What determines firm growth? The role of demand and TFP shocks*

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Abstract

We disentangle the contribution of unobserved heterogeneity in idiosyncratic demand and productivity to firm growth. We use a model of monopolistic competition with Cobb-Douglas production and a dataset of Italian manufacturing firms containing unique information on firm-level prices to reach three main results. First, demand is at least as important for firm growth as productivity. Second, firms' responses to shocks are lower than those predicted by our frictionless model, suggesting the existence of adjustment frictions. Finally, the deviation is more substantial for TFP shocks. We provide direct evidence that sluggish price adjustment influences responses to shocks, magnifying the effect of market appeal and dampening that of TFP. Moreover, organizational rigidity within the firm also contributes to reducing the response to TFP shocks, while it has no effects on that to demand shocks. These findings emphasize the importance of considering both dimensions of unobserved heterogeneity. They also imply that it is more difficult to fully adjust to TFP shocks.

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1 Introduction

Modern theories of industry dynamics (Jovanovic 1982, Hopenhayn 1992, Ericson & Pakes 1995) assume that firms are heterogeneous along a single dimension, productivity, which determines the firm's performance and growth. The empirical literature on the topic has followed this view, tracing back firms' growth to the evolution of productivity (see Syverson (2011) for a recent survey). However, one can think of several other dimensions of heterogeneity which may matter form firm's growth. In particular, the assumption that all firms look alike to consumers fails to capture an important ingredient of firm performance. Differences in firms' prowess in marketing their goods, the strength of the relationship with customers, and brand image are only some potential elements leading to heterogeneity across firms on the demand side. Indeed, there is no reason to believe that demand factors are less important than productive efficiency in shaping a firm's success and its growth. For example, in many sectors marketing and advertising budgets are larger than research and development ones.

There are at least two reasons for which distinguishing between demand and productivity factors is important. First, heterogeneity in market appeal and in productivity are fundamentally distinct from an economic point of view. The first refers to the ability of selling products at a premium, the latter implies that some firms can produce more output for a given inputs level. Considering both of them simultaneously can help unmask different mechanisms responsible for firm growth. Furthermore, it is well known that not accounting for heterogeneity in demand leads to biased productivity estimates. As pointed out by Klette & Griliches (1996), if real output is obtained dividing revenues by a sectoral price deflator, within-sector dispersion in prices that may be due to demand effects will instead reflect into differences in TFP. This bias can severely affect the results of empirical exercises. For example, Foster, Haltiwanger & Syverson (2008) show that not taking into account demand factors leads to substantially underestimate the contribution of new entrants to productivity growth.

Although the relevance of demand is hardly disputable, in practice its role in determining firms' growth has been almost completely neglected. In fact, identifying this component requires firm level price data, something typically not available in the datasets used to study firm performance. In this paper firms are characterized by two unobserved idiosyncratic variables, *market appeal* and *TFP*, defined as shifters of the demand and the production function respectively. Our goal is to estimate these factors and study their individual contribution to firm's growth. We use a unique dataset with information on a representative panel of Italian manufacturing firms with more than 50 employees (INVIND) yearly surveyed by the Bank of Italy since 1984. Crucially for our purposes, firms are asked about the average percentage change in prices of goods and services sold, which is the key piece of information allowing us to separately identify market appeal and TFP.

We use a standard model of monopolistic competition on the demand side and Cobb-Douglas production, each with its own stochastic shifter. The purpose of the model is to flesh out the assumptions needed for correctly identifying shocks to TFP and to market appeal. Since price information is only provided as a growth rate, the estimation is performed in first differences. We start backing out the unobserved demand component as the residual of the demand equation. We circumvent the usual simultaneity problem in demand estimation (Trajtenberg 1989, Berry 1994) by using a direct assessment of the elasticity of demand provided by the managers in the survey. Estimated price elasticities range between 4.5 and 6, the typical ballpark for manufacturing products. Productivity shocks are then identified as residuals of the production function equation. To solve the problem of the endogeneity of inputs, we extend the Olley & Pakes (1996) procedure to accommodate for non scalar unobserved heterogeneity. In particular, we show that, under standard assumptions, the invertibility of the policy function is preserved even when dealing with a vector of unobservables. The production functions of all our sectors are characterized by decreasing returns to scale, with the degree of returns to scale ranging between .8 and .9. We show that estimates of the production function that do not take advantage of firm level prices provide different estimated parameters and result in a distorted estimated productivity.

Under our assumptions, demand appeal and TFP are exogenous determinants of firms growth. To study their effects, therefore, we can simply regress measures of output and inputs growth on their estimated values. The exercise reveals that demand factors play a non negligible role. One standard deviation increase in $\Delta\xi$ generates a 12% increase in nominal sales, twice as large as the effect of TFP. We turn to the model for guidance in interpreting these estimated effects. In fact, given estimates of the parameters of the demand and production functions, and under the (hardly realistic) assumption of no frictions in adjusting the scale of operation, our theoretical framework delivers quantitative predictions on the impact of the shocks on firms' growth. We compare the figures implied by the model with those emerging from the empirical exercise to find a surprising result. Whereas the measured impact of demand appeal is close to that implied by the model, the correlation of TFP with firm growth is much smaller than expected. We interpret this as evidence of frictions which affect the transmission of shock, not accounted for in the model. Consistent with this, we find that both shocks have lagged effects on growth of output and inputs, particularly strong and persistent in the case of TFP.

The analysis of dynamics effects helps shedding light on the nature of the wedge between the model's predictions and the estimation results. First, the comparison of the dynamic response to changes in TFP and market appeal shocks hints at the discrepancy being related to nominal rigidities, ie., to a sluggish price response. In fact, firms's output over-react to demand shocks on impact, as the firms adjusts prices to the new equilibrium value gradually. Second, the deviation is much stronger for TFP than for demand appeal shocks. The pattern implies that some of the adjustment costs muffling the impact of the shocks must be specific to productivity. We focus on one such friction: the presence of hurdles to internal reorganization. Improvements in demand appeal only require a firm to scale up its operations to cater larger demand. Instead, fully exploiting a TFP shock may involve more complex organizational adjustments. The INVIND survey contains information on both the price adjustment policy and the difficulties in reshaping the firm's organization. We exploit it to test directly their role in determining the firms' responses to the two shocks. We find evidence of both nominal rigidities and organizational frictions. In fact, firms reporting to adjust their prices more sluggishly display lower elasticity of output and input growth measures to TFP and overreact to demand shocks. The elasticity of growth to TFP is also especially low for firms reporting difficulties in undertaking organizational restructuring.

These findings have important implications. The large wedge between the model predictions and the actual adjustment to shocks imply that factors are not allocated efficiently across firms, in line with the findings of Hsieh & Klenow (2009) for China, India and the US. We also show that such phenomenon is much stronger for productivity than for demand shocks. This suggest that the barriers to the efficient allocation of resources cannot be only of regulatory nature, as the literature on this subject typically assumes (Hopenhayn & Rogerson 1993, Restuccia & Rogerson 2008, Hsieh & Klenow 2009). If that were the case, there is no reason to expect different wedges for the two shocks. Instead, our results support that frictions specifically affecting productivity should be blamed for causing resource misallocation. The evidence we provide is consistent with differences in managerial abilities and in the attitude towards organizational change of the type studied by Bloom & Van Reenen (2007) and Bloom, Sadun & Van Reenen (Forthcoming) playing a prominent role in that sense.

This study links to a vast literature interested in understanding the determinants of firm growth (Dunne, Roberts & Samuelson 1988, Dunne, Roberts & Samuelson 1989, Evans

1987a, Evans 1987b). We expand their analysis by considering multiple sources of unobserved heterogeneity. In particular, we try to capture simultaneously the effect of asymmetries in productive efficiencies and in appeal to customers. The importance of demand factors has been long recognized but quantitative assessment of its role have been prevented by lack of data. Foster et al. (2008) were the first, to our knowledge, to provide an empirical estimate of the role of demand in affecting firm survival. We differ from their study in two main respects. First we focus on a different outcome, growth. Furthermore, since we observe firm prices and not only quantities, we are not restricted to look only at sector producing homogeneous output but can consider a broader and more representative set of industries. Examining markets where goods are differentiated we are assessing the role of demand factors in a contest where they are likely to be of critical importance. Marchetti & Nucci (2005) and Marchetti & Nucci (2007) have pointed to the role of price sluggishness in explaining the low response of firms' outcome to productivity shocks using a different approach but our same data. With respect to their contributions, we introduce demand shocks in the model leading to the conclusion that nominal rigidities alone cannot explain the whole phenomenon.

The rest of the paper is organized as follows. Section 2 presents a standard model of a monopolistic competitive firms characterized by a demand and productivity shifters. Section 3 introduces the data while Section 4 presents the estimation approach. Section 5 discusses the main results on the effects of the shocks on firm growth and points out the discrepancy between that and the theoretical predictions of the model. Section 6 attempts at rationalizing this finding by analyzing the role of dynamic mechanism that could explain it.

2 The model

Our theoretical framework relies on a model of monopolistic competition where firms choose inputs to produce output, subject to a CES demand function and a Cobb-Doublas production function as in Melitz (2000). Modeling a firm production decision and its demand and introducing unobserved heterogeneity in both settings we complicate the estimation procedure. Formalizing our problem allows to stress the assumptions needed for our estimation approach to work in this environment. Furthermore, the model helps illustrating the consequences of ignoring firm prices on estimates of productivity. Finally, it will give us a benchmark against which to evaluate the results of the growth regressions. In presenting the model, we distinguish between the static and the dynamic part.

2.1 Static choices

The firm faces a constant elasticity demand function:

$$Q_{it} = P_{it}^{-\sigma} \Xi_{it} \tag{1}$$

where $\sigma > 1$ is the elasticity of demand and Ξ_{it} is a demand shifter. Other time specific factors, constant across firms, can be ignored without loss of generality as they will be captured by time dummies in the empirical specification.

The firm enters the period with a given level of capital stock $\bar{K}_t$, cumulated through investment up to period $t-1$:

$$\bar{K}_{it} = (1-\delta)\bar{K}_{it-1} + I_{it-1} \tag{2}$$

where δ is the depreciation rate. Although the firm cannot modify the capital stock in place for this period, it decides the degree of capital utilization u_t, where $0 \leq \mathrm{u}_t \leq 1$. The effective capital used for production is then $K_t = \mathrm{u}_t \bar{K}_t$. We assume that using capital is costly[1] so that it may be optimal to use less than the whole installed capacity. For simplicity, we assume that capital depreciation is independent from usage.[2] The firm produces output combining utilized capital, intermediate inputs and labor with a Cobb-Douglas production function

$$Q_{it} = \Omega_{it} K_{it}^{\alpha} L_{it}^{\beta} M_{it}^{\gamma} \tag{3}$$

where Ω_{it} is firm TFP. We assume that labor L and intermediates M are free variables and have no dynamic implications, while capital input can be varied through the degree of utilization, up to full utilization. The firm observes Ω before choosing inputs. Moreover, due to strikes, power shortages and machines breakdowns there might be variations in K and L independent from Ω_{it}.[3]

Below, we solve for the per-period output and pricing decisions. In the appendix we show that the firm uses less of its full capacity, that is $U_t < 1$, if and only if

$$\bar{k}_t \geq c_{\bar{k}} + \frac{(\sigma-1)}{\theta}\omega_t + \frac{1}{\theta}\xi_t \tag{4}$$

[1] For example, it may be the case that capital must be used in a fixed proportion $1/a$ with energy. If the price of energy is p^e, then the cost of using capital is defined as $r = a * p^e$, where we use r as the standard notation for the cost of capital usage.

[2] For some types of capital, such as buildings, this seems the most natural assumption. In general, a component of depreciation is clearly linked to time. Moreover, when capital is used it might be easier to maintain it in an efficient state.

[3] Alternatively, one can assume the DGP postulated by Ackerberg, Caves & Frazer (2006), where labor, intermediates and capital are set prior to the investment decision, and Ω changes between the two points in time.

where lowercase letters are logs, $\theta \equiv \alpha + \beta + \gamma + \sigma(1-\alpha-\beta-\gamma)$ and $c_{\bar{k}}$ is a constant that depends on factor prices and the coefficients of the demand and production functions. Condition (4) states that the capital stock in place does not bind as long as the productivity and demand shocks are not too large. In fact, as we show below, output is increasing in both shocks. We focus on the case in which condition (4) is satisfied and analyze the case where the constraint binds in the appendix.[4] In this case, equilibrium quantities do not depend on the capital stock in place. The firm observes ω_{it} and ξ_{it} and chooses inputs to maximize profits. The optimal quantity, price and inputs demand functions are:

$$q^*_{it} = c_q + \frac{\sigma}{\theta}\omega_{it} + \frac{(\alpha+\beta+\gamma)}{\theta}\xi_{it} \quad (5)$$

$$p^*_{it} = c_P - \frac{1}{\theta}\omega_{it} + \frac{(1-\alpha-\beta-\gamma)}{\theta}\xi_{it} \quad (6)$$

$$x^*_{it} = c_x + \frac{(\sigma-1)}{\theta}\omega_{it} + \frac{1}{\theta}\xi_{it} \quad (7)$$

where $x = k, l, m$ and c_q, c_p, c_x are constants. Under decreasing returns to scale ($\alpha+\beta+\gamma < 1$), output increases with both productivity and demand shocks; whereas price decreases with productivity and increases with demand, and inputs demand increases with both. Instead, with constant returns to scale, p^* only depends on costs parameters and not on demand ones. Note that, although the markup is constant at $\frac{\sigma}{\sigma-1}$, prices differ across firms. In fact, firms' marginal costs differ for two reasons. First, they are characterized by different efficiency levels ω_{it}, which directly affect marginal costs given output. Second, if the production function displays decreasing returns to scale, different levels of ω and ξ entails different level of output, and therefore, of marginal costs.

Measuring TFP from physical output (TFPQ, in the language of Foster et al. (2008)) and from output deflated with the sectoral price deflator (TFPR) leads to identify different objects. In our setting, $tfpr_{it} = \omega_{it} + p_{it} - \tilde{p}_t$, where $\tilde{p}_t$ is the (log of the) sectoral price deflator. Using equation (6) and suppressing the constant, we can show that not accounting for firm level prices introduces a bias in our estimate of TFP:

$$tfpr_{it} = (1 - \frac{1}{\theta})\omega_{it} + \frac{(1-\alpha-\beta-\gamma)}{\theta}\xi_{it} - \tilde{p}_t$$

The bias has two sources. First, true TFP (ω) enters with a coefficient smaller than one, as higher productivity in part translates into lower prices (see equation 6). The effect is

[4] In our data, only 2% of the observations pertain to firms that report full capacity utilization. Note that hitting the capital constraint does not affect the demand or the production function estimation. As we show in the appendix, what changes are output and input demand as function of the shocks. We therefore use all the available observations to estimate demand and productivity shocks and exclude firms at the capital constraint in the second part of the paper.

stronger the higher the returns to scale. In fact, with CRS, θ is equal to 1 and there is full pass-through from productivity to prices. Therefore, TFPR does not measure any contribution of TFP. Second, TFPR also depends on demand shocks. In the revenue based approach, any increase in firm level prices would incorrectly be measured as a quantity change and would therefore affect the estimate of productivity. This bias is stronger the lower the demand elasticity and the returns to scale. With CRS the firm level price is unaffected by demand shocks and the effect disappear.

The lack of firm prices also implies that the coefficients estimated using revenue data are inconsistent (Klette & Griliches 1996). In fact, using (1) and (3) and taking logs, it is immediate to show that a revenue production function can be expressed as:

$$q_{it} + p_{it} = \frac{\sigma - 1}{\sigma}\alpha k_{it} + \frac{\sigma - 1}{\sigma}\beta l_{it} + \frac{\sigma - 1}{\sigma}\gamma m_{it} + \frac{\sigma - 1}{\sigma}\omega_{it} + \frac{1}{\sigma}\xi_{it} \tag{8}$$

Even if we accounted for the endogeneity of inputs, the coefficients of a revenue function underestimate the true degree of returns to scale, with the extent of the biased measured by $\frac{\sigma-1}{\sigma}$. We will use this implication to compare quantity and revenue based estimates.

2.2 The dynamic problem

Prices and quantities are static variables and, by choosing the input levels, the firm maximizes profits within period. The only dynamic choice the firm face is investment. As discussed above, the firm cannot alter its level of capital in place within the period, while it chooses the degree of capital utilization. Capital in place can be increased through investments, that will deliver capital stock the next period. A higher level of investment decreases the likelihood that the firm will be capital constrained next year. The state variables are demand and TFP shocks and the capital stock in place. We formulate the firm's problem using a dynamic programming approach in the appendix. Standard considerations ensure that, if $I_t > 0$, the policy function for investment $g(\bar{K}_{it}, \Xi_{it}, \Omega_{it})$ is increasing in Ξ_{it}, Ω_{it} for each level of $\bar{K}_t$. This implies that we can invert it and express the productivity shock as:

$$\Omega_{it} = \Omega(I_{it}, \Xi_{it}, \bar{K}_{it}) \tag{9}$$

This is the control function approach to production function estimation introduced by Olley & Pakes (1996). An important difference with their setting is that our investment function depends on two unobservables: the firm's market appeal ξ and productivity ω. Ackerberg, Benkard, Berry, & Pakes (2007) shows that the Olley & Pakes (1996) procedure can be extended to such cases by including the demand shifter in the control function of the first stage. Since we independently estimate market appeal from the demand equation, we can implement their suggested strategy to recover TFP.

3 Data description

3.1 Data sources and selection of the sample

Data used in this study come from the "Indagine sugli investimenti delle imprese manifatturiere" (Inquiry on investments of manufacturing firms; henceforth, INVIND), a survey collected yearly since 1984 by the Bank of Italy. The survey is a panel representative of Italian manufacturing firms (no plant information is available) with more than 50 employees[5] and contains rich information on revenues, ownership, capital and debt structure, as well as on usage of production factors. Additional firm information is drawn from "Centrale dei Bilanci" (Company Accounts Data Service; henceforth, CB), which contains balance sheets data of around 30,000 Italian firms. Firms in INVIND can be matched to their balance sheet data in CB using the tax identifier.

To ensure homogeneity of the final good produced we group firms into sectors. We use an aggregation of the ATECO 2002 classification of economic activities leading to seven sectors, listed in Table 1. We drop observations pre-1988 since firm-level prices are collected starting in that year. We also drop firms not matched with CB and without two consecutive years. After applying these refinements, we are left with a pooled sample of 11,560 firm-years over the period 1988-2007.

3.2 Construction of the main variables

The information on firm prices contained in the INVIND survey is instrumental to our goal of disentangling demand from TFP shocks. Deflating revenues with firm-level prices enables us to recover actual quantities and address the critique set forth by Klette & Griliches (1996). Foster et al. (2008) relied on information on firm-level quantities and used them to back out prices from revenues. For this strategy to work, they had to restrict themselves to sectors producing homogeneous output. Direct observation of firm level prices instead allows us to include in the analysis also industries were output differentiation is important.

An important caveat to our analysis is that price data are not reported in levels in the survey. Instead, firms are asked to state the "average percentage change in the prices of

[5]Since 2002 the survey was extended to service firms and the employment threshold lowered to 20. However, these firms are given a shorter questionnaire, which excludes some of the key variables for our analysis. We therefore focus on manufacturing firms with at least 50 employees throughout.

goods sold". Thus causes two types of challenges. First, it makes the price variable somewhat vulnerable to introduction of new products and dismission of old ones. Furthermore, we are forced to estimated the model in first differences. We use the figure in the survey to obtain the first difference in the logarithm of price[6] (Δp) and do likewise for all the other variables. Luckily, the survey that asks for most variables the current level but also the past year's one and the forecast for the next, making it easy to compute growth rates for the magnitudes of interest. In Section 4.2 we comment extensively on the challenges of estimating demand and production function in first differences. It is worth noting, however, that using growth rates provides some advantages when dealing with multiproduct firms for which the average growth in prices may be a more meaningful object than the average price. Moreover, first differences net out any fixed unobserved heterogeneity that might distort the estimates.

Nominal output is obtained from balance sheets data in CB. We deflate its growth rate using firm level price changes reported in INVIND to obtain real output growth. Our measure of labor input is the growth in the number of hours worked, reported in INVIND. Intermediate inputs come from CB and are deflated with sectoral prices. To measure capital inputs, we exploit questions in INVIND on both production capacity and the degree of capacity utilization. Firms report the percentage change in the technical capacity ($\bar{K}_t$ in the notation of Section 2), defined as *"the maximum output that can be obtained using the plants at full capacity, without changing the organization of the work shifts"*. Standard measures based on book values or permanent inventory method are subject to measurement error, due to depreciation/discouting problems and lags in the timing in which different investment are actually in place. We bypass all these issues using firms' direct assessment of the change in installed productive capacity.[7]

We define utilized capital as $K_t = U_t \bar{K}_t$, where U_t is the degree of utilization of technical capacity, also recorded in the survey. It follows that the change in utilized capital is $\Delta k_t = \Delta u_t + \Delta \bar{k}_t$. When using installed capital stock in the estimation of the production function, it is implicitly assumed that the degree of utilization of capital is 100%. Our data show

[6]Firms report % price change $\equiv \frac{P_t}{P_{t-1}} - 1$. We obtain the growth rate of the logged variables using the transformation $\Delta p = \ln(1 + \%\text{ price change})$. All the variables reported in the survey as percentage changes are transformed in the same way.

[7]Note that the question ask the change in the maximum output obtained using the plants at full capacity, *"without changing the organization of the work shifts"*. This excludes the possibility that the measure of capital so obtained already incorporates changes in productivity. Any TFP gain should in fact entail a certain degree of work reorganization. We have also experimented with traditional measures of the capital stock, constructed with the permanent inventory method using sectoral deflators and depreciations rates. Results are unchanged.

that utilization is high but far from full, stressing that taking into account the actual degree of utilization may be important.[8] We observe an average degree of capacity utilization of 81%, with a standard deviation of 13%. The 5^{th} and the 95^{th} percentile are 60% and 98% respectively, indicating substantial variation in capital utilization. Finally, utilized capital displays additional variation that is useful for identification. Estimating the production function in first differences, we rely exclusively on the within firm variation in the capital input. This poses a challenge for the estimation of its coefficient, as capital tends to have limited within firm variability. Utilized capital displays greater within variation than capital stock.

3.3 Summary statistics

Table 1 displays descriptive statistics both in levels (Panel A) and in growth rates (Panel B). Textile and leather and Mechanical machinery are the most represented industries, reflecting the Italian sectoral specialization. There is substantial cross-industry variation in sales, which stretch from an average of around 60m euros in Textile and leather up to almost 500m euros in Vehicles. Variation in the average number of employees is more limited, ranging between 300 and 600 workers, with Vehicles being the outlier at almost 2,000 workers.

A first look at growth rates shows that real sales and output grew on average 2% per year over the sample period. The labor input contracted slightly, whereas capital input grew at 4% yearly. The average firm in the sample raises prices by 2% per year. Average price growth shows little cross-sectoral dispersion ranging between 1.6% (Paper) and 2.7% (Metal). In the Appendix, we take a closer look at this key variable comparing the growth rate in prices implied by answers in the INVIND survey to that documented by the National Statistical Office in the official deflators. We show that the two series are similar, supporting the validity of the price indicator reported in INVIND.

4 Demand and TFP Estimation

4.1 Demand estimation

Firms face a CES demand function of the form expressed in equation (1). Since the information on firm level prices is only available in growth rates, we use the following equation:

[8] Not only is the level of utilization well below 100% but we also find it to be negatively correlated with the capital stock (correlation=-.03). Ignoring utilization would then lead us to underestimate productivity of firms with larger installed technical capacity.

$$\Delta q_{it} = \sigma \Delta p_{it} + \Delta \xi_{it} \tag{10}$$

where the i and t subscripts indicate firm and year, respectively. Δq_{it} is the growth rate of quantity sold, Δp_{it} is the growth rate of price and $\Delta \xi_{it}$ is a demand shock capturing variations in the *market appeal* of the firm. The shock is known to the firm but unobserved to the econometrician. If we obtained consistent estimates of the parameters of the demand function -namely, the price elasticity σ- we could estimate $\Delta \xi_{it}$ as follows

$$\widehat{\Delta \xi_{it}} = \Delta q_{it} - \hat{\sigma} \Delta p_{it} \tag{11}$$

Estimation of equation (10) is complicated by the familiar simultaneity problem. Positive unobserved shocks to market appeal may lead producers to raise prices, making Δp and $\Delta \xi$ positively correlated. Therefore, estimating the equation by OLS would understate demand elasticity. The literature has addressed this concern using cost shifters as instruments; instead, our approach exploits unique information contained in the INVIND database to recover estimates of the price elasticity.

In 1996, and again in 2007, the interviewed managers were directly asked to report the elasticity of the demand faced by their firm through the following question: *"Consider the following thought experiment: if your firm increased prices by 10% today, what would be the percentage variation in its nominal sales, provided that competitors did not adjust their pricing and all other things being equal?".* Since managers are explicitly asked to perform a thought exercise isolating the effect of price changes on demand, the estimates we derive from their answers should not be plagued by simultaneity. Therefore, we choose to rely upon answers to this question to estimate a sector-specific demand elasticity as the average of the elasticities reported by firms belonging to a given sector.

The survey question refers to a revenue-elasticity and mentions a 10% change in price. Define $\varepsilon^{R}_{10\%}$ the number provided by the interviewee; it is immediate to show that the elasticity can be obtained as: $\varepsilon^{Q}_{1\%} = \frac{\varepsilon^{R}_{10\%}}{10} - 1$. We have information on self-reported elasticities from two different waves. In our model, demand elasticity is not indexed by t; therefore, using answers to the 1996 or the 2007 wave should not matter. We use elasticities reported by the cross-section of representative firms interviewed in 1996 to estimate σ since this wave falls mid-through our sample period and the response rate is higher than in the 2007 wave (over 80%). In the Appendix we report kernel densities by sector for the distribution of self-reported elasticities in the two waves. They look similar and a Kolmogorov-Smirnov test does not reject the equality of the distribution in the two waves for five of our seven sectors.

Table 2 presents estimated demand elasticities for each of our seven sectors. In the first column, we list average sectoral self-reported demand elasticities from the 1996 wave of INVIND. Textile and leather and Chemical products are the least elastic with a σ of 4.5 and 4.7, respectively. Firms in the Vehicles sector face the most elastic demand (σ=6). These values are in the range of those found of the literature. For instance, the average elasticity for Vehicles is close to the price elasticity found by Berry, Levinsohn & Pakes (1995) for compact cars, which make up most of the market of Italian car producers (mostly Fiat and its suppliers). Similar values are found by Broda & Weinstein (2006) and Hendel & Nevo (2006). Hsieh & Klenow (2009) in their calibration use a conservative value of 3 and check the robustness of their results with an alternative value of 5.

The next two columns report the results from direct estimation of the demand function in equation (10). The OLS estimates are much lower than the self-reported ones. This is expected since the endogeneity of price should bias the elasticity towards zero. To obtain a number that should be more comparable to self-reported elasticities, we follow an instrumental variables approach. As Foster et al. (2008), we take our estimate of TFP as cost shifters and use it to instrument for price changes.[9] The estimates of σ obtained though instrumental variables are larger, in absolute value, than the OLS ones and in the same ballpark as the self-reported ones.

A concern on the reliability of self-reported price elasticity comes from the presence of multiproduct firms. For firms selling more than one line of products both the price change variable and the reported elasticities are harder to interpret. In fact, the figures are most likely some average of price changes for different products and of the elasticities of different demand curves. This is particularly problematic if managers report averages weighted by revenues. In such cases, products experiencing larger positive shocks to $\Delta\xi$ would at the same time gain weight on influencing the average price change figure. In our sample, 33% of the firms report deriving all their revenues from a single product line and 51% derive at least 80% of their sales from a single product line. The third column in Table 2 shows average self-reported elasticities only for firms deriving most (>80%) of their sales from a single product line. The inclusion of multiproduct firms does not seem to confuse the analysis in a substantial way. Once they are excluded, self-reported elasticities do not change significantly. A similar problem arises with exporting firms that face different demands in different countries and might set different prices for domestic and

[9] In detail, we follow Olley & Pakes (1996) and obtain estimates of $\Delta\omega$ and ϵ from equation 12; the sum of the two being our measure of ΔTFP. Our IV estimate uses ϵ, the unobserved (when choosing inputs) part of the variation in ΔTFP, as instrument for price.

foreign markets. Since INVIND contains information on the amount of revenue generated through export by each firm, we can concentrate our attention on those that do not export. The last column displays demand elasticities for non exporting firms; these firms appear to face a more elastic demand. This suggests that the "best" firms (i.e. those with some degree of market power) are more likely to become exporters. Overall, though, elasticities estimated using the subsample of non-exporting firms are not all that different from our baseline figures.

4.2 TFP estimation

Our approach to estimating productivity differs from the standard one in several aspects. To begin with, we directly estimate a quantity production function as opposed to a revenue production function. We back out quantities using unique information on firm level prices contained in our data, thus eliminating the bias introduced by sectoral deflators. The information on firm prices is only available to us as percentage changes. Therefore, we estimate the production function in first differences as in the equation below:

$$\Delta q_{it} = \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta m_{it} + \Delta \omega_{it} + \epsilon_{it} \tag{12}$$

where ϵ_{it} is an iid random shock unobserved to the firm when choosing inputs, or measurement error. We compute the growth rate of real output by subtracting the price change from the nominal output.[10]

In estimating the production function we face the usual problem of the endogeneity of input choice. We address it using the control function approach first introduced by Olley & Pakes (1996). Whereas Olley & Pakes (1996) assumes scalar unobservability, we introduce an additional unobserved component, a demand shifter. It follows that the policy function for investments depends not only on the initial capital stock and on productivity, but also on demand, as shown in equation (9) and we need to include controls for demand. Given that demand can be estimated independently from production, we address the issue by including our estimate of $\Delta\xi$ in the control function. As shown in Section 2.2, this gives us a valid control function. By log linearizing equation (9) and taking first differences, we can express the change in log of TFP as a function of the change in the log of the demand shock, the capital stock in place and investment. To improve the fit, we include also the interactions of the changes, up tho the third degree polynomial.[11]

[10] There is a long standing debate on the pros and cons of using value added or final output to estimate productivity (Bruno 1978). Recently, Gandhi, Navarro & Rivers (2011) have shown that estimating TFP using value added can lead to overstate the productivity dispersion.

[11] Although we can only compute the first difference of the demand shock, we do observe the levels of both

A final distinctive characteristic of our setting is that we allow the firm to choose the degree of capital utilization. Thus, effective capital is not a predetermined variable, but it is chosen after observing $\{\omega_{it}, \xi_{it}\}$, like labor and intermediates. This implies that, provided a valid control function is used, we can estimate all inputs' coefficients in a first stage, without the need of the second stage as in most applications of the Olley & Pakes (1996) procedure.[12] We estimate the coefficients using the following regression equation:

$$\Delta q_{it} = \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta m_{it} + h(\Delta \xi_{it}, \Delta i_{it}, \Delta \bar{k}_{it}) + \epsilon_{it} \tag{13}$$

where h is a third degree polynomial in its arguments. Once we have estimated the coefficients, we recover the changes in TFP (up to the random component ϵ_{it}) as $\hat{\Delta} tfp_{it} = \Delta q_{it} - \hat{\alpha}\Delta k_{it} - \hat{\beta}\Delta l_{it} - \gamma \Delta m_{it}$

Table 3 reports sector-by-sector estimates of the coefficients of the production function. All regressions include year dummies. To reduce the effects of extreme values on the estimates, we exclude the observations in the first and last percentile of the distribution of Δq_{it}, Δk_{it}, Δl_{it} and Δm_{it}. Panel A shows the baseline results. We find evidence of decreasing returns to scale for all sectors: the degree of returns to scale $\alpha + \beta$, reported in the last row of the panel, ranges between .74 in Minerals and .92 in Chemicals. [13] In Panel B we run the estimation procedure using output deflated with sectoral prices rather than with firm level prices. For all sectors, the parameters of the production function are higher than in the revenue based estimates, as predicted by Klette & Griliches (1996). Ignoring firm level prices leads to a downward bias in the estimated coefficient since an increase in output leads to a less than proportional increase in sales. In fact the firm lowers the price to sell the additional output. The size of the bias depends on the elasticity of substitution. The relation between the true parameters of the production function and the estimates derived using revenue based measures is as follows: $\alpha + \beta + \gamma = \frac{\sigma}{\sigma - 1}(\tilde{\alpha} + \tilde{\beta} + \tilde{\gamma})$, where $\tilde{\alpha}, \tilde{\beta}, \tilde{\gamma}$ are the OLS estimates that do not correct for the own price deflator. In the last row of

k and i. We have experimented with a specification in which the polynomial is in the change in the demand shock and in the current and lagged levels of k and i, finding similar results.

[12] We ignore the problem of selection also stressed by Olley & Pakes (1996). Unfortunately, in our data we cannot distinguish exit from simple nonresponse to the questionnaire.

[13] These figures are lower than those typically estimated with levels production functions. For example, Levinsohn & Petrin (2003) report returns to scale close to 1. Compared to their estimates, we find a lower elasticity of the capital coefficient: their sectoral estimates vary between .19 and .29, while ours are between .1 and .2. A low elasticity of output to capital is typically found in fixed effects estimations, which are known to give low and imprecise estimates of the capital coefficient. Olley & Pakes (1996) attributes this to the fact that the capital stock has little within firm variability. Such critique is less likely to apply in our setting. In fact, we observe capital utilization, which makes utilized capital more variable than the capital stock. All our results are robust to using TFP computed using factor shares and imposing constant returns to scale.

the table we compute the implied returns to scale, using the sectoral elasticity reported in Table 2. Applying the correction to the OLS estimates brings them close to those obtained using output deflated with firm level prices, although for four sectors the impled coefficients become larger than those in Panel A.

4.3 Descriptive statistics on ΔTFP and $\Delta\xi$

The procedures described above delivered a measure of firm productivity, ΔTFP, and a measure of a firm's demand appeal $\Delta\xi$. In this section we briefly describe these objects. Panel A of Table 4 shows descriptive statistics for ΔTFP. In addition to the Olley & Pakes (1996) estimates, we also report those based on factor shares. The figures are close and indicate that productivity was on average increasing slowly during the sample period. Panel B reports analogous information for $\Delta\xi$. All the reported estimates for $\Delta\xi$ are based on the self-reported elasticities contained in the INVIND survey. Our preferred approach involves averaging by sector the answers of the respondent to the 1996 wave of the survey, the first time the question on price elasticity. The so obtained sectoral price elasticities are used to calculate $\Delta\xi$ for all the firm in the sample as described in equation (11). These estimates are labeled as "$\Delta\xi$ sector" in the table.

We check for robustness of the procedure by using alternative ways of deriving estimates of *demand appeal*. First, we average INVIND answers at the class, rather than the sector, level of disaggregation. ATECO classes define narrower and more homogeneous groups of firms.[14] The row labeled "$\Delta\xi$ individual" reports estimates of $\Delta\xi$ only for firms that answered directly the question in INVIND. The last row reports descriptive statistics for $\Delta\xi$ if we only consider non exporting firms. Three of the four measures deliver qualitatively similar results and imply that market appeal has been growing 1.4% per year on average. Estimates based on individual elasticities are different and denote a negative growth rate for ξ. However, the discrepancy is entirely due to outliers. If we compare the median of the four distributions, they coincide.

5 Shocks and firm growth

We now analyze the role of TFP and demand appeal shocks in determining firms' growth patterns. In doing so, it is useful to utilize a benchmark against which to evaluate the

[14] As an example, production of iron and non iron metals belong to different classes of activities within the sector Metals. Similarly, the classes within the Chemicals sector distinguish between firms producing paint and those producing soap and detergents.

findings. Taken literally, the theoretical framework setup in Section 2 delivers quantitative assessments of the impact of demand and supply shocks on inputs and output growth. In fact, with the exception of firms hitting the capital constraints, which we exclude in what follows, the relationship between TFP and demand appeal shocks can be obtained by first differencing equations (5), (6) and (7). Given our estimates of the demand elasticity and of the production function coefficients, we could therefore predict the response of output and inputs growth to TFP and market appeal growth. However, the model 's goal was to inform our identification strategy rather than to offer a tool to understand firms' dynamics. As such, we abstracted from many features that may influence firms' growth patterns, such as inputs adjustment frictions (Hamermesh & Pfann 1996), borrowing constrains (Cabral & Mata 2003), etc. To asses the role of market appeal and TFP shocks on firm growth we therefore estimate reduced form elasticities by directly regressing measures of firm growth on the demand and TFP shocks backed out in the previous section. We estimate regressions of the form

$$\Delta y_{it} = a_0 + a_1 \Delta TFP_{it} + a_2 \Delta \xi_{it} + a_3 X_{it} + e_{it} \tag{14}$$

where Δy_{it} is the growth rate of some variable of interest (sales, end of the year employment, etc.), ΔTFP and $\Delta \xi$ are the estimated idiosyncratic shocks, and X_{it} contains a number of controls.

To interpret the results, we compare them to the quantitative predictions delivered from our theoretical. In fact, given estimates of the returns to scale and demand elasticity, the model implies a specific values for the elasticity of the endogenous variables to the idiosyncratic shocks. In the computation, we set the degree of returns to scale of .8 and an elasticity of demand of 5 (roughly the averages across sectors)and summarize the implied elasticities in Table 5. A one percent increase in TFP should bring about a 2.2 percent increase in nominal output and a 2.8 percent increase in real output, whereas price should go down by .56 percent. The predicted effects are smaller for demand shocks: the elasticity of nominal output is .56, that of real output .16.

5.1 Revenues and output

The model does not distinguish between production and sales, while in the data the two do not necessarily coincide, due to the presence of inventories. Given that we estimate the demand function using quantity sold and the production function using quantity produced, we look at both variables as measures of output growth. Technical efficiency and demand appeal affect sales through different channels. $\Delta \xi$'s have a direct effect on firms sales as they capture shocks to the customers' valuation of firm products. For instance, they can represent improvements in the quality of the goods produced or more immaterial factors such as increases in brand image and marketing effort. Instead, improvements in TFP affects sales in an indirect fashion. Higher productivity implies, other things equal, lower costs. Therefore, the firm can reduce its prices and move down the demand curve.

Table 6 reports the results of a regression of the change in log sales on our estimates of TFP and demand shocks. For parsimony, from now on we only report pooled cross sectoral estimates. We account flexibly for cross sectoral heterogeneity through a full set of time-sector dummies and also include location dummies for five macro-regions of Italy. Sectoral estimates, reported in the Appendix, are fully in line with the pooled ones.[15] We account for the fact that some of the right-hand side variables in the regressions, TFP and ξ are estimated, by reporting bootstrapped standard errors. Column (1) shows that shocks to demand and to TFP have a positive impact on *nominal* sales growth.[16] The elasticity of sales to TFP shocks is larger than that to market appeal (0.6 vs 0.41). Once we factor in dispersion of the shocks, however, we find that one standard deviation change in ΔTFP would increase sales by 5%, whereas a similar change in $\Delta\xi$ would have twice that impact. Demand shocks, therefore, seem more important than productivity shocks to determine the evolution of market shares.

If we compare this results with the model's implications, we find that the elasticity to demand shocks we recover is slightly lower (.41 vs. .56); however, our estimate of the elasticity to productivity is well below the predicted value (.58 vs. 2.2). We take this a first indication that the model abstracts from important features to characterize the dynamics of firm growth. Moreover, the fact that the elasticity to productivity is more off target suggests that the frictions, whatever their nature, are more important for TFP than for market appeal shocks.

Once we move from measuring sales with revenues to looking at quantities sold, the theoretical prediction is that the role of TFP should grow and that of demand should shrink. In fact, quality improvements to the firm's products embodied in $\Delta\xi$ reflect both on quantity and sale price. A firm with a large $\Delta\xi$ should not only increase the quantity sold but also the price. On the other hand, the effect of TFP growth on sales comes thanks

[15] We have also performed firm fixed effects regressions to control for unobserved heterogeneity even within sector, finding no significant variation in the results. We take this as an indication that, since our analysis involves first differences, we are already purging unobserved firm heterogeneity that might affect both shocks and sales. Results from the fixed effect regression are available upon request.

[16] Note that with sector-year dummies there is no difference between using nominal or real values obtained through sectoral price deflators.

to a price reduction. Indeed, positive shocks to TFP lead to price cuts and improvements in demand appeal trigger price raises (Column (2)). Interestingly, the positive effect of demand shocks on prices is consistent with decreasing returns to scale. Moreover, once we consider real sales (Column (3)), the elasticity to TFP shocks grows to 0.74 and that to demand shocks decreases to 0.27. It is still the case that the elasticity to TFP shocks is much below that implied by the model (2.8). One standard deviation increase of the two forcing variables has a similar effects on real output, around 6.6%.

A large share of the firms in our sample are involved in export activity. Following the seminal contribution by Melitz (2003), a vast literature has investigated the relation between export activity and productivity, establishing that more productive firms are more likely to engage in trade.[17] We complement this literature by looking at the intensive margin of this issue. In columns (4)-(5) we decompose the growth rate of nominal revenues into domestic and export driven. We find that the effects of growth in both TFP and in market appeal are larger for export revenues than for domestic ones. Exporting firms experiencing improvement in productivity increase their engagement in trade; this is consistent with the results of the prior literature on the extensive margin (i.e. the decision to start exporting). Our findings on the role of demand, which goes in the same direction, represent completely new evidence on the determinants of export activity.

One possible explanation for the low elasticity to TFP shocks is that we are using sales rather than production, which is the variable directly linked to TFP. In the last two columns of Table 6 we repeat the exercise using output as the dependent variable. We find that the elasticity of TFP shocks increases by about 0.2 when compared to the sales regressions, both in the nominal and in the real output regressions, while the coefficients of demand shocks decrease slightly. Even so, the elasticity to TFP shocks remains well below that predicted by the model. For example, the response of real output is around 1, still far from 2.8. Interestingly, a unit elasticity is implied by a model in which TFP shocks increase output only directly, without setting in motion any change in input demand. This is what we analyze next.

5.2 Inputs

We now consider how the shocks affect inputs demand. We look at the growth rate in number of workers measured at the end of the year and at the rate of capital accumulation, defined as investment over the capital stock in place. We call these "quasi-fixed" inputs, to

[17] See, as an example, De Loecker (Forthcoming) and reference therein.

distinguish them from intermediates, the number of hours worked and the effective capital usage that enter the production function directly. They can be considered as indicators of the "steady-state" productive capacity of the firm, net of usage intensity. The growth in the number of workers and the investment rate (Table 7, Panel A) are positively correlated with TFP shocks, with coefficients of a similar magnitude (0.06-0.07). Demand shocks also exert a positive effect on both input measures, with similar values. One standard deviation increase in ΔTFP and in $\Delta\xi$ produce an increase of 0.7 and 0.8 percentage points respectively in the investment rate, around 10 percent of the median investment rate in our sample (7.3%). In terms of magnitude, the responses are substantially lower than those implied by the model, particularly for TFP.

To gain further insight we break down the employment growth rate into its determinants, looking separately at hiring and separation rate (hirings and separations over employment). Most of the action is taking place on the hiring margin, whereas the elasticity of separations to demand appeal is low and that to TFP is not significant. This can be interpreted as evidence of firing costs, a well known characteristic of the Italian labor market (Schivardi & Torrini 2008). Firms react to productivity and demand shocks by adjusting their intake of new workers but exercise less control on the outflow, driven in large part by exogenous processes (retirements, quits).

It is also instructive to consider what happens to variable inputs. Only intermediate inputs are responsive to TFP shocks, while hours worked and utilized capital are not (Table 7, Panel B). On the contrary, all inputs react to a demand shock. These results complement those on output reported in Table 6. By totally differentiating equation (12), the total contribution of a TFP shock to output growth is:

$$\frac{d\Delta q_{it}}{d\Delta\omega_{it}} = 1 + \alpha\frac{\partial\Delta k_{it}}{\partial\Delta\omega_{it}} + \beta\frac{\partial\Delta l_{it}}{\partial\Delta\omega_{it}} + \gamma\frac{\partial\Delta m_{it}}{\partial\Delta\omega_{it}} \tag{15}$$

A TFP shock increases output both directly, with unit elasticity, and by increasing the inputs demand. The fact that we found a unit coefficient in the output growth regression is consistent with TFP only increasing output directly: firms do not increase their input usage when hit by a TFP shock. Demand shocks have no direct impact on output. The change in output that we found in Table 6 has to be met by corresponding changes in inputs, as we actually find in Table 7.

Taken together, this evidence points to two conclusions. First, and not surprisingly, the fact that firms modify "quasi-fixed" inputs substantially less than predicted by the model and that most action occurs on the hiring rate is indicative of adjustment costs. Second, deviations from the frictionless model are substantially stronger for TFP shocks. We further investigate these issues in the next section.

6 Adjustment frictions

6.1 Dynamic effects

There exists a large literature on adjustment costs in factor demand.[18] Directly inferring the shape of an adjustment cost function is beyond the scope of this paper. Rather, we consider a general implication of adjustment costs: shocks can have lagged effects. If adjusting prices or inputs takes time, we should find that current output is a function not only of contemporaneous but also of lagged shocks. Note that, even in the presence of adjustment costs, the production and demand functions are static: output produced depends on current inputs, and quantity sold on price. Introducing dynamic effects does not affect our identification strategy for demand. Instead, it causes complications for the control function approach. Since the firm chooses investment based also on the lagged values of the shocks, we need to increase the number of controls. We use the forecast for next year investment, the expected change in technical capacity and two lags of the demand appeal shocks as additional controls. In the Appendix we show that this is a valid control function for the case at hand. We recompute the coefficients of the production function and the corresponding TFP levels for this modified setting and use these estimates for the regressions in Table 8. The resulting coefficients are similar to those obtained in the basic specification.

We investigate the importance of lagged shocks in Table 8. We consider two lags of both TFP and demand appeal shocks. Past TFP shocks have a sizeable effect on the growth rate of output (Column (1)): .15 at lag 1 and .036 at lag 2. Even considering this significant dynamic effects, however, the cumulative response is around 1.2, half of that predicted by the model.[19] Slow adjustments implies that real output should keep growing after impact and that the price should keep falling. Column (2) shows that pattern for price is consistent with this prediction. A positive shocks to TFP leads to price cuts in the current year (-.16), as well as in the next two (-.04 and -.02, respectively). The lagged effects are more consistent on "quasi-fixed" inputs, that is in the (end of the year) number of employees and in the investment rate (columns (3) and (4)). Even at lag two the elasticity is similar to the contemporaneous one. This indicates that the time required to update the productive

[18] See Hamermesh & Pfann (1996) for a survey of this literature. Skedinger (2010) offers an up-to-date survey of the literature on employment protection legislation, typically seen as the main obstacle to adjusting labor.

[19] To save on space, we do not report results for sales in what follows. They are similar to those for output.

capacity to a TFP shocks are substantial.

The dynamic of demand shocks follows a rather different scheme. Lagged demand shocks have a small negative effect on output at lag 1 and no effect at lag 2. The negative effect at lag one might seem counterintuitive, but can be understood by considering the fact that prices keep increasing in response to higher market appeal also one period after the shock occurred. This pattern is consistent with nominal rigidities, that is to a sluggish price adjustment. After a positive demand shock, firms do not immediately increase prices to the new equilibrium level. As a result, the immediate increase in output is larger than the "long run" one. As prices are further increased, output falls.

Inputs follow a similar pattern to that of TFP shocks, with positive response at all lags. This is not ad odds with the output results: in fact, in unreported regressions we found that variable inputs display a negative elasticity at lag one, as does output. Still, the firm upgrades the productive capacity slowly, consistently with adjustment costs. Lagged effects are smaller than for TFP, suggesting that frictions are present but less relevant than for TFP shocks.

Taken together, the evidence on lagged effects offers several insights. First, shocks do have dynamic effects: they keep influencing performance even after two years. Second, the evidence points to some form or price rigidity. In fact, only the sluggish adjustment of prices can explain the overshooting of output to demand shocks. Finally, even considering lagged effects, the response to a TFP shock remains well below the theoretical prediction, confirming that there is an asymmetry in the degree of frictions characterizing responses to the two types of shocks.

6.2 Sluggish price adjustments

The literature has found ample evidence of both costs in adjusting *prices* (menu costs, inattention etc.) and in adjusting quantities (costs of adjusting inputs). By distinguishing between market appeal and productivity shocks, our model has the identification power to assess which one of the two is the most likely source of friction in the data. Figure 1 describes the response to a positive TFP (panel a) and demand shock (panel b). A TFP shock shifts the marginal cost curve downward, increasing output from q to q'. This increase is absorbed from the market thanks to the simultaneous fall in price (from p to p'). Note that a TFP shock cannot help us discriminate between price and quantity rigidities: a sluggish response of price would imply a sluggish response of output and viceversa. The implications are different for demand shocks. If the adjustment costs are on quantities, we should observe that the immediate response of output is lower than the steady state one, and that prices jumps above the new equilibrium on impact and then gradually decrease to the new equilibrium. If the adjustment is on price, the opposite occurs: the price moves gradually from p to p', and the quantity overshoots on impact its long run level. In the extreme case of totally rigid prices, the quantity jumps from q to q'' in the short run, and then converges to the new steady state q'. The evidence presented in Table 8 was more consistent with this second story, suggesting that the adjustment frictions may affect prices, rather than inputs.

Using questions on price setting behavior included in the 1996 and in the 2003 questionnaires of the INVIND survey, we are able to provide direct evidence of the role of price sluggishness at the firm level. Managers were asked how often their firms review prices.[20] To be conservative, we define a firm to have sluggish price adjustment if it reviews prices less frequently than every six months. We use the answer to the 1996 questionnaire to classify firms up to 1999 and the answer given in 2003 after that. Following this procedure, we categorize approximately 60% of the firms in a given year as slow adjusting.

As a first check of the reliability of our measure of price sluggishness, we regress the price changes on the shocks and on their interaction with the slow adjusting dummy. Table 9, column (1) shows that firms classified as slow adjusting do decrease price less than "flexible price" firms. Symmetrically, the increase in price following a demand shock is lower for sluggish firms. As a natural consequence, output and sales in sluggish firms respond less to productivity than in flexible firms. For instance, the elasticity of output to TFP is 1.15 in flexible firms and .95 in sluggish firms. Conversely, sluggish firms have a higher elasticity to demand shocks: given that their price increases less, output and sales have to increase more. The evidence is less clear cut for quasi-fixed inputs (columns 4 and 5 in Table 9). Although the signs are in line with the previous results, employment is the only variable responding differently in sluggish and flexible firms.

6.3 Organizational inertia

A nominal rigidity, like slow price adjustment, should impact in the same way on both idiosyncratic variables. However, our accounting exercise reveals that the elasticity of firm performance to TFP is further away from what theory would predict than it happens for

[20] The possible answers differ slightly. In 1996 the options were: 1) more than once a month; 2) every month; 3) every three month; 4) every six months 5) once a year or less often. Options provided in 2003 are: 1) more than once a month; 2) every 1 to 3 months; 3) every 4 to 6 months; 4) every 7 to 11 months; 5) every year; 6) less than once a year.

demand factors. This finding leaves room for other potential source of rigidity, specific to productivity, to play a role. Here we explore the possibility that hurdles to organizational restructuring are responsible for the scarce sensitivity of growth measure to changes in productivity. An improvement in productivity has a direct effect on firms' outcomes. For example, hiring a better manager or adopting a new technology will make a firm produce more output even though the mix of the inputs of production is not touched. However, part of the effect is indirect: given the productivity jump, the firm will want to update not only the optimal level of inputs needed but quite possibly the way in which they are organized. If this transition cannot happen or it is not swift, the impact of any given TFP gain will be attenuated. On the other hand, to respond to an improvement to the demand appeal the firm needs not to undertake reorganization: it simply needs to increase the scale of operation. Therefore, inertia in organizational restructuring should not affect the impact of demand shocks.

Each year the INVIND questionnaire asks the interviewees to compare actual investments with planned ones[21] and, in case the two do not coincide, to identify the reasons that led to the discrepancy. One of the causes listed is "reasons related to the internal organization of the firm". We assume that firms selecting this option were facing higher cost of organizational restructuring in that year and check in Table 10 whether organizationally constrained and unconstrained firms react differently to TFP and demand appeal shocks.

The indicator variable for organizational bottlenecks is not significant for any of the growth measures we analyzed but output. Instead, the interaction between TFP shocks and the dummy for internal organization problems are negative and, in most cases, significant. This signals that facing organizational problems does not affect growth per se but only through its interplay with response to TFP shocks. Organizationally challenged firms experience lower growth in sales and in employment after a positive TFP shock. The interactions is negative for investment as well, however the coefficient is not significant. Most important, there is no difference in how firms with and without internal problems respond to demand shocks. This is consistent with the idea that TFP shocks require some degree of restructuring to fully take advantage of them, while accommodating demand shocks requires no specific reorganization activity.

The differential response of firm growth to TFP and demand appeal shocks has implications for the literature on factor misallocation, which focuses on frictions that prevent

[21] The survey also asks each year to report planned investments. Therefore, the interviewee is asked about unfulfilled plans on the basis of an objective forecast on record from the past year. Of course, this implies that the question can only be answered by managers in firms that appears in the survey in consecutive years.

the efficient allocation of resources across firms (Hopenhayn & Rogerson 1993, Restuccia & Rogerson 2008). Typically, misallocation is attributed to the institutional environment, that is, to factors external to the firm hindering the efficient reallocation of resources. For example, Hsieh & Klenow (2009) cite corruption as a possible reason preventing more efficient firms to grow (and less efficient to contract) in India and China. If obstacles to reallocation are only external to the firm, it is unclear why we should observe asymmetric responses according to whether the shocks come from the demand or the production side. Our evidence points to factors internal to the firm, such has organizational hurdles, as an important source of misallocation following TFP but not a demand shock. In fact, a recent literature has found a large degree of heterogeneity in managerial practices and organizational structures (Bloom & Van Reenen 2007, Bloom et al. Forthcoming). Our evidence suggests that such differences might also explain why firms tend to be less capable to take full advantage of a TFP improvement with respect to an increase in demand.

7 Conclusions

In this paper we took advantage of unique dataset on a panel of Italian manufacturing firms that contain information on firm level prices to separately identify the role of productivity and idiosyncratic demand on firm growth. We show that, though mostly neglected in the literature, heterogeneity in demand is an important determinant of growth. Furthermore, the measured effect of idiosyncratic variables is lower than what would be predicted by a frictionless theoretical framework. Exploiting the heterogeneity in this effect across different outcome variables and between demand and supply factors, we are able to test the role of some friction that may help explaining the pattern. In particular, we present evidence that both nominal (lags in price adjustment) and real (resistance to organizational changes within the firm) rigidities contribute to reduce the impact of idiosyncratic factors.

One limitation of our approach is that demand and supply shocks are considered exogenous. In reality, firms can affect evolution of both, for example investing in R&D and advertising. Endogenizing productivity and market appeal is an exciting avenue to explore in future research.

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Table 1: Summary statistics for main variables, by sector

	All	Textile and leather	Paper	Chemicals	Minerals	Metals	Machinery	Vehicles
Panel A: Levels								
Sales	126,619	54,055	114,224	169,000	71,758	116,618	107,045	483,668
	(595,802)	(109,611)	(254,860)	(312,986)	(119,067)	(341,266)	(245,620)	(2,117,926)
Output	126,562	54,370	110,263	173,603	73,187	119,816	108,749	461,125
	(572,481)	(110,007)	(234,334)	(319,110)	(121,902)	(342,676)	(247,169)	(2,018,199)
Workers	525	314	445	510	331	335	565	1,950
	(2,454)	(559)	(823)	(972)	(479)	(903)	(1,271)	(8,852)
Panel B: Growth rates								
ΔSales	.020	-.005	.027	.020	.016	.021	.036	.035
	(.19)	(.17)	(.13)	(.14)	(.18)	(.17)	(.19)	(.38)
ΔOutput	.023	-.007	.035	.029	.023	.034	.030	.043
	(.22)	(.20)	(.16)	(.20)	(.19)	(.20)	(.23)	(.30)
ΔInterm. inputs	.003	-.012	.039	.026	.027	.031	.038	.058
	(.30)	(.31)	(.25)	(.31)	(.25)	(.32)	(.34)	(.44)
Δhours worked	-.004	-.017	-.005	.001	-.008	.004	.001	-.003
	(.13)	(.14)	(.09)	(.11)	(.12)	(.14)	(.14)	(.15)
Δutilized capital	.038	.015	.052	.041	.040	.053	.043	.044
	(.20)	(.20)	(.19)	(.21)	(.20)	(.18)	(.19)	(.25)
Δprices	.021	.023	.016	.021	.026	.027	.017	.016
	(.06)	(.05)	(.08)	(.06)	(.05)	(.08)	(.06)	(.04)
Obs.	12,110	2,718	705	1,666	1,192	1,887	3,159	783

Notes: Figures reported are sample averages; standard deviations are in parentheses. Sales and Output are expressed in thousands of 2007 euros. ΔSales and ΔValue added are computed net of growth in firm level prices.

Table 2: Estimates of σ, by sector

Sector	INVIND	OLS	IV	INVIND Single product	INVIND Non exporters
Textile and leather	4.5	.27	6.1	4.7	8
Paper	5.1	.39	4.6	4.7	5.6
Chemicals	4.7	.40	5.2	5.7	5.6
Minerals	5.4	-.04	-5.5	3.5	6.1
Metals	5.5	.28	4.9	6.4	7
Machinery	5	.39	5.7	5.1	7.4
Vehicles	6	.63	7.1	8.4	8.2

Notes: Estimates in the columns labeled "INVIND" are obtained as simple sectoral averages of the self-reported elasticities in 1996 (first time the question on elasticity was asked). "INVIND-Single product" only includes firms declaring to owe at least 80% of their sales to a single product line. OLS estimates are all significant at 1% with the exception of Vehicles (significant at 5%) and Minerals (not significant at conventional levels). The IV column uses unexpected variation in ΔTFP as instrument. IV estimates are all significant at 1%.

Table 3: Production function estimation: OP and OLS results

	Txt+leather	Paper	Chemicals	Minerals	Metals	Machinery	Vehicles
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Output deflated with firm prices						
Δk	0.14***	0.09**	0.11***	0.12***	0.09***	0.11***	0.17**
	(0.027)	(0.042)	(0.023)	(0.033)	(0.028)	(0.023)	(0.066)
Δl	0.17***	0.31***	0.23***	0.24***	0.24***	0.17***	0.33***
	(0.025)	(0.055)	(0.030)	(0.045)	(0.031)	(0.029)	(0.070)
Δm	0.49***	0.37***	0.58***	0.38***	0.52***	0.52***	0.38***
	(0.023)	(0.045)	(0.027)	(0.032)	(0.023)	(0.019)	(0.053)
$\alpha + \beta + \gamma$	0.8	0.77	0.92	0.74	0.85	0.8	0.88
Obs.	1,805	443	1,083	815	1,354	2,072	419
R^2	0.67	0.55	0.71	0.59	0.65	0.72	0.63
	Panel B: Output deflated with sectoral prices						
Δk	0.11***	0.06	0.08***	0.10***	0.07***	0.08***	0.13**
	(0.023)	(0.038)	(0.020)	(0.030)	(0.024)	(0.018)	(0.062)
Δl	0.13***	0.20***	0.17***	0.23***	0.17***	0.15***	0.31***
	(0.022)	(0.050)	(0.025)	(0.039)	(0.027)	(0.023)	(0.064)
Δm	0.43***	0.36***	0.55***	0.34***	0.47***	0.50***	0.36***
	(0.020)	(0.041)	(0.025)	(0.029)	(0.021)	(0.017)	(0.050)
$\frac{\sigma(\tilde{\alpha}+\tilde{\beta}+\tilde{\gamma})}{\sigma-1}$	0.86	0.77	1.01	.82	.86	.91	.96
Obs.	1,806	446	1,083	816	1,356	2,076	419
R^2	0.77	0.72	0.82	0.70	0.76	0.79	0.67

Notes: The dependent variable is the growth rate of value added, deflated with firm level prices. Δk is the growth rate of the stock of capital used in production, taking capital utilization into account. Δl is the growth rate in the number of hours worked. All regressions include year dummies and robust standard errors in parenthesis.

Table 4: Descriptive statistics: ΔTFP and $\Delta\xi$

	N	*Mean*	*Std.dev.*	Percentiles *5th*	*25th*	*50th*	*75th*	*95th*
Panel A: ΔTFP								
ΔTFP-OP	12,110	.008	.14	-.16	-.04	.008	.06	.16
ΔTFP-factor	12,110	.001	.14	-.18	-.05	.00	.05	.17
Panel B: $\Delta\xi$								
$\Delta\xi$ sector	12,110	.014	.32	-.46	-.12	.02	.16	.47
$\Delta\xi$ class	10,315	.010	.34	-.48	-.12	.02	.15	.31
$\Delta\xi$ individual	1,089	-.013	.46	-.65	-.13	.02	.15	.49
$\Delta\xi$ non exporters	12,110	.010	.41	-.58	-.15	.02	.19	.57

Notes: ΔTFP-OP and ΔTFP-factor refer to estimates of TFP recovered using Olley and Pakes and total factor shares respectively. $\Delta\xi$ sector and $\Delta\xi$ class refer to estimates of $\Delta\xi$ obtained using self-reported elasticities averaging firm responses at the sector and class level respectively. $\Delta\xi$ individual reports estimates of $\Delta\xi$ relying only on the firms that replied directly to the question on price elasticity in the 1996 wave of INVIND. $\Delta\xi$ non exporters uses sectoral averages but considers only firms that do not export.

Table 5: Implied elasticities of prices, output and inputs from the production function and the demand estimation

	$\Delta p + q$	Δq	Δp	Δx
$\Delta\omega$	2.2	2.8	-0.56	2.2
$\Delta\xi$	0.56	0.44	0.11	0.56

Notes: Each entry represents the elasticity of the corresponding column variable to TFP and demand shocks. $p + q$ is nominal output, q is real output deflated with firm level prices, x is inputs (labor, capital and intermediates).

Table 6: Sales and output growth

	Sales					Output	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Nominal	Price	Quantity	Export	Domestic	Nominal	Quantity
ΔTFP	0.597***	-.154***	0.735***	0.721***	0.476***	0.806***	0.982***
	(0.017)	(0.004)	(0.021)	(0.044)	(0.030)	(0.019)	(0.022)
$\Delta\xi$	0.408***	.132***	0.265***	0.452***	0.344***	0.356***	0.222***
	(0.006)	(0.002)	(0.008)	(0.017)	(0.009)	(0.006)	(0.007)
Observations	10,617	10,720	10,613	9,240	9,246	10,655	10,656
R^2	0.67	0.76	0.46	0.20	0.29	0.59	0.51

Notes: All dependent variables and the demand and TFP shocks are in delta logs. ΔTFP is calculated using Olley & Pakes (1996) control function approach. $\Delta\xi$ is computed using self-reported sectoral price elasticities from the INVIND survey 1996. The columns labeled "quantity" use output and sales deflated using individual firm prices, rather than a sectoral deflator. All specifications include region and industry-year fixed effects. Both dependent and independent variables are trimmed to drop outliers above the 99th or below the 1st percentile. Standard errors are calculated from 500 bootstrap simulations. Robust standard errors are reported in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%

Table 7: Inputs growth

Panel A: Quasi-fixed inputs

	(1) Employment	(2) Hires	(3) Separations	(4) Investment rate
ΔTFP	0.061***	0.065***	-0.006	0.077***
	(0.010)	(0.012)	(0.012)	(0.014)
$\Delta\xi$	0.074***	0.068***	-0.015***	0.033***
	(0.004)	(0.004)	(0.004)	(0.005)
Observations	10,559	10,658	10,657	8,463
R-squared	0.11	0.10	0.04	0.05

Panel B: Variable inputs

	(1) Hours worked	(2) Intermediate inputs	(3) Utilized capital
ΔTFP	0.013	0.240***	0.007
	(0.013)	(0.037)	(0.020)
$\Delta\xi$	0.103***	0.373***	0.110***
	(0.005)	(0.010)	(0.007)
Observations	10,576	10,652	10,580
R-squared	0.12	0.28	0.09

Notes: All dependent variables and the demand and TFP shocks are in delta logs. ΔTFP is calculated using Olley & Pakes (1996) control function approach. $\Delta\xi$ is computed using self-reported sectoral price elasticities from the INVIND survey 1996. The columns labeled "firm price" use output and sales deflated using individual firm prices, rather than a sectoral deflator. All specifications include region and industry-year fixed effects. Both dependent and independent variables are trimmed to drop outliers above the 99th or below the 1st percentile. Standard errors are calculated from 500 bootstrap simulations. Robust standard errors are reported in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%

Table 8: Lagged effects

	(1) Output	(2) Price	(3) Employment	(4) Investment rate
ΔTFP_t	0.987***	-0.160***	0.076***	0.088***
	(0.031)	(0.006)	(0.014)	(0.020)
ΔTFP_{t-1}	0.155***	-0.041***	0.110***	0.071***
	(0.020)	(0.004)	(0.014)	(0.021)
ΔTFP_{t-2}	0.036*	-0.020***	0.062***	0.069***
	(0.022)	(0.004)	(0.013)	(0.021)
$\Delta\xi_t$	0.240***	0.133***	0.075***	0.035***
	(0.010)	(0.003)	(0.005)	(0.006)
$\Delta\xi_{t-1}$	-0.027***	0.010***	0.024***	0.015**
	(0.008)	(0.002)	(0.004)	(0.007)
$\Delta\xi_{t-2}$	0.001	-0.001	0.023***	0.028***
	(0.007)	(0.001)	(0.004)	(0.006)
Observations	5,425	5,436	5,378	4,390
R-squared	0.52	0.79	0.16	0.07

Notes: All dependent variables, with the exception of the investment rate, and the demand and TFP shocks are in delta logs. ΔTFP is calculated using Olley & Pakes (1996) control function approach. Since lags are included in the specification, the control function is augmented to include forecast for next year investment, the expected change in technical capacity and two lags of the demand appeal shocks as additional controls. $\Delta\xi$ is computed using self-reported sectoral price elasticities from the INVIND survey 1996. Output and sales are deflated using firm level prices. Employment is measured as the number of workers employed at the firm at the end of the year. All specifications include region and industry-year fixed effects. Both dependent and independent variables are trimmed to drop outliers above the 99th or below the 1st percentile.Robust standard errors are reported in parenthesis. Standard errors are calculated from 500 bootstrap simulations. Robust standard errors are reported in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%

Table 9: Evidence of price sluggishness

	(1) Price	(2) Output	(3) Employment	(4) Investment rate
ΔTFP	-0.181***	1.146***	0.094***	0.124***
	(0.010)	(0.037)	(0.016)	(0.025)
$\Delta TFP \times$ Sluggish	0.030***	-0.194***	-0.019	-0.051
	(0.012)	(0.052)	(0.023)	(0.035)
$\Delta\xi$	0.146***	0.192***	0.063***	0.027***
	(0.003)	(0.010)	(0.005)	(0.008)
$\Delta\xi \times$ Sluggish	-0.021***	0.069***	0.022***	0.009
	(0.004)	(0.015)	(0.008)	(0.011)
Sluggish	0.002***	-0.006**	-0.001	0.002
	(0.001)	(0.003)	(0.002)	(0.004)
Observations	7,404	7,381	7,337	5,786
R-squared	0.80	0.55	0.13	0.07

Notes: All dependent variables, with the exception of the investment rate, and the demand and TFP shocks are in delta logs. ΔTFP is calculated using Olley & Pakes (1996) control function approach. $\Delta\xi$ is computed using self-reported sectoral price elasticities from the INVIND survey 1996. *Sluggish* is an indicator variable for firm that adjust prices sluggishly. It takes value 1 for firms reporting that they adjust prices once every 7-11 months or less frequently. Output and sales are deflated using firm level prices. Employment is measured as the number of workers employed at the firm at the end of the year. All specifications include region and industry-year fixed effects. Both dependent and independent variables are trimmed to drop outliers above the 99th or below the 1st percentile.Robust standard errors are reported in parenthesis. Standard errors are calculated from 500 bootstrap simulations. Robust standard errors are reported in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%

Table 10: Evidence of organizational hurdles

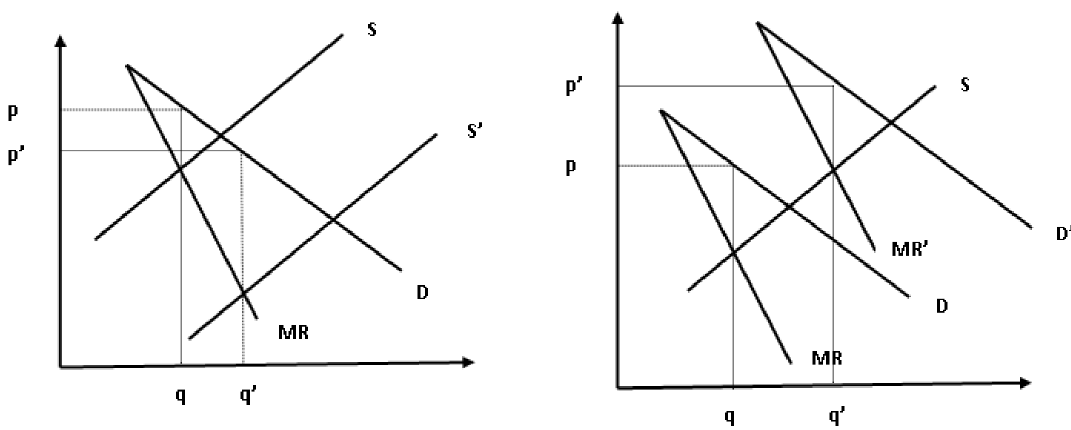
	(1) Output	(2) Price	(3) Employment	(4) Investment rate
ΔTFP	1.039***	-0.167***	0.097***	0.097***
	(0.035)	(0.007)	(0.018)	(0.024)
$\Delta TFP \times$Organizational hurdles	-0.112**	0.020**	-0.045**	-0.035
	(0.047)	(0.009)	(0.023)	(0.036)
$\Delta\xi$	0.226***	0.131***	0.076***	0.034***
	(0.010)	(0.003)	(0.006)	(0.010)
$\Delta\xi\times$ Organizational hurdles	-0.005	0.001	0.002	0.001
	(0.011)	(0.003)	(0.007)	(0.012)
Organizational hurdles	0.006**	-0.001	0.002	-0.003
	(0.002)	(0.001)	(0.002)	(0.003)
Observations	8,038	8,075	7,964	6,426
R-squared	0.51	0.77	0.13	0.05

Notes: All dependent variables, with the exception of the investment rate, and the demand and TFP shocks are in delta logs. ΔTFP is calculated using Olley & Pakes (1996) control function approach. $\Delta\xi$ is computed using self-reported sectoral price elasticities from the INVIND survey 1996. *Sluggish* is an indicator variable for firm that adjust prices sluggishly. It takes value 1 for firms reporting that they adjust prices once every 7-11 months or less frequently. Output and sales are deflated using firm level prices. Employment is measured as the number of workers employed at the firm at the end of the year. All specifications include region and industry-year fixed effects. Both dependent and independent variables are trimmed to drop outliers above the 99th or below the 1st percentile.Robust standard errors are reported in parenthesis. Standard errors are calculated from 500 bootstrap simulations. Robust standard errors are reported in parenthesis. Significance levels: *: 10%, ** : 5%, *** : 1%

Figure 1: Price sluggishness and response to shocks

(a) Positive shock to TFP

(b) Positive shock to ξ



Notes: The two figures illustrate adjustments after demand (a)and TFP shocks (b). For ease of illustration, we use linear demand and marginal cost functions.