0.026)	(0.031)		(0.018)
Observations	4,171	2,734	3,055	9,960
Number of fixed effects	1,673	1,280	1,298	4,251
AR(2) Test Stat	1.658	1.354	1.070	2.074
P-value AR(2)	0.097	0.176	0.284	0.038

Firm-level clustered standard errors in parentheses

^{a} $p<0.01$, ^{b} $p<0.05$, ^{c} $p<0.1$

D De Loecker and Warzynski Revenue-based Productivity

In this Section we obtain log total factor productivity computed from a standard two factors (labor and capital) Cobb-Douglas production function model where output is measured by firm value-added. Productivity shocks are modeled as in De Loecker and Warzynski (2012) and in particular the capital stock, the expenditure in materials and firm export status are used as proxies in the control function. The estimation of the model is carried using the Wooldridge (2009) GMM approach.

In all tables, two digit industry dummies and year dummies are included in estimations but are not reported here. Standard errors clustered at the firm level.

Table D-1: De Loecker and Warzynski (2012) revenue contemporaneous. Sequence type regressions, OLS

	(1)	(2)	(3)	(4)
VARIABLES	Increasing	Decreasing	Constant	All
Productivity t-1	0.782^{a}	0.838^{a}	0.876^{a}	0.836^{a}
	(0.021)	(0.021)	(0.026)	(0.016)
Change in layers	-0.068^{a}	-0.101^{a}		-0.075^{a}
	(0.011)	(0.016)		(0.008)
Constant	-0.009	-0.017	-0.016	-0.010
	(0.017)	(0.032)	(0.025)	(0.013)
Observations	4,127	2,708	2,989	9,824
Adjusted R^2	0.639	0.587	0.744	0.664

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table D-2: De Loecker and Warzynski (2012) revenue contemporaneous. Sequence type regressions, Within.

	(1)	(2)	(3)	(4)
VARIABLES	Increasing	Decreasing	Constant	All
Productivity t-1	0.110^{a}	-0.076	0.068	0.059^{b}
	(0.042)	(0.046)	(0.043)	(0.027)
Change in layers	-0.027^{a}	-0.065^{a}		-0.040^{a}
	(0.009)	(0.012)		(0.007)
Constant	-0.088^{a}	-0.059	0.024^{b}	0.094^{a}
	(0.013)	(0.036)	(0.016)	(0.019)
Observations	4,127	2,708	2,989	9,824
Number of fixed effects	1,655	1,268	1,276	4,199
Adjusted R^2	0.064	0.036	0.033	0.032

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table D-3: De Loecker and Warzynski (2012) revenue contemporaneous. Sequence type regressions, Dynamic Panel

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.363^{a}	0.382^{a}	0.542^{a}	0.445^{a}
	(0.070)	(0.105)	(0.073)	(0.049)
Change in layers	-0.036^{b}	-0.085^{a}		-0.054^{a}
	(0.010)	(0.012)		(0.007)
Constant	0.056^{c}	-0.011	0.028	0.031^{c}
	(0.033)	(0.034)	(0.031)	(0.019)
Observations	4,127	2,708	2,989	9,824
Number of fixed effects	1,655	1,268	1,276	4,199
AR(2) Test Stat	1.955	1.124	1.145	2.277
P-value AR(2)	0.051	0.261	0.252	0.023

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

E Supplementary Quantity-based Productivity Results

In this Appendix we provide results that are complementary to those in Section 5.2 using the within estimator.

Table E-1: Quantity TFP. Firm-product-sequence FE. Within estimator

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.207^{a}	0.103	0.162^{a}	0.163^{a}
	(0.043)	(0.070)	(0.055)	(0.034)
Change in layers	0.007	0.021^{c}		0.014^{c}
	(0.011)	(0.011)		(0.008)
Constant	0.001	0.041	0.032	0.040
	(0.016)	(0.037)	(0.019)	(0.025)
Observations	4,171	2,840	3,055	10,066
Number of fixed effects 1,673	1,280	1,298	4,251	
Adjusted R^2	0.041	0.012	0.030	0.027

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table E-2: Quantity TFP. Firm-product-sequence FE. Level effects using layers. Within estimator.

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.316^a	0.348^b	0.359^a	0.341^a
	(0.056)	(0.170)	(0.092)	(0.067)
Number of layers	0.040^c	0.013		0.032^b
	(0.022)	(0.022)		(0.014)
Constant	-0.113^c	-0.008	-0.001	-0.034
	(0.062)	(0.035)	(0.023)	(0.041)
Observations	4,171	2,840	3,055	10,066
Number of fixed effects	1,673	1,280	1,298	4,251
Adjusted R^2	0.076	0.111	0.101	0.094

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

F Alternative Grouping of Firms

In this Appendix we present results for an alternative grouping of firms. We present the effect of changing layers on productivity as a function of the difference between the current and the initial number of layers; the latter corresponding to what we observe when we see the firm switching for the first time (first observed reorganization). In particular, each table contains 4 columns referring to the number of layers (0, 1, 2 or 3) firms have in the year of the first observed reorganization.

F.1 Revenue-based Productivity OLS Results

Table F-1: Alternative grouping. Wooldridge Revenue TFP. OLS

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.438^a	0.613^a	0.813^a	0.814^a
	(0.081)	(0.035)	(0.023)	(0.017)
Change in layers	-0.067^a	-0.065^a	-0.071^a	-0.085^a
	(0.022)	(0.017)	(0.010)	(0.018)
Constant	0.120^c	-0.015	0.000	-0.028
	(0.071)	(0.041)	(0.019)	(0.023)
Observations	528	1,630	3,645	3,446
Adjusted R^2	0.414	0.535	0.639	0.641

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-2: Alternative grouping. Revenue Labor Productivity. OLS

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.645^a	0.782^a	0.865^a	0.897^a
	(0.063)	(0.026)	(0.015)	(0.017)
Change in layers	-0.102^b	-0.128^a	-0.100^a	-0.153^a
	(0.047)	(0.019)	(0.015)	(0.030)
Constant	4.048^a	2.511^a	1.620^a	1.221^a
	(0.708)	(0.301)	(0.183)	(0.200)
Observations	533	1,665	3,690	3,569
Adjusted R^2	0.581	0.768	0.792	0.812

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-3: Alternative grouping. Value added per worker. OLS

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.477^a	0.578^a	0.762^a	0.822^a
	(0.058)	(0.037)	(0.026)	(0.024)
Change in layers	-0.091^b	-0.086^b	-0.105^a	-0.143^a
	(0.037)	(0.019)	(0.015)	(0.028)
Constant	5.533^a	4.301^a	2.484^a	1.836^a
	(0.631)	(0.370)	(0.269)	(0.253)
Observations	533	1,665	3,690	3,569
Adjusted R^2	0.489	0.521	0.650	0.706

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-4: Alternative grouping. OLS TFP. OLS

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.489^a	0.611^a	0.663^a	0.698^a
	(0.065)	(0.031)	(0.026)	(0.019)
Change in layers	-0.019^b	-0.017^a	-0.013^a	-0.010^b
	(0.008)	(0.004)	(0.003)	(0.004)
Constant	0.048^b	0.000	0.000	-0.003
	(0.022)	(0.011)	(0.006)	(0.006)
Observations	532	1,649	3,674	3,523
Adjusted R^2	0.444	0.394	0.418	0.507

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-5: Alternative grouping. Olley and Pakes TFP. OLS

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.540^{a}	0.660^{a}	0.841^{a}	0.908^{a}
	(0.062)	(0.030)	(0.021)	(0.021)
Change in layers	-0.069^{a}	-0.054^{a}	-0.071^{a}	-0.085^{a}
	(0.024)	(0.016)	(0.011)	(0.018)
Constant	0.052	-0.054	-0.002	-0.032
	(0.073)	(0.041)	(0.019)	(0.022)
Observations	532	1,649	3,674	3,523
Adjusted R^2	0.493	0.526	0.657	0.719

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-6: Alternative grouping. Levinsohn and Petrin TFP. OLS

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.610^{a}	0.742^{a}	0.864^{a}	0.888^{a}
	(0.068)	(0.029)	(0.019)	(0.014)
Change in layers	-0.041^{b}	-0.023	-0.040^{a}	-0.044^{a}
	(0.020)	(0.016)	(0.010)	(0.013)
Constant	0.059	-0.026	0.003	-0.025
	(0.064)	(0.037)	(0.019)	(0.022)
Observations	532	1,649	3,674	3,523
Adjusted R^2	0.568	0.587	0.671	0.720

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

F.2 Revenue-based Productivity Within Estimator Results

Table F-7: Alternative grouping. Wooldridge Revenue TFP. Firm-product FE. Within estimator

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.001	0.015	0.185^a	0.126^a
	(0.044)	(0.048)	(0.042)	(0.039)
Change in layers	-0.047^a	-0.021	-0.038^a	-0.055^a
	(0.018)	(0.015)	(0.008)	(0.012)
Constant	0.004	-0.035	-0.057^a	0.048^a
	(0.032)	(0.027)	(0.012)	(0.015)
Observations	525	1,602	3,591	3,385
Number of fixed effects	159	535	1,119	1,096
Adjusted R^2	0.049	0.011	0.059	0.040

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-8: Alternative grouping. Revenue labor productivity. Firm-product FE. Within estimator

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	-0.042	0.190^a	0.126^b	0.041
	(0.060)	(0.050)	(0.049)	(0.069)
Change in layers	-0.050	-0.051^a	-0.061^a	-0.097^a
	(0.034)	(0.014)	(0.013)	(0.019)
Constant	11.572^a	9.152^a	9.964^a	11.062^a
	(0.671)	(0.572)	(0.555)	(0.792)
Observations	533	1,665	3,690	3,569
Number of fixed effects	164	552	1,157	1,161
Adjusted R^2	0.047	0.054	0.043	0.063

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-9: Alternative grouping. Value added per worker. Firm-product FE. Within estimator

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	-0.048	0.069	0.095^c	0.076
	(0.056)	(0.062)	(0.050)	(0.068)
Change in layers	-0.066^b	-0.031^c	-0.062^a	-0.093^a
	(0.029)	(0.017)	(0.014)	(0.019)
Constant	10.587^a	9.429^a	9.249^a	9.536^a
	(0.565)	(0.629)	(0.508)	(0.695)
Observations	533	1,665	3,690	3,569
Number of fixed effects	164	552	1,157	1,161
Adjusted R^2	0.025	0.015	0.039	0.051

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-10: Alternative grouping. OLS TFP. Firm-product FE. Within estimator

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	-0.012	-0.059	0.040	0.024
	(0.081)	(0.059)	(0.043)	(0.043)
Change in layers	-0.013^c	-0.003	-0.006^b	-0.006^c
	(0.007)	(0.004)	(0.003)	(0.003)
Constant	0.006	-0.004	-0.011^a	0.010^c
	(0.011)	(0.006)	(0.004)	(0.005)
Observations	532	1,649	3,674	3,523
Number of fixed effects	163	549	1,149	1,148
Adjusted R^2	0.011	0.002	0.013	0.007

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-11: Alternative grouping. Olley and Pakes TFP. Firm-product FE. Within estimator

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	-0.004	0.019	0.165^a	0.237^a
	(0.061)	(0.063)	(0.044)	(0.042)
Change in layers	-0.051^a	-0.020	-0.040^a	-0.052^a
	(0.018)	(0.014)	(0.008)	(0.013)
Constant	-0.115^a	-0.148^a	-0.066^a	-0.105^a
	(0.035)	(0.032)	(0.012)	(0.017)
Observations	532	1,649	3,674	3,523
Number of fixed effects	163	549	1,149	1,148
Adjusted R^2	0.053	0.020	0.062	0.079

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-12: Alternative grouping. Levinsohn and Petrin TFP. Firm-product FE. Within estimator

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.040	-0.014	0.217^a	0.227^a
	(0.069)	(0.060)	(0.041)	(0.038)
Change in layers	-0.033^b	0.006	-0.022^a	-0.031^a
	(0.016)	(0.014)	(0.007)	(0.009)
Constant	-0.076^b	-0.118^a	-0.055^a	0.090^a
	(0.035)	(0.031)	(0.012)	(0.015)
Observations	532	1,649	3,674	3,523
Number of fixed effects	163	549	1,149	1,148
Adjusted R^2	0.025	0.027	0.068	0.067

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

F.3 Revenue-based Productivity Dynamic Panel Results

Table F-13: Alternative grouping. Wooldridge Revenue TFP. Firm-product FE. Dynamic panel

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.251^{a}	0.183^{b}	0.481^{a}	0.533^{a}
	(0.092)	(0.089)	(0.053)	(0.066)
Change in layers	-0.058^{a}	-0.028^{b}	-0.052^{a}	-0.066^{a}
	(0.014)	(0.013)	(0.008)	(0.016)
Constant	0.192^{c}	0.081	0.007	-0.008
	(0.101)	(0.066)	(0.025)	(0.026)
Observations	528	1,630	3,645	3,446
Number of fixed effects	162	543	1,138	1,122
AR(2) Test Stat	1.212	0.359	3.188	1.510
P-value AR(2)	0.226	0.719	0.001	0.131

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-14: Alternative grouping. Revenue labor productivity. Firm-product FE. Dynamic panel

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.369^{a}	0.577^{a}	0.386^{a}	0.469^{a}
	(0.108)	(0.136)	(0.072)	(0.090)
Change in layers	-0.072^{b}	-0.083^{a}	-0.067^{a}	-0.115^{a}
	(0.032)	(0.022)	(0.013)	(0.024)
Constant	7.241	0.000	0.000	0.000
	(1.270)	(0.000)	(0.000)	(0.000)
Observations	533	1,665	3,690	3,569
Number of fixed effects	164	552	1,157	1,161
AR(2) Test Stat	0.890	0.712	2.547	0.785
P-value AR(2)	0.373	0.476	0.011	0.432

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-15: Alternative grouping. Value added per worker. Firm-product FE. Dynamic panel

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.150	0.301^{a}	0.370^{a}	0.456^{a}
	(0.094)	(0.101)	(0.068)	(0.087)
Change in layers	-0.060^{b}	-0.045^{b}	-0.074^{a}	-0.113^{a}
	(0.028)	(0.018)	(0.013)	(0.024)
Constant	0.000	7.110^{a}	0.000	0.000
	(0.000)	(1.039)	(0.000)	(0.000)
Observations	533	1,665	3,690	3,569
Number of fixed effects	164	552	1,157	1,161
AR(2) Test Stat	1.217	0.372	3.104	0.857
P-value AR(2)	0.224	0.710	0.002	0.391

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-16: Alternative grouping. OLS TFP. Firm-product FE. Dynamic panel

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.201^{b}	0.180^{b}	0.299^{a}	0.302^{a}
	(0.093)	(0.081)	(0.059)	(0.053)
Change in layers	-0.014^{a}	-0.008^{b}	-0.009^{a}	-0.008^{b}
	(0.005)	(0.003)	(0.003)	(0.004)
Constant	0.081^{a}	-0.001	0.013	-0.003
	(0.030)	(0.017)	(0.010)	(0.010)
Observations	532	1,649	3,674	3,523
Number of fixed effects	163	549	1,149	1,148
AR(2) Test Stat	1.338	0.203	2.092	0.073
P-value AR(2)	0.181	0.839	0.036	0.942

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-17: Alternative grouping. Olley and Pakes TFP. Firm-product FE. Dynamic panel

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.233^{a}	0.178^{b}	0.506^{a}	0.589^{a}
	(0.079)	(0.081)	(0.063)	(0.058)
Change in layers	-0.060^{a}	-0.016	-0.052^{a}	-0.064^{a}
	(0.016)	(0.013)	(0.009)	(0.015)
Constant	0.121	-0.008	0.008	0.022
	(0.115)	(0.061)	(0.026)	(0.029)
Observations	532	1,649	3,674	3,523
Number of fixed effects	163	549	1,149	1,148
AR(2) Test Stat	1.178	0.681	2.732	-0.259
P-value AR(2)	0.239	0.496	0.006	0.795

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-18: Alternative grouping. Levinsohn and Petrin TFP. Firm-product FE. Dynamic panel

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.324^{a}	0.153^{c}	0.610^{a}	0.648^{a}
	(0.111)	(0.087)	(0.047)	(0.050)
Change in layers	-0.037^{a}	0.001	-0.032^{a}	-0.038^{a}
	(0.014)	(0.012)	(0.008)	(0.012)
Constant	0.065	0.065	0.038	0.007
	(0.114)	(0.072)	(0.026)	(0.025)
Observations	532	1,649	3,674	3,523
Number of fixed effects	163	549	1,149	1,148
AR(2) Test Stat	0.693	0.158	2.986	0.995
P-value AR(2)	0.488	0.874	0.003	0.320

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

F.4 De Loecker and Warzynski Revenue-based Productivity

Table F-19: Alternative grouping. De Loecker and Warzynski (2012) revenue contemporaneous. OLS

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.627^a	0.677^a	0.842^a	0.875^a
	(0.082)	(0.030)	(0.020)	(0.024)
Change in layers	-0.070^a	-0.058^a	-0.064^a	-0.083^a
	(0.025)	(0.017)	(0.010)	(0.019)
Constant	0.082	-0.019	-0.000	-0.029
	(0.068)	(0.039)	(0.019)	(0.021)
Observations	528	1,630	3,645	3,446
Adjusted R^2	0.610	0.571	0.660	0.732

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-20: Alternative grouping. De Loecker and Warzynski (2012) revenue contemporaneous. Within estimator

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.024	0.024	0.141^a	0.151^a
	(0.064)	(0.065)	(0.039)	(0.046)
Change in layers	-0.047^b	-0.017	-0.033^a	-0.051^a
	(0.019)	(0.015)	(0.008)	(0.012)
Constant	-0.058^c	-0.078^b	-0.060^a	0.081^a
	(0.034)	(0.031)	(0.012)	(0.015)
Observations	528	1,630	3,645	3,446
Number of fixed effects	162	543	1,138	1,122
Adjusted R^2	0.048	0.024	0.052	0.048

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-21: Alternative grouping. De Loecker andWarzynski (2012) revenue contemporaneous. Dynamic panel

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.307[a]	0.241[a]	0.464[a]	0.546[a]
	(0.109)	(0.087)	(0.064)	(0.066)
Change in layers	-0.057[a]	-0.027[b]	-0.048[a]	-0.065[a]
	(0.014)	(0.013)	(0.009)	(0.016)
Constant	0.173	0.088	0.011	-0.031
	(0.127)	(0.056)	(0.027)	(0.030)
Observations	528	1,630	3,645	3,446
Number of fixed effects	162	543	1,138	1,122
AR(2) Test Stat	1.343	0.496	3.466	1.434
P-value AR(2)	0.179	0.620	0.001	0.152

Firm-level clustered standard errors in parentheses
[a] p<0.01, [b] p<0.05, [c] p<0.1

F.5 Quantity-based Productivity Results

Table F-22: Alternative grouping. Quantity TFP. OLS

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.849^a	0.904^a	0.884^a	0.892^a
	(0.051)	(0.020)	(0.013)	(0.014)
Change in layers	0.008	0.003	0.035^a	0.038^a
	(0.025)	(0.013)	(0.010)	(0.014)
Constant	0.589^c	0.127^a	0.304^a	0.368^b
	(0.323)	(0.047)	(0.027)	(0.166)
Observations	532	1,649	3,674	3,523
Adjusted R^2	0.772	0.805	0.765	0.782

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-23: Alternative grouping. Quantity TFP. Firm-product FE. Dynamic panel

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.344^a	0.622^a	0.646^a	0.676^a
	(0.109)	(0.071)	(0.085)	(0.057)
Change in layers	-0.011	-0.003	0.029^a	0.029^b
	(0.020)	(0.013)	(0.010)	(0.012)
Constant	-1.566^a	0.025	0.635^b	0.397^a
	(0.340)	(0.031)	(0.256)	(0.074)
Observations	532	1,649	3,674	3,523
Number of fixed effects	163	549	1,149	1,148
Adjusted R^2				
AR(2) Test Stat	-1.564	-0.0881	1.587	2.191
P-value AR(2)	0.118	0.378	0.113	0.0284

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-24: Alternative grouping. Quantity TFP. Firm-product FE. Within estimator

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.154^b	0.226^a	0.263^a	0.215^a
	(0.067)	(0.062)	(0.039)	(0.059)
Change in layers	-0.003	0.004	0.023^a	0.027^b
	(0.016)	(0.013)	(0.009)	(0.011)
Constant	0.209^a	0.080^a	-0.015	0.041^c
	(0.049)	(0.023)	(0.015)	(0.022)
Observations	532	1,649	3,674	3,523
Number of fixed effects 163	549	1,149	1,148	
Adjusted R^2	0.017	0.062	0.069	0.051

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-25: Alternative grouping. Quantity TFP. Firm-product FE. Level effects using layers. Within estimator.

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.240^b	0.276^a	0.408^a	0.480^a
	(0.066)	(0.056)	(0.061)	(0.099)
Number of layers	0.055	-0.013	0.029^c	0.049^a
	(0.028)	(0.023)	(0.017)	(0.018)
Constant	0.110^c	0.063	-0.069	-0.086
	(0.065)	(0.048)	(0.044)	(0.053)
Observations	532	1,649	3,674	3,523
Number of fixed effects	163	549	1,149	1,148
Adjusted R^2	0.053	0.079	0.140	0.186

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

F.6 Instrumental Variables Results

Table F-26: Alternative grouping. Wooldridge Revenue TFP. Instrumental Variable. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.694^{a}	0.844^{a}	0.941^{a}	0.906^{a}
	(0.076)	(0.021)	(0.011)	(0.011)
Change in layers	-0.068	-0.170^{a}	-0.059^{b}	-0.063^{b}
	(0.048)	(0.053)	(0.031)	(0.035)
Change in quantity	-0.784^{a}	-0.449^{a}	-0.466^{a}	-0.085
	(0.213)	(0.141)	(0.124)	(0.067)
Observations	525	1,602	3,591	3,385
Kleibergen-Paap stat.	16.92	101.1	238.4	153.4
Adjusted R^2	0.514	0.629	0.817	0.834

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table F-27: Alternative grouping. Quantity TFP. Instrumental Variable. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.942^{a}	0.924^{a}	0.944^{a}	0.951^{a}
	(0.041)	(0.030)	(0.015)	(0.019)
Change in layers	-0.017	0.053	0.120^{a}	0.069^{b}
	(0.048)	(0.053)	(0.031)	(0.035)
Change in quantity	0.055	-0.057	0.268^{b}	0.004
	(0.266)	(0.108)	(0.111)	(0.087)
Observations	532	1,649	3,674	3,523
Kleibergen-Paap stat.	14.8	108.0	259.2	157.7
Adjusted R^2	0.841	0.795	0.851	0.868

Firm-level clustered standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

G Supplementary IV Tables

In this Appendix we provide results that are complementary to those in Section 5.3. The trade instruments that are used below are built using initial period fixed weights while in Section 5.3 weights are time-varying. Results are qualitatively identical and quantitatively very similar.

Table G-1: Wooldridge Revenue TFP. Instrumental Variable with initial period fixed weights for trade instruments. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.920[a]	0.916[a]	0.912[a]	0.919[a]
	(0.011)	(0.020)	(0.016)	(0.009)
Change in layers	-0.065[a]	-0.083[a]		-0.071[a]
	(0.017)	(0.027)		(0.017)
Change in quantity	0.078	0.749[b]	-0.219	0.368
	(0.392)	(0.335)	(0.253)	(0.266)
Observations	4,057	2,686	2,934	9,677
Kleibergen-Paap stat.	12.11	10.84	12.04	18.09
Adjusted R^2	0.826	0.686	0.849	0.809

Firm-level clustered standard errors in parentheses
[a] p<0.01, [b] p<0.05, [c] p<0.1

Table G-2: Alternative grouping. Wooldridge Revenue TFP. Instrumental Variable with initial period fixed weights for trade instruments. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.696[a]	0.844[a]	0.941[a]	0.906[a]
	(0.076)	(0.021)	(0.011)	(0.011)
Change in layers	-0.068	-0.166[a]	-0.060[b]	-0.063[b]
	(0.048)	(0.046)	(0.024)	(0.027)
Change in quantity	-0.740[a]	-0.450[a]	-0.470[a]	-0.085
	(0.204)	(0.142)	(0.123)	(0.067)
Observations	525	1,602	3,591	3,385
Kleibergen-Paap stat.	16.91	98.43	239.5	153.8
Adjusted R^2	0.528	0.630	0.817	0.834

Firm-level clustered standard errors in parentheses
[a] p<0.01, [b] p<0.05, [c] p<0.1

Table G-3: Quantity TFP. Approach one. Instrumental Variable with initial period fixed weights for trade instruments. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.953[a]	0.905[a]	0.967[a]	0.954[a]
	(0.014)	(0.018)	(0.017)	(0.012)
Change in layers	0.054[b]	0.049[b]		0.079[a]
	(0.021)	(0.022)		(0.020)
Change in quantity	0.034	-0.026	0.139	0.046
	(0.058)	(0.131)	(0.107)	(0.061)
Observations	4,171	2,840	3,055	10,066
Kleibergen-Paap stat.	46.70	304.4	44.25	602.0
Adjusted R^2	0.855	0.771	0.902	0.872

Firm-level clustered standard errors in parentheses
[a] p<0.01, [b] p<0.05, [c] p<0.1

Table G-4: Alternative grouping. Quantity TFP. Instrumental Variable with initial period fixed weights for trade instruments. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.942[a]	0.924[a]	0.944[a]	0.951[a]
	(0.041)	(0.030)	(0.015)	(0.019)
Change in layers	-0.017	0.053	0.120[a]	0.069[b]
	(0.048)	(0.053)	(0.031)	(0.035)
Change in quantity	0.055	-0.057	0.268[b]	0.004
	(0.266)	(0.108)	(0.111)	(0.087)
Observations	532	1,649	3,674	3,523
Kleibergen-Paap stat.	14.8	108.0	259.2	157.7
Adjusted R^2	0.841	0.795	0.851	0.868

Firm-level clustered standard errors in parentheses
[a] p<0.01, [b] p<0.05, [c] p<0.1

H Results Using Prices

In this Appendix we present results on the effect of a reorganization on prices. We infer prices as follows: In our dataset a product is identified by a 10-digit code. The first 8 digits correspond to the European PRODCOM classification while the additional two have been added by INE to further refine PRODCOM. The volume is recorded in units of measurement (number of items, kilograms, liters) that are product-specific while the value is recorded in current euros. For each product-firm-year combination we are able to compute a detailed price. In our analysis we aggregate products into coarser categories that we label as product groups. For each product within a product group we compute, as suggested in Forlani et al. (2015), the average log price across firms producing that product in a given year. We then aggregate quantities produced across products within a firm-product group-year by first considering the product of the exponential of such average and the actual quantity and then summing across products. The ratio between firm revenue and aggregate quantity referring to a particular firm-product group-year combination—normalized by its product group-year mean—is what we use as price in our regressions. Table H-1 presents the results using OLS.

Table H-1: Price effects contemporaneous. Sequence type regressions. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
(log) Price t-1	0.805[a]	0.904[a]	0.834[a]	0.841[a]
	(0.023)	(0.041)	(0.028)	(0.017)
Change in layers	-0.014	-0.004		-0.012[c]
	(0.011)	(0.012)		(0.006)
Constant	0.202[a]	0.100[a]	0.152[a]	0.158[a]
	(0.030)	(0.045)	(0.029)	(0.018)
Observations	4,206	2,750	3,090	10,046
Adjusted R^2	0.641	0.709	0.721	0.687

Firm-level clustered standard errors in parentheses

[a] p<0.01, [b] p<0.05, [c] p<0.1

I First stage IV Regressions

The next two tables show the first stage estimates for tables 16 and 17, for the change in the number of layers for all firms and firms that increase and decrease the number of layers. First stage estimates for the change in quantity are available upon requests.

Table I-1: Wooldridge Revenue TFP. Instrumental Variable. Both change in layers and change in quantity as endogenous variables. First stage estimates for change in layers

VARIABLES	Increasing	Decreasing	All
Productivity t-1	-0.025	-0.010	-0.003
	(0.024)	(0.038)	(0.019)
Exports real exch. rate	-0.000^{a}	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Imports real exch. rate	-0.010	0.080	-0.006
	(0.010)	(0.050)	(0.023)
Capital first year	0.039^{b}	0.042^{c}	0.076^{a}
	(0.018)	(0.023)	(0.012)
Sales t-1	0.020	-0.027	0.023
	(0.018)	(0.023)	(0.014)
Sales first year	-0.037	0.020	-0.027
	(0.023)	(0.032)	(0.018)
Number of layers t-1	-0.669^{a}	-0.706^{a}	0.205^{a}
	(0.017)	(0.020)	(0.010)
Number of layers first year	0.542^{a}	0.653^{a}	0.152^{a}
	(0.026)	(0.027)	(0.009)
Productivity t-2	-0.026	0.013	-0.009
	(0.025)	(0.032)	(0.018)
Productivity first year	0.070^{a}	-0.007	0.023
	(0.027)	(0.043)	(0.019)
Markup t-1	0.049	-0.057	-0.124
	(0.129)	(0.159)	(0.012)
Demand shock t-1	-0.006	-0.001	0.005
	(0.009)	(0.012)	(0.008)
Markup first year	-0.131	0.284	0.146
	(0.145)	(0.216)	(0.128)
Demand shock first year	0.009	-0.017	-0.012
	(0.011)	(0.015)	(0.009)
Observations	4,057	2,686	9,677

Firm-level clustered standard errors in parentheses

^{a} $p<0.01$, ^{b} $p<0.05$, ^{c} $p<0.1$

Table I-2: Quantity TFP. Instrumental Variable. Both change in layers and change in quantity as endogenous variables. First stage estimates for change in layers

VARIABLES	Increasing	Decreasing	All
Productivity t-1	-0.020	-0.053^{c}	-0.027^{a}
	(0.018)	(0.032)	(0.011)
Exports real exch. rate	-0.000^{a}	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Imports real exch. rate	-0.008	0.084^{c}	-0.023^{b}
	(0.010)	(0.051)	(0.011)
Markup t-1	0.180	0.340^{c}	0.210^{a}
	(0.209)	(0.181)	(0.070)
Demand shock t-1	-0.016	-0.027^{c}	-0.018^{a}
	(0.015)	(0.015)	(0.006)
Capital t	0.039^{b}	0.031	0.016
	(0.016)	(0.025)	(0.013)
Markup first year	-0.112	-0.162^{a}	-0.029
	(0.215)	(0.064)	(0.031)
Demand shock first year	0.009	0.012	0.000
	(0.015)	(0.008)	(0.004)
Capital first year	0.028	0.011	0.054^{a}
	(0.021)	(0.031)	(0.016)
Quantity t-1	-0.047^{c}	0.048	-0.032
	(0.028)	(0.046)	(0.023)
Quantity first year	0.031	-0.089^{c}	-0.019
	(0.032)	(0.047)	(0.024)
Sales t-1	0.073^{b}	0.057	0.059^{b}
	(0.034)	(0.048)	(0.026)
Sales first year	-0.051	-0.051	-0.010
	(0.041)	(0.056)	(0.027)
Number of layers t-1	-0.666^{a}	-0.686^{a}	-0.240^{a}
	(0.017)	(0.022)	(0.011)
Number of layers first year	0.535^{a}	0.613^{a}	-0.119^{a}
	(0.026)	(0.028)	(0.009)
Productivity t-2	0.026^{c}	0.017	0.018^{b}
	(0.015)	(0.018)	(0.008)
Productivity first year	-0.009	0.029	0.007
	(0.018)	(0.031)	(0.010)
Observations	4,057	2,686	9,677

Firm-level clustered standard errors in parentheses

^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1