Demand or productivity:  
What determines firm growth?*

Andrea Pozzi  
EIEF

Fabiano Schivardi  
LUISS,  
EIEF and CEPR

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Abstract

We disentangle the contribution of unobserved heterogeneity in idiosyncratic demand and productivity to firm growth using a model of monopolistic competition with Cobb-Douglas production and a dataset of Italian manufacturing firms containing unique information on firm-level prices. We find that demand shocks are at least as important as productivity shocks for firm growth. We also document that firms respond to shocks less than a frictionless model would predict, suggesting the existence of adjustment frictions. Finally, our results reveal that the degree of under-response is larger for TFP shocks. This implies the existence of frictions with differential effects according to the nature of the shock, unlike those typically studied by the literature on factor misallocation. We argue that hurdles to firm reorganization display this property and show that they hamper firms’ responses to TFP shocks but not to demand shocks. Therefore, managerial practices are not only important for within firm productivity growth, but also to enhance the process of efficient factors allocation across firms.

JEL classification: D24, L11.

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1 Introduction

Modern theories of industry dynamics assume that firms are heterogeneous along a single unobserved dimension, productivity, which determines the firm’s performance and growth (Jovanovic 1982, Hopenhayn 1992). The empirical literature on the topic has followed this view, tracing back firms’ growth to the evolution of productivity (see Syverson (2011) for a comprehensive survey). However, several other dimensions of heterogeneity may matter. In particular, the assumption that all firms look alike to consumers fails to capture an important ingredient of firm performance. Differences in the effectiveness in marketing, in developing relationships with customers, in maintaining brand image and in generating word-of-mouth are only some sources of heterogeneity across firms on the demand side.

The relevance of distinguishing between these two sources of heterogeneity goes beyond the well known measurement issues (Klette and Griliches 1996). It also provides insights on the determinants of firm entry, survival and growth. For example, Foster, Haltiwanger and Syverson (2008) show that, contrary to a large body of previous evidence, entrants are as productive as incumbents once heterogeneity in demand is properly accounted for. The data requirements to pursue this line of investigation are, however, quite stringent. To separately identify shocks to demand and productivity one needs to observe firm level prices, rarely available in the datasets used in the literature. The body of work analyzing idiosyncratic demand and productivity simultaneously is, therefore, still scant.

In this paper, we use a dataset with survey information on firm level prices to study how demand and productivity contribute to firm growth. We first disentangle demand and productivity shocks and then analyze the transmission mechanism of these shocks to growth. We reach two main conclusions: i) firms only partially react to shocks; ii) the lack of responsiveness is more severe after productivity than after demand shocks. We conclude that not only firms face frictions that constrain their response to shocks, as documented by a large literature, but the transmission mechanism of productivity also appears to be burdened by higher frictions than that of demand. We show that this asymmetry can be explained by heterogeneity in ability of firms to undertake restructuring, a dimension whose relevance is stressed by the growing literature on managerial practices (Bloom, Sadun and Van Reenen 2010).

We start our analysis by setting up a standard model of monopolistic competition on the demand side and Cobb-Douglas technology on the production side, each with its own stochastic shifter. The model is estimated using data on Italian manufacturing firms in the Textile and Leather, Metals, and Machinery sectors, for which the monopolistic com-
petition assumption is likely to be a good representation of market structure. We estimate idiosyncratic demand shocks as the residual of the demand function and circumvent the usual simultaneity problem in demand estimation (Trajtenberg 1989, Berry 1994) using a direct assessment of the elasticity of demand provided by the managers in the survey. Productivity shocks are then identified as residuals of the production function equation, with output deflated with firm level prices. To address the endogeneity of inputs choice, we adapt the Olley and Pakes (1996) procedure to accommodate for non scalar unobserved heterogeneity.

Next, we use the model and the parameter estimates (but not our estimates of the shocks) to compute a quantitative prediction of firms’ response to TFP and demand changes under the assumption that firms response to shocks is frictionless. We compare these magnitudes to those obtained by regressing directly measures of output and inputs growth on the estimated shocks in a reduced form setting. The comparison between the elasticities implied by the model and directly measured in the reduced form regressions is informative about the magnitude of adjustment frictions. In fact, the main difference between the two approaches is that the model posits the absence of frictions, whereas their effect is captured in the reduced form estimates. Since this inference is correct only under the assumption that the presence of frictions does not bias our estimates of the production function, we offer evidence that this is indeed the case.

A striking and novel fact emerges from the comparison: the degree of under-response is larger for TFP shocks than for demand ones. For example, the elasticity derived from the model implies that a TFP shock equal to one standard deviation of TFP growth would increase output by 29%, whereas using the elasticity estimated in the reduced form regressions entails only an 11% effect. In the case of demand, the gap between model predictions and measured effects is much smaller: 18% versus 12%. This calls for introducing a class of frictions that hamper response to TFP shocks without necessarily impeding the transmission of demand ones. We argue that hurdles to firms’ ability to reshape their organization have this property. In fact, TFP shocks represent a shift in the production technology. Responding to such a shift might entail some business process reorganization, a change in the skill mix of the employees, the use of different types of capital inputs, etc. If firms miss the expertise to implement these complementary innovations, they would be prevented from fully taking advantage of TFP shocks. In contrast, a demand shock requires catering to a larger mass of customers which can be achieved by simply scaling up production without involvement of any organizational challenge.
We offer direct evidence that the larger under-response to TFP shocks is due to the presence of frictions linked to the internal organization of the firm. Under this maintained hypothesis, firms less capable of reorganizing production should under-respond more to TFP shocks, but not necessarily to demand ones. We construct four proxies for the ability to reorganize and restructure and check whether scoring low in this metric correlates with low response to TFP shocks. Our first proxy is a self-assessment on organizational flexibility reported by respondent in the survey. The other proxies are based on measures of managerial and workforce skills that the literature has indicated as complementary to restructuring (Caroli and Van Reenen 2001, Bresnahan, Brynjolfsson and Hitt 2002, Bloom, Sadun and Van Reenen 2012). We begin by comparing family firms to firms controlled by a financial institution or by a conglomerate. In fact, there is ample evidence that family firms tend to be characterized by less efficient managerial practices (Bloom and Van Reenen 2007) and could therefore be less effective in managing the reorganization and restructuring activities entailed by TFP shocks. As an alternative, we use a direct measure of managerial ability, estimated from matched employer-employee data using the techniques introduced by Abowd, Kramarz and Margolis (1999). Finally we focus on the education of the workforce, since less qualified employees may hamper re-organization by taking more time to adjust to changes in their tasks. All these exercises deliver a consistent message. Firms that are more organizationally constrained under-respond more to TFP shocks, while no difference emerges for demand shocks.

Our results tie two burgeoning streams of literature. We confirm the presence of hurdles to the efficient allocation of factors across firms as highlighted by a series of contributions documenting their role in generating misallocation of resources (Hsieh and Klenow 2009, Bartelsman, Haltiwanger and Scarpetta 2013, Asker, Collard-Wexler and De Loecker 2013, Midrigan and Xu Forthcoming). However, the large asymmetry we find in the level of frictions in the transmission of demand and TFP shocks suggests that such barriers cannot be only due to institutional factors like labor market rigidities (Hopenhayn and Rogerson 1993, Restuccia and Rogerson 2008) or bribery and political favoritism (Hsieh and Klenow 2009) as this literature routinely assumes. Such frictions would, in fact, constrain adjustment independently from the nature of the shock. To explain this result, we rely on insights from scholars emphasizing the role of managerial ability and corporate practices for the exploitation of technology shocks (Bloom et al. 2012, Dranove, Forman, Goldfarb and Greenstein 2012). Our results show that managerial practices are not only important for within firm productivity growth, but also to enhance the process of efficient
factors allocation across firms.

This study relates to a vast literature interested in understanding the determinants of firm growth (Dunne, Roberts and Samuelson 1988, Dunne, Roberts and Samuelson 1989, Evans 1987a, Evans 1987b). We extend it by considering multiple sources of unobserved heterogeneity. The importance of disentangling demand and productivity heterogeneity has been stressed by a recent literature. Using data on homogeneous products, Foster et al. (2008) were the first to separately identify demand and productivity shocks. They show that failing to disentangle demand and TFP shocks leads to an underestimation of new entrants’ contribution to productivity growth. Foster, Haltiwanger and Syverson (2012) study the process of accumulation of idiosyncratic demand, finding that demand stock builds up slowly and that it depends on past firm sales. Our results complement theirs: while it takes time to build idiosyncratic demand, we show that reacting to its fluctuations is easier than reacting to changes in productivity. Our methodological approach to separately identifying productivity and idiosyncratic demand components takes advantage of the recent availability of datasets containing direct information on firms’ prices (De Loecker, Goldberg, Khandelwal and Pavcnik 2012, Fan, Roberts, Xu and Zhang 2012). This strategy allows to expand the set of industries considered beyond those selling homogeneous goods, on which Foster et al. (2008) were forced to focus. It is also less reliant on functional form assumptions than studies that isolate physical productivity from confounding demand factors without the benefit of data on firms’ prices (De Loecker 2011).

The rest of the paper is organized as follows. Section 2 presents a standard model of a monopolistic competitive firm characterized by demand and productivity shifters. Section 3 introduces the data, while Section 4 presents the estimation approach. Section 5 discusses the effects of the shocks on firm growth and points out their divergence from the theoretical predictions of the model. Section 6 analyzes the implications of our findings for misallocation and proposes hurdles to reorganization as an example of a friction that generates it. Section 7 concludes.

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 and a Cobb-Douglas production function as in Melitz (2000). The purpose of this setup is twofold. On the one hand, it formalizes the assumptions needed for consistently estimating the parameters of the production and the demand functions. On the other hand, the quantitative predictions based on the struc-
tural estimates provide a benchmark to evaluate the results of the growth regressions we will perform in the second part of the paper.

Firm $i$ faces a constant elasticity of demand function:

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

where $\sigma > 1$ is the elasticity of demand and $\Xi_{it}$ is a demand shifter, observed by the firm (but not by the econometrician) when choosing output. 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 market appeal component ($\Xi_{it}$) picks up heterogeneity in firms' demand driven by differences in the perceived quality of the product, controlling for its physical attributes. It relates to similar concepts introduced by Foster et al. (2012) and Gourio and Rudanko (2012) who link it to the stock of consumers who have tried the product in the past (the "customer base"). Other instances of demand shocks consistent with our setting are spreading of good word-of-mouth, improvements in the brand image and the perception or the visibility of the products, for example as a result of advertising.

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

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

where $\delta$ is the depreciation rate. Although the firm cannot modify the capital stock in place for the current period, it decides the degree of capital utilization $U_{it}$. The effective capital used for production is then:

$$K_{it} = U_{it} \bar{K}_{it}, \quad 0 \leq U_{it} \leq 1.$$  

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

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

$^1$For example, if capital must be used in a fixed proportion $1/a$ with energy, and the price of energy is $p^e$; then the cost of using capital is defined as $r = a \cdot p^e$, 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, independently from usage. Moreover, when capital is used it might be easier to maintain it in an efficient state.
where $\Omega_{it}$ is firm TFP. Labor ($L$) and intermediates ($M$) can be chosen freely and have no
dynamic implications, whereas capital input can be varied through the degree of utilization,
up to full utilization. Given $K_{it}$ and after observing $\Omega_{it}, \Xi_{it}$, the firm chooses inputs to
maximize profits:

$$
\text{Max}_{\{K_{it}, L_{it}, M_{it}\}} \quad P_t Q_t - p_K K_{it} - p_L L_{it} - p_M M_{it}
$$

subject to the demand equation (1), the capital constraint (3) and the production func-
tion (4), where $p_K, p_L, p_M$ are the costs of utilizing capital, labor and intermediate input,
respectively.

Assume first that the capital constraint is not binding. In this case, equilibrium quan-
tities do not depend on the capital stock in place. Using lowercase letters to denote logs,
the optimal quantity, price and inputs demand functions are:

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

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

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

where $\theta \equiv \alpha + \beta + \gamma + \sigma(1 - \alpha - \beta - \gamma)$, $x = k, l, m$ 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 market appeal,
and inputs demand increases with both. With constant returns to scale, however, $p^*$ depends
only 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. Firstly, they are characterized by different
efficiency levels $\omega_{it}$, which directly affect marginal costs given output. Secondly, if the
production function displays non constant returns to scale, different levels of $\omega$ and $\xi$ entail
different level of output, and therefore, of marginal costs.

In terms of the capital constraint, from equation (8) it follows that the firm uses its full
capacity, that is $U_{it} = 1$, if and only if

$$
\bar{k}_{it} \leq c_k + \frac{(\sigma - 1)}{\theta} \omega_{it} + \frac{1}{\theta} \xi_{it}
$$

Condition (9) states that the capital stock in place is not a binding constraint as long as
the productivity and demand shocks are not too large. In fact, as equation 6 shows, output
is increasing in both shocks. We analyze the case where the constraint binds in Appendix
A.1.

The only dynamic choice the firm faces in our setting is investment, through which the firm can increase the stock of capital in place next period. Following Olley and Pakes (1996), we use investment to control for unobserved productivity in the estimation of the production function. In Appendix A.2 we set up the dynamic problem and show that our investment function depends not only on the capital in place \( k \) and productivity \( \omega \), as in the standard case, but also on the firm’s market appeal \( \xi \), violating the assumption of scalar unobservability. Ackerberg, Benkard, Berry, and Pakes (2007) argue that the Olley and Pakes (1996) procedure can be generalized to this case by including the demand shifter in the control function:

\[
\omega_{it} = h(i_{it}, \xi_{it}, \bar{k}_{it})
\]

We assume that market appeal and TFP follow first order Markov processes such that \( F_{\Omega}(\cdot|\Omega_{it-1}) \) first order stochastic dominates \( F_{\Omega}(\cdot|\Omega_{it-1}) \) for \( \Omega_{it-1} > \Omega_{it-1} \) and \( F_{\Xi}(\cdot|\Xi_{it-1}) \) first order stochastic dominates \( F_{\Xi}(\cdot|\Xi_{it-1}) \) for \( \Xi_{it-1} > \Xi_{it-1} \). High TFP (market appeal) today implies high expected TFP (market appeal) tomorrow. This assumption is important for the invertibility of the investment function. Intuitively the policy function is invertible if, given two firms with the same installed capital and demand shock, investment is strictly higher in the firm with the higher productivity shock.

The setup presented assumed that firms produce a single product. Multi-product firms pose additional challenges for the estimation as our data report average price changes, total output and input usage at firm level with no disaggregation for single product lines. In Appendix A.3 we extend the theoretical framework to the case of multi-product firms and show that demand and productivity shocks can be recovered also under this scenario. In particular, if demand and productivity shocks are identical across products, as typically assumed in empirical work (Foster et al. 2008, De Loecker 2011),\(^4\) the distinction between working with product or firm level data blurs. Our methodology works even if demand

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\(^3\)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. In fact, in the demand equation price depends only on output, independently from how it is produced. In the production function, output depends on the input combination, independently of whether the firm is at the corner in terms of capital utilization. Therefore, we can use the entire sample to estimate the demand and production functions. However, in the appendix we show that the relationship between output and input demand and the shocks does depend on whether the capital constraint is binding. As a consequence, we exclude observations where the capital constraint has been met in the second part of the paper, where we look at the elasticity of output and input to shocks.

\(^4\)An important exception is De Loecker et al. (2012), who use a unique dataset of Indian firms with information on prices and sales at the product level to estimate marginal costs at the product level. They assume that each product has its own production function, but that there is a unique productivity shock common to all products within the firm.
shocks are specific to individual products, as long as there is a unique production function for all products at the firm level. The use of aggregate firm level data is, however, problematic when there are product-specific productivity shocks. As far as we know, such a case has not yet been addressed in the empirical literature.

3 Data description

The data used in this study come from the “Indagine sugli investimenti delle imprese manifatturiere” (Inquiry into 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 with at least 50 employees, no plant level information is available. It contains detailed 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 includes balance sheets data of around 30,000 Italian firms. Firms in INVIND can be matched to their balance sheet data in CB using their tax identification number.

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 and focus on three major sectors: Textile and Leather, Metals, and Mechanical and Electronic Machinery. The characteristics of these three sectors are broadly consistent with the structure of monopolistic competition we impose in the model. The average Herfindahl index over the sample period is 0.001 for Textile and Leather, 0.006 for Metals, and 0.004 for the Machinery sector. The average market share of the top four firms in the sample is 5% for textile, 10.5% for metals and 8.4% for machinery.

We drop observations pre-1988, since prior waves of the survey do not contain information on firm-level prices. We also ignore firms not matched with CB (25% of the INVIND respondents) as well as those not surveyed for at least two consecutive years (22% of the residual sample). After applying these refinements, we are left with a pooled sample of 7,759 firm-years over the period 1988-2007.

The information on firm prices contained in the INVIND survey is key to our goal of disentangling demand from TFP shocks. Foster et al. (2008) attained the same goal using

\footnote{From 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 throughout on manufacturing firms with at least 50 employees.}

\footnote{Note that since firms with fewer than 50 employees are excluded from the sample, we are overestimating the concentration detected by the Herfindahl index.}
directly firm-level quantities. Their strategy can only be applied to industries producing homogenous output. Direct observation of firm level prices, however, allows us to extend the analysis to industries where product differentiation is important.\footnote{Since the information in the INVIND survey, and in particular the price data, is self-reported by the interviewee, we perform several checks to validate the variable. First, for a number of variables (e.g. revenues, investments, etc.) appearing both in the INVIND survey and balance sheet data, we find that the figures match well. Therefore, there is no indication that entrepreneurs are more inclined to lie or to provide inaccurate answers in the survey than they are when compiling official documents. The Bank of Italy itself relies on the INVIND pricing information for its official reports. Finally, in Appendix B.1 we compare a price index built upon INVIND prices with that constructed by the national statistical office (ISTAT). The two series are highly correlated.}

Firms are asked to state the “average percentage change in the prices of goods sold”. This implies that we will only be able to exploit this information estimating the model in first differences.\footnote{Firms report \( \% \) price change \( \frac{P_{it}}{P_{it-1}} - 1 \). We use this figure to obtain the first difference in the logarithm of price \( \Delta p \). We obtain the growth rate of the logged prices 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.} Using the average price change is problematic in cases of introduction of new products and dismissal of old ones; in those instances the price change is not defined. We implicitly assume that the share of products introduced or retired by any firm in a given year is small enough not to affect significantly the average growth rate of price. At the same time, using growth rates also delivers some advantages. For example, for multi-product firms the average growth in prices is a more meaningful object than the average price level. Leaving aside the introduction of new products, using first differences nets out any fixed unobserved heterogeneity that might distort the estimates. This is important because the model assumes that market appeal does not pick up quality differences embodied in physical attributes of the product. Exploiting only variation within firms ensures that: i) cross-firm differences in product quality level do not contribute to identification; ii) the bulk of the variation in \( \Delta p \) for a given firm relates to a given set of products with fixed physical attributes.

Nominal output is obtained from balance sheets data in CB. We deflate its growth rate using firm level price changes to obtain real output growth. Labor input is measured as hours worked and intermediate inputs come from CB and are deflated with sectoral prices. To measure capital inputs, we exploit questions in INVIND on both production capacity\footnote{This variable corresponds to \( \bar{K}_{it} \) in the notation of Section 2 and is defined as “the maximum output that can be obtained using the plants at full capacity, without changing the organization of the work shifts".} and the degree of capacity utilization. Direct assessment of the change in installed productive capacity \( \Delta \bar{k} \) helps us to circumvent issues of measurement error linked to standard
measures of capital based on book values or permanent inventory method. Utilized capital is a better measure of capital services in the production function than installed capital. Using installed capital implicitly assumes that the degree of capital utilization is 100%. This is not borne in the data: the average degree of capacity utilization is 81%, with a standard deviation of 13%; the 5th and the 95th percentile are 60% and 98% respectively. Moreover, 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 in place tends to have limited within-firm variability. Utilized capital displays greater within-firm variation than capital in place.

Table 1 reports descriptive statistics for our key variables both in levels (Panel A) and in growth rates (Panel B). A first look at growth rates shows that real sales and output grew on average 1.8% per year over the sample period, with a standard deviation of .18. Labor input contracted slightly, whereas capital input grew at 3.5% yearly. The average firm in the sample raises prices by over 2% per year. Figure 1 shows the distribution of price changes for each of the three sectors in one year of our data. The picture confirms that there is substantial dispersion around the sectoral average and reaffirms the importance of having information on firm level price adjustments.

4 Demand and TFP Estimation

4.1 Demand estimation

Firms face a CES demand function of the form expressed in equation (1). We estimate a first differences specification of the following form separately for each of the sectors in our sample:

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

(11)

The shock to market appeal, $\Delta \xi_{it}$, is known to the firm but unobserved to the econometrician. If we obtained consistent estimates of the price elasticity ($\sigma$), we could estimate $\Delta \xi_{it}$ as follows:

$$\tilde{\Delta} \xi_{it} = \Delta q_{it} - \hat{\sigma} \Delta p_{it}$$

(12)
Estimation of equation (11) is complicated by the familiar simultaneity problem. Positive shocks to market appeal lead producers to raise prices, as shown in equation (7), making $\Delta p$ and $\Delta x$ positively correlated. Therefore, estimating the equation by OLS would understate demand elasticity. In our context, finding valid instruments for price constitutes a challenge. To solve this problem, we exploit a unique piece of information included in our data. 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 affected 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. Figure 2 reports 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 distributions. We use elasticities reported by the cross-section of representative firms interviewed in 1996 to estimate $\sigma$ since this wave falls in the middle of our sample period and the response rate (over 80%) is higher than in 2007.

Table 2 presents estimated demand elasticities separately for each sector. In the first column, we list average sectoral self-reported demand elasticities from the 1996 wave of INVIND. Elasticities range between 4.5 and 5.5. These values are in the order of those found of the literature. For instance, our estimate for textile is similar to that reported by De Loecker (2011), who looks at several segments within the textile sector in Belgium. Hsieh and Klenow (2009) in their calibration exercise use what they refer to as a conservative value of 3 and check the robustness of their results with an alternative value of 5. In appendix B.2, we comment on additional results reported in Table 2, where we check whether the presence of multiproduct, multiplant and exporting firms affects our estimates of price elasticity. We also compare the results based on self-reported information with a more traditional approach to estimating demand using OLS and IV techniques. The findings are in line with those in Column 1, with the exception of OLS, where, as expected, not accounting for endogeneity leads to substantially lower estimates.
4.2 TFP estimation

We directly estimate a quantity (as opposed to revenue) production function in first differences as in the equation below:

\[ \Delta q_{it} = \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta m_{it} + \Delta \omega_{it} + \Delta \eta_{it} \] (13)

where the overall TFP shocks is given by the sum of \( \omega_{it} \), the component of TFP inputs react to, and which is the source endogeneity, and \( \eta_{it} \), the component unrelated to inputs choice. We compute the growth rate of real output by subtracting the price change from the nominal output.\(^{11}\)

To account for the endogeneity of inputs, we follow the control function approach introduced by Olley and Pakes (1996). Our setting differs from the standard one along three dimensions: first, we estimate the production function in first differences rather than in levels. Second, firms are characterized by two unobservables, TFP and \( \xi \), rather than just one, so we need to relax the scalar unobservability assumption. Finally, we measure the capital input as utilized capital, so that the capital actually used in production can be adjusted after observing the shocks, rather than being pre-determined. These deviations to the basic setting raise technical issues that we discuss in details in Appendix B.3. We use as control function a third degree polynomial in \( \Delta \xi_{it}, \Delta i_{it}, \Delta \bar{k}_{it} \) and estimate the production function using the following regression equation (year dummies are included in each specification):

\[ \Delta q_{it} = \alpha \Delta k_{it} + \beta \Delta l_{it} + \gamma \Delta m_{it} + h(\Delta \xi_{it}, \Delta i_{it}, \Delta \bar{k}_{it}) + \Delta \eta_{it} \] (14)

Once we have estimated the coefficients, we recover the changes in TFP as

\[ \Delta TFP_{it} = \Delta q_{it} - \alpha \Delta k_{it} - \beta \Delta l_{it} - \gamma \Delta m_{it} \] (15)

Table 3 reports sector-by-sector estimates of the coefficients of the production function. To reduce the effects of extreme values on the estimates, we exclude the observations in the top and bottom centiles of the distribution of \( \Delta q_{it}, \Delta k_{it}, \Delta l_{it} \) and \( \Delta m_{it} \). Panel A shows the baseline results. We find evidence of decreasing returns to scale for all sectors: the degree

\(^{11}\)Using output instead of value added delivers several advantages. First, the use of value added implicitly imposes strong assumptions on the degree of substitutability between intermediates and other inputs. Second, Gandhi, Navarro and Rivers (2011) have shown that estimating TFP using value added can lead to overstate the productivity dispersion. Third, and most important, we want to ensure comparability between shocks to market appeal and to TFP. Shocks to market appeal are computed using sales. Estimating TFP from output therefore ensures that shocks are computed from comparable quantities, as sales and output only differ due to inventories, while value added also subtract intermediates.
of returns to scale $\alpha + \beta + \gamma$, reported in the last row of the panel, is between .8 and .9.\(^{12}\)

Klette and Griliches (1996) show that without knowledge of firm prices not only estimated productivity will be different from effective one\(^{13}\) but also the coefficients estimated using revenue data will be inconsistent. In fact, using (1) and (4) and taking logs, it is straightforward to show that a revenue production function can be expressed as:

$$q_{it} + p_{it} = \frac{\sigma - 1}{\sigma} \alpha k_{it} + \frac{\sigma - 1}{\sigma} \beta l_{it} + \frac{\sigma - 1}{\sigma} \gamma m_{it} + \frac{\sigma - 1}{\sigma} \omega_{it} + \frac{1}{\sigma} \xi_{it} \quad (16)$$

Even if we accounted for the endogeneity of inputs, the coefficients of a revenue function underestimate the true degree of returns to scale. As shown in Melitz (2000), the size of the bias is $\frac{\sigma - 1}{\sigma}$. Intuitively, when a firm expands its output, it must decrease the price to move down the demand curve, so that the increase of physical output reflects less than proportionally in the increase in revenues.

In Panel B we run the estimation procedure using output deflated with sectoral prices rather than with firm level prices. For all sectors, the real output based estimates are larger than the revenue based estimates, as predicted by Klette and Griliches (1996). In the last row of the table we compute the returns to scale obtain used the Melitz (2000) correction, where $\sigma$ is the sectoral self-reported elasticities reported in Table 2. Applying the correction to the estimates based on sectoral deflators brings them close to those obtained using output deflated with firm level prices, with the exception of Machinery, where the correction delivers a higher elasticity.

First differencing may exacerbate measurement error in the independent variables introducing downward bias in the coefficients. Although we cannot run the regressions in levels, we rule out this possibility by repeating the exercise increasing the length of the lag on which the production function is estimated. As the lag increases the size of the measurement error should decline, since we consider lower frequency movements in inputs and output. Estimates of the production function using differences over a three year are reported in Appendix (Table A-1). The degree of returns to scale increases but the resulting TFP estimates are similar to the baseline ones, with a correlation of .97.

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\(^{12}\)These figures are lower than those typically estimated with level production functions. For example, Levinsohn and Petrin (2003) report returns to scale close to 1. Compared to their estimates, we find a lower elasticity of the capital coefficient: their estimates for textile and metals are .18 and .29, while ours are .14 and .08. 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 and Pakes (1996) attribute this to the fact that the capital stock has little within firm variability. Such a critique is less likely to apply in our setting. In fact, with capital utilization we can compute utilized capital, which is more variable than the capital stock. Doraszelski and Jaumandreu (2012) find evidence of decreasing returns to scale for similar sectors at the same level of aggregation as ours.

\(^{13}\)In the language of Foster et al. (2008), using a sectoral deflator leads to estimate TFPR rather than TFPQ.
4.3 Robustness to adjustment costs

Following a large literature, we have estimated the production function abstracting from adjustment costs, with the exception of the one period lag in building capital. One of the goal of this study, however, is to detect adjustment frictions in input choices and our empirical strategy hinges on the estimates of the parameters of the production function being consistent both in presence and absence of frictions. Below we discuss under which conditions our estimates are robust to the presence of frictions.

To begin with, it must be stressed that only adjustment costs that modify the amount of output obtained for given inputs are problematic for our approach. Many examples of adjustment costs, such as firing costs on labor or bureaucratic and administrative costs to modify the scale of operation, do distort input choices away from the unconstrained optimum but not the inputs-output relationship. These types of adjustment costs do not bias estimates of the production function. In fact, if firing is costly, a firm might keep workers whose marginal product is below the marginal costs. Yet, conditional on employing such workers, the firing cost does not modify the technical relationship between inputs and output.

Frictions that enter the production function pose more serious challenges to our estimation procedure. Cooper and Haltiwanger (2006) estimate a general capital adjustment cost function, allowing for the possibility that new investments disrupt production. For example, adjusting the capital stock may require the firm to temporarily shut down operations to install the new machinery or to retrain workers to use the technology. Ignoring such costs would lead to biased estimates, as we observe lower output while the firm is increasing its capital stock.

There are, however, several reasons to believe that our production function estimates are robust to the presence of disruption costs. First, our measures of inputs, unlike those typically used in the literature, account for this type of disruption. In fact, whereas the installed capital and the number of workers do not fluctuate as a result of a temporary plant shutdown, this will be picked up by a lower utilization of installed capital and fewer hours worked. Therefore, even without explicitly introducing frictions in the production function, our input measures protect us from the bias they may introduce. Second, as we argue in Appendix B.4, any fixed costs of changing the capital stock drop out when first differencing, as the control function approach forces us to only use the observations in which firms are investing. Finally, we note that at lower frequencies the size of variation in production inputs should be large enough to swamp any disruption cost. The change in
output over a few years’ arc will result from the cumulated investments over those years; whereas only current disruption costs should be reflected in current output. Although the estimates of coefficients of the production function increase slightly (see Table A-1), those of TFP change only marginally and all the results in the paper are confirmed.

Finally, the presence of frictions can cause problem for the invertibility of the control function. We have experimented by expanding the set of controls included (see Sections B.3 and B.5 in the Appendix). As a further robustness check, we have estimated the production function coefficients using factor shares, correcting for the markup induced by monopolistic competition. In all cases, we have obtained estimates of productivity similar to our preferred ones and all the results presented in the paper hold.

4.4 Descriptive statistics on $\Delta$TFP and $\Delta\xi$

Panel A of Table 4 shows descriptive statistics for estimated shocks to productivity ($\Delta$TFP) pooled across sectors. The average growth rate is below 1%, consistently with the well documented low productivity growth that has characterized the Italian economy since the early nineties (Brandolini and Cipollone 2001). There is also substantial dispersion in TFP growth (the standard deviation is .13). The second row reports the distribution of TFP computed using the estimates of the production function based on three year differences. The two distributions are virtually identical.

Panel B reports analogous information for $\Delta\xi$. The row labeled “Sector averages” displays estimates for $\Delta\xi$ based on the self-reported elasticities contained in the 1996 wave of the INVIND survey, averaged at the sectoral level. We also report estimates of $\Delta\xi$ based on elasticities averaged at the ATECO class level, a much finer definition of the area of activity. The estimates labeled “individual reported” are obtained using the individually reported estimates, rather than sectoral averages. In that case, we can only use the firms that directly answered the question in 1996. There are some differences in the means of the distributions of the $\Delta\xi$ estimated using different level of aggregation. However, these discrepancies are entirely due to outliers. If we compare several percentiles of the distributions, the estimates are nearly identical.

The correlation between $\Delta\xi$ and $\Delta$TFP is nearly zero, validating the assumption of independence made by Foster et al. (2008) when using TFP as an instrument for $\xi$ in the

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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 Machine sector distinguish between firms producing components for computers and those making them for telecommunication devices.

We have also looked at the distribution of $\Delta\xi$ implied by using only single product firms or only firms that do not export, and found no substantial differences.
pricing equation. Estimating the degree of serial correlation under the assumption that both \( \xi \) and \( TFP \) are AR(1) processes is more complicated, as first differencing invalidates OLS regressions of each variable on its value at \( t - 1 \). However, it is easy to show that both \( \Delta \xi_{t-2} \) and \( \Delta TFP_{t-2} \) are valid instruments, as they are correlated with lags at \( t - 1 \) but uncorrelated with the residual. The same reasoning applies to \( TFP \). Using lags past the first as instruments we find a degree of serial correlation of approximately 1 for TFP and of .2 for \( \xi \) (although the statistical significance is around 10% in both cases). The first number is consistent with that of Foster et al. (2008), while the latter is substantially lower. Both should be taken with caution, as they are sensitive to the choice of instruments and to the treatment of outliers.

5 Shocks and firm growth

Armed with our estimates of shocks to TFP and market appeal, we are now ready to quantify their importance in driving firm growth. Moreover, using the model developed in Section 2, we will be able to analyze the transmission mechanism and detect the presence of frictions that prevent firms’ adjustment.

5.1 Measurement

Under our maintained assumption that the process generating shocks to TFP and market appeal is exogenous, we can assess the elasticity of growth measures to these shocks by estimating regressions of the following form

\[
\Delta y_{it} = a_0 + a_1 \Delta TFP_{it} + a_2 \Delta \xi_{it} + a_X X_{it} + e_{it}
\]

(17)

where \( \Delta y_{it} \) is the growth rate of some variable of interest (sales and output, prices, inputs), \( \Delta TFP \) and \( \Delta \xi \) are the estimated shocks and \( X_{it} \) are additional controls.

Table 5 reports the results of a set of such regressions for output and price. For reasons of brevity, 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 in line with the pooled ones.\(^{16}\) We account for the fact that \( \Delta TFP \) and \( \Delta \xi \) are generated regressors by bootstrapping the standard errors.

\(^{16}\)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 to be an indication that, since our analysis involves first differences, we are already purging unobserved firm heterogeneity that might affect both shocks and sales.
Column (1) shows that shocks to demand and to TFP have a positive impact on nominal sales growth.\textsuperscript{17} The elasticity of sales to TFP shocks is larger than that to market appeal (0.66 vs 0.44). Once we factor in dispersion of the shocks, however, we find that one standard deviation change in $\Delta \text{TFP}$ would increase sales by 11%, whereas a similar change in $\Delta \xi$ would have an impact of 12%. Demand shocks, therefore, have even a stronger effect than productivity ones in determining the evolution of market shares. Once we move from nominal to real sales (Column 2), however, the elasticity to TFP grows and that to demand shrinks: a standard deviation increase in TFP increases real sales by 10% against 9% for market appeal. This is not surprising since we are removing the price effect that tends to inflate the response of revenue after demand shocks and reduce that following productivity gains. In fact, a firm experiencing a positive demand shock should not only increase the quantity sold but also the price, while the opposite should occur for TFP shock. Accordingly, in Column (3) we show that positive shocks to TFP lead to price cuts and improvements in demand appeal trigger price raises. The positive effect of demand shocks on prices is also consistent with our findings of decreasing returns to scale. In fact, in a constant returns to scale scenario, variations in market appeal should not affect the price.

A lingering concern may be that we have used sales as a proxy for output. Whereas this is the measure we want to consider when thinking about demand and, therefore, the market appeal component, it could affect measurement when we turn to productivity. In fact, quantity sold and quantity produced do not have to coincide, due to inventories. Since we have information on quantity produced, in the last two columns of Table 5 we repeat the exercise using it as the dependent variable and check whether results are robust. We find that the elasticity of TFP shocks increases by about 0.2 relative to the sales regressions, both in the nominal and in the real output regressions, while the coefficients of demand shocks decrease slightly.

The figures presented above refer to the overall effect of productivity and market appeal on output. For TFP this is the sum of a direct and an indirect effect. Positive changes in TFP directly increase the quantity produced or sold but should also have an indirect impact as they affect demand for factors of production: $l, k, m$. For $\xi$, however, the effect comes entirely through the indirect channel, as demand shocks have no direct contribution to the quantity produced. Total differentiation of equation (13) delivers a decomposition of

\textsuperscript{17}Note that with sector-year dummies there is no difference between using nominal or real values obtained through sectoral price deflators.
the overall effect of the two shocks on output:

\[
\frac{d\Delta q_{it}}{d\Delta \omega_{it}} = \frac{1}{\text{direct effect}} + \alpha \frac{\partial \Delta k_{it}}{\partial \Delta \omega_{it}} + \beta \frac{\partial \Delta l_{it}}{\partial \Delta \omega_{it}} + \gamma \frac{\partial \Delta m_{it}}{\partial \Delta \omega_{it}} \tag{18}
\]

\[
\frac{d\Delta q_{it}}{d\Delta \xi_{it}} = \alpha \frac{\partial \Delta k_{it}}{\partial \Delta \xi_{it}} + \beta \frac{\partial \Delta l_{it}}{\partial \Delta \xi_{it}} + \gamma \frac{\partial \Delta m_{it}}{\partial \Delta \xi_{it}} \tag{19}
\]

where, according to equation (8), \(\frac{\partial \Delta x_{it}}{\partial \omega_{it}} = \frac{\sigma-1}{\sigma}\) and \(\frac{\partial \Delta x_{it}}{\partial \xi_{it}} = \frac{1}{\sigma}\), for \(x = \{k, l, m\}\). Given that we found a unit elasticity of output to TFP shocks in Table 5, we expect that the indirect effect of inputs demand close to zero. Panel A of Table 6 reports the growth of inputs on demand and TFP shocks. Inputs appear more responsive to demand than productivity shocks and, with the exception of intermediate goods, the elasticity of inputs to TFP is negligible in magnitude.

We assumed that variable inputs (hours worked, utilized capital, intermediates) can be adjusted in the short run, thus representing an intensive margin. However, there is a limit to the number of hours that can be squeezed out of a fixed number of workers and a firm cannot use more than 100 percent of its installed capital. If firms experiencing improvements in productivity or market appeal want to increase their scale they must act on what we call quasi-fixed input of production: the number of workers and the installed capital. The reallocation of inputs from less to more productive units (and, in our setting, from low to high market appeal units) is a major source of productivity growth in market economies. For example, Olley and Pakes (1996) attribute to capital reallocation most of the productivity growth that occurred after the deregulation of the US telecom sector. Moreover, a growing literature focuses on the obstacles to the efficient allocation of resources across production units as a major impediment to growth (Restuccia and Rogerson 2008, Hsieh and Klenow 2009). Panel B of Table 6 considers the extensive margin of inputs adjustment displaying the correlation of growth in the number of workers and the investment rate with changes in TFP and market appeal. One standard deviation increase in market appeal raises investment rate by roughly 1.3 percentage points, a similar increase in \(\Delta TFP\) has half that impact. Figures for the elasticity of growth in the (end of the year) labor force are similar. Breaking down the employment growth rate into its determinants, hiring and separation rates, provides additional insights (Columns (2) and (3), Table 6 - Panel B). Most of the action takes 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 adjustment costs on the firing margin, consistent with the fact that in the Italian labor market employment
protection legislation imposes firing costs on firms (Schivardi and Torrini 2008).

5.2 The asymmetric (under)response to demand and TFP shocks

In the previous section we showed that input demand is rather insensitive to TFP shocks but not to market appeal shocks. This is an indication of potential frictions preventing firms from adjusting. To further investigate this issue, we exploit our theoretical framework. In fact, given estimates of the demand elasticity and of the production function coefficients, the theoretical framework we setup in Section 2 delivers quantitative predictions on the impact of demand and supply shocks on inputs and output growth. The relationship between output, price, and inputs growth and shocks to TFP and market appeal can be obtained by first differencing equations (6), (7) and (8), respectively. Given that the model is frictionless, for a given set of estimates of the demand and production function parameters it predicts the “full” firm response to changes in productivity and market appeal. We can therefore compare the elasticities predicted from the model and those measured and use any gap between the two to provide a quantification of these frictions.

To compute the model predictions, we assume returns to scale of .8 and an elasticity of demand of .5 (roughly the cross-sectoral averages from our estimates). The elasticities implied by the model are reported in Tables 7. For convenience, we also report the corresponding estimates from Table 5 and 6. The differences of the effects estimated under the two approaches is clear. A TFP shock equal to a standard deviation of TFP growth would increase nominal output by 11%, much less than the 29% implied by the model parameters estimate. For demand the figures are 12% and 18%, respectively. These large differences survive in all the specifications and for all the outcome variables considered. We state this finding explicitly.

**Finding 1.** The responsiveness of growth measures to productivity and market appeal shocks is substantially lower than that predicted by a frictionless model.

The comparison of our estimates of the elasticities to demand and productivity shocks with the model predictions delivers a second interesting result. Not only are measured elasticities lower than those that the model predicts, but the gap is significantly larger for the response to productivity than to market appeal. For example, the predicted elasticity of nominal output to TFP changes is 2.2, whereas we estimate it to be .85; our estimate of the elasticity to market appeal is .37, closer to the predicted value of 0.56. The response of price to shocks is very similar for demand (0.11 vs. 0.13), while much smaller in absolute value for TFP shocks (-0.56 vs. -0.17). This evidence can be summarized as follows.
Finding 2. Deviations between actual and predicted responses are substantially larger for TFP than for market appeal shocks.

We rationalize these findings in the light of the vast literature pointing to the existence of frictions limiting firms’ ability to respond to productivity shocks.\(^{18}\) The gap between measured and predicted responses to shocks is indicative of the size of these frictions. However, our contribution is not limited to measurement. Our second finding is, to the best of our knowledge, completely novel and sheds light on the nature of the frictions. It implies the existence of frictions affecting asymmetrically firms responses to demand and TFP; in particular, stronger when adjusting to changes in productivity. Detecting that frictions are not independent of the nature of the shock necessarily requires a model allowing for multiple forcing variables and our paper is one of the first taking this approach.\(^{19}\) We analyze a class of frictions displaying this distinctive feature in the next section.

6 Managerial ability as a firm-specific adjustment friction

The optimal response of firms to shocks in the model of Section 2 is derived under the assumption that firms equalize the marginal value product of inputs to their marginal cost. The fact that we detect under-response implies that this condition is not met in the data; therefore, factors are not efficiently allocated. This observation is in line with a growing empirical literature that measures factor misallocation through the dispersion in the marginal value product of inputs (see for example Hsieh and Klenow (2009) for China and India or Yang (2012) for Indonesia). However, we also find that the degree of under-response is different for demand and for TFP shocks. The frictions commonly considered by the literature do not display this property. For example, the need to pay bribes (Hsieh and Klenow 2009) or the presence of firing costs (Hoppenhain and Rogerson 1993) are often cited as obstacles for firms’ growth. These frictions would have the same impact whether a firm wanted to grow because it became more productive or because of an increase in its market appeal.

\(^{18}\)Recent contributions include studies of investment adjustment costs (Asker et al. 2013), financial constraints (Banerjee and Moll 2012, Midrigan and Xu Forthcoming), and employment protection legislation (Petrin and Sivadasan Forthcoming). Hamermesh and Pfann (1996) provides a comprehensive survey of the earlier literature.

\(^{19}\)The low response of investment to shocks could be explained without introducing adjustment costs if the persistence of the processes were low. However in Section 3 we showed that, if anything, TFP shocks seem to be more persistent than demand shocks. If the lack of response were driven by low persistence, we should have found the opposite of what stated in Finding 2. Another potential explanation of the under-response is pure measurement error, possibly more important for TFP. We discuss this possibility in the next section and in Appendix B.6.
To explain the asymmetric response to demand and TFP shocks we move from the premise that demand and TFP shocks are fundamentally different. The growing literature on firm organization and managerial practices\textsuperscript{20} suggests that responding to a TFP shock may require significant reorganization and the presence of complementary skills inside the firm.\textsuperscript{21} TFP shocks entail a shift in the production technology itself; these can occur in a variety of ways, possibly implying different responses of firms to different types TFP shocks. Some increases in productivity may come as simple improvement in the production process, that do not require much restructuring and therefore can be easily accommodated by the firm. Others might require deeper changes that the firm is not willing or able to undertake. In fact, some classic examples of productivity improvements have the distinctive feature of being transformative events that require substantial reorganization of work routines within the firm. For example, access to broadband connection has a direct impact on productivity, as workers can now access the web at higher speed. At the same time, in order to fully exploit the opportunities offered by such a shock the firm might require some reorganization of business operations, a different skill mix, different types of capital inputs etc. We argue that shocks to market appeal do not share this need for complementary assets within the firm. When demand increases, the firm is enjoying more recognition by customers and needs to cater to a larger residual demand. This can be done by simply scaling up operations, moving along a given cost function. From firm’s growth point of view, there is less heterogeneity in the type of market appeal shocks that hit a firm.

A simple way to formalize this idea is to assume that firms face TFP shocks product of two components:

$$\text{TFP}_{it} = \omega_{it} + \eta_{it}.$$

The first, $\omega$, is a TFP shock to which the firm reacts; the second component, $\eta$, is the “complex” TFP shock to which the firm is not able or willing to respond. This representation is fully consistent with the one assumed in equation (15) to estimate TFP. In fact, the Olley and Pakes (1996) procedure allows to break the residual of the production function into the two components: the control function captures the transmitted component while the residual (net of the control function) measures the untransmitted one. The untransmitted component is generally modeled as an i.i.d. shock that realizes after the firm has decided the inputs level. In this view the untransmitted component should be treated as measurement error and purged (Petrin and Sivadasan Forthcoming). We take instead a structural

\textsuperscript{20}See Bloom and Van Reenen (2010) for a recent survey.

\textsuperscript{21}In fact, the literature on ICT adoption (Caroli and Van Reenen 2001, Bresnahan et al. 2002) has shown that ICT affects firm performance only if the firm also reorganizes.
perspective on the untransmitted component, and assume that firms are not able to take advantage of it due to organizational hurdles. In this view, the untransmitted component does not contain noise but it is instead informative on the size of the hurdles that force the firm to inaction.

A direct way to test our conjecture would have been to decompose market appeal shocks in a similar fashion and show that the untransmitted component’s size is negligible. Unfortunately, while our procedure allows us to retrieve both components separately for TFP shocks, we cannot do so for demand ones. In the Appendix (Table A-2) we show that when we isolate the transmitted component of a productivity shock the asymmetry in the response to TFP and demand shocks narrows. The result stresses that it is the untransmitted component that plays the key role in differentiating the response to shocks originating from different sources.

The presence of error in our measures of demand and productivity shocks provides an alternative explanations to some of our findings. Several elements, however, seem to weight against this alternative story. To begin with, measurement error could generate incomplete response but not the asymmetry in the response to TFP and market appeal shocks, unless we believe that measurement error should affect estimates of the TFP more than those of the demand shock. Moreover, the use of detailed data, which include accounting data for output, hours worked and capacity utilization should limit the presence of measurement error in our analysis. The most compelling argument in favor of our interpretation is presented in the exercises commented in this section. We show that the degree of under-response to productivity shocks is correlated with indicators of firm organizational ability and managers’ skills. That would not be the case if under-response were driven by measurement error. Two additional pieces of evidence consistent with the incomplete response being due to frictions and not only to measurement error are explored in the appendix. In appendix B.5 we provide evidence that past realization of the shocks contribute to explain current output and demand for inputs. This is consistent with a sluggish adjustment scenario. In appendix B.6 we estimate the model at longer lags -which should make measurement error less of a concern- and obtain similar results.

Our evidence indicates that firms face higher adjustment costs when reacting to a TFP than to a market appeal shock. We have conjectured that this may be due to the fact that certain types of TFP shocks require more reorganization and complementary skills, which the firm may lack. We now offer some direct evidence in support of this hypothesis. We classify firms according to characteristics that can be meaningfully related to their capacity
to restructure after shocks. To test our conjecture, we allow the sensitivity to shocks to differ according to the firm categorization by running the following regression:

$$\Delta y_{it} = b_0 + b_1 \Delta TFP_{it} + b_2 D_R \Delta TFP_{it} + b_3 \Delta \xi_{it} + b_4 D_R \Delta \xi_{it} + b_5 D_R + b_6 X_{it} + e_{it} \tag{20}$$

where $D_R$ is an indicator that takes value 1 if the firm is characterized by high restructuring costs. We will construct four proxies for firms’ ability to restructure and check whether firms that score low in this metric are also less responsive to TFP shocks, but not to demand shocks.

Our first proxy exploits the information in the INVIND survey which provides a direct measure of reorganization hurdles internal to the firm. Each year the interviewees are asked to compare actual investments with planned ones\(^{22}\) and, when the two differ by more than 5%, to identify the causes of the discrepancy. One of the causes listed is “reasons related to the internal organization of the firm”. Around 55% of firms not fulfilling their investment plans list problems with internal reorganization among the causes. We assume that firms selecting this option are facing higher costs of organizational restructuring. In the first two columns of Table 8 we report the results when classifying firms according to the self-reported measure of organizational hurdles. We find that, following a TFP shock, firms reporting internal organization problems adjust output and prices less than the other firms. There is no difference, however, in how firms with and without internal problems respond to demand shocks. Moreover, the indicator variable for organizational bottlenecks in itself is weakly, if at all, significant for any of the growth measures we analyze. Facing organizational problems seems not to affect growth in directly but rather through its interplay with responses to productivity shocks.

Our second proxy is based on the identity of the controlling shareholder. A recent literature has documented a large degree of heterogeneity in firm’s managerial practices and organizational structures (Bloom and Van Reenen 2007, Bloom et al. 2012) and linked their quality to the ownership structure. In particular, family or government controlled firms tend to be managed less efficiently than widely-held or institutionally controlled firms because they are more inclined to favoring personal acquaintance such as family membership when selecting their management (Lippi and Schivardi Forthcoming). We use direct information on ownership structure and proxy management quality, with an indicator equal to one if the firm is controlled by a family or the government (around half of the sample), and

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\(^{22}\)The survey asks firms each year to report planned investments. Therefore, information on unfulfilled plans is derived from 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 appear in the survey in consecutive years.
zero if controlled by a financial institution, a conglomerate or a foreign entity. Columns 3 and 4 of Table 8 report the results. We find that firms controlled by a family or the government adjust output and price less than other firms. On the other hand, ownership structure is not a factor in the responses to demand shocks. We obtain similar results using a finer partition, creating a dummy for each of the five types of ownership structure present in the data.

In columns 5 and 6 of Table 8 we directly address the role of managerial ability in determining the reaction to shocks. For the period up to 1997 we have access to the individual records of all the employees of the firms. We compute the individual fixed effects in the wage equation following Abowd et al. (1999) (see Macis and Schivardi (2013) for details). This fixed effect is interpreted in the literature as a measure of ability. For each firm we compute the average effect of the executives and use this as a measure of managerial ability. Given that we only have data up to 1997, our sample shrinks considerably. To increase statistical power, we exploit the fact that the executive turnover is low (the probability that an executive leaves a firm is around 10% per year) and impute the last (first) value of executive quality forward (backward) for four years, obtaining a final sample of around 2,100 firm-year observations. We then construct a dummy that takes value 1 if the executive quality is below the median value at the year-sectoral level and interact it with demand and productivity shocks. All the data limitations notwithstanding, we find that firms with low abilities executives increase output and decrease prices significantly less following a productivity shock. As before, we see no difference in response to demand shocks.

Finally, we consider another characteristic that has been typically associated to the capacity of firms to restructure: the human capital of its workforce. For example, Caroli and Van Reenen (2001) for a set of French firms and Bresnahan et al. (2002) for US firms show that ICT adoption and firm restructuring is complementary to the share of workers with a college degree. We investigate whether firms with a higher share of college graduates are better able to respond to TFP shocks. Information on the share of college graduate is only available in 2000 and 2006. For each of these years, we create a dummy equal to one if a firm is below the median of college graduate at the sectoral level. We use the 2000 dummies for the years 1995-2002, and the 2006 dummy for the following years. The results of this exercise are reported in the final columns of Table 8. We observe that firms with a share of college graduate below the median expand output and decrease prices less than the others following a TFP. No difference emerges for demand shocks.

The pattern emerging is striking. Several distinct proxies of the ability of a firm to
handle reorganization show a significant relationship with the degree of response to TFP but appear uncorrelated to changes in market appeal of the firm. Overall, we take this as evidence in favor of the idea that productivity shocks require some degree of restructuring to fully take advantage of them, entail specific reorganization activity and that there is substantial cross-firm heterogeneity in firms’ restructuring capacity. The fact that no similar requirement seems necessary to accommodate demand shocks accounts for the asymmetry in the adjustment frictions between the two sources.

7 Conclusions

In this paper we use a unique dataset on a panel of Italian manufacturing firms which contains information on firm level prices. We identify and distinguish the roles of idiosyncratic productivity and demand in firm growth, and proceed to show that, though mostly neglected in the literature, heterogeneity in demand is an important determinant of growth. We also document that the measured effect of idiosyncratic variables is lower than that a frictionless theoretical framework would predict, which is consistent with the presence of adjustment costs to shocks. Finally, we show that the size of this gap is different for technology and demand shocks, suggesting a role for frictions that can generate such asymmetry.

The main insights from this study is that the barriers to the efficient allocation of resources are not exclusively of a regulatory nature, as the literature on this subject has typically assumed (Hopenhayn and Rogerson 1993, Restuccia and Rogerson 2008, Hsieh and Klenow 2009). This conclusion has important implications for the debate on how to reduce productivity losses from misallocation. On the one hand, regulation and corruption call directly government policies into question. On the other hand, the type of firm idiosyncratic friction we stress -managerial practices and capabilities and the propensity to restructure- are much less under the direct policy influence. Recent literature (Bloom and Van Reenen 2010) has shown them to depend on a plurality of factors, such as corporate governance and control, managerial and entrepreneurial abilities, work attitudes, competition in the product markets, etc. Our results show that managerial practices are not only important for within firm productivity growth, but also to enhance the process of efficient factors allocation across firms. Bloom, Eifert, Mahajan, McKenzie and Roberts (2013) document that managerial training is an effective policy to reduce internal frictions. Improving our understanding of the determinants of managerial practices and capabilities, as well as how to improve their quality, is of paramount importance,
References


Table 1: Summary statistics for main variables, by sector

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<th>All</th>
<th>Textile Metals and leather</th>
<th>Metals</th>
<th>Machinery</th>
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<tr>
<td><strong>Panel A: Levels</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales</td>
<td>92,011</td>
<td>54,555</td>
<td>120,329</td>
<td>107,534</td>
</tr>
<tr>
<td></td>
<td>(241,680)</td>
<td>(110,161)</td>
<td>(345,491)</td>
<td>(245,949)</td>
</tr>
<tr>
<td>Output</td>
<td>93,374</td>
<td>54,876</td>
<td>122,603</td>
<td>109,255</td>
</tr>
<tr>
<td></td>
<td>(242,981)</td>
<td>(110,557)</td>
<td>(346,912)</td>
<td>(247,527)</td>
</tr>
<tr>
<td>Workers</td>
<td>426</td>
<td>314</td>
<td>341</td>
<td>568</td>
</tr>
<tr>
<td></td>
<td>(995)</td>
<td>(562)</td>
<td>(915)</td>
<td>(1,275)</td>
</tr>
<tr>
<td><strong>Panel B: Growth rates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔSales</td>
<td>.018</td>
<td>-.005</td>
<td>.021</td>
<td>.037</td>
</tr>
<tr>
<td></td>
<td>(.18)</td>
<td>(.17)</td>
<td>(.17)</td>
<td>(.19)</td>
</tr>
<tr>
<td>ΔOutput</td>
<td>.019</td>
<td>-.006</td>
<td>.034</td>
<td>.031</td>
</tr>
<tr>
<td></td>
<td>(.21)</td>
<td>(.20)</td>
<td>(.20)</td>
<td>(.23)</td>
</tr>
<tr>
<td>ΔIntern. inputs</td>
<td>.020</td>
<td>-.010</td>
<td>.030</td>
<td>.039</td>
</tr>
<tr>
<td></td>
<td>(.32)</td>
<td>(.30)</td>
<td>(.31)</td>
<td>(.34)</td>
</tr>
<tr>
<td>Δhours worked</td>
<td>-.005</td>
<td>-.018</td>
<td>.003</td>
<td>.001</td>
</tr>
<tr>
<td></td>
<td>(.14)</td>
<td>(.14)</td>
<td>(.13)</td>
<td>(.14)</td>
</tr>
<tr>
<td>Δutilized capital</td>
<td>.035</td>
<td>.014</td>
<td>.052</td>
<td>.043</td>
</tr>
<tr>
<td></td>
<td>(.19)</td>
<td>(.20)</td>
<td>(.18)</td>
<td>(.19)</td>
</tr>
<tr>
<td>Δprices</td>
<td>.022</td>
<td>.023</td>
<td>.027</td>
<td>.017</td>
</tr>
<tr>
<td></td>
<td>(.06)</td>
<td>(.05)</td>
<td>(.08)</td>
<td>(.06)</td>
</tr>
<tr>
<td>Obs.</td>
<td>7,654</td>
<td>2,686</td>
<td>1,836</td>
<td>3,132</td>
</tr>
</tbody>
</table>

**Notes:** Figures reported are sample averages; standard deviations are in parentheses. Sales and Output are expressed in thousands of 2007 euros. ΔSales and ΔOutput are computed net of growth in firm level prices.
Table 2: Estimates of $\sigma$, by sector

<table>
<thead>
<tr>
<th>Sector</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Single product</td>
<td>Single plant</td>
<td>Non exporting</td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td>Textile and leather</td>
<td>4.5</td>
<td>4.7</td>
<td>4.6</td>
<td>8</td>
<td>.27</td>
<td>6.1</td>
</tr>
<tr>
<td></td>
<td>(3.3)</td>
<td>(3.3)</td>
<td>(3.4)</td>
<td>(3.7)</td>
<td>(.08)</td>
<td>(.54)</td>
</tr>
<tr>
<td>Metals</td>
<td>5.5</td>
<td>6.4</td>
<td>5.3</td>
<td>7</td>
<td>.26</td>
<td>4.9</td>
</tr>
<tr>
<td></td>
<td>(3.5)</td>
<td>(3.5)</td>
<td>(3.6)</td>
<td>(0)</td>
<td>(.05)</td>
<td>(.62)</td>
</tr>
<tr>
<td>Machinery</td>
<td>5</td>
<td>5.1</td>
<td>5.1</td>
<td>7.4</td>
<td>.39</td>
<td>5.7</td>
</tr>
<tr>
<td></td>
<td>(3.2)</td>
<td>(3.1)</td>
<td>(3.2)</td>
<td>(4)</td>
<td>(.10)</td>
<td>(.46)</td>
</tr>
</tbody>
</table>

Notes: In the first four columns we report the average of the self-reported price elasticities and their standard deviations (in parentheses). In the last two columns, we report the coefficient of the price variable in an OLS and IV specification, respectively, and the standard error of the estimate (in parentheses). Single product firms are defined as those claiming to derive at least 80% of their revenues from a single product line. Single plant firms are those reporting that all their employees work in the same macro-region. The IV column uses unexpected variation in $\Delta$TFP as instrument (see Appendix B.2).
Table 3: Production function estimation

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Txt+leather</td>
<td>Metals</td>
<td>Machinery</td>
</tr>
<tr>
<td>Δk</td>
<td>0.14***</td>
<td>0.08***</td>
<td>0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.028)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Δl</td>
<td>0.17***</td>
<td>0.24***</td>
<td>0.17***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.031)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Δm</td>
<td>0.49***</td>
<td>0.52***</td>
<td>0.52***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.023)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>α + β + γ</td>
<td>0.8</td>
<td>0.85</td>
<td>0.8</td>
</tr>
<tr>
<td>Obs.</td>
<td>1,800</td>
<td>1,354</td>
<td>2,071</td>
</tr>
<tr>
<td>R²</td>
<td>0.67</td>
<td>0.65</td>
<td>0.72</td>
</tr>
</tbody>
</table>

Panel B: Output deflated with sectoral prices

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Txt+leather</td>
<td>Metals</td>
<td>Machinery</td>
</tr>
<tr>
<td>Δk</td>
<td>0.11***</td>
<td>0.07***</td>
<td>0.08***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.024)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Δl</td>
<td>0.13***</td>
<td>0.17***</td>
<td>0.15***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.027)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Δm</td>
<td>0.43***</td>
<td>0.47***</td>
<td>0.50***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.021)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>α + β + γ</td>
<td>0.67</td>
<td>0.71</td>
<td>0.73</td>
</tr>
<tr>
<td>σ(α + β + γ) / σ-1</td>
<td>0.86</td>
<td>.86</td>
<td>.91</td>
</tr>
<tr>
<td>Obs.</td>
<td>1,806</td>
<td>1,356</td>
<td>2,076</td>
</tr>
<tr>
<td>R²</td>
<td>0.77</td>
<td>0.76</td>
<td>0.79</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is the growth rate of output, deflated with firm level prices. Δk is the log difference of the stock of capital used in production, taking capital utilization into account, Δl is the log difference of the number of hours worked and Δm is the log difference of intermediates. All regressions include the control function and year dummies. Robust standard errors are reported in parenthesis. Significance levels: *: 10%, **: 5%, ***: 1%
Table 4: Descriptive statistics: ΔTFP and Δξ

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Std.dev.</th>
<th>5th</th>
<th>25th</th>
<th>50th</th>
<th>75th</th>
<th>95th</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: ΔTFP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔTFP Olley and Pakes</td>
<td>7,654</td>
<td>.005</td>
<td>.13</td>
<td>-.15</td>
<td>-.04</td>
<td>.007</td>
<td>.05</td>
<td>.16</td>
</tr>
<tr>
<td>Δ³ TFP</td>
<td>7,654</td>
<td>.003</td>
<td>.14</td>
<td>-.16</td>
<td>-.04</td>
<td>.003</td>
<td>.05</td>
<td>.16</td>
</tr>
<tr>
<td><strong>Panel B: Δξ</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sectoral avg.</td>
<td>7,654</td>
<td>.010</td>
<td>.32</td>
<td>-.46</td>
<td>-.12</td>
<td>.01</td>
<td>.15</td>
<td>.46</td>
</tr>
<tr>
<td>Class avg.</td>
<td>6,490</td>
<td>.005</td>
<td>.34</td>
<td>-.48</td>
<td>-.12</td>
<td>.01</td>
<td>.14</td>
<td>.45</td>
</tr>
<tr>
<td>Individual reported</td>
<td>720</td>
<td>.004</td>
<td>.42</td>
<td>-.56</td>
<td>-.11</td>
<td>.03</td>
<td>.16</td>
<td>.53</td>
</tr>
</tbody>
</table>

**Notes:** Olley and Pakes refers to estimates of TFP recovered using Olley and Pakes (1996); Δ³ TFP reports estimates obtained through the same methodology but using 3-year differences in the estimation of the production function (rather than first differences). Sectoral and class rows refer to estimates of Δξ obtained using self-reported elasticities averaging firm responses at the sector and class level respectively. The row individual reports estimates of Δξ which rely only on the firms that replied directly to the question on price elasticity in the 1996 wave of INVIND.
Table 5: Sales and output growth

<table>
<thead>
<tr>
<th>Sales</th>
<th>Price</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>Nominal</td>
<td>Real</td>
</tr>
</tbody>
</table>

\[
\begin{align*}
\Delta \text{TFP} & \quad 0.66^{***} \quad 0.82^{***} \quad -0.17^{***} \quad 0.85^{***} \quad 1.03^{***} \\
& \quad (0.019) \quad (0.024) \quad (0.005) \quad (0.024) \quad (0.023) \\
\Delta \xi & \quad 0.44^{***} \quad 0.29^{***} \quad 0.13^{***} \quad 0.37^{***} \quad 0.24^{***} \\
& \quad (0.007) \quad (0.008) \quad (0.002) \quad (0.006) \quad (0.007) \\
\end{align*}
\]

Observations: 6,566 6,566 6,555 6,587 6,543  

\[R^2\] 0.70 0.50 0.76 0.61 0.53

**Notes:** All dependent variables and the demand and TFP shocks are in delta logs. \(\Delta \text{TFP}\) is calculated using Olley and Pakes (1996) control function approach. \(\Delta \xi\) is computed using self-reported sectoral price elasticities from the INVIND survey 1996. The columns labeled “Real” 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. Significance levels: *: 10%, **: 5%, ***: 1%
Table 6: Inputs growth

Panel A: Variable inputs

<table>
<thead>
<tr>
<th></th>
<th>(1) Hours worked</th>
<th>(2) Intermediate inputs</th>
<th>(3) Utilized capital</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\Delta TFP)</td>
<td>0.05***</td>
<td>0.23***</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.043)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>(\Delta \xi)</td>
<td>0.11***</td>
<td>0.41***</td>
<td>0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.011)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,527</td>
<td>6,569</td>
<td>6,509</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.12</td>
<td>0.30</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Panel B: Quasi-fixed inputs

<table>
<thead>
<tr>
<th></th>
<th>(1) Employment</th>
<th>(2) Hires</th>
<th>(3) Separations</th>
<th>(4) Investment rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\Delta TFP)</td>
<td>0.08***</td>
<td>0.09***</td>
<td>-0.01</td>
<td>0.06***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.017)</td>
<td>(0.017)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>(\Delta \xi)</td>
<td>0.08***</td>
<td>0.07***</td>
<td>-0.02***</td>
<td>0.04***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,517</td>
<td>6,565</td>
<td>6,571</td>
<td>5,334</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.12</td>
<td>0.11</td>
<td>0.04</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Notes: All dependent variables and the demand and TFP shocks are in delta logs. \(\Delta TFP\) is calculated using the Olley and Pakes (1996) control function approach. \(\Delta \xi\) is computed using self-reported sectoral price elasticities from the INVIND survey 1996. 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. Significance levels: *: 10%, **: 5%, ***: 1%
Table 7: Responses to changes in TFP and market appeal: Model’s prediction vs. empirical estimates

<table>
<thead>
<tr>
<th></th>
<th>Δ(p + q)</th>
<th></th>
<th>Δq</th>
<th></th>
<th>Δp</th>
<th></th>
<th>Δx</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predicted</td>
<td>Actual</td>
<td>Predicted</td>
<td>Actual</td>
<td>Predicted</td>
<td>Actual</td>
<td>Predicted</td>
<td>Actual</td>
</tr>
<tr>
<td>ΔTFP</td>
<td>2.2</td>
<td>0.85</td>
<td>2.8</td>
<td>1.03</td>
<td>-0.56</td>
<td>-0.17</td>
<td>2.2</td>
<td>0.1</td>
</tr>
<tr>
<td>Δξ</td>
<td>0.56</td>
<td>0.37</td>
<td>0.44</td>
<td>0.24</td>
<td>0.11</td>
<td>0.13</td>
<td>0.56</td>
<td>0.21</td>
</tr>
</tbody>
</table>

Notes: $p + q$ indicates nominal output, $q$ is real output deflated with firm level prices, $x$ represents inputs (labor, capital and intermediates). The columns labeled Predicted report the elasticity implied by the theoretical model, conditional on the estimates of the parameters of the demand and production functions. The columns labeled Actual display the reduced form estimate of the same elasticity. For these latter, we report the estimate obtained using output for TFP (Table 5, columns (4) and (5)) and sales for market appeal (Table 5, columns (1) and (2)). For inputs, we use the simple average of the elasticities of variable inputs in Panel A of Table 6.
<table>
<thead>
<tr>
<th>Hurdle:</th>
<th>Self-reported</th>
<th></th>
<th>Family Firms</th>
<th></th>
<th>Low manager quality</th>
<th></th>
<th>Low workforce quality</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Output</td>
<td>(2) Price</td>
<td>(3) Output</td>
<td>(4) Price</td>
<td>(5) Output</td>
<td>(6) Price</td>
<td>(7) Output</td>
<td>(8) Price</td>
</tr>
<tr>
<td>ΔTFP</td>
<td>1.09***</td>
<td>-0.18***</td>
<td>1.11***</td>
<td>-0.18***</td>
<td>1.17***</td>
<td>-0.20***</td>
<td>1.13***</td>
<td>-0.17***</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.009)</td>
<td>(0.038)</td>
<td>(0.07)</td>
<td>(0.055)</td>
<td>(0.012)</td>
<td>(0.043)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>ΔTFP × Hurdle</td>
<td>-0.14**</td>
<td>0.02*</td>
<td>-0.16***</td>
<td>0.30***</td>
<td>-0.17**</td>
<td>0.04**</td>
<td>-0.17***</td>
<td>0.02*</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.012)</td>
<td>(0.051)</td>
<td>(0.009)</td>
<td>(0.085)</td>
<td>(0.018)</td>
<td>(0.065)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Δξ</td>
<td>0.25***</td>
<td>0.13***</td>
<td>0.24***</td>
<td>0.13***</td>
<td>0.25***</td>
<td>0.14***</td>
<td>0.24***</td>
<td>0.13***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.003)</td>
<td>(0.010)</td>
<td>(0.002)</td>
<td>(0.016)</td>
<td>(0.004)</td>
<td>(0.013)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Δξ × Hurdle</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.01</td>
<td>-0.00</td>
<td>-0.03</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.004)</td>
<td>(0.015)</td>
<td>(0.004)</td>
<td>(0.023)</td>
<td>(0.006)</td>
<td>(0.019)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Hurdle</td>
<td>0.01**</td>
<td>-0.00</td>
<td>-0.01**</td>
<td>0.00***</td>
<td>-0.00</td>
<td>0.00</td>
<td>-0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.005)</td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Observations</td>
<td>4,970</td>
<td>5,000</td>
<td>6,219</td>
<td>6,258</td>
<td>2,050</td>
<td>2,065</td>
<td>3,647</td>
<td>3,669</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.52</td>
<td>0.76</td>
<td>0.53</td>
<td>0.76</td>
<td>0.54</td>
<td>0.81</td>
<td>0.52</td>
<td>0.74</td>
</tr>
</tbody>
</table>

**Notes:** All dependent variables as well as the demand and TFP shocks are in delta logs. ΔTFP is calculated using the Olley and Pakes (1996) control function approach. Δξ is computed using self-reported sectoral price elasticities from the INVIND survey 1996. Self-reported is an indicator variable for firms that face higher costs in reshaping their internal organization. It takes value 1 for firms reporting in the INVIND survey that they have not met their investment plans for the past year due to “problems with the internal organization of the firm”. Family firms is an indicator variable for firms that are controlled by an individual/family or by the government. Low manager quality is an indicator variable for firms whose manager fixed effects is below the median. Low workforce quality is an indicator variable for firms whose share of college graduates in the workforce is below the median. Output is 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. Standard errors are calculated from 500 bootstrap simulations. Significance levels: *: 10%, **: 5%, ***: 1%
Figure 1: Distribution of price changes in 2004, by sector

(a) Textile and leather  
(b) Metals  
(c) Machinery

Figure 2: Distribution of self-reported elasticities in 1996 and 2007, by sector

(a) Textile and leather  
(b) Metals  
(c) Machinery
Appendix

A Model details and extensions

A.1 Equilibrium with full capacity utilization

We derive the optimal firm choices when the capital stock is binding. When equation (9) holds with equality, the firm is characterized by a high level of demand and/or productivity shocks, so that it wants to expand its production accordingly, but the capital stock in place is below the optimal unconstrained level. In this case, the firm uses all its capital stock, which becomes a parameter, and the production function is Cobb-Douglas in just $L$ and $M$:

$$Q_{it} = (\Omega_{it} \bar{K}_{it}^\alpha) L_{it}^\beta M_{it}^\gamma$$  \hfill (A-1)

It is then straightforward to derive the optimal quantities when the capital constraint binds:

$$q_{it}^* = \bar{c}_q + \sigma \frac{\lambda}{\lambda} (\omega_{it} + \alpha \bar{k}_{it}) + \frac{(\beta + \gamma)}{\lambda} \xi_{it}$$  \hfill (A-2)

$$p_{it}^* = \bar{c}_p - 1 \frac{\lambda}{\lambda} (\omega_{it} + \alpha \bar{k}_{it}) + \frac{(1 - \beta - \gamma)}{\lambda} \xi_{it}$$  \hfill (A-3)

$$x_{it}^* = \bar{c}_x + \frac{(\sigma - 1)}{\lambda} (\omega_{it} + \alpha \bar{k}_{it}) + \frac{1}{\lambda} \xi_{it}$$  \hfill (A-4)

where $\lambda \equiv \beta + \gamma + (1 - \beta - \gamma)\sigma$ and $x = l, m$. When the firm hits the capital constraint, the degree of returns to scale decreases from $\alpha + \beta + \gamma$ to $\beta + \gamma$, as the capital stock is now a fixed input. As a consequence, all the endogenous variables become less responsive to shocks, given that $\lambda > \theta$ (recall that the elasticity to productivity and demand in the unconstrained case is $\frac{\sigma - 1}{\theta}$ and $\frac{1}{\theta}$ respectively). Given the elasticity of output and inputs to shocks changes for constrained firms, we exclude these observations from the analysis in Section 6 of the paper.

A.2 The dynamic problem

As discussed in the text, the firm cannot alter its level of capital in place within the period, but it chooses the degree of capital utilization. Capital in place can be increased through investments which will deliver capital in the next period. A higher level of investment decreases the likelihood that the firm will face capital constraints in the following year. The problem is described by the three state variables $\{\bar{K}_{it}, \Omega_{it}, \Xi_{it}\}$. Let $I_{it} \equiv I(\bar{K}_{it}, \Omega_{it}, \Xi_{it})$ be the indicator function for the case in which the capital stock is not constrained, i.e.,
when the inequality in equation (9) is strict. To ease the notation, we have dropped the
dependence on the state variables. Similarly, define $\Pi_{it}$ and $\bar{\Pi}_it$ as the static profits for the
constrained and unconstrained case respectively. Simple algebra shows that

$$
\Pi_{it} = C_{Pi}\Omega_{\sigma-1}^{\sigma-1}\Xi_{it}^{\frac{1}{\sigma}} \tag{A-5} \\
\bar{\Pi}_it = C_{Pi}\Omega_{\sigma}^{\sigma-1}\Xi_{it}^{\frac{1}{\sigma}}K_{it}^{\sigma(\sigma-1)} - p_KK_{it} \tag{A-6}
$$

where $c_{Pi}, c_{\Pi}$ are constants. Note that in the unconstrained case the within-period profits
do not depend on $K_{it}$.

The recursive formulation of the dynamic problem is as follows:

$$
V(K_{it}, \Omega_{it}, \Xi_{it}) = \max_{K_{it+1}} \left\{ \Pi_{it}I_{it} + \bar{\Pi}_it(1 - I_{it}) - p_I(K_{it+1} - (1 - \delta)K_{it}) + \psi E(V(K_{it+1}, \Omega_{it+1}, \Xi_{it+1})|\Omega_{it}, \Xi_{it}) \right\} \\
\text{subject to} \\
K_{it+1} = I_{it} + (1 - \delta)K_{it} \\
\Omega_{it+1} \sim F_\Omega(\cdot|\Omega_{it}) \\
\Xi_{it+1} \sim F_\Xi(\cdot|\Xi_{it}) \tag{A-7}
$$

where $\psi$ is the discount factor and $p_I$ is the price of investment. Under the assumptions on
the stochastic processes followed by the shocks, standard dynamic programming considerations ensure that, if $I_t > 0$, the policy function for investment $g(K_t, \Omega_{it}, \Xi_{it})$ is increasing in
$\Xi_{it}, \Omega_{it}$ for each level of $K_{it}$. This implies that we can invert it and express the productivity
shock as function of $\{I_{it}, \Xi_{it}, K_{it}\}$

### A.3 Extension to multi-product firms

33% of the firms in our sample report deriving all of their revenues from a single product
line; for 51% of the firms the share is at least 80%. This implies that half of the firms in
our sample obtains revenues from selling a variety of products. Since we are assuming the
same elasticity for all firms in the same sector, the fact that a firm sells different products
in the same sector (e.g. shirts and sweaters within textiles) has no consequence for us. Here
we show that even the presence of generic multiproduct firms does not cause problems for
our identification of the demand and productivity shocks. To keep the notation simple, we
eliminate both the firm and time subscript and focus on the product subscript. Each firm
produces $G$ goods. We assume that the number of goods produced by each firm is constant
over time. We want to show under what assumptions our procedure based on aggregate
firm level data still recovers meaningful indicators of demand and productivity shocks. For
demand, it is natural to assume that each product has its own demand schedule. Then
we can either assume that the demand shock is common to all goods, $\xi_g = \xi$, or that
each good has its own shock $\xi_g$. For production, one can assume that the firm has a
unique production line on which all goods are produced or that each good is produced
with a separate production function. In the latter case, the productivity shock can be
common to all production functions, $\omega_g = \omega$, or each production function can have its
own productivity shock $\omega_g$. In what follows, we use capital boldface to indicate aggregate
quantities: $X \equiv \sum_g X_g$ and small case boldface for its log: $x \equiv \log \left(\sum_g X_g\right)$.

The typical assumption in the literature is that each good has its own production func-
tion but that both the demand and the productivity shocks are common across all goods
(Foster et al. 2008, De Loecker 2011):

$$Q_g = \Omega K_g^\alpha L_g^\beta M_g^\gamma$$
$$Q_g = P_g^{\sigma} \Xi$$

In this case, the solution for the single product case applies to each single good, so that:

$$q_g^* = q^* = c_q + \frac{\sigma}{\theta} \omega + \frac{(\alpha + \beta + \gamma)}{\theta} \xi$$
$$p_g^* = p^* = c_P - \frac{1}{\theta} \omega + \frac{(1 - \alpha - \beta - \gamma)}{\theta} \xi$$

So the firm produces exactly the same amount and applies the same price for all goods. As
a consequence, the average price change is just the price change of the common price, $\Delta p$.
Moreover, using the fact that $\sum_g P_g Q_g = G \ast P^* Q^*$ and the assumption that $G$ is fixed over
time, the change in the log of revenues is given by:

$$\Delta \ln \left(\sum_g P_g Q_g\right) = \Delta p^* + \Delta q^*$$

Therefore, when deflating the change in the log of the revenues with the average change in
prices $\Delta p^*$, we obtain the correct measure of real output. Now use the production function
and the fact that each product accounts for an equal share of total output:

$$Q \equiv \sum_g Q_g = \Omega \sum_g K_g^\alpha L_g^\beta M_g^\gamma = G^{1 - \alpha - \beta - \gamma} \Omega K^\alpha L^\beta M^\gamma$$

where $K = \sum_g K_g = G \ast K$ ad similarly for $L$ and $M$, so that

$$\Delta q = \Delta \omega + \alpha \Delta k + \beta \Delta l + \gamma \Delta m$$
This shows that, under the stated assumptions, the estimation procedure correctly recovers TFP even in the presence of multi-product firms. Similarly, using the fact that 
\[ \ln \left( \sum_g Q_g \right) = \ln (G \cdot Q) \] and \[ \ln \left( \sum_g P_g^{-\sigma} \right) = \ln (G \cdot P_g^{-\sigma}) \], we can quickly verify that from firm-level aggregate sales and average price changes we recover the demand shock:
\[ \Delta \xi = \Delta q - \sigma \Delta p. \]

Things are slightly more complicated when the firm sells \( G \) products, each with its own demand shock:
\[ Q_g = P_g^{-\sigma} \Xi_g \]  
(A-8)
As long as the all goods are produced with only one production function,
\[ Q = \sum_g Q_g = \Omega K^\alpha L^\beta M^\gamma \]  
(A-9)
we can still recover TFP and a meaningful aggregate measure of demand shocks. The assumption of one production function for all goods is consistent with a production technology in which the firm has one production line on which it can produce alternatively the different goods it sells. Define \( C(Q) \) as the cost function to produce the aggregate quantity \( Q \). Simple algebra shows that \( C(Q) = c_x \left( \frac{Q}{\Omega} \right)^{1/(\alpha + \beta + \gamma)} \) where \( c_x \) is a constant that depends on input prices and the production function coefficients. The firm problem is
\[ \max \sum_g \left( Q_g^{1-\sigma} \Xi_g^{1-\sigma} \right) - c_x \left( \frac{Q}{\Omega} \right)^{1/(\alpha + \beta + \gamma)} \]  
(A-10)
subject to (A-8) and (A-9). The FOCs are:
\[ \frac{\sigma - 1}{\sigma} Q_g^{-\sigma} \Xi_g^{-\sigma} = \frac{c_x}{\alpha + \beta + \gamma} \left( \frac{Q}{\Omega} \right)^{1-1/(\alpha + \beta + \gamma)} \Omega^{-1} \]  
(A-11)
from which we obtain:
\[ \frac{Q_g}{Q_h} = \frac{\Xi_g}{\Xi_h}. \]

Summing over \( h \), total output is:
\[ Q = \sum_g \Xi_g \Xi_h = \Xi_g \Xi. \]

Substitute in (A-11), solve for price and quantities and take logs:
\[ q_g^* = C_q + \frac{\sigma}{\theta} \omega + \xi_g - \left( \frac{1 - (\alpha + \beta + \gamma)}{\theta} \right) \sigma \xi \]  
(A-12)
\[ p_g^* = C_p - \frac{1}{\theta} \omega + \left( \frac{1 - (\alpha + \beta + \gamma)}{\theta} \right) \xi \]  
(A-13)
So the price of the single good does not depend on the idiosyncratic demand shock (apart from the effect through $\Xi$, common to all goods). The average price is therefore equal to the individual price, so that the average price change is the correct aggregator of the change in individual prices. It is immediate to verify that log total output is:

$$q^* = c_q + g + \frac{\sigma}{\theta} \omega + \frac{\alpha + \beta + \gamma}{\theta} \xi$$  \hspace{1cm} (A-14)

This shows that our estimation procedure recovers the correct measure of TFP and an aggregate indicator of demand appeal shocks, $\xi = \ln \left( \sum g \Xi_g \right)$.

Consider finally the case in which each product has its own demand and production function shocks. Given the CES demand assumption, the firm can be seen as a collection of products. In this case, revenues are equal to:

$$P \times Q \equiv \sum_g P_g \times Q_g \propto \sum_g \Omega_g^{\frac{\sigma+1}{\sigma}} \Xi_g^{\frac{1}{\theta}}$$  \hspace{1cm} (A-15)

Unfortunately, from this expression we cannot factor out any combination of $\omega_g$ and $\xi_g$. When we subtract the average price change from the change in revenues, therefore, we do not recover exactly real output.

**B Robustness**

**B.1 Validation of INVIND price variable**

The changes in firm-level prices are the key piece of information for this study; without such variable we would not be able to separately identify productivity and market appeal. Like all the information contained in the INVIND survey, price changes are self reported by the interviewee and one may worry about the accuracy of these statements.

To assess the reliability of the price variable, we compare a price index based on price changes reported by respondent to the INVIND survey with the official producer price index (PPI) constructed by the National Statistical Office (ISTAT). The INVIND price index is constructed as the average of the price changes reported by individual firms weighted using sampling weights provided by the Bank of Italy. ISTAT releases estimates of the inflation in producer prices monthly; we use the estimates released in the month of March since INVIND interviews take place in that same month. Both the INVIND price index and the official PPI are normalized to 1 for the year 2009.

In Figure A-1 we plot the time series of the two price indexes for each ATECO sector used in the analysis. The two series are highly correlated and generally close in levels.
The only exception is the electrical machinery sector where the INVIND price index shows prices falling over the sample period, whereas the ISTAT PPI indicates positive price growth. Whereas the correlation could be simply driven by inflation, which would lead both series to trend up, the fact that the actual level of the two indexes are quite similar provides strong evidence that the INVIND price variable picks up more than just noise.

### B.2 Estimates of price elasticity of demand

The INVIND survey question eliciting elasticity actually refers to the elasticity of revenues to a 10% increase in price. We apply the following transformation to obtain the familiar price elasticity of quantity. Define $\varepsilon^{R}_{10\%}$ as the number provided by the interviewee; the elasticity can be obtained as: $\varepsilon^{Q}_{1\%} = \frac{\varepsilon^{R}_{10\%}}{10} - 1$. Also note that the phrasing of the question induces censoring in the self-reported revenue elasticities. In fact, for every firm with elasticity above 10, a 10% increase in price would cause the maximum revenue loss reportable, 100%. This implies that all firms with revenue elasticity greater than 10 (or price elasticity greater than 11) will be bunched at 10 (11). Inspecting the data, the share of firms bunched at 10 does not seem alarmingly large. Furthermore, we have checked the robustness of the results estimating a Tobit model that accounts for censoring. The results (available upon request) are not significantly affected.

We now discuss alternative estimates of price elasticity reported in Table 2. The first potential problem we want to address relates the presence of multiproduct firms. Though we have presented in appendix A.3 a theoretical argument for the robustness of our procedure to the presence of multiproduct firms, in the second column of Table 2 we present a robustness check to dispel any residual concern. Exploiting a question of the survey, we compute sectoral averages of self-reported elasticities for the subset of firms reporting that they have earned at least 80% of their revenues from a single product line. Figures for single product firms are similar to the sample averages. Next, we check whether using firm level, rather than plant level, information has any effect on the elasticities by reporting estimates based on the group of single plant firms.\(^{23}\) Once again, the estimates do not change much.

Exporting firms face residual demand curves with different slopes in the domestic and foreign markets, leaving some doubt on the which figures they are reporting in the survey.

\(^{23}\)We define as single plant firms those that report to have 100% of their workforce employed in a single macro-region of Italy. The INVIND survey includes an explicit question on the number of plants but the question was introduced long after 1996 and we therefore elected not to use it. However, all the firms in the sample reporting that the entirety of their labor works in a single region also say that they are single plant in the wave of the survey asking such question.
Since INVIND contains information on the amount of revenue generated through exports by each firm, we can concentrate our attention on the small number of firms in our sample that do not export. The fourth column displays demand elasticities for non exporting firms; these results must be taken with caution because the number of observation reduces significantly. These firms appear to face a more elastic demand suggesting 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 in line with our baseline figures, with the noticeable exception of Textile and leather, for which the elasticity almost doubles.

In the last two columns, we report elasticity values from direct estimation of the demand function in equation (11). 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 analogous to that in Foster et al. (2008) by using the estimates of TFP as cost shifters to instrument for price changes. However, the construction of the instrument is different in our case and requires further explanation. We start by obtaining estimates of the market appeal shock ($\Delta \xi$) following the steps described in section 4 and using the self reported measure of price elasticity. The estimated $\Delta \xi$’s are necessary to run the Olley and Pakes (1996) procedure and obtain $\Delta \omega$ and $\eta$ from equation (13); the sum of the two being our measure of $\Delta \text{TFP}$. The figures showed in column 6 of Table 2 are obtained instrumenting prices with the $\eta$ component.

Instrumenting prices using $\eta$ allows using cost variation that is completely unexpected by the firm. Using the whole $\Delta \text{TFP}$, as done in Foster et al. (2008), involves including in the instrument also the persistent part of the TFP process ($\Delta \omega$) to which firms can react, at least in expectation. In that sense the exclusion restriction is more likely to hold for our instrument. At the same time, our IV estimates of price elasticities are not independent from the self reported ones, which are still used in the first step of the procedure. This means that our IV estimates of elasticities cannot completely validate the self-reported measure we use in our preferred specifications. However, the fact that the results obtained with these two approaches are similar is surely a comforting sign.
B.3 Production function estimation details

In estimating the production function we face the usual problem of the endogeneity of inputs. We address it using the control function approach first introduced by Olley and Pakes (1996). Whereas they assume scalar unobservability, we introduce a vector of unobserved components, a demand and a productivity 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 (10). We therefore need to include controls for demand as well. 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 suggested by Ackerberg et al. (2007). As discussed in Section A.2, this gives us a valid control function. By log linearizing equation (10) 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 also include the interactions of the changes, up to the third degree polynomial.

Ideally, one should use the contemporaneous and lagged values of the variables rather than their first difference, as $\Delta h(x) \neq h(\Delta x)$. Unfortunately, we can only compute the first difference of the demand shock. As a further check, given that we do observe the levels of both $k$ 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 $i$. The estimated coefficients, reported in the Appendix Table A-1, are virtually unchanged. This suggests that a polynomial in the first differences is flexible enough to proxy for the unobserved productivity shock.

A final distinctive characteristic of our setting is that we allow firms 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 single regression, without the need of the second stage as in most applications of the Olley and Pakes (1996) procedure.\textsuperscript{24} Finally, the control function approach has been criticized by Ackerberg, Caves and Frazer (2006) on the basis of the fact that the input demand functions should be perfectly collinear with the control function $h$. The survey reports the occurrence of events, like strikes, power shortages, machines breakdowns and delivery lags that generate variation

\textsuperscript{24}We ignore the problem of selection also stressed by Olley and Pakes (1996): in our data we cannot distinguish exit from simple nonresponse to the questionnaire.
in \( k_{it}, l_{it} \) and \( m_{it} \) independent from \( \omega_{it} \) and \( \xi_{it} \).\(^{25}\)

### B.4 Frictions and production function estimates

Although we have argued in the main text that input usage should account for temporary shutdowns, we could still worry that output might be reduced even when capital utilization and hours are not, for example if part of the inputs are used not for production but to put new capital in place. In this (quite special) case, our estimates could be biased. Cooper and Haltiwanger (2006) estimate that disruption of production caused by new investment reduces profits by nearly 20 percent, while Bloom (2009) obtains a substantially smaller number. Disruption costs in the form of reduced output given inputs would bias our estimates of \( \alpha, \beta, \) and \( \gamma. \) In fact, instead of observing the output \( Q_{it} \) that should be delivered by a given combination of production factors as in equation (4) we would observe a lower level of output \((\widetilde{Q}_{it})\), scaled down by the disruption costs \((\lambda)\)

\[
\widetilde{Q}_{it} = [\Omega_{it}K_{it}^{\alpha}L_{it}^{\beta}M_{it}^{\gamma}] \cdot \lambda(I)
\]

where \( \lambda \) is lower than one when investment is strictly positive. This would lead us to underestimate the coefficients of the production function, as we observe lower output when the firm is increasing its capital stock. Note however that our estimates are robust to any cost that is proportional to output and that is paid whenever the firm invests, which is the case considered in Cooper and Haltiwanger (2006). Since we follow Olley and Pakes (1996) in estimating the production function, we only consider periods with positive investment, so that this cost is always paid in the observations used to estimate production. As such, it drops out once we take the first difference of the logs. A more serious problem arises when forgone output depends on the size of the investment, rather than being a fixed proportion. We are not aware of any estimation of such specification of the adjustment cost function.

### B.5 Lagged effects

To provide evidence that the wedge between the model’s prediction and our estimates is indeed caused by adjustment frictions and that the untransmitted component should be included in the exercise, we consider a general implication of adjustment costs: they should

\(^{25}\)Alternatively, one can assume the DGP postulated by Ackerberg et al. (2006), where labor, intermediates and capital are set prior to the investment decision, and \( \Omega \) changes between the two points in time.
induce lagged response to changes in TFP and market appeal.\textsuperscript{26} If adjusting takes time, we should find that current output growth 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 depends on price.

Introducing dynamic effects does not affect our general identification strategy but it does complicate 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 the next year’s investment, the expected change in technical capacity and two lags of the demand appeal shocks as additional controls. Therefore, we have 7 state variables (the capital stock in place and the current, lag one and lag two values of each shock) and 7 controls (the investment rate, the installed capital stock, the current, lag one and lag two values of the demand shock, and the forecast for the next year’s investment and the expected change in technical capacity). For these to be a valid set of controls, we need to assume that not only current investment but also the forecast for the next year’s investment and the expected change in technical capacity are monotonic functions of the shocks: higher demand or TFP today implies higher expected investment next year and higher expected change in technical capacity. Given the monotonicity that characterizes the model, these are natural assumptions.

We recompute the coefficients of the production function and the corresponding TFP levels for this modified setting. The resulting coefficients are similar to those obtained in the basic specification. We investigate the importance of lagged shocks in Table A-3. Both shocks have dynamic effects on output, prices and input demand. In terms of asymmetry, lagged effects are stronger for TFP shocks, confirming that adjustment costs are more important for them. Even if we take into account dynamic effects, the cumulated response is far from that predicted by the frictionless model, and the larger deviation for TFP shocks still persist.

\textsuperscript{26}Although it is generally true that the presence of adjustment costs induces lagged response, the dynamic pattern of adjustment itself depends on the form of the adjustment cost function. For example, convex adjustment costs imply smooth adjustment, while fixed costs lead to bunching. In both cases, adjustment depends not only on current but also on past shocks. The literature has been inconclusive on the shape of the adjustment cost function. Contributing to this debate is beyond the scope of this paper.
B.6 Measurement error in TFP

Throughout the analysis, we follow Foster et al. (2008) and measure the productivity shocks using the whole residual of the production function: \( \Delta TFP = \Delta \omega + \Delta \eta \). Although we interpret \( \eta \) as something different from measurement error, one could still be concerned with the fact that this could be the explanation for the asymmetry of responses that we find. To control for this possibility, we analyze the relationship between shocks and the endogenous variables at longer lags. As argued for the production function, with longer lags the importance of measurement error should be reduced. We have estimated equation (17) using lags computed over 3 years, i.e., regressing \( y_t - y_{t-3} \) on \( TFP_t - TFP_{t-3} \) and \( \xi_t - \xi_{t-3} \). The results, unreported for parsimony, show that the coefficients increase somehow for TFP and decrease slightly for market appeal. However, this is unlikely to be due to measurement error. In Table A-3 we report the results of a regression in which 2 lags for \( \Delta TFP \) and \( \Delta \xi \) are included. The coefficients we obtain in the regressions using 3-year lags are basically the same as the sum of the coefficients on \( \Delta TFP_{t}, \Delta TFP_{t-1}, \Delta TFP_{t-2} \) (and similarly for \( \Delta \xi \)). This suggests that the modest differences in the coefficients between the 3-year differences and first differences specifications are driven by dynamic effects, rather than being due to dissipation of measurement error. All in all, we conclude that the two main findings stated in Section 5 are not a mere product of measurement error in our measure of TFP.

B.7 Elasticities to shock, sector by sector

Table A-4 reports sector-by-sector elasticities to shocks of the main growth measures analyzed in the paper. It emerges that the results of the pooled data are not driven by specific sectors. The qualitative patterns are the same for each of the sectors included in the analysis.
Figure A-1: Comparison of price index based on INVIND self-reported price changes and official Producer Price Index computed by the Italian Statistical Office (ISTAT)

(a) Textile

(b) Leather

(c) Metals

(d) Machinery, mechanical

(e) Machinery, electrical

Notes: The INVIND price index is computed averaging firm-reported price changes using sample weights provided by the Bank of Italy. The ISTAT PPI refers to the figure released in the month of March. Both indexes are normalized to 1 in 2009.
Table A-1: Additional estimates of the production function

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<td></td>
<td>Txt+leather</td>
<td>Metals</td>
<td>Machinery</td>
</tr>
<tr>
<td>( \Delta k )</td>
<td>0.14***</td>
<td>0.08***</td>
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<td>(0.026)</td>
<td>(0.028)</td>
<td>(0.024)</td>
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<td>( \Delta l )</td>
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<td>( \Delta m )</td>
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<td>0.51***</td>
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<td>(0.023)</td>
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<td>( R^2 )</td>
<td>0.70</td>
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Panel B: Using three year differences

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<td>( \Delta k )</td>
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<td>(0.038)</td>
<td>(0.041)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>( \Delta l )</td>
<td>0.23***</td>
<td>0.27***</td>
<td>0.20***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.033)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>( \Delta m )</td>
<td>0.58***</td>
<td>0.64***</td>
<td>0.63***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.028)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,043</td>
<td>738</td>
<td>1,098</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.77</td>
<td>0.76</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Notes: Panel A reports the estimates of the production function when using the current and lagged levels of \( i, k \) in the control function instead of their first difference. Panel B reports the estimates of the production function when using 3 year differences instead of first differences. Robust standard errors are reported in parentheses. Significance levels: *: 10%, **: 5%, ***: 1%
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>1.478***</td>
<td>-0.309***</td>
<td>0.364***</td>
<td>0.473***</td>
</tr>
<tr>
<td>Price</td>
<td>(0.112)</td>
<td>(0.024)</td>
<td>(0.053)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Employment</td>
<td>0.230***</td>
<td>0.128***</td>
<td>0.080***</td>
<td>0.040***</td>
</tr>
<tr>
<td>(0.010)</td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>Investment</td>
<td>7,371</td>
<td>7,451</td>
<td>7,337</td>
<td>7,431</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.26</td>
<td>0.69</td>
<td>0.12</td>
<td>0.06</td>
</tr>
</tbody>
</table>

**Notes:** This table replicates some of the pooled estimates displayed in Tables 5 and 6 using the $\Delta \omega$ in equation (13) as the measure of productivity rather than the $\Delta TFP = \Delta \omega + \varepsilon$ we used in the main specification. All dependent variables and the demand and productivity shocks are in delta logs. $\Delta \omega$ is calculated using Olley and Pakes (1996) control function approach. $\Delta \xi$ is computed using self-reported sectoral price elasticities from the INVIND survey 1996. 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. Significance levels: *: 10%, **: 5%, ***: 1%
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output Price</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TFP_t</td>
<td>1.03***</td>
<td>-0.17***</td>
<td>0.09***</td>
<td>0.09***</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.007)</td>
<td>(0.018)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>TFP_{t-1}</td>
<td>0.20***</td>
<td>-0.05***</td>
<td>0.12***</td>
<td>0.07***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.006)</td>
<td>(0.018)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>TFP_{t-2}</td>
<td>0.03</td>
<td>-0.02***</td>
<td>0.08***</td>
<td>0.08**</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.005)</td>
<td>(0.017)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Δξ_t</td>
<td>0.28***</td>
<td>0.13***</td>
<td>0.08***</td>
<td>0.03***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Δξ_{t-1}</td>
<td>-0.03***</td>
<td>0.01***</td>
<td>0.03***</td>
<td>0.02***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.002)</td>
<td>(0.006)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Δξ_{t-2}</td>
<td>-0.01</td>
<td>-0.00</td>
<td>0.02***</td>
<td>0.02**</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.002)</td>
<td>(0.006)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Observations</td>
<td>3,392</td>
<td>3,410</td>
<td>3,382</td>
<td>2,802</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.53</td>
<td>0.77</td>
<td>0.17</td>
<td>0.05</td>
</tr>
</tbody>
</table>

**Notes:** All dependent variables (except investment rate) and the demand and TFP shocks are in delta logs. ΔTFP is calculated using the Olley and Pakes (1996) control function approach. Since lags are included in the specification, the control function is augmented to include the forecast for the next year’s investment, the expected change in technical capacity and two lags of the demand appeal shocks as additional controls; more details are in Appendix B.5. Δξ is computed using self-reported sectoral price elasticities from the INVIND survey 1996. Output is 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. Significance levels: *: 10%, **: 5%, ***: 1%
Table A-4: Elasticities to demand and TFP shocks, by sector

Panel A: Output

<table>
<thead>
<tr>
<th></th>
<th>Txt+leather</th>
<th>Metals</th>
<th>Machinery</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔTFP</td>
<td>0.925***</td>
<td>0.928***</td>
<td>0.980***</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.055)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Δξ</td>
<td>0.296***</td>
<td>0.173***</td>
<td>0.292***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.011)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,926</td>
<td>1,733</td>
<td>2,944</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.55</td>
<td>0.45</td>
<td>0.53</td>
</tr>
</tbody>
</table>

Panel B: Price

<table>
<thead>
<tr>
<th></th>
<th>Txt+leather</th>
<th>Metals</th>
<th>Machinery</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔTFP</td>
<td>-0.159***</td>
<td>-0.141***</td>
<td>-0.151***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Δξ</td>
<td>0.140***</td>
<td>0.142***</td>
<td>0.109***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,939</td>
<td>1,736</td>
<td>2,984</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.73</td>
<td>0.84</td>
<td>0.66</td>
</tr>
</tbody>
</table>
Table A-4: Elasticities to demand and TFP shocks, by sector (continued)

Panel C: Employment

<table>
<thead>
<tr>
<th></th>
<th>Txt+leather</th>
<th>Metals</th>
<th>Machinery</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \text{TFP}$</td>
<td>0.076***</td>
<td>0.040</td>
<td>0.054***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.029)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>$\Delta \xi$</td>
<td>0.113***</td>
<td>0.045***</td>
<td>0.086***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,910</td>
<td>1,697</td>
<td>2,925</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.17</td>
<td>0.07</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Panel D: Investment

<table>
<thead>
<tr>
<th></th>
<th>Txt+leather</th>
<th>Metals</th>
<th>Machinery</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \text{TFP}$</td>
<td>0.094***</td>
<td>0.112***</td>
<td>0.056**</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.037)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>$\Delta \xi$</td>
<td>0.042***</td>
<td>0.037***</td>
<td>0.046***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.012)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,590</td>
<td>1,465</td>
<td>2,313</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.05</td>
<td>0.06</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Notes: This table replicates sector by sector some of the pooled estimates displayed in Tables 5 and 6. All dependent variables and the demand and TFP shocks are in delta logs. $\Delta \text{TFP}$ is calculated using Olley and Pakes (1996) control function approach. $\Delta \xi$ is computed using self-reported sectoral price elasticities from the INVIND survey 1996. All specifications include region and year fixed effects. Both dependent and independent variables are trimmed to drop outliers above the 99th or below the 1st percentile for each sector. Standard errors are calculated from 500 bootstrap simulations. Significance levels: *: 10%, ** : 5%, *** : 1%