



Working Papers

www.cesifo.org/wp

Productivity and Organization in Portuguese Firms

Lorenzo Caliendo
Giordano Mion
Luca David Opromolla
Esteban Rossi-Hansberg

CESIFO WORKING PAPER NO. 5678

CATEGORY 11: INDUSTRIAL ORGANISATION

ORIGINAL VERSION: DECEMBER 2015

THIS VERSION: APRIL 2018

An electronic version of the paper may be downloaded

- from the SSRN website: www.SSRN.com
- from the RePEc website: www.RePEc.org
- from the CESifo website: www.CESifo-group.org/wp

ISSN 2364-1428

Productivity and Organization in Portuguese Firms

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.

JEL-Codes: D220, D240, L230, F160, J240, J310.

Lorenzo Caliendo
Department of Economics
Yale University
USA - New Haven, CT 06511-3729
lorenzo.caliendo@yale.edu

Giordano Mion
Department of Economics
University of Sussex
UK - Brighton, BN1 9RH
g.mion@sussex.ac.uk

Luca David Opromolla
Economic Research Department
Banco de Portugal
Portugal – 1150-012 Lisbon
luca.opromolla@nyu.edu

Esteban Rossi-Hansberg
Department of Economics
Princeton University
USA - Princeton, NJ, 08544
erossi@princeton.edu

October 6, 2017

We thank Serguey Braguinsky, Jan De Loecker, Jakub Kastl, Steve Redding, Ananth Seshadri, and seminar participants at various institutions and conferences for useful comments and discussions. Financial support by FCT (Fundação para a Ciência e a Tecnologia), Portugal is gratefully acknowledged. This article is part of the Strategic Project (UID/ECO/00436/2013). The analyses, opinions, and findings represent the views of the authors and they are not necessarily those of Banco de Portugal.

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. To illustrate the parallel case when a firm receives a negative shock, consider the example of a Portuguese firm producing “Knitted and crocheted pullovers, cardigans, and similar articles”. This firm downsized heavily between 2002 and 2005 as a result of China's entry into the WTO and the resulting reduction in quotas and increased import competition. We observe that the quantity sold by the firm declines by 50%, but its prices increases by 30%. The firm reduced its layers of management by firing several managers and employees performing secondary tasks, and focusing on its main expertises by maintaining its "sewers and embroiderers". Overall its labor force declines by 27 employees. Using the measures of productivity we explain in detail below, the result is a reduction in quantity based productivity of 53% combined with an increase in revenue-based productivity of 9.2%. The experience and behavior of this firm is by no means unique. Using many examples and a host of empirical measures, we show that

reorganization and productivity are systematically linked in the way we describe.

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 empirically identify the changes in organization using occupational classifications. 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 productivity and 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 when 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 these 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

¹Following 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.

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 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 us to quantify the past productivity, demand, and markups shocks that motivate firms to expand or contract production scale, but that are 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

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

³In 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.

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.

Finally, we go one step further, and use the quota removals in sub-industries of the “Textile and Apparel” sector, that resulted from China’s entry into the WTO, as an instrument for a firm’s reorganization. Focusing on this sector allows us to explore the implications of a clearly exogenous negative demand shock on reorganization and productivity. Overall, we find that the behavior of firms as a result of the reduction in quotas is very much in line with the rest of our findings. This is confirmed with a couple of detailed examples of individual firms in this industry where we describe in more detail the way these firms changed their labor force composition and therefore their organization and productivity.

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.⁴ 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).

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. We finish this section with several examples of Portuguese firms that went through a process of reorganization. Section 3 discusses the Portuguese manufacturing data set we use in the paper and 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 4 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 5 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.

⁴Our results also relate to the cost pass-through literature given that a reorganization affects cost and, in turn, prices. As a result, in the paper we also calculate the cost-pass through for all firms (what we refer to as the unconditional measure) and for firms that change organization (conditional). We find that the unconditional cost pass-through estimates are similar to the ones in the literature, but that the estimates conditional on firms reorganizing are somewhat larger, as expected.

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

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

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 $F(z)$ with $F''(z) < 0$. 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, $n_L^1 = hn_L^0(1 - F(z_L^0))$, managers of layer one are needed. In general, managers in layer ℓ learn $[Z_L^{\ell-1}, Z_L^\ell]$ 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 $w(z_L^\ell)$ where $w'(z_L^\ell) > 0$ and $w''(z_L^\ell) \geq 0$. 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 layers⁵ at a prevailing wage schedule $w(\cdot)$, namely,

$$C_L(O; w) = \min_{\{n_L^\ell, z_L^\ell\}_{\ell=0}^L \geq 0} \sum_{\ell=0}^L n_L^\ell w(z_L^\ell) \quad (2)$$

⁵Throughout 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.

subject to

$$O \leq F(Z_L^L)n_L^0, \tag{3}$$

$$n_L^\ell = hn_L^0[1 - F(Z_L^{\ell-1})] \text{ for } L \geq \ell > 0, \tag{4}$$

$$n_L^L = 1. \tag{5}$$

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 below 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 thresholds⁶) 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 $\gamma = 1$).

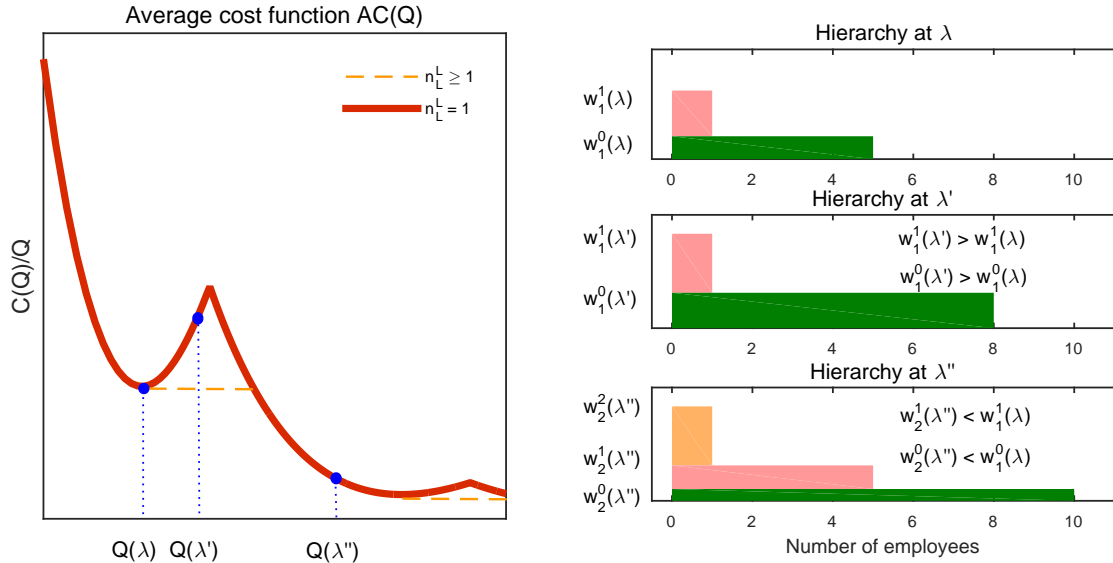
Consider the three dots in the figure, which correspond to firms that face different levels of demand as parametrized by λ .⁷ Suppose that after solving the corresponding profit maximization using the cost function above, a firm that faces a demand level of λ decides to produce $Q(\lambda)$ (or $q(\lambda)$ 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

⁶Note 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 .

⁷In 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.

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 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.⁸

⁸Alternatively, 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 $n_L^L = \epsilon$.

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 than 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.

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, $\pi(\bar{\lambda}, L) = \pi(\bar{\lambda}, L + 1) \geq 0$.

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 $\epsilon \rightarrow 0$, 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).

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.⁹ 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

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

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 chosen a quantity level associated with the same average cost but on the increasing segment of the average cost curve, i.e. $Q''(\bar{\lambda}, L+1) \geq Q_{L+1}^*$ such that

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

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

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

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

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

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

⁹To ease notation we drop from the proof, from now on, ε .

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

i.e. the profits associated with $Q'(\bar{\lambda}, L+1)$ are higher than those associated with $Q(\bar{\lambda}, L+1)$. 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 $\pi(\bar{\lambda}, L) = \pi(\bar{\lambda}, L+1)$,

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

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

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

or

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

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.

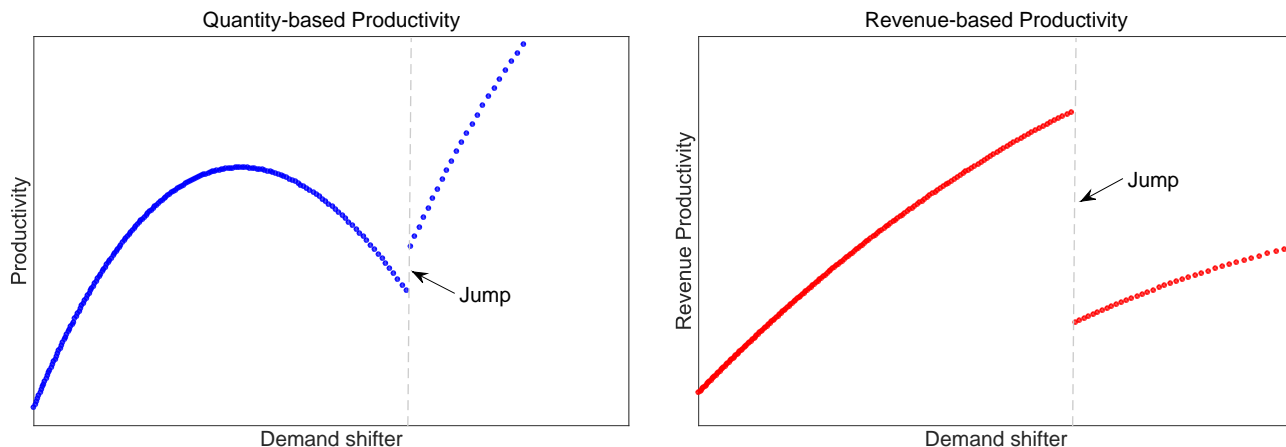
In sum, firms that add layers as a result of a marginal revenue shock increase their quantity discontinuously. The new organization is more productive at the new scale, resulting in an increase in quantity-based productivity, but the quantity expansion decreases price and revenue-based productivity.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

2.1.1 Some Portraits of Actual Reorganizations

The mechanism described above is naturally an abstraction of reality. To illustrate the way in which firms actually reorganize in the data, we present a series of examples of firms that go through this process of reorganization. We choose a variety of examples that includes firms in many industries, some that grow and some that decline. We start with 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 man-

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



agement 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).¹⁰ 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 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.

One issue with the previous example is that we do not know what caused the growth of this firm. Fortunately, our sample covers the period in which China entered the WTO. So we now present two more examples of firms producing in the “Textile and Apparel” industry. The reorganization of these firms was arguably triggered by an exogenous event, namely, the reductions in quotas that resulted from China’s entry into the WTO.¹¹

¹⁰We describe the precise methodology and data used to measure both types of productivity in detail in Section 4.

¹¹As a consequence of China joining the WTO a number of quotas that were imposed at the EU-level on Chinese imports—as well as on imports from other non-WTO countries—were removed. Later on, in Section 4.3.1, we describe in greater detail how we identify the shock and the implications that this shock had for the entire industry.

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

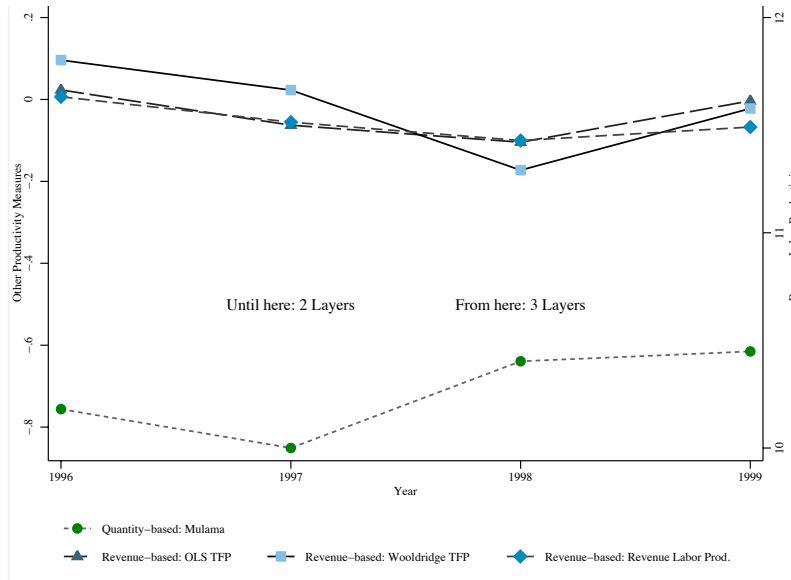
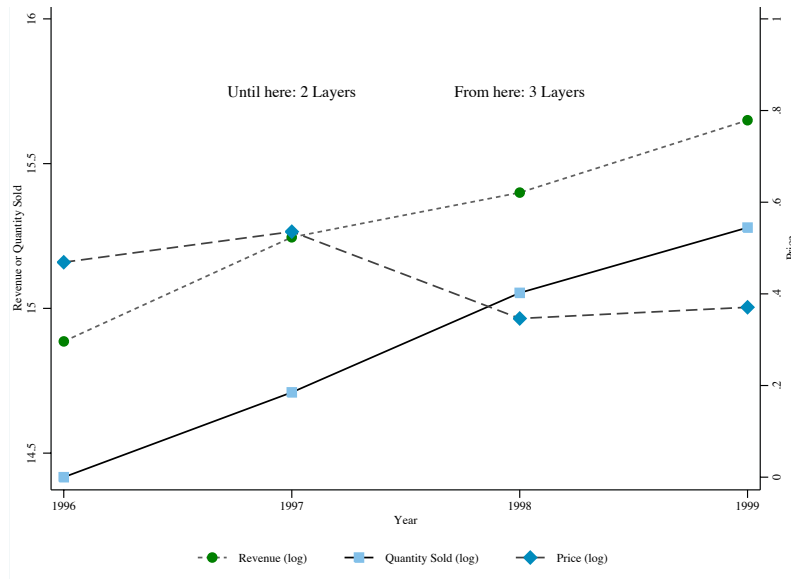


Figure 4: An Example of a Firm that Adds Layers: Output, Price, and Revenue



The first firm we analyze is one that was hit hard by the (quota) shock and that we already referred to in the introduction. The firm produces “Knitted and crocheted pullovers, cardigans, and similar articles” (Nace 1772). Between 2002 and 2005, as a result of the quota reduction, it downsizes rapidly. Table 1 illustrates the organization of the firm before and after the shock.¹² Labor force goes down from 37 to 10 employees.

¹²As we describe later, throughout the paper we use the variable `qualif` (see Table A.1 in Appendix A) to map occupations

Table 1: Textile and Apparel Firm Reorganization, Nace 1772 Example

Firm with 3 Layers (2004)				
Occupation	Layer 0	Layer 1	Layer 2	Layer 3
Managers			1	2
Technicians and Assoc. Professionals		1		
Clerks	2			
Crafts Workers	15		4	
Plant and Machine Operators	11			
Elementary Occupations	1			
Firm with 2 Layers (2005)				
Managers				
Technicians and Assoc. Professionals		1	1	
Clerks		1		
Crafts Workers	4			
Plant and Machine Operators	1		1	
Elementary Occupations	1			

Notes: Occupations correspond to ISCO-88 1-digit major groups.

The quantity sold by the firm declines by 50 percent, value added by 84 percent, and prices increase by 30 percent. Imported inputs double. We see that the firm reorganizes and decreases the number of management layers from 3 to 2. Accordingly, and as expected, the firm reduces quantity-based productivity by 53 percent and revenue-based productivity increases by 9.2 percent.

The reorganization of the firm takes a natural form. It fires the 3 managers it used to have (two in “production and operations” and one in “sales and marketing”).¹³ In lower layers, the firm fires its “fibre preparers” and “textile, leather pattern-makers and cutters” and now focuses on “sewers and embroiderers” (reduces the total number but hires a new one). Similarly, it fires a variety of machine operators to focus exclusively on “sewing-machine operators”. It also fires the one designer it used to employ. The result is the elimination of the top layer, and reductions in employment in the bottom layers. Essentially, the firm focuses on its top tasks and substitutes some of the others by producing less and importing more intermediate goods. Even though the firm is shrinking tremendously, the workforce that remains now earns more, as our model predicts, with increases in median wages of 73 percent in layer 2, 33 percent in layer 1 and 3 percent in layer 0.

Our second example of a firm affected by the quota is a larger firm producing “Woven fabrics” (Nace 1720). This firm also goes through a substantial downsizing from 1999 to 2000. Quantity sold decreases by 46 percent, value added by 30 percent, but prices rise by 13 percent. In the previous example we saw

to layers. However, for illustration purposes, while describing the reorganization of the firm we use the occupational variable *profissão* (which is built following ISCO-88). This variable allows us to talk about more concrete and detailed occupations like “Sewers and embroiderers”.

¹³Note that within each of the broad occupational categories that we present in the table there are several subcategories of occupations that can map to different layers. In Appendix A we present in greater detail how we map occupations to layers based on the tasks performed and skill requirements (*qualif*). For example, in 2004 the firm has two clerks, a statistical and finance clerk and a stock clerk. The statistical and finance clerk has a *qualif* of 60 which corresponds to semi-skilled professionals (with higher numbers representing lower skilled employees). Based on this *qualif* we assign it to layer 0. The stock clerk has a *qualif* of 71 which corresponds to non-skilled professionals. Based on this *qualif* we assign it to layer 0 as well. The stock clerk is “fired” in 2005. The remaining statistical and finance clerk changes *qualif* from 60 to 51 which corresponds to skilled professional. Based on this *qualif* we assign it to layer 1. That is, this clerk got a promotion to a more demanding job.

Table 2: Textile and Apparel Firm Reorganization, Nace 1720 Example

Firm with 3 Layers (1999)				
Occupation	Layer 0	Layer 1	Layer 2	Layer 3
Professionals				3
Technicians and Assoc. Professionals	1	5	2	
Clerks	14	10	2	
Crafts Workers	17			
Plant and Machine Operators	71	2	1	
Elementary Occupations	17			
Firm with 2 Layers (2000)				
Professionals			2	
Technicians and Assoc. Professionals	1	5	2	
Clerks	16	8	1	
Crafts Workers	15			
Plant and Machine Operators	49	3	1	
Elementary Occupations	17			

Notes: Occupations correspond to ISCO-88 1-digit major groups.

that the firm shrank by focusing on its core activities. In contrast, this firm reduces its product scope. It specializes in cotton fabrics (its core product) and drops the production of synthetic fabrics. This is achieved with a reduction in the number of layers of management from 3 to 2, and a 46 percent smaller labor force. Correspondingly, the firm’s quantity-based productivity decreases by 19 percent but its revenue-based productivity increases by 30 percent. Table 2 presents the organization of the firm before and after the reorganization.

The firm reduces the number of workers in the lowest layer by firing the workers that are not involved in the production process of the core product. The firm fires its “Fibre-preparing-, spinning- and winding-machine operators”, “Weaving- and knitting-machine operators”, “Bleaching-, dyeing- and cleaning-machine operators”, and “Steam-engine and boiler operators”. In addition, the firm reduces the number of designers (“Decorators and commercial designers”) from three, to one, to none within three years. Regarding the top layers of the firm, we see clear changes in its leading structure. In 1999 the top layer of the hierarchy includes 3 top management business professionals, specialized in accounting. In 2000 the firm drops the top layer. Layer 2, the new top layer, now focusses on dealing with less specialized tasks, including two middle management business professionals, and two administrative secretaries and related associate professionals—to “implement and support the communication, documentation and internal managerial coordination activities of an organizational unit to assist the head of unit” (ISCO 3411). As a result of the restructuring, the median wage in layer 0 goes up, by 7.5 percent, while in layers 1 and 2 they do not change much (reductions of 1.4 percent in median wages but an increase of 1 percent in the mean wages of layer 0).

These cases exemplified well the way in which the abstract mechanism highlighted by our theory works in practice. However, one concerned is that the way the restructuring took place could be particular to the textile and apparel industry and not present in other industries. Therefore, we finish this section by briefly presenting two other examples: one of a negative shock to a firm in the footwear industry and one of a positive shock to a firm in the cork industry (were Portugal is a main producer).¹⁴ In these cases we have

¹⁴Footwear and cork are two traditional Portuguese industries. For instance, footwear represents about 6 percent of Portuguese

Table 3: Footwear Firm Reorganization, Nace 19301352 Example

Firm with 3 Layers (1998)				
Occupation	Layer 0	Layer 1	Layer 2	Layer 3
Managers				1
Technicians and Assoc. Professionals		1		
Clerks		1		1
Crafts Workers	56	1	1	
Elementary Occupations	9			
Firm with 2 Layers (1999)				
Managers				
Technicians and Assoc. Professionals		1		
Clerks		1		
Crafts Workers	47		2	
Elementary Occupations	7			

Notes: Occupations correspond to ISCO-88 1-digit major groups.

Table 4: Cork Firm Reorganization, Nace 2052 Example

Firm with 1 Layer (2004)				
Occupation	Layer 0	Layer 1	Layer 2	Layer 3
Managers				
Clerks		1		
Crafts Workers	8	1		
Firm with 2 Layers (2005)				
Managers			2	
Clerks		1		
Crafts Workers	9			

Notes: Occupations correspond to ISCO-88 1-digit major groups.

not identified the exact source of the shock, but we observe similar, theory-consistent, behavior of firms as they expand or contract.

Consider a firm producing “Women’s town footwear with leather uppers” (Nace 19301352) that goes through a downsizing process from 1998 to 1999. The firm experienced a reduction in value added of 10 percent, reduced its labor force from 71 to 58 workers, and switched from 3 to 2 layers of management. Accordingly, the firm’s quantity-based productivity decreases by 17 percent, its revenue-based productivity increases by 9 percent, quantity sold decreases by 24 percent, and prices rise by 12 percent. Table 3 presents the organizational structure of the firm in 1998—the last year the firm has three layers of management—and in 1999—when the firm has 2 layers of management. The firm reorganizes by simplifying its management structure. The new organization has neither a manager nor a statistical and finance clerk. The firm also reduces the number of shoe makers (identified in the table as crafts workers). As a result of the restructuring, the median wage rises in all the pre-existing layers (by 3 percent in layer 2, 23 percent in layer 1, and 8 percent in layer 0).

Our final example studies a small firm producing “Manufacture of articles of cork, straw and plaiting materials” (Nace 2052) which goes through a growth spell between 2004 and 2005, experiencing a 3 percent increase in value added. The firm started with one layer of management and added another layer. Its labor force goes from 9 to 12 workers. As expected, the firm’s quantity-based productivity increases by

exports in the 1993-2009 period, while Portugal is the biggest producer of cork in the world.

6 percent, its revenue-based productivity decreases by 29 percent, quantity sold increases by 28 percent, and prices decreases by 6 percent. Table 4 portrays the organizational structure of the firm before and after the reorganization. The structure of the firm remains simple, with the only addition of a layer of management that includes two production and operations department managers. The small reinforcement of layer 0, where the number of craft workers—all of them "wood treaters"—rises from 8 to 9, hides a more substantial churning, with two wood treater leaving the firm and three new ones entering. As a result of the restructuring, the median wage decreases in all the pre-existing layers (by 1.4 percent in layer 1, and 7 percent in layer 0).

The examples above are illustrative, we believe, of the different forms that reorganizations take in practice. Sometimes firms focus or expand the set of production tasks performed, sometimes they restrict or increase the set of products produced, and sometimes they simply add or take away managerial structure to do less of more of the same. In all these cases, however, we find that the behavior of these firms exhibits the patterns we expect, even though these patterns are quite complicated and multidimensional. Not only do the firms reshuffle their labor force as predicted, but the wages they pay, as well as the implications for both types of productivity, are consistent with our mechanism. Of course, they are some exceptions, so the rest of the paper is dedicated to present systematic evidence of the ubiquitousness of these patterns 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 1995-2005.¹⁵ 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 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.¹⁶ Currently, the data set collects data on about 350,000 firms and 3 million

¹⁵Information for the year 2001 for the matched employer-employee dataset was not collected. Hence, our sample excludes the year 2001 (see Appendix A).

¹⁶Public administration and non-market services are excluded. *Quadros de Pessoal* has been used by, amongst others,

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 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.¹⁷

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).¹⁸

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.

¹⁷The 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.

¹⁸In our analysis, we also experimented with using the sample of single-product firms only. Results, available upon request,

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.¹⁹ 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. 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.²⁰

Table 5 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.

3.2 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. We focus here on the main findings and, for brevity, we relegate all the tables and figures with the exact results to Appendix B.

Firms with different numbers of layers are different. If we group firms by their number of management layers, firms with more layers are larger in terms of value added, hours, and that they pay on average higher wages (see Table B-1). In fact, the distributions of value added, employment, and the hourly wage by layer

are qualitatively identical and quantitatively very similar.

¹⁹Following 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 2nd 1978) which is not the ISCO.

²⁰One 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.

Table 5: Firm-level data description by year

Year	Firms	Mean			# of layers
		Value Added	Hours	Wage	
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.

for firms with more layers are shifted to the right and exhibit higher variance (see Figures B-1 to B-3). Thus, these results underscore our claim that the concept of layers we use is economically meaningful.

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. The implied hierarchical structure of firms is hierarchical in the majority of cases (Table B-2). The implied ranking holds for 76% of the cases when comparing any individual pair of layers. As for compensation, employees in lower layers command lower wages in the vast majority of cases (Table B-3). For example, the proportion of firms that exhibits a hierarchical ranking for any given bilateral comparison between layers is also greater than 75%. We conclude that, although with some exceptions, 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.²¹ In a given 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 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. To see this, we divided 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. First, we find that firms that either expand or contract substantially do so by reorganizing. This is the case both in terms of hours and value added. Furthermore, changes in either hours or value added seem to be symmetric, but with opposite sign, for firms that add or drop layers. After detrending, firms that add (drop) layers tend to pay higher (lower) average wages. However, once we focus on average wages

²¹Table B-4 presents a transition matrix across layers.

in preexisting layers wages decline (increase), as the theory predicts. So, in firms that add layers, 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).²²

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. Hence, we expect 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 should be positive. This prediction is confirmed for all elasticities except for one case where the estimate is not significant (see Tables B-6 and B-7). We conclude that firms that grow without reorganizing increase employment and wages in all layers.

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 (see Table B-8). 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.

4 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

²²All these results are presented in Table B-5.

better isolate reorganization events and ease comparability of an otherwise complex structure we break firms 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.²³ 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).²⁴ In Appendix G, we revisit all our results using an alternative grouping of firms based on their number of layers the first time we see them reorganize in the data.²⁵

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.

4.1 Revenue-based Productivity

The purpose of this section is to study the relationship between organization and revenue-based productivity. We start by showing that, for essentially all industries, adding (dropping) layers of management is associated with decreases (increases) in revenue productivity if we use simply value-added per worker, a measure of revenue-based productivity that does not depend on our structural assumptions. We then proceed to employ measures of revenue-based productivity that are much more refined.

²³To 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.

²⁴More specifically, we implement this with the `xtabond2` command in Stata.

²⁵The 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.

4.1.1 The Effect of Organization Across Industries: Some Simple Statistics

The arguments and examples presented so far indicate that when a firm receives a positive (negative) shock that makes it reorganize by adding (dropping) layers, its revenue-based productivity decreases (increases). Note, however, that this is the expected response only for firms that reorganize by changing the number of management layers. Firms that receive similar shocks but do not change layers, do not expand as much as a result of a positive shock, which implies that the price response is more muted and so revenue-based productivity increases due to the direct effect of the reduction in costs. We now show evidence of these patterns at the sectoral level.

Figure 5 Panel a shows the change in value-added per worker between 1996 and 2005 by industry if we condition on firms that do not reorganize. Clearly, for firms that grow in terms of sales value-added per worker increases as well. In contrast, firms that experience a decrease in total sales see their value-added per worker decline. The figure shows that all 19 industries exhibit this relationship. This is not surprising, after all revenue productivity and sales are positively related in many theories of the firm.

Figure 5: Reorganization and Value added per Worker

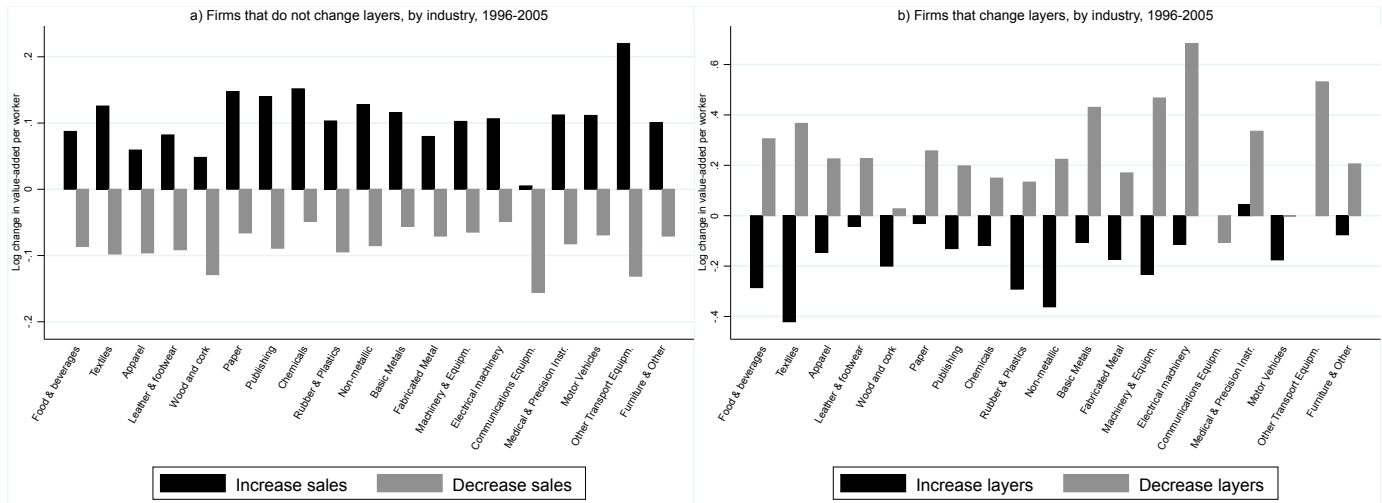


Figure 5 Panel b presents again the change in value-added per worker but now for firms that increase or decrease the number of layers (transition across layers). As predicted by our theory, but perhaps more surprising in light of the previous literature, in this case we see that firms that increase layers tend to decrease value-added per worker, and vice-versa for firms that drop layers. This is the case for all industries except “Communications Equipment”, “Medical and Precision Instruments” and “Other Transportation Equipment” where some of the effects are not significant. The switch in sign depending on whether a firm reorganizes or not is remarkable, given that increases (decreases) in sales are highly correlated with increases (decreases) in layers.

4.1.2 The Effects on Revenue TFP: Structural Estimation

These first set of results should help bring confidence about the response of revenue-based productivity when firms reorganize. Yet, 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

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

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

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

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 in standard data) while the denominator, $AC(O_{it}; w) = C(O_{it}; w)/O_{it}$, is the unit cost of the labor input (which is, by contrast, unobservable). Indeed, while average wages per worker are observable in standard data, $C(O_{it}; w)/O_{it}$ 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 by the price leads to an equation for revenue given by

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

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 $\epsilon > 0$. 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 $\Delta L_{it} \equiv L_{it} - L_{it-1}$:

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

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 4.3 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 Akerberg 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.²⁶ In particular,

²⁶Wooldridge (2009) builds on Olley and Pakes (1996), Levinsohn and Petrin (2003), and Akerberg 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).

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

$$va_{it} = \alpha'_O \ln C(O_{it}; w) + \alpha'_K k_{it} + \phi'_a g(k_{it-1}, m_{it-1}) + \beta' \Delta L_{it} + \nu_{ait}. \quad (11)$$

where va_{it} is value added and, for example, the coefficient α'_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

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

Equipped with \hat{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 \hat{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 D and E many of the results obtained with these alternative techniques. We also provide in Appendix D 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 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 6 provides our baseline results. The dependent variable is productivity at time t (\hat{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 6 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 6 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 6 closely matches our assumption about the productivity process (10)

Table 6: Wooldridge Revenue TFP. OLS

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.741 ^a (0.030)	0.769 ^a (0.032)	0.805 ^a (0.021)	0.785 ^a (0.017)
Change in layers	-0.068 ^a (0.011)	-0.108 ^a (0.016)		-0.079 ^a (0.008)
Constant	-0.006 (0.018)	-0.028 (0.036)	-0.018 (0.026)	-0.010 (0.014)
Observations	4,057	2,086	2,934	9,677
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 $p < 0.1$

Table 7: Wooldridge Revenue TFP. Firm-product-sequence FE. Dynamic panel

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.373 ^a (0.061)	0.436 ^a (0.085)	0.518 ^a (0.072)	0.462 ^a (0.045)
Change in layers	-0.036 ^a (0.009)	-0.087 ^a (0.012)		-0.056 ^a (0.006)
Constant	0.049 (0.032)	-0.016 (0.034)	0.012 (0.034)	0.019 (0.016)
Observations	4,057	2,086	2,934	9,677
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 $p < 0.1$

in that—besides the issue of endogeneity we deal with in Section 4.3—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 7 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 D and E. The two sets of results are qualitatively identical and quantitatively very similar.

Table 7 portrays a picture very similar to the one emerging from Table 6.²⁷ While the effect of changing

²⁷As far as test diagnostic is concerned, system GMM estimations in Table 7 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 8: Revenue Labor Productivity. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.772 ^a (0.020)	0.898 ^a (0.014)	0.914 ^a (0.014)	0.855 ^a (0.011)
Change in layers	-0.118 ^a (0.015)	-0.181 ^a (0.024)		-0.132 ^a (0.012)
Constant	2.717 ^a (0.240)	1.185 ^a (0.165)	0.971 ^a (0.157)	1.705 ^a (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 $p < 0.1$

layers is now a bit smaller across the board, it is negative and significant in all specifications. At the same time Table 7 indicates that decreasing the number of layers has a bigger impact on productivity 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 7 as being more accurate than those in Table 6.

Last but not least we present in Table 8 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 D and E 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 8 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.

4.2 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 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 4.3 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 4.3. Before moving forward it is important to highlight that, for 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.

4.2.1 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

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

and

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

where $MC(O_{it}; w)$ 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 $O_{it}MC(O_{it}; w)$ is the total expenditure on the labor input when we allow $n_L^t \geq \epsilon$, 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

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

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,

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

where $z_{1it} = k_{it}$, $z_{2it} = LHS_{it-1}$, $z_{3it} = k_{it-1}$, $z_{4it} = \frac{r_{it-1}}{s_{Mit-1}}$, $z_{5it} = q_{it-1}$, $u_{it} = (\nu_{ait} + \nu_{\lambda it})/\alpha_M$. Appendix C.1 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 $b_6 = \gamma$.²⁸ Note that since k_{it} is predetermined in t we can instrument for z_{6it} with k_{it} . This is what

²⁸Note 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

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.

4.2.2 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 4.1, while further experimenting in Sections 5.2.3 and 5.2.4 with other approaches, in order to solve the two very same 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 nor 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 C.1 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

right-hand side variables.

Table 9: Quantity TFP. OLS

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.892 ^a (0.014)	0.873 ^a (0.015)	0.905 ^a (0.013)	0.895 ^a (0.008)
Change in layers	0.029 ^a (0.011)	0.032 ^b (0.014)		0.026 ^a (0.007)
Constant	0.926 ^a (0.048)	0.113 ^a (0.035)	0.320 ^b (0.131)	0.081 ^b (0.033)
Observations	4,171	2,734	3,055	9,960
Adjusted R^2	0.781	0.748	0.804	0.782

Firm-level clustered standard errors in parentheses

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

and fixed effects. We deal with endogeneity in Section 4.3. Table 9 provides OLS estimation results. All of the 3 estimates of β in Table 9 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 10 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 10. We report below estimates obtained with the dynamic panel data system GMM estimator²⁹ and show in Appendix F almost identical results obtained with the within estimator. Estimates in Table 10 are in line with OLS results in Table 9. 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 the result of some measurement error magnified when first-differencing the data.

4.2.3 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

²⁹Note that the same observation we made in Footnote 19 applies for the case of Table 10.

Table 10: Quantity TFP. Firm-product-sequence FE. Dynamic panel data

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.622 ^a (0.090)	0.712 ^a (0.084)	0.641 ^a (0.065)	0.678 ^a (0.045)
Change in layers	0.029 ^a (0.011)	0.016 (0.014)		0.018 ^b (0.007)
Constant	0.019 (0.222)	0.150 (0.092)	0.409 (0.274)	0.081 ^{ac} (0.047)
Observations	4,171	2,734	3,055	9,960
Number of fixed effects	1,673	1,280	1,298	4,251
Adjusted R^2				
AR(2) Test Stat	1.101	0.143	2.372	2.234
P-value AR(2)	0.271	0.886	0.018	0.025

Firm-level clustered standard errors in parentheses

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

specifically, one could assume for quantity productivity:

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

and for revenue productivity

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

We provide in Appendices D (for revenue productivity) and F (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.

4.2.4 The Effect of Organization on Prices

As we have emphasized, the main difference between the impact of a reorganization on revenue-based and quantity-based productivity is its effect on prices. Given this, one obvious reaction is to try to look directly at the effect of reorganizations on prices. While it is important to note that we do not actually observe prices in our data –we have information on quantities sold and related revenues– we can still construct unit

values (revenue over quantity) in lieu of actual prices and study how they change as firms reorganize.

There are several potential problems related to using unit values as a measure of prices to measure relative changes in revenue and quantity-based productivity. 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 the relative changes in a firm's quantity-based and revenue-based productivity.

In Appendix I we measure the effect of a firm's reorganization on our measure of prices. We find that the results using prices are consistent with our main results but are, as expected for this constructed measure, more noisy.

4.3 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.³⁰

³⁰More 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

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).³¹ 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.³² 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 captured 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

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

and for quantity productivity

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

We show in Appendix C.1 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.³³ 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

meet the requirements of good instruments under the assumptions of our model.

³¹In Appendix A we describe in greater detail how we follow the literature to construct these instruments.

³²Of 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.

³³In 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.

Table 11: Wooldridge Revenue TFP. Instrumental Variable. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.921 ^a (0.013)	0.917 ^a (0.021)	0.912 ^a (0.016)	0.920 ^a (0.009)
Change in layers	-0.070 ^a (0.021)	-0.082 ^a (0.028)		-0.072 ^a (0.017)
Change in quantity	0.765 ^b (0.374)	0.792 ^b (0.343)	-0.230 (0.255)	0.395 (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 $p < 0.1$

Table 12: Quantity TFP. Instrumental Variable. Both change in layers and change in quantity as endogenous variables

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.953 ^a (0.014)	0.906 ^a (0.019)	0.967 ^a (0.017)	0.955 ^a (0.012)
Change in layers	0.054 ^b (0.021)	0.053 ^c (0.029)		0.077 ^a (0.020)
Change in quantity	0.034 (0.058)	-0.032 (0.133)	0.139 (0.107)	0.050 (0.061)
Observations	4,171	2,734	3,055	9,960
Kleibergen-Paap stat.	45.1	341.4	39.4	594.0
Adjusted R^2	0.855	0.767	0.902	0.872

Firm-level clustered standard errors in parentheses

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

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 11 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.³⁴ 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

³⁴The first stage estimates for tables 11 and 12 are presented in Appendix J.

Table 12 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 C.1 presents further results using our IV strategy.³⁵

Finally, in order to provide a further validation of our results, we estimated quantity-based productivity using the estimation procedure described in De Loecker et al. (2016). Table H-5, in Appendix H presents the results. We find that when we pull all the observations together, the effect of a change in layers on quantity-based productivity is 3 percent and significant. A slightly lower value compared to the results using MULAMA.

4.3.1 A Case Study: Textile and Apparel

As a final attempt to identify a causal effect of reorganization, we now use the textile sector as an example of an industry that experienced an exogenous shock. The shock we study is the changes in quotas applied to the “Textile and Apparel” industry associated to China’s entry into the WTO. This shock provides a cleaner, albeit more narrow in scope, identification of the effect of organization on productivity.

We use the data on reductions in quotas across sub-industries and follow the methodology in Bloom, Draca, and Van Reenen (2016)³⁶ who calculate that these reduction in quotas created a 240% increase in Chinese imports in that industry. This large EU-wide shock affected Portuguese firms in the “Textile and Apparel” industry differently depending on the set of products they produce. Firms that produced products that were protected by a quota, experienced a 24% negative demand shock (as measured by the demand metric we calculate in the main text), an 11% reduction in actual sales, and an 11% reduction in employment (all significant at the 1% level).

These firms also reduced the numbers of layers. We use the firm-level variation in the reductions in quotas as an instrument for the change in layers in a first stage of a two-stage-least-squares (2SLS) specification. We compute for each 6-digit Prodcom product category, the proportion of the more detailed 6-digit HS products that were covered by a quota, weighting each HS6 product by its share of EU15 imports over the period 1995-1997. Then, for each firm, we measure the firm-level exposure to the quota by adding each of the 6-digit Prodcom products weighted by the initial share of sales of the firm in that product.³⁷ We label this variable $QuotaCoverage_i$, and focus on the period 2000-2005. Figure K-1 in Appendix K shows that the number of layers tend to increase progressively for firms that were not affected by the quota removals,

³⁵We also investigated whether our results are affected if we restrict the sample to firms that are never foreign-owned at any point in time in our dataset. We find that our results carry through and point estimates are virtually unaffected. Similarly, it would be interesting to see if family-owned or managed firms behave differently. Unfortunately our dataset does not include this information.

³⁶The underlying identifying assumption of this strategy is that unobserved demand/technology shocks are uncorrelated with the strength of quotas to non-WTO countries (like China) in 2000. Since these quotas were built up from the 1950s, and their phased abolition negotiated in the late 1980s was in preparation for the Uruguay Round, Bloom, Draca, and Van Reenen (2016) conclude that this seems like a plausible assumption.

³⁷As in the rest of the paper, we refer as a firm to a two-digit Prodcom product within an enterprise.

while it decreases for firms that were affected by the quota removal. We instrument the change in the number of management layers with the $QuotaCoverage_i$, with the lagged number of layers, and with the stock of capital of the firm at the initial period of analysis. Given that the quota removal might be more important if it affects the core product of the firm, we included as an additional instrument the squared value of $QuotaCoverage_i$. Overall, we find that the instruments have predictive power and in Table K-1 in Appendix K we present the results of the first stage.

Table 13: Textile and Apparel, OLS and IV estimates

VARIABLES	Revenue TFP	Quantity TFP	IV estimates	
			Revenue TFP	Quantity TFP
Change in number of layers	-0.070^a (0.031)	0.043 (0.029)	-0.194^a (0.058)	0.128^c (0.071)
Constant	0.047 (0.039)	-0.037 (0.034)	-0.072 ^a (0.025)	-0.021 (0.027)
Observations	831	831	831	831
Kleibergen-Paap stat.			63.12	63.12

Firm-product-level clustered standard errors in parentheses

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

Table 13 reports IV estimates of the effect of the change in the number of layers on either revenue or quantity-based productivity. The first two columns report the results from a simple OLS specification where changes in layers are not instrumented and the last two columns presents the IV estimates. We find in both specifications that firms that reduce layers exhibit an increase in revenue-based productivity (significant at 1%) and a reduction in quantity-based productivity (significant at 10% for the IV). The results are consistent with the main claim of our paper, significant, and quite large. When focusing on the firms that experienced the shock, the IV results show that in this industry reducing a layer increases revenue-based productivity by about 19% and reduces quantity-based productivity by 13%. Without instrumenting we find that these results are dampened, as we would expect in the presence of reverse causality (particularly for revenue productivity). The results are also larger than for the whole manufacturing sector. This might be the result of the tighter identification of the shock, or of the particular characteristics of the textile sector. Firms in the textile sector are larger and more labor intensive than firms in the rest of manufacturing.

In sum, throughout our investigation we did not find any significant evidence to falsify the hypothesis proposed by the knowledge-based hierarchy model. All the significant evidence was in line with the main implications. Hence, we conclude that when firms receive an exogenous shock that makes them reorganize, both quantity-based and revenue-based productivity are significantly affected. On average for the whole manufacturing sector, 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.

4.3.2 Cost Pass-through Conditional on Reorganization

One way to think about the price responses implied by our results above is through the pass-through of a change in cost into prices. A simple calculation taking the ratio of the responses of revenue-based and quantity-based productivity to a change in layers delivers a cost pass-through that is around, but sometimes clearly above, one (1.30, 1.55 and 0.94 for firms that add, drop, or all that reorganize according to Tables 11 and 12). These numbers might seem high relative to other studies of cost pass-through that in general find values between 0.6 and 0.9. However, note that this calculation measures the cost pass-through conditional on a reorganization. This conditional pass-through has never been estimated before and so has no direct counterpart in the literature. In order to compare the cost pass-through into prices in our data to the estimations in the literature, we need to instead calculate an unconditional measure. In doing so, we follow two approaches.

First, we use Portuguese trade data to study the effect of exchange rate shocks on export behavior of multi-product firms, following the recent approach of Chatterjee, Dix-Carneiro, and Vichyanond (2013). We find an import price elasticity to the real exchange rate of 0.85, which is very close to what that study finds for Brazil. Berman, Martin, and Mayer (2012) find 0.83 with firm-level French data, while Campa and Goldberg (2010) find 0.64 with country- and industry-level OECD data. Therefore, our findings for this period in Portugal are clearly in line with the literature.

These results use export prices and not the Prodcop-based prices we use in our main analysis. So, as an additional exercise, we compute the price response of changes in quantity-based productivity (obtained using the procedure in our main exercise). We find almost identical elasticities with respect to cost changes (we can do the estimation separately for multiproduct and single product firms and find price elasticities to quantity-based productivity of 0.86 and 0.81 respectively, exactly in line with the literature).

Why do we obtain results that seem to suggest large pass-through? The key is that our results are not measuring average responses of prices to changes in costs or demand. They are measuring changes in prices (or revenue-based productivity) conditional on changes in layers. That is, a cost or demand shock can be quite small, but it might trigger a reorganization since the firm was right at the threshold that determines the decision to reorganize. The reorganization then changes the firm size substantially which results in a large change in prices (as we argue in the main text). As a result, the associated pass-through will seem too large because the original shock was small relative to the change in prices due to the reorganization (even the augmented shock, once we take into account the endogenous effect on quantity-based productivity of the reorganization, will seem small). Given that the literature has only calculated average pass-throughs without conditioning on shocks that trigger a reorganization, our results are not directly comparable with the literature and predictably somewhat larger. However, as we discussed above, once we calculate the unconditional pass-through we obtain exactly the same numbers others have computed.

Table 14: Change in Quantity TFP due to Reorganization

Percentiles	Firms that increase layers		Firms that reduce layers	
	Overall change	Due to reorganization	Overall change	Due to reorganization
10%	-0.562	0.064	-0.633	-0.134
25%	-0.193	0.070	-0.304	-0.077
50%	0.057	0.073	-0.021	-0.077
75%	0.342	0.077	0.266	-0.071
90%	0.739	0.138	0.795	-0.067
Mean	0.065	0.083	-0.010	-0.082
Observations	817	817	466	466

4.4 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

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

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. Note that, because of mean-reversion, the second and third component explain more than 100% of the overall change in productivity. We now explore how large is the second term, the change in productivity due to a reorganization, relative to the total.

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 in column 4 of Table 12 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 14 present the distribution of the overall changes in productivity and the change in productivity due to changes in layers.³⁸ 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.

³⁸The unit of observation is actually a firm-product and we allow $t - T$ and T to vary across firm-product pairs.

The results are stark. On average, or for the median firm, the increase in productivity due to reorganization explains more than the total increase in overall mean 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 more than the aggregate mean variation. The result is that reorganization can account for an increase in quantity-based productivity, when firms reorganize by adding layers, of about 8.3% while the average increase in productivity for these firms was 6.5%. Similarly, when firms reduce the number of layers, reorganization accounts for a 8.2% 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 change in productivity of expanding and downsizing firms! These results underscore the importance of the reorganization of firms as a source of aggregate productivity gains in the economy.

5 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 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 build 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.

We also provide new evidence on how firms change prices conditional on changes in layers. These results relate to a large body of literature trying to underscore the magnitude of cost pass-through into prices. While our conditional results are larger than the ones found in this literature, once we calculate the unconditional pass-through we obtain exactly the same numbers others have computed in similar datasets. Hence, conditioning on whether or not a firm has reorganized is important to understand the pricing decisions of firms.

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.³⁹ This, among other factors, could explain why firms in developing countries tend to grow less rapidly (Hsieh and Klenow, 2014).

³⁹See Bloom et al. (2013) for some evidence on potential impediments in India.

References

- [1] Akerberg, D. A., K. Caves, and G. Frazer, 2015. "Identification properties of recent production function estimators." *Econometrica*, 83:6, 2411-2451.
- [2] Arellano, M. and Bover, O., 1995. "Another look at the instrumental variable estimation of error-components models." *Journal of econometrics*, 68:1, 29-51.
- [3] Berman, N., P. Martin, and T. Mayer, 2012. "How Do Different Exporters React to Exchange Rate Changes?." *Quarterly Journal of Economics*, 127:1, 437-92.
- [4] Berry, S. J. Levinsohn, and A. Pakes, 1995. "Automobile Prices in Market Equilibrium." *Econometrica*, 63:4, 841-890.
- [5] Bertrand, M., 2004. "From the invisible handshake to the invisible hand? How import competition changes the employment relationship." *Journal of Labor Economics*, 22:4, pp.723–765.
- [6] Bilir, L.K. and Morales, E., 2016. "The Impact of Innovation in the Multinational Firm." National Bureau of Economic Research, Working paper 22160.
- [7] Blanchard, O. and Portugal, P., 2001. "What Hides Behind an Unemployment Rate: Comparing Portuguese and U.S. Labor Markets." *American Economic Review*, 91:1, 187-207.
- [8] Bloom, N., B. Eifert, D. McKenzie, A. Mahajan, and J. Roberts, 2013. "Does Management Matter: Evidence from India." *Quarterly Journal of Economics*, 128:1, 1-51.
- [9] Bloom, N., M. Draca, and J. Van Reenen, 2016. "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, It and Productivity." *The Review of Economic Studies*, 83:1, 87-117.
- [10] Cabral, L. and Mata, J., 2003. "On the Evolution of the Firm Size Distribution: Facts and Theory." *American Economic Review*, 93:4, 1075-1090.
- [11] Campa, J. M., and L. S. Goldberg, 2010. "The Sensitivity of the CPI to Exchange Rates: Distribution Margins, Imported Inputs, and Trade Exposure." *Review of Economics and Statistics*, 92:2, 392-407.
- [12] Caliendo, L., Monte, F., and Rossi-Hansberg, E., 2015. "The Anatomy of French Production Hierarchies." *Journal of Political Economy*, 123:4, 809-852.
- [13] Caliendo, L. and E. Rossi-Hansberg, 2012. "The Impact of Trade on Organization and Productivity." *Quarterly Journal of Economics*, 127:3, 1393-1467.
- [14] Chatterjee, A., R. Dix-Carneiro, and J. Vichyanond, 2013. "Multi-Product Firms and Exchange Rate Fluctuations." *American Economic Journal: Economic Policy*, 5:2, 77-110.
- [15] De Loecker, J. and F. Warzynski, 2012. "Markups and Firm-level Export Status." *American Economic Review*, 102:6, 2437-2471.
- [16] De Loecker, J., Goldberg, P.K., Khandelwal, A.K. and N. Pavcnik, 2016. "Prices, Markups, and Trade Reform." *Econometrica*, 84:2, 445-510.

- [17] Foster, L., Haltiwanger, J. and C. Syverson, 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?." *American Economic Review*, 98:1, 394-425.
- [18] Friedrich, B.U. 2015. "Trade Shocks, Firm Hierarchies and Wage Inequality." Yale University, mimeo.
- [19] Forlani, E., Martin, R., Mion, G. and Muuls, M., 2015 "Unraveling Firms: Demand, Productivity and Markups Heterogeneity." CEPR Discussion Papers 11058.
- [20] Garicano, L., 2000. "Hierarchies and the Organization of Knowledge in Production." *Journal of Political Economy*, 108:5, 874-904.
- [21] Garicano, L. and E. Rossi-Hansberg, 2006. "Organization and Inequality in a Knowledge Economy." *Quarterly Journal of Economics*, 121:4, 1383-1435.
- [22] Garicano, L. and E. Rossi-Hansberg, 2015. "Knowledge-based Hierarchies: Using Organizations to Understand the Economy." *Annual Reviews of Economics*, 7, 1-30.
- [23] Garcia-Marin, A. and N. Voigtländer, 2014. "Exporting and Plant-Level Efficiency Gains: It's in the Measure." NBER Working Paper No. 19033.
- [24] Hsieh, C. and P. Klenow, 2014. "The Life Cycle of Plants in India and Mexico." *Quarterly Journal of Economics*, 129:3, 1335-1384..
- [25] Klette, T. J. and Griliches, Z., 1996. "The inconsistency of common scale estimators when output prices are unobserved and endogenous." *Journal of Applied Econometrics* 11, 343-361.
- [26] Levinsohn, J. and Petrin, A., 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *The Review of Economic Studies*, 70:2, 317-341.
- [27] Marschak, J. and Andrews, W., 1944. "Random simultaneous equations and the theory of production." *Econometrica* 12, 143-205.
- [28] Mion, G. and Opromolla, L., 2014. "Managers' Mobility, Trade Performance, and Wages." *Journal of International Economics*, 94:1, 85-101.
- [29] Olley, S. and A. Pakes, 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica*, 64:6, 1263-97.
- [30] Park, A., Yang, D., Shi, X. and Jiang, Y., 2010. "Exporting and firm performance: Chinese exporters and the Asian financial crisis." *The Review of Economics and Statistics*, 92:4, pp.822-842.
- [31] Revenga, A.L., 1992. "Exporting jobs?: The impact of import competition on employment and wages in US manufacturing." *The Quarterly Journal of Economics*, 107:1, pp.255-284.
- [32] Rosen, S., 1982. "Authority, Control, and the Distribution of Earnings." *The Bell Journal of Economics*, 13:2, 311-323.
- [33] Tåg, J. 2013. "Production Hierarchies in Sweden." *Economics Letters* 121:2, 210-213.
- [34] Wooldridge, J.M. 2009. "On estimating firm-level production functions using proxy variables to control for unobservables." *Economics Letters* 104:3, 112-114.

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.⁴⁰ 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 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

⁴⁰From 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.

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:

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

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 (*qualif*). 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 5: 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 B-1: Table B-1 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 B-2 and B-3: Table B-2 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 $l = 0, \dots, L - 1$ 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 $N_L^l \geq N_L^{l+1} \quad \forall l = 0, \dots, L - 1$, 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 $l = 0, \dots, L - 1$ (second to fourth column).

Table B-3 is the same as Table B-2 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 B-4: Table B-4 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 ($L = 0, \dots, 3$) in any year from 1996 to 2004, the columns report the fraction of firms that have layers $0, \dots, 3$ 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 B-5: 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 B-6: 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 B-7: 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 B-8: This table shows estimates of the average log change in normalized hours and 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 $l = 0, \dots, \min\{L, L'\}$. $d \ln n_{Lit}^l$ 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. $d \ln w_{Lit}^l$ 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 6: The data underlying Table 6 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 6 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 year and industry dummies. Firm-level clustered standard errors are in parentheses. The last column of Table 6 shows estimates of a regression that pools all types of sequences.

Table 7: Table 7 shows estimates of the same type of regressions described for Tables 6 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 8: Table 8 shows estimates of the same type of regressions described for Table 6 and 7. The only difference being that the dependent variable is (log) revenue labor productivity.

Table 9 and Table 10: This set of Tables show estimates of the same type of regressions described for Tables 6 and 7. 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 4.2.2. 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 11 and Table 12: 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 B-1, B-2, and B-3: These figures report kernel density estimates of the distribution of log value added (Figure B-1), log hours worked (Figure B-2) and log hourly wage (Figure B-3) by number of layers in the firm. One density is estimated for each group of firms with the same number of layers.

B Portuguese Production Hierarchies: 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.

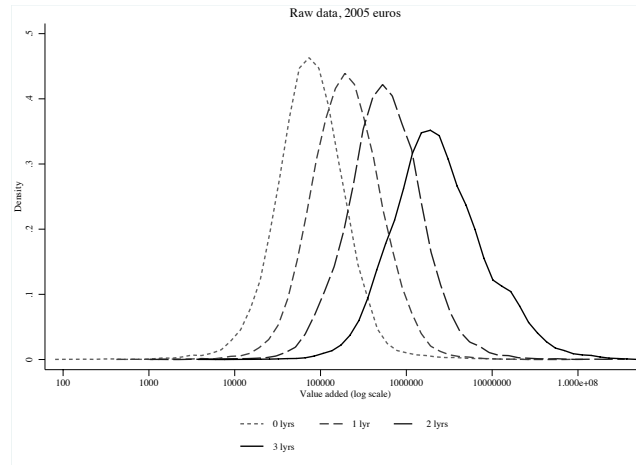
Table B-1: Firm-level data description by number of layers

# of layers	Firm-years	Mean			Median
		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 B-1 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 B-1

Figure B-1: Value Added Density



to B-3 present the distributions of value added, employment and the hourly wage by layer. The distributions are clearly ordered. In Figure B-2 the modes in the distribution of hours corresponds to the number of hours of one full-time employee, two full-time employees, etc. The peaks presented in firms with zero number of layers corresponds to the number of hours of discrete numbers of full time workers. This is also appreciated, although to a lesser degree in firms with one management layer. For a similar depiction of how hours are distributed for firms with different number of layers please see Figure 3 in Caliendo et al. (2015). The figures show that firms with different numbers of layers are in fact very different.

Table B-2 shows that the implied hierarchical structure of firms is hierarchical in the majority of cases.

Figure B-2: Employment (Hours) Density

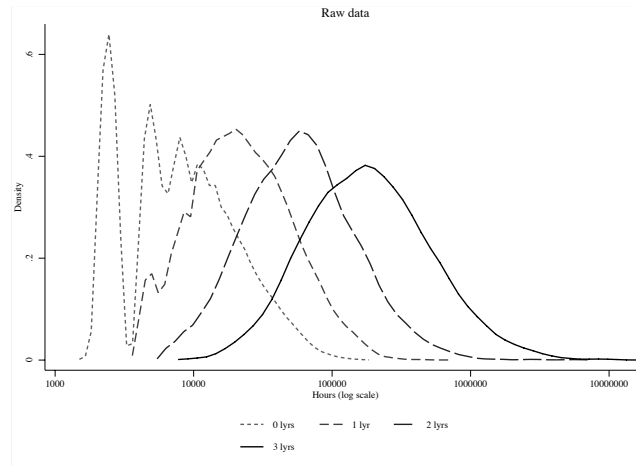


Figure B-3: Hourly Wage Density

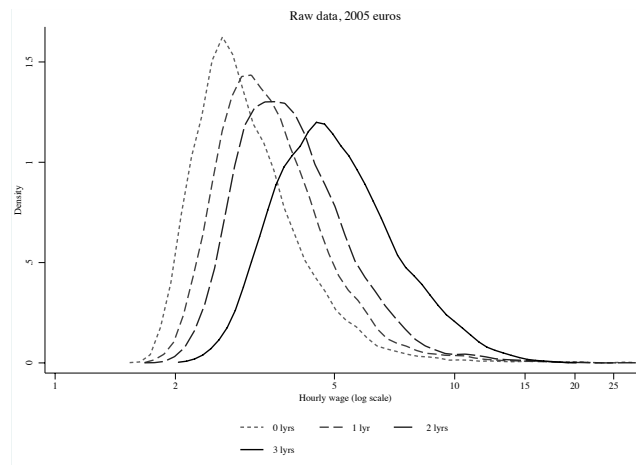


Table B-3 shows that lower layers command lower wages in the vast majority of cases. Table B-4 presents a transition matrix across layers. In Table B-5 we divide firms depending on whether they add, do not change, or drop layers, and present measured changes in the total number of hours, number of hours 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. Tables B-6 and B-7 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. Table B-8 shows 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.

Table B-2: 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.

Table B-3: 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

C 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 C.1), for the MULAMA procedure with change in layers (Appendix C.2), and for the MULAMA procedure with change in layers and quantity (Appendix C.3). In Appendix C.4 we also provide an extension of the Wooldridge (2009) revenue productivity methodology to account for changes in layers and quantities.

C.1 Baseline MULAMA

Demand in log is given by

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

the markup then is

$$\mu_{it} = \frac{\eta_{it}}{\eta_{it} - 1}. \quad (2)$$

The production function in log is

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

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

$$a_{it} = \phi_a a_{it-1} + \nu_{ait}, \quad (4)$$

$$\lambda_{it} = \phi_\lambda \lambda_{it-1} + \nu_{\lambda it}. \quad (5)$$

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

$$\frac{\partial C_i}{\partial Q_i} = \frac{1}{\alpha_O + \alpha_M} \frac{C_i}{Q_i} \quad (6)$$

Table B-4: Distribution of layers at $t + 1$ conditional on layers at t

	# of layers at $t + 1$						Total
	Exit	0	1	2	3		
	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
# of layers at t	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

Table B-5: 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 $p < 0.1$.

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

$$r_{it} = \frac{1}{\mu_{it}} (q_{it} + \lambda_{it}). \quad (7)$$

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

$$\frac{1}{\mu_{it}} = \frac{s_{Oit}}{\alpha_O} = \frac{s_{Mit}}{\alpha_L}. \quad (8)$$

First stage

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

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

then substituting this expression into (7)

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

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

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

Table B-6: 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 B-7: 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.

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 (7) note that

$$\lambda_{it-1} = \mu_{it-1} r_{it-1} - q_{it-1}, \quad (11)$$

then using this expression into (5) we obtain

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

Now from (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 (11) we get

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

and after substituting this expression in (4),

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

Table B-8: $d \ln n_{Lit}^\ell$ and $d \ln w_{Lit}^\ell$ for firms that transition

# of layers		Layer	$d \ln n_{Lit}^\ell$	$d \ln w_{Lit}^\ell$	# observations
before	after				
0	1	0	1.2777 ^a	0.0062	1,614
0	2	0	1.6705 ^a	0.0207	218
0	3	0	2.3055 ^a	-1.1878 ^a	37
1	0	0	-1.2304 ^a	0.0557 ^a	1,275
1	2	0	0.5178 ^a	0.0038	1,410
1	2	1	0.4920 ^a	-0.0624 ^a	1,410
1	3	0	0.9402 ^a	-0.0230 ^a	188
1	3	1	0.8367 ^a	-0.1710 ^a	188
2	0	0	-1.6449 ^a	0.0692 ^a	150
2	1	0	-0.5645 ^a	0.0373 ^a	1,215
2	1	1	-0.5060 ^a	0.1192 ^a	1,215
2	3	0	0.6806 ^a	-0.0015	1,520
2	3	1	0.7098 ^a	-0.0113 ^b	1,520
2	3	2	0.6340 ^a	-0.0676 ^a	1,520
3	0	0	-2.5187 ^a	0.2673 ^a	38
3	1	0	-0.9772 ^a	0.0691 ^a	149
3	1	1	-0.8636 ^a	0.1672 ^a	149
3	2	0	-0.7977 ^a	0.0313 ^a	1,312
3	2	1	-0.7532 ^a	0.0467 ^a	1,312
3	2	2	-0.6465 ^a	0.1114 ^a	1,312

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

Using (13) and (12) into (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 (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 (4) and (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 $b_6 = \gamma$.

C.2 MULAMA with Change in Layers

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

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

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

The processes for productivity and demand shocks are

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

$$\lambda_{it} = \phi_\lambda \lambda_{it-1} + \nu_{\lambda it}, \quad (16)$$

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

$$\frac{\partial C_{it}}{\partial Q_{it}} = \frac{1}{\alpha_O + \alpha_M} \frac{C_{it}}{Q_{it}}. \quad (17)$$

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

$$r_{it} = \frac{1}{\mu_{it}} (q_{it} + \lambda_{it}). \quad (18)$$

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

$$\frac{1}{\mu_{it}} = \frac{s_{Mit}}{\alpha_M} = \frac{s_{Oit}}{\alpha_O}. \quad (19)$$

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

Using (14) and (15) one obtains:

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

then substituting this expression into (18):

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

First stage

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

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

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

$$\lambda_{it-1} = \mu_{it-1} r_{it-1} - q_{it-1}, \quad (22)$$

then using this expression into (16) we obtain:

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

Now from (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 (22) we get:

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

and after substituting this expression in (15)

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

Using (24) and (23) into (21) we obtain:

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

that we can rewrite as

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

where $z_{1it}=k_{it}$, $z_{2it}=LHS_{it-1}$, $z_{3it}=k_{it-1}$, $z_{4it}=\frac{r_{it-1}}{s_{Mit-1}}$, $z_{5it}=q_{it-1}$, $z_{6it}=\Delta L_{it}$, $u_{it}=\frac{1}{\alpha_M} (\nu_{ait} + \nu_{\lambda it})$ as well as $b_1=\frac{\gamma}{\alpha_M}$, $b_2=\phi_a$, $b_3=-\gamma \frac{\phi_a}{\alpha_M}$, $b_4=(\phi_\lambda - \phi_a)$, $b_5=\frac{1}{\alpha_M} (\phi_a - \phi_\lambda)$ 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 (20) and (24) we have that log output is given by

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

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

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

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

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

where:

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

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

$$\hat{a}_{it} = q_{it} - \frac{\hat{\gamma}}{\hat{\beta}} \frac{s_{Oit}}{s_{Mit}} (\ln WB_{it} - k_{it}) - \frac{\hat{\gamma}}{\hat{\beta}} (m_{it} - k_{it}) - \hat{\gamma} k_{it} \\ \hat{\mu}_{it} = \frac{\hat{\gamma}}{\hat{\beta} s_{Mit}} \text{ and } \hat{\lambda}_{it} = \frac{\hat{\gamma}}{\hat{\beta} s_{Mit}} r_{it} - q_{it}.$$

C.3 MULAMA with Change in Layers and Quantity

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

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

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

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

$$\lambda_{it} = \phi_\lambda \lambda_{it-1} + \nu_{\lambda it}, \quad (30)$$

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 (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

$$\frac{\partial C_{it}}{\partial Q_{it}} = \frac{1 - \phi_q}{\alpha_O + \alpha_M} \frac{C_{it}}{Q_{it}}. \quad (31)$$

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

$$r_{it} = \frac{1}{\mu_{it}} (q_{it} + \lambda_{it}) \quad (32)$$

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

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

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

Using (28) and (29) one obtains:

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

then substituting this expression into (32)

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

First stage

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

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

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

$$\lambda_{it-1} = \mu_{it-1} r_{it-1} - q_{it-1}, \quad (36)$$

then using this expression into (30) we obtain:

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

Now from (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 (36) we get

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

and after substituting this expression in (29)

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

Using (38) and (37) into (35) we obtain

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

that we can rewrite as:

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

where $z_{1it}=k_{it}$, $z_{2it}=LHS_{it-1}$, $z_{3it}=k_{it-1}$, $z_{4it}=\frac{r_{it-1}}{s_{Mit-1}}$, $z_{5it}=q_{it-1}$, $z_{6it}=\Delta L_{it}$, $u_{it}=\frac{1}{\alpha_M} (\nu_{ait} + (1-\phi_q) \nu_{\lambda it})$ as well as $b_1=\frac{\gamma}{\alpha_M}$, $b_2=\phi_a$, $b_3=-\gamma \frac{\phi_a}{\alpha_M}$, $b_4=(\phi_\lambda - \phi_a)$, $b_5=\frac{1}{\alpha_M} (\phi_a - \phi_\lambda - \phi_q + \phi_q \phi_\lambda)$ 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 $z_{6it}=\Delta L_{it}$ that we instruments with ΔL_{it-1} and L_{it-2} . Therefore (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 (34) and (38) we have that log output is given by:

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

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

$$q_{it} = \frac{\gamma}{1 - \phi_q} \frac{1}{\hat{\beta}} \frac{sO_{it}}{sM_{it}} (\ln WB_{i,t} - k_{it}) + \frac{\gamma}{1 - \phi_q} \frac{1}{\hat{\beta}} (m_{it} - k_{it}) + \frac{\gamma}{1 - \phi_q} k_{it} + \frac{\gamma}{1 - \phi_q} \frac{\hat{\phi}_a}{\hat{\beta}} LHS_{it-1} - \frac{\gamma}{1 - \phi_q} \hat{\phi}_a k_{it-1} - \frac{\gamma}{1 - \phi_q} \frac{1}{\hat{\beta}} \frac{\hat{\phi}_a}{sM_{it-1}} r_{it-1} + \frac{\phi_a - \phi_q}{1 - \phi_q} q_{it-1} + \frac{\phi_L}{1 - \phi_q} \Delta L_{it} + \frac{1}{1 - \phi_q} \nu_{ait}.$$

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

$$q_{it} = b_7 z_{7it} + b_8 z_{8it} + b_9 z_{9it} + \varepsilon_{it}, \quad (41)$$

where:

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

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

$$\begin{aligned} \hat{a}_{it} &= q_{it} - \frac{\hat{\gamma}}{\hat{\beta}} \frac{sO_{it}}{sM_{it}} (\ln WB_{it} - k_{it}) - \frac{\hat{\gamma}}{\hat{\beta}} (m_{it} - k_{it}) - \hat{\gamma} k_{it} \\ \hat{\mu}_{it} &= \frac{\hat{\gamma}}{\hat{\beta} sM_{it} (1 - \hat{\phi}_q)} \text{ and } \hat{\lambda}_{it} = \frac{\hat{\gamma}}{\hat{\beta} sM_{it} (1 - \hat{\phi}_q)} r_{it} - q_{it}. \end{aligned}$$

C.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

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

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 (42) into the production function and multiplying

by the price leads to an equation for revenue given by

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

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 $n_L^I \geq \epsilon$, 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}):

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

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 Akerberg 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 (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

$$va_{it} = \alpha'_O \ln C(O_{it}; w) + \alpha'_K k_{it} + \phi'_a g(k_{it-1}, m_{it-1}) + \beta' \Delta L_{it} + \phi'_q \Delta q_{it} + \nu_{ait}. \quad (45)$$

where va_{it} is value added and, for example, the coefficient α'_O equals α_O times a scaling factor common to all other coefficients. The error term ν_{ait} in (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 (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 (45) by IV and ultimately get an estimate of revenue TFP as

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

D Supplementary Revenue-based Productivity Results

In this Appendix we provide revenue-productivity results—complementing those of Section 4.1—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 D-1: Value added per worker. OLS

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.627 ^a (0.028)	0.811 ^a (0.026)	0.833 ^a (0.017)	0.748 ^a (0.016)
Change in layers	-0.097 ^a (0.013)	-0.179 ^a (0.023)		-0.124 ^a (0.012)
Constant	3.858 ^a (0.289)	1.932 ^a (0.257)	1.726 ^a (0.183)	2.611 ^a (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 D-2: OLS TFP. OLS

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.661 ^a (0.024)	0.648 ^a (0.025)	0.683 ^a (0.021)	0.671 ^a (0.015)
Change in layers	-0.012 ^a (0.003)	-0.020 ^a (0.004)		-0.014 ^a (0.002)
Constant	-0.001 (0.006)	-0.003 (0.008)	0.005 (0.007)	0.001 (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 D-3: Olley and Pakes TFP. OLS

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.779 ^a (0.021)	0.846 ^a (0.021)	0.886 ^a (0.025)	0.843 ^a (0.014)
Change in layers	-0.078 ^a (0.011)	-0.106 ^a (0.016)		-0.082 ^a (0.008)
Constant	-0.015 (0.018)	-0.023 (0.034)	-0.023 (0.025)	0.017 (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 D-4: Levinsohn and Petrin TFP. OLS

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.839 ^a (0.018)	0.867 ^a (0.019)	0.855 ^a (0.020)	0.857 ^a (0.011)
Change in layers	-0.041 ^a (0.010)	-0.062 ^a (0.013)		-0.044 ^a (0.007)
Constant	0.003 (0.016)	-0.023 (0.033)	-0.018 (0.026)	0.007 (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 D-5: Wooldridge Revenue TFP. Firm-product-sequence FE. Within estimator

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.091 ^b (0.038)	-0.064 ^c (0.038)	0.065 (0.041)	0.053 ^b (0.0245)
Change in layers	-0.033 ^a (0.009)	-0.074 ^a (0.014)		-0.048 ^a (0.008)
Constant	-0.084 ^a (0.018)	-0.022 (0.036)	0.050 ^b (0.026)	0.075 ^a (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 D-6: Revenue labor productivity. Firm-product-sequence FE. Within estimator

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.083 ^b (0.036)	0.020 (0.064)	0.090 ^c (0.053)	0.081 ^a (0.028)
Change in layers	-0.038 ^a (0.011)	-0.136 ^a (0.022)		-0.074 ^a (0.012)
Constant	10.439 ^a (0.414)	11.183 ^a (0.718)	10.527 ^a (0.617)	10.509 ^a (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 D-7: Value added per worker. Firm-product-sequence FE. Within estimator

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.076 ^c (0.039)	-0.035 (0.078)	0.030 (0.051)	0.050 (0.031)
Change in layers	-0.037 ^a (0.012)	-0.138 ^a (0.023)		-0.074 ^a (0.012)
Constant	9.412 ^a (0.400)	10.611 ^a (0.788)	10.032 ^a (0.532)	9.720 ^a (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 D-8: OLS TFP. Firm-product-sequence FE. Within estimator

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	-0.048 (0.042)	-0.059 (0.055)	-0.098 ^b (0.043)	-0.063 ^b (0.028)
Change in layers	-0.007 ^b (0.003)	-0.013 ^a (0.004)		-0.008 ^a (0.002)
Constant	-0.025 ^a (0.004)	0.003 (0.008)	-0.005 (0.005)	0.020 ^a (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 D-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 (0.037)	-0.031 (0.066)	0.142 ^a (0.054)	0.097 ^a (0.029)
Change in layers	-0.033 ^a (0.009)	-0.076 ^a (0.013)		-0.050 ^a (0.008)
Constant	-0.096 ^a (0.013)	-0.078 ^b (0.035)	-0.055 ^a (0.017)	0.100 ^a (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 D-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 (0.043)	-0.048 (0.055)	0.124 ^a (0.040)	0.089 ^a (0.027)
Change in layers	-0.017 ^b (0.008)	-0.047 ^a (0.010)		-0.029 ^a (0.007)
Constant	-0.074 ^a (0.012)	-0.096 ^a (0.037)	-0.013 (0.016)	0.093 ^a (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 D-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 (0.082)	0.548 ^a (0.082)	0.641 ^a (0.071)	0.505 ^a (0.050)
Change in layers	-0.057 ^a (0.014)	-0.154 ^a (0.019)		-0.095 ^a (0.010)
Constant	7.234 ^a (0.977)	0.000 (0.000)	4.258 ^a (0.838)	0.000 (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 D-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 (0.064)	0.484 ^a (0.086)	0.491 ^a (0.072)	0.462 ^a (0.043)
Change in layers	-0.059 ^a (0.013)	-0.152 ^a (0.019)		-0.095 ^a (0.010)
Constant	0.000 (0.000)	5.301 ^a (0.873)	5.258 ^a (0.735)	5.545 ^a (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 D-13: OLS TFP. Firm-product-sequence FE. Dynamic panel

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.255 ^a (0.057)	0.314 ^a (0.063)	0.179 ^b (0.078)	0.265 ^a (0.039)
Change in layers	-0.006 ^b (0.003)	-0.016 ^a (0.003)		-0.010 ^a (0.002)
Constant	0.002 (0.009)	-0.000 (0.009)	0.013 (0.012)	0.014 ^b (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 D-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 (0.069)	0.452 ^a (0.095)	0.579 ^a (0.085)	0.499 ^a (0.047)
Change in layers	-0.050 ^a (0.009)	-0.092 ^a (0.012)		-0.061 ^a (0.007)
Constant	0.041 (0.026)	-0.025 (0.034)		0.018 (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 D-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 (0.076)	0.517 ^a (0.078)	0.573 ^a (0.068)	0.530 ^a (0.045)
Change in layers	-0.022 ^a (0.008)	-0.058 ^a (0.011)		-0.035 ^a (0.006)
Constant	0.017 (0.026)	-0.002 (0.031)		0.027 (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

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

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.782 ^a (0.021)	0.838 ^a (0.021)	0.876 ^a (0.026)	0.836 ^a (0.016)
Change in layers	-0.068 ^a (0.011)	-0.101 ^a (0.016)		-0.075 ^a (0.008)
Constant	-0.009 (0.017)	-0.017 (0.032)	-0.016 (0.025)	-0.010 (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 E-2: De Loecker and Warzynski (2012) revenue contemporaneous. Sequence type regressions, Within.

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.110 ^a (0.042)	-0.076 (0.046)	0.068 (0.043)	0.059 ^b (0.027)
Change in layers	-0.027 ^a (0.009)	-0.065 ^a (0.012)		-0.040 ^a (0.007)
Constant	-0.088 ^a (0.013)	-0.059 (0.036)	0.024 ^b (0.016)	0.094 ^a (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 E-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 (0.070)	0.382 ^a (0.105)	0.542 ^a (0.073)	0.445 ^a (0.049)
Change in layers	-0.036 ^b (0.010)	-0.085 ^a (0.012)		-0.054 ^a (0.007)
Constant	0.056 ^c (0.033)	-0.011 (0.034)	0.028 (0.031)	0.031 ^c (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

F Supplementary Quantity-based Productivity Results

This Appendix provides results complementary to those in Section 4.2 using the within estimator.

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

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.207 ^a (0.043)	0.097 (0.073)	0.162 ^a (0.055)	0.162 ^a (0.034)
Change in layers	0.007 (0.011)	0.025 ^c (0.013)		0.013 (0.009)
Constant	0.001 (0.016)	0.069 (0.050)	0.052 (0.048)	0.040 (0.012)
Observations	4,171	2,734	3,055	9,960
Number of fixed effects	1,673	1,280	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 F-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 (0.056)	0.345 ^c (0.177)	0.359 ^a (0.092)	0.339 ^a (0.068)
Number of layers	0.040 ^c (0.022)	0.008 (0.023)		0.030 ^b (0.015)
Constant	-0.113 ^c (0.062)	0.061 (0.089)	0.028 (0.060)	0.065 ^c (0.035)
Observations	4,171	2,734	3,055	9,960
Number of fixed effects	1,673	1,280	1,298	4,251
Adjusted R^2	0.076	0.112	0.101	0.094

Firm-level clustered standard errors in parentheses

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

G 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.

G.1 Revenue-based Productivity OLS Results

Table G-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 (0.081)	0.613 ^a (0.035)	0.813 ^a (0.023)	0.814 ^a (0.017)
Change in layers	-0.067 ^a (0.022)	-0.065 ^a (0.017)	-0.071 ^a (0.010)	-0.085 ^a (0.018)
Constant	0.120 ^c (0.071)	-0.015 (0.041)	0.000 (0.019)	-0.028 (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 G-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 (0.063)	0.782 ^a (0.026)	0.865 ^a (0.015)	0.897 ^a (0.017)
Change in layers	-0.102 ^b (0.047)	-0.128 ^a (0.019)	-0.100 ^a (0.015)	-0.153 ^a (0.030)
Constant	4.048 ^a (0.708)	2.511 ^a (0.301)	1.620 ^a (0.183)	1.221 ^a (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 G-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 (0.058)	0.578 ^a (0.037)	0.762 ^a (0.026)	0.822 ^a (0.024)
Change in layers	-0.091 ^b (0.037)	-0.086 ^b (0.019)	-0.105 ^a (0.015)	-0.143 ^a (0.028)
Constant	5.533 ^a (0.631)	4.301 ^a (0.370)	2.484 ^a (0.269)	1.836 ^a (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 G-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 (0.065)	0.611 ^a (0.031)	0.663 ^a (0.026)	0.698 ^a (0.019)
Change in layers	-0.019 ^b (0.008)	-0.017 ^a (0.004)	-0.013 ^a (0.003)	-0.010 ^b (0.004)
Constant	0.048 ^b (0.022)	0.000 (0.011)	0.000 (0.006)	-0.003 (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 G-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 (0.062)	0.660 ^a (0.030)	0.841 ^a (0.021)	0.908 ^a (0.021)
Change in layers	-0.069 ^a (0.024)	-0.054 ^a (0.016)	-0.071 ^a (0.011)	-0.085 ^a (0.018)
Constant	0.052 (0.073)	-0.054 (0.041)	-0.002 (0.019)	-0.032 (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 G-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 (0.068)	0.742 ^a (0.029)	0.864 ^a (0.019)	0.888 ^a (0.014)
Change in layers	-0.041 ^b (0.020)	-0.023 (0.016)	-0.040 ^a (0.010)	-0.044 ^a (0.013)
Constant	0.059 (0.064)	-0.026 (0.037)	0.003 (0.019)	-0.025 (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 $p < 0.1$

G.2 Revenue-based Productivity Within Estimator Results

Table G-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 (0.044)	0.015 (0.048)	0.185 ^a (0.042)	0.126 ^a (0.039)
Change in layers	-0.047 ^a (0.018)	-0.021 (0.015)	-0.038 ^a (0.008)	-0.055 ^a (0.012)
Constant	0.004 (0.032)	-0.035 (0.027)	-0.057 ^a (0.012)	0.048 ^a (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 G-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 (0.060)	0.190 ^a (0.050)	0.126 ^b (0.049)	0.041 (0.069)
Change in layers	-0.050 (0.034)	-0.051 ^a (0.014)	-0.061 ^a (0.013)	-0.097 ^a (0.019)
Constant	11.572 ^a (0.671)	9.152 ^a (0.572)	9.964 ^a (0.555)	11.062 ^a (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 G-9: Alternative grouping. Value added per worker. Firm-product FE. Within estimator

VARIABLES	(1)	(2)	(3)	(4)
	0 layers	1 layer	2 layers	3 layers
Productivity t-1	-0.048 (0.056)	0.069 (0.062)	0.095 ^c (0.050)	0.076 (0.068)
Change in layers	-0.066 ^b (0.029)	-0.031 ^c (0.017)	-0.062 ^a (0.014)	-0.093 ^a (0.019)
Constant	10.587 ^a (0.565)	9.429 ^a (0.629)	9.249 ^a (0.508)	9.536 ^a (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 G-10: Alternative grouping. OLS TFP. Firm-product FE. Within estimator

VARIABLES	(1)	(2)	(3)	(4)
	0 layers	1 layer	2 layers	3 layers
Productivity t-1	-0.012 (0.081)	-0.059 (0.059)	0.040 (0.043)	0.024 (0.043)
Change in layers	-0.013 ^c (0.007)	-0.003 (0.004)	-0.006 ^b (0.003)	-0.006 ^c (0.003)
Constant	0.006 (0.011)	-0.004 (0.006)	-0.011 ^a (0.004)	0.010 ^c (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 G-11: Alternative grouping. Olley and Pakes TFP. Firm-product FE. Within estimator

VARIABLES	(1)	(2)	(3)	(4)
	0 layers	1 layer	2 layers	3 layers
Productivity t-1	-0.004 (0.061)	0.019 (0.063)	0.165 ^a (0.044)	0.237 ^a (0.042)
Change in layers	-0.051 ^a (0.018)	-0.020 (0.014)	-0.040 ^a (0.008)	-0.052 ^a (0.013)
Constant	-0.115 ^a (0.035)	-0.148 ^a (0.032)	-0.066 ^a (0.012)	-0.105 ^a (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 G-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 (0.069)	-0.014 (0.060)	0.217 ^a (0.041)	0.227 ^a (0.038)
Change in layers	-0.033 ^b (0.016)	0.006 (0.014)	-0.022 ^a (0.007)	-0.031 ^a (0.009)
Constant	-0.076 ^b (0.035)	-0.118 ^a (0.031)	-0.055 ^a (0.012)	0.090 ^a (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 $p < 0.1$

G.3 Revenue-based Productivity Dynamic Panel Results

Table G-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 (0.092)	0.183 ^b (0.089)	0.481 ^a (0.053)	0.533 ^a (0.066)
Change in layers	-0.058 ^a (0.014)	-0.028 ^b (0.013)	-0.052 ^a (0.008)	-0.066 ^a (0.016)
Constant	0.192 ^c (0.101)	0.081 (0.066)	0.007 (0.025)	-0.008 (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 G-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 (0.108)	0.577 ^a (0.136)	0.386 ^a (0.072)	0.469 ^a (0.090)
Change in layers	-0.072 ^b (0.032)	-0.083 ^a (0.022)	-0.067 ^a (0.013)	-0.115 ^a (0.024)
Constant	7.241 (1.270)	0.000 (0.000)	0.000 (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 G-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 (0.094)	0.301 ^a (0.101)	0.370 ^a (0.068)	0.456 ^a (0.087)
Change in layers	-0.060 ^b (0.028)	-0.045 ^b (0.018)	-0.074 ^a (0.013)	-0.113 ^a (0.024)
Constant	0.000 (0.000)	7.110 ^a (1.039)	0.000 (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	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 G-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 (0.093)	0.180 ^b (0.081)	0.299 ^a (0.059)	0.302 ^a (0.053)
Change in layers	-0.014 ^a (0.005)	-0.008 ^b (0.003)	-0.009 ^a (0.003)	-0.008 ^b (0.004)
Constant	0.081 ^a (0.030)	-0.001 (0.017)	0.013 (0.010)	-0.003 (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 G-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 (0.079)	0.178 ^b (0.081)	0.506 ^a (0.063)	0.589 ^a (0.058)
Change in layers	-0.060 ^a (0.016)	-0.016 (0.013)	-0.052 ^a (0.009)	-0.064 ^a (0.015)
Constant	0.121 (0.115)	-0.008 (0.061)	0.008 (0.026)	0.022 (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 G-18: Alternative grouping. Levinsohn and Petrin TFP. Firm-product FE. Dynamic panel

VARIABLES	(1)	(2)	(3)	(4)
	0 layers	1 layer	2 layers	3 layers
Productivity t-1	0.324 ^a (0.111)	0.153 ^c (0.087)	0.610 ^a (0.047)	0.648 ^a (0.050)
Change in layers	-0.037 ^a (0.014)	0.001 (0.012)	-0.032 ^a (0.008)	-0.038 ^a (0.012)
Constant	0.065 (0.114)	0.065 (0.072)	0.038 (0.026)	0.007 (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 $p < 0.1$

G.4 De Loecker and Warzynski Revenue-based Productivity

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

VARIABLES	(1)	(2)	(3)	(4)
	0 layers	1 layer	2 layers	3 layers
Productivity t-1	0.627 ^a (0.082)	0.677 ^a (0.030)	0.842 ^a (0.020)	0.875 ^a (0.024)
Change in layers	-0.070 ^a (0.025)	-0.058 ^a (0.017)	-0.064 ^a (0.010)	-0.083 ^a (0.019)
Constant	0.082 (0.068)	-0.019 (0.039)	-0.000 (0.019)	-0.029 (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 G-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 (0.064)	0.024 (0.065)	0.141 ^a (0.039)	0.151 ^a (0.046)
Change in layers	-0.047 ^b (0.019)	-0.017 (0.015)	-0.033 ^a (0.008)	-0.051 ^a (0.012)
Constant	-0.058 ^c (0.034)	-0.078 ^b (0.031)	-0.060 ^a (0.012)	0.081 ^a (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 G-21: Alternative grouping. De Loecker and Warzynski (2012) revenue contemporaneous. Dynamic panel

VARIABLES	(1) 0 layers	(2) 1 layer	(3) 2 layers	(4) 3 layers
Productivity t-1	0.307 ^a (0.109)	0.241 ^a (0.087)	0.464 ^a (0.064)	0.546 ^a (0.066)
Change in layers	-0.057 ^a (0.014)	-0.027 ^b (0.013)	-0.048 ^a (0.009)	-0.065 ^a (0.016)
Constant	0.173 (0.127)	0.088 (0.056)	0.011 (0.027)	-0.031 (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 $p < 0.1$

G.5 Quantity-based Productivity Results

Table G-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 (0.051)	0.904 ^a (0.020)	0.884 ^a (0.013)	0.892 ^a (0.014)
Change in layers	0.008 (0.025)	0.003 (0.013)	0.035 ^a (0.010)	0.038 ^a (0.014)
Constant	0.589 ^c (0.323)	0.127 ^a (0.047)	0.304 ^a (0.027)	0.368 ^b (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 G-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 (0.109)	0.622 ^a (0.071)	0.646 ^a (0.085)	0.676 ^a (0.057)
Change in layers	-0.011 (0.020)	-0.003 (0.013)	0.029 ^a (0.010)	0.029 ^b (0.012)
Constant	-1.566 ^a (0.340)	0.025 (0.031)	0.635 ^b (0.256)	0.397 ^a (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 G-24: Alternative grouping. Quantity TFP. Firm-product FE. Within estimator

VARIABLES	(1)	(2)	(3)	(4)
	0 layers	1 layer	2 layers	3 layers
Productivity t-1	0.154 ^b (0.067)	0.226 ^a (0.062)	0.263 ^a (0.039)	0.215 ^a (0.059)
Change in layers	-0.003 (0.016)	0.004 (0.013)	0.023 ^a (0.009)	0.027 ^b (0.011)
Constant	0.209 ^a (0.049)	0.080 ^a (0.023)	-0.015 (0.015)	0.041 ^c (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 G-25: Alternative grouping. Quantity TFP. Firm-product FE. Level effects using layers. Within estimator.

VARIABLES	(1)	(2)	(3)	(4)
	0 layers	1 layer	2 layers	3 layers
Productivity t-1	0.240 ^b (0.066)	0.276 ^a (0.056)	0.408 ^a (0.061)	0.480 ^a (0.099)
Number of layers	0.055 (0.028)	-0.013 (0.023)	0.029 ^c (0.017)	0.049 ^a (0.018)
Constant	0.110 ^c (0.065)	0.063 (0.048)	-0.069 (0.044)	-0.086 (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 $p < 0.1$

G.6 Instrumental Variables Results

Table G-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 (0.076)	0.844 ^a (0.021)	0.941 ^a (0.011)	0.906 ^a (0.011)
Change in layers	-0.068 (0.048)	-0.170 ^a (0.053)	-0.059 ^b (0.031)	-0.063 ^b (0.035)
Change in quantity	-0.784 ^a (0.213)	-0.449 ^a (0.141)	-0.466 ^a (0.124)	-0.085 (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 G-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 (0.041)	0.924 ^a (0.030)	0.944 ^a (0.015)	0.951 ^a (0.019)
Change in layers	-0.017 (0.048)	0.053 (0.053)	0.120 ^a (0.031)	0.069 ^b (0.035)
Change in quantity	0.055 (0.266)	-0.057 (0.108)	0.268 ^b (0.111)	0.004 (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 Supplementary IV Tables

In this Appendix we provide results that are complementary to those in Section 4.3. The trade instruments that are used below are built using initial period fixed weights while in Section 4.3 weights are time-varying. Results are qualitatively identical and quantitatively very similar.

Table H-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)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
Productivity t-1	0.920 ^a (0.011)	0.916 ^a (0.020)	0.912 ^a (0.016)	0.919 ^a (0.009)
Change in layers	-0.065 ^a (0.017)	-0.083 ^a (0.027)		-0.071 ^a (0.017)
Change in quantity	0.078 (0.392)	0.749 ^b (0.335)	-0.219 (0.253)	0.368 (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 H-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)	(2)	(3)	(4)
	0 layers	1 layer	2 layers	3 layers
Productivity t-1	0.696 ^a (0.076)	0.844 ^a (0.021)	0.941 ^a (0.011)	0.906 ^a (0.011)
Change in layers	-0.068 (0.048)	-0.166 ^a (0.046)	-0.060 ^b (0.024)	-0.063 ^b (0.027)
Change in quantity	-0.740 ^a (0.204)	-0.450 ^a (0.142)	-0.470 ^a (0.123)	-0.085 (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 H-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 (0.014)	0.906 ^a (0.019)	0.967 ^a (0.017)	0.955 ^a (0.012)
Change in layers	0.054 ^b (0.021)	0.051 ^c (0.029)		0.077 ^a (0.020)
Change in quantity	0.034 (0.058)	-0.032 (0.133)	0.139 (0.107)	0.050 (0.061)
Observations	4,171	2,840	3,055	9,960
Kleibergen-Paap stat.	46.70	341.7	40.65	594.4
Adjusted R^2	0.855	0.767	0.902	0.872

Firm-level clustered standard errors in parentheses

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

Table H-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 (0.041)	0.924 ^a (0.030)	0.944 ^a (0.015)	0.951 ^a (0.019)
Change in layers	-0.017 (0.048)	0.053 (0.053)	0.120 ^a (0.031)	0.069 ^b (0.035)
Change in quantity	0.055 (0.266)	-0.057 (0.108)	0.268 ^b (0.111)	0.004 (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 $p < 0.1$

Table H-5: De Loecker et al. (2016) QTFP. IV. Change in layers and quantity as endogenous variables.

VARIABLES	(1) Increasing	(2) Decreasing	(3) Constant	(4) All
Productivity t-1	0.779 ^a (0.022)	0.830 ^a (0.022)	0.837 ^a (0.023)	0.821 ^a (0.013)
Change in layers	0.007 (0.015)	0.028 (0.022)		0.034 ^b (0.014)
Change in quantity	0.140 (0.226)	0.060 (0.227)	0.416 ^c (0.242)	0.256 ^c (0.145)
Observations	4,171	2,734	3,055	9,960
Kleibergen-Paap stat.	6.226	11.58	13.54	19.27
Adjusted R^2	0.634	0.634	0.676	0.668

Firm-level clustered standard errors in parentheses

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

I 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 I-1 presents the results using OLS.

I.1 Cost Pass-through

We now perform two separate exercises to study the pricing behavior of the firms in our sample. First, we use the Portuguese trade data to study the effect of exchange rate shocks on export behavior of multi-product firms, following the approach, and reproducing the main findings of Chatterjee, Dix-Carneiro, and Vichyanond (2013), who use Brazilian data. Second, we perform a comparable exercise with the Prodcum data to show the relationship between producer prices, quantity-based productivity, and demand shocks. In both cases we find comparable response of prices to increases in marginal costs, in the order of 15 percent.

Chatterjee, Dix-Carneiro, and Vichyanond (2013) propose a theoretical framework to describe how heterogeneous firms adjust their prices, quantities and product scope in the event of an exchange rate depreciation. The key ingredients of the theoretical framework are two: (i) Each firm faces a product ladder, i.e., there is a core product that the firm is most efficient at producing and efficiency decreases along the ladder;

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

VARIABLES	(1)	(2)	(3)	(4)
	Increasing	Decreasing	Constant	All
(log) Price t-1	0.805 ^a (0.023)	0.904 ^a (0.041)	0.834 ^a (0.028)	0.841 ^a (0.017)
Change in layers	-0.014 (0.011)	-0.004 (0.012)		-0.012 ^c (0.006)
Constant	0.202 ^a (0.030)	0.100 ^a (0.045)	0.152 ^a (0.029)	0.158 ^a (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 $p < 0.1$

and (ii) Each firm pays a local per-unit distribution cost, in the destination country currency, which implies that markups vary depending on how far the product is from the firm's core competency. We consider the following predictions of their model: (i) Producer prices increase following a real depreciation; and (ii) Producer prices increases are more pronounced for more productive firms, and within-firm for products closer to the core competency. The intuition for these predictions is the following. A real depreciation implies an increase in the per unit distribution costs that a firm has to pay in order to serve its foreign customers. Then a larger share of the consumer price does not depend on the producer price, resulting in a lower perceived elasticity of demand and hence higher markups. Producer prices are then increasing in the real exchange rate. This effect is even stronger for more productive firm, whose producer price is generally lower, and within firms for the products they are more efficient at producing. We test these predictions estimating the following model,

$$\log p_{ijct} = \mu_{ijc} + \Phi(t) + \beta \log(RER_{ct}) + X_{jt-1}\gamma + Z_{ict}\delta + \varepsilon_{ijct}, \quad (1)$$

where p_{ijct} is the producer price in 2005 Euros charged by firm j for product i in destination c in year t , μ_{ijc} is a product-firm-destination fixed effect, $\Phi(t)$ is a quadratic time polynomial, RER_{ct} is the real exchange rate of country c in year t with respect to Portugal, Z_{ict} is a vector of characteristics of destination c in year t that may also be product i specific, X_{jt-1} is a vector of firm j 's characteristics in year $t-1$, and ε_{ijct} is an error term.⁴¹ The main coefficient of interest, β , captures the long-run response of the producer price to real exchange rate fluctuations and is the key parameter to be estimated. Since the real exchange rate is defined as units of Portugal currency per unit of country c currency at time t an increase represents a real depreciation of the Portugal currency. We estimate (1) using the fixed effect estimator in the presence of firm-product-destination fixed effects: the variation that we exploit to identify β consists then in the deviations of the real exchange rate, for a given destination, with respect to its mean over time and in the deviations of the export price, for a given firm-product-destination, with respect to its mean over time. We control for both firm-time and destination-product-time factors. The X_{jt-1} vector includes firm j 's characteristics, in year $t-1$, that the literature has proven to be positively correlated with a firm productivity: a firm's size, average wage, share of high skilled worker, as well as a measure of the importance of exports and imported inputs, both relative to the firm's wage bill. The Z_{ict} vector includes destination and destination-product

⁴¹We also ran a specification with year fixed effects instead of the quadratic polynomial. Results are quantitatively similar.

time varying characteristics: a country GDP, GDP per capita, as well as a measure of demand for product i in country c at time t constructed as the total imports of product i from all countries except Portugal.

Table I-2: Export Price and Quantity Responses to Exchange Rate Shocks

VARIABLES	(1) Price	(2) Price	(3) Quantity	(4) Quantity	(5) Price	(6) Price
$\log RER_{ct}$	0.150 ^a (0.021)	0.131 ^a (0.023)	0.123 ^a (0.058)	0.206 ^a (0.062)	0.108 ^b (0.053)	0.089 ^c (0.053)
$\log RER_{ct} * Ranking_{ijct}$					-0.003 ^a (0.000)	-0.003 ^a (0.000)
$\log RER_{ct} * \log Employment_{jt-1}$					0.005 ^b (0.002)	0.004 ^b (0.002)
$\log RER_{ct} * \log Avg. Wage_{jt-1}$					0.003 (0.005)	0.003 (0.005)
$\log RER_{ct} * \log Export Importance_{jt-1}$					0.004 ^c (0.002)	0.004 ^c (0.002)
$\log RER_{ct} * \log Import Importance_{jt-1}$					0.004 ^b (0.002)	0.004 ^b (0.002)
$\log RER_{ct} * \log Share High Skill_{jt-1}$					-0.000 (0.008)	-0.000 (0.008)
Firm-time controls	X	X	X	X	X	X
Destination-product-time controls	X	X	X	X	X	X
Firm-product-destination fixed effects	X	X	X	X	X	X
Time fixed effects		X		X		X
Time trend	X		X		X	
Observations	410,781	410,781	410,781	410,781	410,781	410,781
Number of firm-product-destination fixed effects	236,263	259,088	236,263	259,088	236,263	259,088
R^2	0.006	0.933	0.010	0.874	0.012	0.933

Robust standard errors clustered at the firm-level in parentheses. Within R^2 for specifications with time trend.

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

The first column of Table I-2 shows that our baseline estimate of β is 0.15, which implies that the import price elasticity to the real exchange rate is 0.85. This figure is consistent with what found in the literature for other countries: Chatterjee, Dix-Carneiro, and Vichyanond (2013), using Brazilian data, find that β is 0.77; Berman, Martin, and Mayer (2012) find 0.83 with firm-level French data, while Campa and Goldberg (2010) find 0.64 with country- and industry-level OECD data. Column 2 of Table I-2 reports the estimate of β for a specification where the dependent variable is the quantity exported. Given that the producer price elasticity with respect to real exchange rates is less than one we find that the quantity response to a real exchange rate depreciation is positive. In the last column of Table I-2 we test the prediction that producer prices increases are more pronounced for more productive firms, and within-firm for products closer to the core competency. We find that firms that become larger or increase their presence in the export and import markets become more sensitive to real exchange rate depreciations. Moreover, when ranking their products according to their position in the firm's sales portfolio, we find that the most important products—those with a ranking closer to 1—have a higher producer price elasticity, consistently with the theory and results in Chatterjee, Dix-Carneiro, and Vichyanond (2013).

We now switch from trade to production data, and consider the relationship between the (firm-time) prices constructed using the Prodcom dataset and the measures of quantity-based productivity and demand

Table I-3: Producer Price Responses to Productivity and Demand Shocks

VARIABLES	(1)	(2)
	Change in Price (Multi-product)	Change in Price (Single-product)
Change in Quantity TFP	-0.140 ^a (0.007)	-0.189 ^a (0.022)
Change in Demand	0.011 ^a (0.001)	0.02 ^a (0.003)
Firm-time controls	X	X
Product fixed effects	X	X
Observations	30,723	2,825
R^2	0.103	0.283

Robust standard errors clustered at the firm-product-level in parentheses

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

shocks considered later on in the paper. This exercise has two goals. First to explore the response of prices constructed using production, instead of trade, data to an increase in costs—captured by a decrease in TFPQ. Second, to provide an implicit test of the measures of quantity-based productivity and demand shocks constructed, and employed, later on in the paper. We expect prices to be negatively related to TFPQ and positively to demand shocks. We estimate the following model,

$$\Delta \log p_{jt} = \mu_i + \beta \Delta \log(TFPQ_{jt}) + \gamma \Delta \log(Demand_{jt}) + \delta \Delta \log(Capital_{jt}) + \varepsilon_{jt}, \quad (2)$$

where $\Delta \log p_{jt}$ is the log change in prices (in 2005 euros) of firm j between $t - 1$ and t , μ_i is a 8-digit product fixed effect, $\Delta \log(TFPQ_{jt})$ and $\Delta \log(Demand_{jt})$ are the main variables of interest and represent the log change in TFPQ and demand of firm j between $t - 1$ and t ; $\Delta \log(Capital_{jt})$ is a firm-time control capturing the log change in the material assets of firm j between $t - 1$ and t . We estimate model (2) twice, using all firms and restricting the sample to single-product firms only. Table I-3 reports the results. The estimate for β in the first column of Table I-3 shows that a reduction in TFPQ, i.e. an increase in marginal costs, of 1 percent corresponds to an increase in production prices of about 0.14 percent, which is almost exactly the same reaction we found using export prices. When considering only single-product firms we find a slightly higher elasticity, 0.19, which is consistent with Chatterjee, Dix-Carneiro, and Vichyanond (2013)'s idea that firms that focus on their core competencies are more reactive to changes in costs. We also find that prices are positively correlated with our measure of demand shocks, in both samples.⁴² Overall, we find that (i) prices from the production data respond in a way similar to export prices to an increase in costs; (ii) And the measures of TFPQ and demand that we build upon later on in the paper show a relationship with prices that is qualitatively consistent with what expected, as well as quantitatively comparable with what found in the pass-through literature.

⁴²While not reported in the table, we find that prices are also positively correlated with material assets, as expected.

J First stage IV Regressions

The next two tables show the first stage estimates for tables 11 and 12, 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 J-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 (0.024)	-0.010 (0.038)	-0.003 (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 (0.010)	0.080 (0.050)	-0.006 (0.023)
Capital first year	0.039 ^b (0.018)	0.042 ^c (0.023)	0.076 ^a (0.012)
Sales t-1	0.020 (0.018)	-0.027 (0.023)	0.023 (0.014)
Sales first year	-0.037 (0.023)	0.020 (0.032)	-0.027 (0.018)
Number of layers t-1	-0.669 ^a (0.017)	-0.706 ^a (0.020)	0.205 ^a (0.010)
Number of layers first year	0.542 ^a (0.026)	0.653 ^a (0.027)	0.152 ^a (0.009)
Productivity t-2	-0.026 (0.025)	0.013 (0.032)	-0.009 (0.018)
Productivity first year	0.070 ^a (0.027)	-0.007 (0.043)	0.023 (0.019)
Markup t-1	0.049 (0.129)	-0.057 (0.159)	-0.124 (0.012)
Demand shock t-1	-0.006 (0.009)	-0.001 (0.012)	0.005 (0.008)
Markup first year	-0.131 (0.145)	0.284 (0.216)	0.146 (0.128)
Demand shock first year	0.009 (0.011)	-0.017 (0.015)	-0.012 (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 J-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 (0.018)	-0.053 ^c (0.032)	-0.027 ^a (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 (0.010)	0.084 ^c (0.051)	-0.023 ^b (0.011)
Markup t-1	0.180 (0.209)	0.340 ^c (0.181)	0.210 ^a (0.070)
Demand shock t-1	-0.016 (0.015)	-0.027 ^c (0.015)	-0.018 ^a (0.006)
Capital t	0.039 ^b (0.016)	0.031 (0.025)	0.016 (0.013)
Markup first year	-0.112 (0.215)	-0.162 ^a (0.064)	-0.029 (0.031)
Demand shock first year	0.009 (0.015)	0.012 (0.008)	0.000 (0.004)
Capital first year	0.028 (0.021)	0.011 (0.031)	0.054 ^a (0.016)
Quantity t-1	-0.047 ^c (0.028)	0.048 (0.046)	-0.032 (0.023)
Quantity first year	0.031 (0.032)	-0.089 ^c (0.047)	-0.019 (0.024)
Sales t-1	0.073 ^b (0.034)	0.057 (0.048)	0.059 ^b (0.026)
Sales first year	-0.051 (0.041)	-0.051 (0.056)	-0.010 (0.027)
Number of layers t-1	-0.666 ^a (0.017)	-0.686 ^a (0.022)	-0.240 ^a (0.011)
Number of layers first year	0.535 ^a (0.026)	0.613 ^a (0.028)	-0.119 ^a (0.009)
Productivity t-2	0.026 ^c (0.015)	0.017 (0.018)	0.018 ^b (0.008)
Productivity first year	-0.009 (0.018)	0.029 (0.031)	0.007 (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

K A Case Study: Firm Outcomes from the Removal of EU Quotas on Textile and Apparel

In this Appendix we focus on a specific industry, “Textile and Apparel”, that experienced a rise in import competition from China during our time frame. As a consequence of China joining the WTO a number of quotas that were imposed at the EU-level on Chinese imports—as well as on imports from other non-WTO countries—were removed. These quotas used to affect some products within the “Textile and Apparel” industry but not others.

We show how the removal of quotas corresponds to a negative demand shock that forced firms to reorganize. In particular, we show that firms that decrease the number of layers experience a reduction in quantity-based productivity and an increase in revenue-based productivity. The data and estimation strategy are borrowed from Bloom, Draca, and Van Reenen (2016) to which the reader may refer for further details. To provide some context, when these quotas were abolished this generated a 240% increase in Chinese imports on average within the affected product groups. The underlying identifying assumption of this strategy is that unobserved demand/technology shocks are uncorrelated with the strength of quotas to non-WTO countries (like China) in 2000. Since these quotas were built up from the 1950s, and their phased abolition negotiated in the late 1980s was in preparation for the Uruguay Round, Bloom, Draca, and Van Reenen (2016) conclude that this seems like a plausible assumption.

Operationally we compute for each 6-digit Prodcom product category, the proportion of the more detailed 6-digit HS products that were covered by a quota, weighting each HS6 product by its share of EU15 imports over the period 1995-1997. Then, for each firm, we measure the firm-level exposure to the quota by adding each of the 6-digit Prodcom products weighted by the initial share of sales of the firm in that product. We keep this sales shares constant. We label this variable $QuotaCoverage_i$, and focus on the period 2000-2005.

Figure K-1: Average number of management layers for firms affected and not affected by the quota removals,

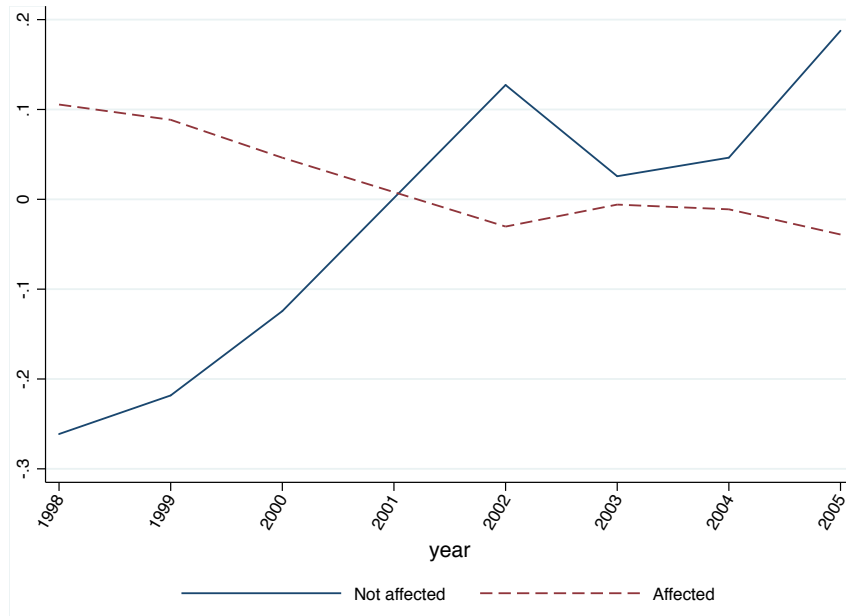


Figure K-1 shows the average number of layers for firms affected and not affected by the quota removals, as a deviation from the common year average. The number of layers tend to increase for firms that were

Table K-1: Textile and Apparel, first stage

VARIABLES	Change in layers
$QuotaCoverage_t$	0.321 (0.212)
$QuotaCoverage_t^2$	-0.395 ^b (0.230)
(log) Capital first year	0.062 ^a (0.013)
# of layers t-1	-0.262 ^a (0.035)
constant	-0.0348 ^a (0.171)
Observations	831
Kleibergen-Paap stat.	63.12
Cragg-Donald Wald F stat.	14.81
Robust standard errors in parentheses ^a p<0.01, ^b p<0.10	

not affected by the quota removals, while it decreases for firms that were affected by the quota removals. We use this relationship as a first stage in a 2SLS specification. Namely, we instrument the change in the number of management layers with the $QuotaCoverage_i$, $(QuotaCoverage_i)^2$, the lagged number of layers and capital stock.

Table K-1 presents the results from the first stage. As we can see, the coefficients from the first stage are significant and with the expected sign. Table 13, in the main text, reports IV estimates of the effect of the change in the number of layers on either revenue-based or quantity based productivity as well as the OLS coefficients.