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Essays on firm-level shocks, expectations and uncertainty

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Contents

Abstract

This thesis is made up by of three chapters, which study the determinants of firm growth, the measurement of firm's uncertainty, and the determinants of capacity utilization using survey data on Italian firms collected by the Bank of Italy since 1984 ("Indagine sugli investimenti delle imprese manifatturiere", INVIND).

The recent literature has emphasized the role of productivity as one crucial determinant of the performance of the firm and of its growth, to the extent this technical feature of the firm has been placed at the center of the debate in industrial economics in order to explain observed differences in firms at the both micro and macro level. However, the empirical evidence on the actual determinants of the firm's performance in terms of output, value added and other relevant variables as well as the dynamic processes governing firm's growth, is scanty. Some author has pointed to the importance of "shocks" that may affect these relevant outcomes, hence suggesting that the role of productivity has been overstated.

The goal of the first chapter of this thesis is to consider demand shocks as unobserved determinants of the performance of the firm which may produce the sort of heterogeneity in output and growth which is documented in the data. The approach of my thesis is mainly an empirical one: I start from a simple model which makes use of a C.E.S. demand function and a Cobb-Douglas production function, as often proposed in the literature. The strategy I follow is to first generate a consistent estimate of the own-price elasticity of demand along with the parameters of the production function; I can then infer demand shocks and productivity shocks and investigate the effect of these shocks on the main firm-level variables.

The main finding is that productivity shocks positively affect variables that in the short-run could be regarded as quasi-fixed, such as investments, while they have no effect on variable inputs. Demand shocks affect all variables including inputs such as hours of work and capital utilization.

In the second chapter, jointly written with Roberto Casarin, I focused on firms expectations and uncertainty about future business conditions as they represent some of the main drivers of the firm-level decisions concerning investment, employment and capacity utilization. In the empirical literature, there are few investigations on the expectations formation mechanisms for firms. Also, there is no general consensus on the measure of uncertainty of the expectations.

I exploiting the rich information contained in INVIND survey to enrich this stream of literature: first, I present some new stylized fact about the firm expectations' formation process and a measure of self-reported uncertainty; second, I propose two new firm-specific uncertainty measures based on the of forecast error and estimated through Panel GARCH models and third, I construct micro-founded macro uncertainty measures and compare them with the standard measures used in the literature.

Finally, in the third chapter, jointly written with Agar Brugiavini, I focused on the determinants of firms' capacity utilization exploiting the availability of measure

of self-reported capacity utilization. According to the European Commission low capacity utilization rates are the main indicator of the low level of investment of manufacturing firms observed in Italy during the crisis. A reduced capacity utilization is typically related to low output growth or even stagnant output, together with inefficient levels of activities of the firm. An adequate level of capacity utilization should stimulate firm's growth and in turn improve firm's performance.

The challenge is to specify an economic model which is capable of distinguishing between factors which are exogenous and might affect production and pricing decisions in a similar fashion to actions dictated by strategic consideration. I find that capacity utilization is negatively affected by the uncertainty faced by the firm, but interesting differences emerge for different sectors and industries. I argue that firms with "high market power" tend to exhibit higher rates of capacity utilization.

Chapter 1

Firms growth: disentangling demand and productivity shocks

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Abstract

The recent literature has emphasized the role of productivity as one crucial determinant of the performance of the firm and of its growth, to the extent this technical feature of the firm has been placed at the center of the debate in industrial economics in order to explain observed differences in firms at the both micro and macro level. However, the empirical evidence on the actual determinants of the firm's performance in terms of output, value added and other relevant variables as well as the dynamic processes governing firm's growth, is scanty. Some author has pointed to the importance of "shocks" that may affect these relevant outcomes, hence suggesting that the role of productivity has been overstated. The goal of this chapter is to consider demand shocks as unobserved determinants of the performance of the firm which may produce the sort of heterogeneity in output and growth which is documented in the data. The approach of my thesis is mainly an empirical one: I start from a simple model which makes use of a C.E.S. demand function and a Cobb-Douglas production function, as often proposed in the literature. The data set is the Bank of Italy Survey of Industrial and Service Firms, which surveys a sample of Italian manufacturing firms and provides a unique source of information on firm-level prices along with the standard variables. The strategy I follow is to first generate a consistent estimate of the own-price elasticity of demand along with the parameters of the production function; I can then infer demand shocks and productivity shocks and investigate the effect of these shocks on the main firm-level variables. The main finding is that productivity shocks positively affect variables that in the short-run could be regarded as quasi-fixed, such as investments, while they have no effect on variable inputs. Demand shocks affect all variables including inputs such as hours of work and capital utilization.

1.1 Introduction

The rate of growth of output is regarded as the main indicator of the performance of the firm as it represents a summary measure of the complex decision process that firms face in a dynamic setting. However, the challenge for a satisfactory economic representation of this process is to describe the link between this outcome variable and the underlying mechanisms, ranging from the optimal production decision and optimal demand of inputs, to the entry/exit decision. An extra layer of complexity pertains empirical studies as proper measures of the relevant variables are hardly available.

There are several aspects to be considered in addressing this challenge, for example the role of expectations over future demand is often overlooked: firms take key decisions such as whether to stay in (or exit from) a specif industry, how much to produce and the level of investments, say, by considering an uncertain environment and comparing the realized and desired rate of growth. This means that the researcher cannot assume that the firm takes decisions on the basis of a simple static optimization principle, as expectations about the future values of the relevant variables may twist some of the key decisions in one direction or the other. Furthermore some of the dynamic variables are strictly related to the firm, such as productivity, and others are exogenous, such as demand[1].

From a technological point of view, the growth rate of the firm is associated to economies of scale, which economic theory relates to efficiency, i.e. to an optimal use of the available resources. Hence, by making the firm more efficient in a competitive environment, economies of scale also increase the probability to survive in the market. In other words, growth provides a competitive advantage and it represents the engine to engage in innovation in order to preserve this advantage. The mechanisms which guarantee such a chain of effects has been at the center of the economic debate for several years - the early contributions, especially the empirical studies - have devoted their efforts to this issue.

The basic problem is that the market structure and the corresponding behaviour of the firm generates a more complex environment: if the market is not perfectly competitive, but it is characterized by monopolistic competition or by some form of oligopoly, firms cannot be assumed to be price takers and they could behave strategically in setting prices of their products. In this latter case, the traditional models of firm's growth and estimation of productivity are challenged by a different line of reasoning, where prices may play a crucial role and where, in order to produce credible estimates of the relevant parameters, the information requirements are quite demanding.

[1] One could argue that demand is also to some extent endogenous if the firm is undertaking massive marketing expenditure, however, even in this case the returns from "marketing investments" are not known in advance and depend on the behaviour of competitors.

In the traditional setting, following the seminal contribution of Jovanovic (1982)[2], and the subsequent work of Hopenhayn (1992), many economists regarded productivity as the main source of firm's heterogeneity and firm's performance, hence providing a direct link to the observed growth of firm output. But this theoretical assumption is challenged by the fact that productivity itself is unobservable, so that the researcher (but also the potential competitors) have to make inferences on the true underlying productivity of the firm based on observable variables. Indeed, the estimation of firm-level productivity has attracted a lot of attention in the applied economic literature, but different estimation approaches lead to different conclusions on the nature of the relationship between productivity and firm growth.

A second generation of papers, nested on Olley and Pakes (1992) as De Loecker (2011) and Foster, Haltiwanger, and Syverson (2008), propose to consistently estimate productivity and demand shocks and to analyze the joint effect of these shocks on the variables of interest such as changes in output. In this chapter, I present both strands of the literature, starting from the earlier approach based on the role of productivity alone, then moving on to the second venue where shocks to demand are included and joint estimates of supply and demand are carried out.

I also propose a model, following the approaches taken by Pozzi and Schivardi (2012) and De Loecker (2011), who emphasizes how different dimensions of heterogeneity may have an impact on the growth of the firm beyond productivity. In particular, I expand their models by playing up the role of demand shocks . This is not a simple task as, from a methodological perspective one needs to disentangle the part of growth due to changes in productivity from the part of growth which can be explained by demand shocks, while being both unobservable to the researcher.

There exits a standard identification problem which can affect the results with different degrees of the implied distortion. At a first level: completely neglecting the heterogeneity of firms due to demand shocks would lead to estimates of the effect of productivity which are markedly upward biased. At a second level, even considering the existence of demand shocks, one has to recognize that these interact with productivity shocks because firms take dynamic decisions on desired output and optimal investment.

To address these issues I develop an econometric model, rather an econometric framework, in line with the papers of Olley and Pakes (1992) and De Loecker (2011) to jointly estimate parameters of the production function along with the demand shocks faced

[2]Jovanovic (1982)'s approach rests on a theoretical model in which firms are able to learn their productivity as well as the productivity of the other firms operating in the market. The mechanism at work is a "firm selection process", whereby more productive firms grow and survive while the less productive ones fail

by the firm. Like in the paper of Pozzi and Schivardi, I introduce the idea of "sector-idiosyncratic demand", i.e. the demand which is specific for the product of a firm or a group of firms. This methodology has clear advantages as it helps recovering the relevant demand parameters, such as the elasticity of demand to own-prices, but it imposes strong data requirements as one has to know firm-level prices in order to separately identify the different mechanisms through which shocks affect output growth.

My work, also, evaluates the impact that productivity shocks and demand shock have on the variables which are under the direct control of the firm, such as employment and investment decisions. I show that demand shocks have a positive impact on both employment and investment, in particular the impact on employment is greater than the one generated by productivity shocks. An interesting twist of this result is that the implied adjustments that the firm has to implement relate to both more hiring (as it is the case for a productivity shocks) but also to lower firings. In fact, the results shows that productivity shocks have a stronger impact on investments than demand shocks do. These are novel results which have useful policy implications as they emphasize, on the one hand, the role of the demand stimulus for inducing the firm to hire (or not to fire), and, on the other hand, the role of innovation and efficiency gains as drivers of investments.

Because the implementation of the framework described above requires a rich set of data, I rely on the Italian sample provided by the Bank of Italy known as the INVIND Survey (Indagine sugli investimenti della imprese manifatturiere). This data-set contains the key variables for a large sample of Italian firms provided in panel form, including firm-level prices, more details are presented in section 4 below.

This chapter is organized as follows: In Section 2 I provide the literature review and highlight the features of the various models which are particularly relevant for my specification of the problem. In Section 3 I rely on the methods presented in Section 2 in order to build a "demand extended" framework which allows me to estimate augmented production functions along with productivity. In section 4, I present the main features on the INVIND database, together with a descriptive analysis. In section 5, I present and discuss the estimated production and demand function parameters compare them with the results based on traditional Fixed Effects and "Olley and Pakes" OP-type estimators. I then relate the estimated production and demand shocks to the main firm-level growth indicators. Section 6 provides some conclusions and a general appraisal of the proposed approach.

1.2 Literature review and modeling approaches

As I mentioned in Section 1 above, the evolution of the literature encompasses two vintages of models: a first group of models focuses the attention on the role of productivity as the main determinant of firm growth, given the optimal demand of capital and labour. This approach is, then, followed by a number of papers which turn the attention to the role of demand shocks and to the joint estimates of the parameters of the production function along with the parameters of the demand faced by the firm.

The underlying market structure has to be taken into account in addressing these issues: one needs to abandon the perfectly competitive firm paradigm and consider prices as part of the model, otherwise some of the basic elements of the model would collapse. As a matter of fact, there is a wide consensus, supported by a large body of evidence, that a large share of firms is not price taker but rather exhibits a markup of prices over marginal costs. Hence the basic model has to be flexible enough as not to lead to partial or over-simplified representation of firm's behaviour.

In light of these considerations, I will consider the firm in the more general case of monopolistic competition, without however providing a fully developed model of the relationship between firms' behavior and market structure. The latter, I shall address more in chapter 3 of the present thesis.

The starting point of this vast literature is a simple model based on the Cobb-Douglas production function, which, despite its limitations, still provides a useful benchmark for empirical work in this area of research. The initial equation is:

$$Q_{it} = A_{it} {L_{it}}^{\beta_l} {K_{it}}^{\beta_k} \tag{1.1}$$

in which firm i at time t produces a certain quantity of output Q_{it} using as inputs labor L_{it} and capital K_{it}. In addition to these inputs, production depends on the firm-specific, Hicks-neutral level of efficiency A_{it}, which is unobservable. proceeding any further, it is useful to provide a few definitions of the crucial variables. Firm growth is normally associated to *productivity*, in equation (1.1) above this is the term A_{it} which is firm-specific and time-specific and it act as a multiplier of the production function. The intuition is that the firm may increase its output, differentially in each period, thanks to specific positive effect of say, firm-specific technological or organizational advances or better knowledge, for a given level of the inputs. Productivity and *efficiency* are treated in the literature as the same concept: a firm becomes more efficient if it makes a better use of the resources, keeping the inputs fixed.

Total Factor Productivity (TFP) is the empirical or "accounting" counterpart of productivity: it is the growth in output which is not explained by the increase in inputs. These concepts should be distinguished by *economies of scale*, which may also produce firm growth, but this is a purely technological characteristic of the production function itself and it is embedded in the assumptions about the β-parameters of the Cobb Douglas specification. Increasing returns to scale would imply that if all inputs increase of the same amount (e.g. they double), the output increases more than proportionally (more than doubles) for a given level of the productivity variable. However in this latter case inputs are not fixed. This introductory remark makes immediately clear that one major problem is to separately identify the drivers of firm growth when more than one route operates.

In order to obtain a more tractable specification a log-transformation is normally applied to (1.1) to generate

$$q_{it} = \beta_l L_{it} + \beta_k K_{it} + ln(A_{it}) \tag{1.2}$$

It is useful to note that this specification naturally lends itself to a simple estimation procedure, as it automatically delivers a decomposition of the different terms and it isolates the Hicksian efficiency term $ln(A_{it})$.
In order to get a better grasp of the role of productivity Eberhardt, Helmers, et al. (2010) assume that the $ln(A_{it})$ term can be further decomposed as follows:

$$ln(A_{it}) = \beta_0 + \omega_i + \omega_t + \omega_{it} + \eta_{it} \tag{1.3}$$

where β_0 represents a time-invariant term, i.e. a constant average efficiency across all firms. Hence, the remaining three effects are in terms of deviation from the mean and they pick up different aspects of the latent variability. In particular:

- ω_i is a firm-specific fixed effect capturing a permanent (time-invariant) firm productivity;
- ω_t is an aggregate time-specific component, affecting all firms in the same way;
- ω_{it} represents the combination of the firm-specific effect and common technological progress in period t. The authors argue that this term captures the effect of unobservable factors such as technology, skills differences and human capital, but also expected weather conditions, expected strikes etc... affecting output observable by the firm but not observable by the econometrician;
- η_{it} is a purely random component, assumed to be i.i.d. This variable would pick up unpredictable breakdowns, unexpected problems for machines and workers, measurement errors and any other random factor.

The specification proposed by Eberhardt, Helmers, et al. (2010) is a good example to start discussing the state of the art. It should be noted that, under the assumption that the researcher has access to firm-level micro-data, ideally in the form of panel data, one can focus the attention on the terms ω_{it} and η_{it}, because first differencing coupled with the introduction of time dummies automatically gets rid of the terms ω_i and ω_t This way one can focus the attention on the term it, which is the only dynamic factor related to the original productivity variable in (1.2).

Before turning the attention to the specifications used to estimate the production function (1.2) while taking into account the structure of the productivity term, it is useful to recall some typical problems affecting this area of empirical research. They arise partly because of the quality and the type of data and partly as a result of the economic behaviour of the firm relating to the mechanism underlying the impact of productivity on output and output growth. It is useful to introduce them upfront because they partly motivate the modeling choices adopted by various authors. They can be grouped into three categories as follows.

1. *Measurement issue*

   Several studies provide estimates of the parameters of the production function and productivity parameters by making use of specific measures of the performance of the firm. While the standard theory is based on output as the outcome variable, revenue variables such as "added value" or "total sales" which contain both prices and quantities $R_{it} = P_{it}Q_{it}$ are used as proxies for the level of output. These choices have shortcomings, as also noticed by Foster, Haltiwanger, and Syverson (2008), because the use of revenues as a proxy for output leads to a mixture of actual measures of productivity and measures of market power as one cannot disentangle the price effect from the quantity effect. Estimates of the parameters of the production functions based on this measure may lead to overestimation of the productivity parameter for those firms which are able to charge higher prices for a given quantity, due to market power. Klette, Griliches, et al. (1996) argue that the standard choice, often dictated by lack of data, is to use a sector-specific price deflator which is a partial solution to the problem. It is clear from this discussion that this cannot be regarded as a standard measurement error problem affecting the dependent variable as the error which would be generated would not be a white noise type error with regard to the other variables of interest. Other measurement issues affect variables such as the labour input and the use of capital: I shall discuss these latter issues as I specify the model below: while the might be less damaging in terms of possible distortions they also contribute to the quality of the final estimates.

2. *Attrition bias*

   Attrition bias is a problem affecting dynamic data and in particular panel data, as the “surviving” sample observations may be characterised by a specific behavior or specific attributes. In this framework what is referred to as attrition bias is indeed due to firms which stay in the market and represent a non-random sample of the universe of firms for reasons which could be strictly related to the nature of the decision problem. As an example let’s consider a productivity-related attrition bias. The mechanism is as follows: a firm can observe its own level of productivity ω_{it} and, based on this piece of information, it may decide whether to exit the market or not. In turn, the demand for inputs is conditional upon this "exit or stay” decision. According Olley and Pakes (1992) firms endowed with higher levels of capital tend to stay in the market, even if their productivity is low, because capital could play the role of a buffer which absorbs negative productivity shocks. At the other extreme: very productive firms, even if endowed with a low capital stock, are less likely to exit the market because they are able to generate sufficient output by exploiting their high efficiency. The researcher observes only firms which continue to operate in the market, firms for which capital and productivity could be negatively correlated as argued above, leading to biased estimates of the relevant parameters.

3. *Endogeneity problem*

   The endogeneity problem is it the hart of the empirical work carried out in this area of research, as the observed heterogeneity of firms calls for several possible explanation. In the production function context, given the specification detailed in (1.1) and (1.2), actors which are not observed by the researcher, but known to the firm, generate underlying unobserved heterogeneity: the main latent variable is once again the productivity, which correlates with the relevant variables in ways which are not captured by the model. The fact that productivity is not observed by the econometrician leads to biased estimates of the parameters of the production function, if no special methodology is used to elicit and control for these correlations. For example, in order to maximize profits, firms choose the level of inputs based on the marginal products of these inputs, but these are in turn affected by productivity which therefore has a direct effect and an indirect effect through the choice of inputs.

Having introduced the potential problems faced by the researcher when one makes use of firm-level data, I can provide more details on how productivity estimates have been developed in the literature. I will stress those aspects which relate to the endogeneity problem described above.

Structural models have been put forward in order to consistently estimate the production function parameters under the assumption that the researcher can use physical investment as a proxy for the unobservable productivity. For example Olley and Pakes (1992) consider TFP (Total Factor Productivity) as a measure of the unobserved productivity which shifts the supply of the firm. But estimates of TFP alone contain a mixture of productivity and demand effects as highlighted by Klette, Griliches, et al. (1996).

In particular, Olley and Pakes (1992) (henceforth OP) proposed a theoretical model in which firms maximize expected discounted profits in each period and optimally choose the level of labour input (l_{it}) and investment (i_{it}). The crucial assumptions are: i) labour is chosen in each period based on current productivity, hence it is totally determined by the contemporaneous variables; ii) the capital stock follows a deterministic dynamic process $k_{it} = (1-\delta)k_{it-1} + i_{it-1}$ such that, in each period, it is determined by both the lagged choice of investments and current productivity; iii) productivity follows a first-order Markov process hence generating the underlying stochastic process. Under these assumptions, it can be shown that the solution of a standard dynamic profit maximization yields an investment function that is strictly increasing in the level of productivity.
Intuitively: high productivity firms invest more as $i_{it} = f(k_{it}; \omega_{it})$ with $\frac{\partial i_{it}(\cdot)}{\partial \omega_{it}} > 0$ *ceteris paribus*. Given this result, by discarding firms which exhibit no investments, it is possible to recover the productivity term by inversion

$$\omega_{it} = f^{-1}(i_{it}; k_{it}) \tag{1.4}$$

From an observational point of view, once k_{it} is known, the investment level generates the productivity level. The authors propose a two-steps estimation procedure for the parameters of the production function so that the endogeneity problem is overcome. To be more specific, they substitute the initial unobserved ω_{it} with a control function, that can be written as a polynomial in (i_{it} and k_{it}, and it allows to control for productivity in the estimation of the β-coefficients.

Similar papers have been proposed as extensions of this approach, e.g. Levinsohn and Petrin (2003) suggest an alternative estimation routine based on the use of intermediate input demand m_{it} function, in place of the level of investment. This alternative specification recovers all the observations, even when investments are zero, as intermediate inputs are missing only in the extreme case in which the firm stops operating[3]

In a companion paper, Ackerberg, Caves, and Frazer (2006) observe that there exists a further problem generated by the fact that in OP approach, the form of the labour demand is unknown and is bound to depend on the capital stock and of productivity $l_{it} = l_{it}(k_{it}; \omega_{it})$ hence generating a potential correlation with the terms in the polynomial control function itself . They solve this problem by assuming a specific form for the demand for labour input and a specific timing. While i_{it} is chosen in period $t-1$, in period t, the capital stock k_{it} is determined by i_{it-1}, then labour input l_{it} is chosen and finally, i_{it} is chosen conditional on k_{it} and l_{it} together with productivity. It is clear that this latter model relies on the assumption that the described timing of decision making is the true one.

In order to obtain more satisfactory estimates of the productivity term, a few papers consider demand shocks as a "background noise" which should simply be filtered out. These models adopt a C.E.S. demand function

$$Q_{it} = Q_{st}(\frac{P_{it}}{P_{st}})^{\sigma} exp(\psi_{it}) \tag{1.5}$$

where σ is the elasticity of demand with respect to the own-price. By assuming that each firm produces an homogeneous output[4], the demand faced by the firm i at time t depends on its own market price P_{it}, an average price in the sector in which the firm operates P_{st}, an aggregate demand shifter Q_{st} and an idiosyncratic demand shifter $exp(\psi_{it})$.

Once again these models have in the background the assumption of monopolistic competition, this specification of the demand equation implies that each firm operates at a constant markup $\frac{\sigma}{\sigma+1}$ measured on its own marginal cost. Note that as stressed by Pozzi and Schivardi, while the markup is constant, prices differ across firms and over time. The term ψ_{it} is the demand shock and it is observed by the firm, but not by the econometrician. This line of reasoning implies that firms can optimally respond to demand shocks, captured by ψ_{it} , by increasing prices rather than operating on quantities, but such responses generate a positive correlation between P_{it} and the error term ψ_{it}, hence affecting the estimation of the elasticity of demand σ.

I n this context, Klette, Griliches, et al. (1996) try to recover productivity estimates through the demand function: they assume that all firms in the same sector face the same

[3]Note that OP methodology is based on the sub-sample of firms with strictly positive investment. As a consequence it can suffer from an efficiency loss, as the subset of firms for which i_{it} is automatically dropped. Such a sample reduction is necessary in order to satisfy the strict monotonicity assumption of the demand for investment, i.e. *conditio sine qua* non for the inversion of investment function.

[4]The hypothesis is forced by the impossibility to have information about different goods produced by each firm.

demand schedule. A sector-specific price deflator is used to "clean" productivity estimates of demand effects.

Building on this idea, De Loecker (2011) combines the two approaches and introduces demand shocks, plus a C.E.S. demand function along with a revenue-based production function. This set up allows the authors to substitute away own-prices and obtain a tractable expression for the firm's revenue as a function of inputs, productivity and demand shocks. In their work, revenues are used as a proxy for output, while the demand function is in the background and it is used to "purge" the productivity estimates.

In a different venue of models, Foster, Haltiwanger, and Syverson (2008) use data on produced quantity (rather than revenues) and firm level price to disentangle productivity shocks from demand shocks. More specifically, they first estimate productivity (also done by Olley and Pakes (1992)) and then use the estimated variable as an instrument for prices in the demand function. This methodology allows the authors to obtain consistent estimation of the demand elasticity as well as of the demand shocks, treated as residuals. However, it should be stressed that the underlying identifying assumption is that productivity shocks and demand shocks are uncorrelated.

These latter papers made a significant progress as they specify productivity in a richer setting also characterized by a demand function and demand shocks, however these models turned out to be quite demanding in terms of data requirements: it is necessary to observe firm-level prices plus one needs measures of output in terms of revenues or added value and then recover quantities, which might explain why these models did not receive all the attention they deserve.

Another problem of this approach is that it is based on the so-called "scalar unobservable assumption": i.e it is assumed that productivity is the only unobservable variable affecting the investment function. As suggested by Ackerberg, Benkard, Berry, and Pakes (2007) the investment level could be chosen by the firm looking at other unobservables, once again demand factors, which calls for dealing with the endogeneity problem in an explicit way.

My main reference is the paper by Pozzi and Schivardi (2012): they generalize the above models by proposing empirical estimates where demand shocks are a direct determinant of the investment function. The starting point is the maximization of firm profits

$$Max_{\{K_{it};L_{it}\}} \; P_{it}Q_{it} - p_K K_{it} - p_L L_{it}$$

where p_K and p_L are utilization costs, respectively, of capital and labour. Substituting production function in (2), the log of demand function in (5) and considering the fact that utilized capital can be a fraction $0 \leq u_{it} \leq 1$ of the installed level of capital $\bar{K}_{it}$

($K_{it} = u_{it}\bar{K}_{it}$), previous maximization problem leads to

$$\begin{aligned} q^*_{it} &= c_q + \frac{\sigma}{\theta}\omega_{it} + \frac{\beta_l + \beta_k}{\theta}\psi_{it} \\ p^*_{it} &= c_p - \frac{1}{\theta}\omega_{it} + \frac{1 - \beta_l - \beta_k}{\theta}\psi_{it} \\ x^*_{it} &= c_x + \frac{\sigma - 1}{\theta}\omega_{it} + \frac{1}{\theta}\psi_{it} \end{aligned}$$

in which $\theta = \beta_l + \beta_k + \sigma(1 - \beta_l - \beta_k)$, $x = k; l$ and c_q, c_p and c_x are constants.

These results can be seen as a reduced form set of equations describing quantities, prices and the implied demand for inputs in terms of the shock only. The authors point out that, if the capital constraint is not binding and the capital is not used at full capacity, equilibrium quantities do not depend on the stock of capital in place. Also, prices differ even if the demand elasticity (and the markup) is constant through differences in the marginal cost. In particular, if the production function exhibits non-constant returns to scale, different levels of the shocks (both shocks) generate different levels of output, hence different levels of marginal cost. They make use of TFP to obtain productivity measures under the assumption that TFP-shocks and demand shocks[5] are exogenous, they exploit a firm self-reported measures of demand elasticity provided by the respondents (firms) in the INVIND Italian Survey. The self-reported elasticity is a "one off" answer, so that they can estimate sector-specific elasticity just by averaging elasticities of firms operating in a given sector. Their work is clearly making an important step in the right direction: however it confines demand shock to an ancillary role as they are not used by the firm directly. A very relevant point of their paper is that they clearly point out the mechanism which is at the hart of the identification strategy I am also adopting: In their model TFP has both a direct and an indirect effect on output as a change in TFP increase Q but also it increases the conditional demands of capital k and and labour l, which in turn have an effect on Q. Demand shocks instead have a different route entirely through the production function itself and therefore through the conditional demands for inputs, but no direct effect.

This overview of the recent literature provides the building blocks for my model. The main points are that it is necessary to rely on a revenue-based framework, that allows the researcher to estimate idiosyncratic demand and productivity shocks exploiting the availability of firm-level prices. At the same time one has to take into account that shocks affect the conditional demand for inputs in a dynamic way, together with the efficiency level[6].

[5] Also referred to as "market appeal" shocks

[6] Another stream of literature driven by De Loecker and Warzynski (2012) and Forlani, Martin, Mion, and Muûls (2016) goes in the direction to jointly estimate productivity, demand shocks

1.3 Model and estimation strategy

In this section, I propose a general model in order to jointly estimate demand and production function parameters. The basic structure is the reduced form obtained by Pozzi and Schivardi (2012), but I also refer to De Loecker (2011) to have a more detailed specification of the investment function. In fact, the latter paper makes use of an investment function which explicitly depends on demand shocks. I also borrow some elements from Ackerberg, Benkard, Berry, and Pakes (2007) in order to include demand shifters in the investment function.

An important difference between my work and the work of Pozzi and Schivardi (2012), is that they use the average of self-reported demand elasticity to compute the residual from the supply function, this in turn enters the investment function to produce estimates of the production function parameters. In my specification I rely, instead, on an "objective" estimate of price elasticity based on sector-specific prices. Tthe novelty of my approach is that I propose a parsimonious specification, which reduces data requirements while leading to satisfactory estimates of the relevant parameters.

I start from a "demand and supply" system which can be obtained by a log-transformation of (1.1) and (1.5) so that the equations are[7]

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it} \tag{1.6}$$

$$q_{it} = q_{st} + \sigma(p_{it} - p_{st}) + \psi_{it} \tag{1.7}$$

These equations represent a production-demand system faced by firms. Note that the labour input and the capital input, relate to the quantity produced q_{it} according the marginal products β_l and β_k and two productivity shocks ω_{it} and η_{it}. Firms face a demand schedule according to their own market price P_{it}, an average price in the sector P_{st}, the demand elasticity $\sigma < -1$ an aggregate demand shifter Q_{st} and an idiosyncratic demand shifter ψ_{it}. It should be stressed that this production and demand setting is embedded in a monopolistic competition environment and in which the firm optimal price level is a constant markup $\frac{\sigma}{\sigma-1}$ applied on the marginal cost.

together with firm-level mark-up. This literature is far from the objective of this chapter.

[7]In equation (6), for the sake of simplicity, I use only $_{it}$ term for the productivity index because in the final specification first differentiation and time dummies inclusion allow me to control for individual firm effects and time effects. In equation (7), the work assumption here is that inventories are negligible, i.e. produced quantity is exactly equal to sold quantity.

According to the decomposition of Eberhardt, Helmers, et al. (2010), $\eta_{it} \sim i.i.d(0;\sigma^2_\eta)$: it is a purely random and unexpected component. I will focus on the properties of ω_{it} and ϕ_{it} because they will be object of specific assumptions that need wider discussion.
I use revenues to measure output, in logs terms:

$$r_{it} = q_{it} + p_{st}. \tag{1.8}$$

From demand equation in (1.7), it is possible to obtain firm-level price as $p_{it} = p_{st} - \frac{1}{\sigma}(q_{st} + q_{it} + \psi_{it})$. Substituting this price equation into the revenues in (1.8) I obtain

$$r_{it} - p_{st} = \frac{\sigma + 1}{\sigma} q_{it} - \frac{1}{\sigma} q_{st} - \frac{1}{\sigma}\psi_{it} \tag{1.9}$$

A final equation can be obtained substituting production function in (1.6) into (1.9):

$$r_{it} - p_{st} = \alpha_l l_{it} + \alpha_k k_{it} + \alpha_q q_{st} + \omega^*_{it} + \psi^*_{it} + \eta^*_{it} \tag{1.10}$$

where the alphas parameters are defined as

$$\alpha_l = \frac{\sigma + 1}{\sigma}\beta_l \qquad \alpha_k = \frac{\sigma + 1}{\sigma}\beta_k \qquad \alpha_q = -\frac{1}{\sigma}$$

while the new shocks are simply scalar multiplication of the original shocks

$$\omega^*_{it} = \frac{\sigma + 1}{\sigma}\omega_{it} \qquad \psi^*_{it} = -\frac{1}{\sigma}\psi_{it} \qquad \eta^*_{it} = \frac{\sigma + 1}{\sigma}\eta_{it}$$

Note that, $\sigma < -1$ so, despite the presence of the coefficients $\frac{\sigma+1}{\sigma}$ and $-\frac{1}{\sigma}$, ω^*_{it}, ϕ^*_{it} and η^*_{it} enter in equation (10) with the same sign of the original shocks ω_{it}, ϕ_{it} and η_{it}.

Labour input is measured in worked hours while capital input is measured in terms of capital utilization. This last choice is due to the fact that when the firm has to decide for the use of capital in a dynamic setting it has to consider costs and benefits over a number of periods: in the short run it may be optimal to use less capital with respect to the installed capacity. Pozzi and Schivardi provide a discussion on which condition on the capital stock would imply a full capacity utilization (also depending on the elasticity of demand) and conclude that the capital stock in place does not bind and firms operate below capacity, unless the above shocks are very large, a condition which is not observed in our sample period. The following set up is based on the contribution of Levinsohn and Melitz (2002) goods produced in differentiated markets, while I borrow their approach to stress the role of demand shocks.
The first step is to formulate a working hypothesis.

Assumption 1: in each period firms observe realization of the two shocks ω_{it} and ψ_{it} and choose labour and capital utilization accordingly.
A direct consequence of this assumption is that both labour and capital are endogenous with respect to the two predicted components of the error term $((\omega^*_{it} + \psi^*_{it}))$ because labour and capital input are chosen according to the expectation about productivity and demand shocks.

The second step consists in specifying a it stochastic process for the shock:

Assumption 2: productivity and demand shocks follow a first order Markov process.
Then one gets:

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}] + \xi^{\omega}_{it} = g(\omega_{it-1}) + \xi^{\omega}_{it}$$
$$\psi_{it} = E[\psi_{it}|\psi_{it-1}] + \xi^{\psi}_{it} = g(\psi_{it-1}) + \xi^{\psi}_{it}$$

This latter assumption is quite restrictive as it implies that productivity and demand shocks have the same serial correlation, the advantage is that it allows a combination of the two shocks into a common unobservable variable, which also follows a first order Markov process[8]:

$$\omega^*_{it} + \psi^*_{it} = g(\omega^*_{it-1} + \psi^*_{it-1}) + \xi_{it} \tag{1.11}$$

where $\xi_{it} = \xi^{\omega}_{it} + \xi^{\phi}_{it}$.

Assumption 3: capital accumulation follows a deterministic dynamic process $\overline{k}_{it+1} = (1-\delta)\overline{k}_{it} + i_{it}$ such that, in each period, it is determined by lagged choice of investment.
According to this assumption, installed capital stock k_{it} is a predetermined variable that does not require to be estimated within the production function, because I use utilized capital k_{it} as the input variable. Installed capital is instead a key-information to deal with the endogeneity problem discussed above: assumption 3 has the direct consequence that in each period investment are chosen by the firm looking at installed capital stock and realized shocks

$$i_{it} = i_{it}(\overline{k}_{it}; \omega^*_{it} + \psi^*_{it}) \tag{1.12}$$

[8]I rely on what Levinsohn and Melitz (2002) do the same in in order to disentangle productivity and quality effect of product in differentiated markets. They argue that the assumption of identical Markov processes allows to exploit the potential of rich data bases that, however, are not "ideal". Nevertheless, allowing for two different Markov process is something that leave space for further and future research.

Equation (1.12) can be use as control function in OP fashion, but differently from OP, it allows to relax "scalar unobservable assumption" and adopt the specification of Ackerberg, Benkard, Berry, and Pakes (2007).
$\omega^*_{it} + \psi^*_{it}$ is a composed index summarizing productivity and demand shocks obtainable by inversion. It says that firms which exhibit a higher level of the index invest more. The inversion of (1.12) as $\omega^*_{it} + \psi^*_{it} = i^{-1}_{it}(i_{it}; \overline{k}_{it})$ along with the substitution into (1.10) generates a specification which partly solves the endogeneity problem. The procedure requires an approximation of the composite (predicted) error term $\omega^*_{it} + \psi^*_{it}$, which I describe in the form of a fourth order polynomial in i_{it} and $\overline{k}_{it}$.
As I will explain in detail in the next section, the INVIND dataset provides prices and capital expressed in terms of percentage changes. Hence, in order to adapt the model to the available data, I write the relevant equations in first differences

$$\Delta r_{it} - \Delta p_{st} = \alpha_l \Delta l_{it} + \alpha_k \Delta k_{it} + \alpha_q \Delta q_{st} + \Delta\omega^*_{it} + \Delta\psi^*_{it} + \Delta\eta^*_{it} \tag{1.13}$$

and to rely on the following inverted investment function

$$\Delta\omega^*_{it} + \Delta\psi^*_{it} = i^{-1}_{it}(\Delta i_{it}; \Delta\overline{k}_{it}) \tag{1.14}$$

As I pointed out in the previous section, first differencing eliminates the fixed component of unobserved heterogeneity. This final specification of the model is designed to jointly and consistently estimate the parameters of both the demand function and the production function. It also allows me to distinguish between idiosyncratic productivity and demand shocks: once a consistent estimation for the demand elasticity σ is obtained for each sector, variation in demand shocks can be obtain as a residual from equation (1.7) in the following way:

$$\Delta\hat{\psi}_{it} = \Delta q_{it} - \Delta q_{st} - \hat{\sigma}(\Delta p_{it} - \Delta p_{st}) \tag{1.15}$$

Finally, using the estimates of the demand shocks together with the estimated sector specific elasticities of substitution β_l and β_k, it is possible to recover the variation in the productivity shock as a residual from equation (1.13)

$$\Delta\hat{\omega}_{it} = \Delta q_{it} - \hat{\alpha_l}\Delta l_{it} - \hat{\alpha_k}\Delta k_{it} - \hat{\alpha_q}\Delta q_{st} + \frac{1}{\hat{\sigma}}\Delta\hat{\psi}_{it} \tag{1.16}$$

1.4 The data

1.4.1 INVIND database

In this section, I focus my attention on the characteristics of the dataset, in particular, I try to explain the choices that I made in order to implement my estimation strategy as detaild in section 3 above.

The sample used in this study comes from the Inquiry into Investment of Manifacturing firms ("Indagine sugli investimenti della imprese manifatturiere", INVIND), a survey collected every year since 1984 by the Bank of Italy. This survey contains a very rich set of information about industrial and service firms: biographic information, employment, investment (realized and projected), turnover, technical capacity, debt and credits and so on. This database is the same used by Pozzi and Schivardi (2012): while they have to rely on self-reported demand elasticities, I recover the estimate of demand-elasticity, and the idiosyncratic demand shocks from the model. I also make use of a revenue approach.

From the original database, I select large industries (more that 50 employees) observed from 1988 to 2016, obtaining an unbalanced panel of 5314 firms observed for 27 years for a total of 38653 firm-year observations. Then, given the choice to estimate the model in first differences, I select only the observations present in the panel for at least two consecutive years. Finally, I rely on a panel of 36348 firm-year observations.

Using the classification by sectors provided by the same Bank of Italy and based on two-digit ATECO 2007 codes, I estimates the relevant parameters sector by sector, thus obtaining a set of production and demand function parameters for the following sectors: Food,Textile, Chemicals, Minerals, Metals and Others.

Table (1.1) shows the sample composition by year and by sector. The largest number of firms belongs to the metals sector (43%) followed by the chemicals sector (15%) while the remaining firms are almost equally distributed among the other sectors. This is in line with the tradition of the Italian economy: metallurgy is the most important manufacturing sector in terms of value added and general performance as reported by the National Italian Statistical Office (ISTAT: "Rapporto sulla competitivita' dei settori produttivi 2015"). Furthermore, as expected, the majority of firms is located in the North-West and North-East. The firms and firms employing between 50 and 99 employees are the most prevalent ones.

Year	Freq.	%	Sector	Freq.	%
1988	1.039	2,69%	Food	4.459	11,54%
1989	1.053	2.72%	Textile	5.838	15,10%
1990	1.071	2.77%	Chemicals	4.739	12,26%
1991	1.027	2.66%	Minerals	2.716	7,03%
1992	993	2.57%	Metals	16.670	43,13%
1993	994	2.57%	Others	4.231	10,95%
1994	953	2.47%	Total	38653	100%
1995	996	2.58%			
1996	1.060	2.74%			
1997	1.002	2.59%			
1998	998	2.58%			
1999	1.107	2.86%	**Geo. Area**	**Freq.**	**%**
2000	1.428	3.69%	NW	13.023	33,69%
2001	1.713	4.43%	NE	8.969	23,20%
2002	1.797	4.65%	CEN	8.003	20,70%
2003	1.848	4.78%	SOUTH	8.658	22,40%
2004	1.861	4.81%	Total	38653	100%
2005	1.890	4.89%			
2006	1.838	4.76%			
2007	1.783	4.61%			
2008	1.752	4.53%			
2009	1.706	4.41%	**Dim. Class**	**Freq.**	**%**
2010	1.666	4,31%	50-99	11.755	30,41%
2011	1.748	4,52%	100-199	10.230	26,47%
2012	1.747	4,52%	200-499	9.262	23,96%
2013	1.780	4,61%	500-999	3,909	10.11%
2014	1.803	4.66%	1000+	3,497	9,05%
Total	38.653	100%	Total	38653	100%

Table 1.1: Sample composition according to year, sector, geographical area and dimensional class

1.4.2 A further look at the attrition problem

The INVIND panel I use in my estimation is clearly unbalanced: a firm can exit the panel if it decides not to answer the questionnaire, if it no longer exists (because of bankruptcy or liquidation), if it has been taken over or merged with another firm or if changes the "stratum" from which it has been originally extracted, hence losing eligibility for the survey. Unfortunately, the reason why a firm exits the panel is not provide by the Survey, so there is a basic limitation to control for selection and say something about panel attrition.

Panel attrition represents a significant concern if there are systematic patterns in the exit process and/or if the replacements which come from the refresher sample do not make up for the lost observations or if the specific factors which determine the non-response are endogenous with respect to the main outcome variable. I provided an example of how attrition may generate negative correlations because of the effect of productivity on the firm performance even in presence of scarce capital, but in the data I can only consider some basic characteristics.

Previous studies (e.g. D'Aurizio, Papadia, et al. (2016)) have carried out a detailed analysis to check for evidence of attrition and concluded that the INVIND survey is not dramatically affected by such a problem.
In order to provide some basic information on this potential hazard, I present, in Appendix B, some descriptive statistics. The first observation is that the size of attrition is far to be negligible: on average a firm is observed for six years and one fifth of the firms exit the sample every year. As a consequence, approximately 80% of the firms which are observed in a given year are also observed in the following year. However, one aspect which is reassuring is that the attrition process presents low variability over time, i.e. it is rather stable, so that events, such as the 2008 economic crises, do not seem to affect the survival rates.

Looking at the specific sectors one can see that attrition affects mainly the metals sector, which exhibits lower survival rates with respect to the other sectors in all years, while in terms of size, firms with less than 100 employees exhibit survival rates which are lower than the survival rates of the other size classes.
Firms with more than 1000 employees have the highest longevity: it could be due to a lower probability of failure and better management, or because they are not an easy target for take-overs.

From a geographical point of view, the survival rate seems to be fairly randomly distributed in Northern and Central Regions, while firms located in Southern Regions have lower survival rates on average. While this is clearly a concern also for policy makers as the higher mortality of firms in the South of Italy leads to higher unemployment etc, in my work, I do control for these characteristics which should not affect the dynamics in a differential manner.

Overall, my conclusion is that panel attrition seems stable across sectors and size, higher in some regions (as also found by D'Aurizio et al).
The basic problem is if characteristics, such as whether the firm is engaged in innovation activities and R&D, vary between stayers and leavers. In this chapter, I do not fully address this issue, as one should build a model that deals with attrition in a complete fashion and I will address this problem in further research.

1.4.3 Definition of the relevant variables

The key variable of my analysis is the self-reported price-variation. This is elicited when firms are asked to answer the following question: *"Which is the average annual percentage change in the selling prices of your goods and services?"*. I call the answer to this question the $PriceVariation$, since the variable of interest is the log price variation Δp_{it} can be easily obtained as

$$\Delta p_{it} = p_{it} - p_{it-1} = log\left(\frac{PriceVariation}{100} + 1\right) \tag{1.17}$$

The fact that this key variable is available just in first differences may seem a problem at first, but in fact it has the advantage that firms are not required to say what is the level of the price and the concept of price change is a meaningful concept if one thinks of the form in a dynamic context and in the face of inflationary shocks.
Indeed the Bank of Italy goes some way into stressing the quality of the information, as the interview is carried out by professional interviewers and ex post checks are carried out to investigate non-coherent answers. It should be also stressed that the Bank of Italy relies on such a variable for its official reports, along with other sources of information.

I use firm-level price variations to construct sector-specific prices, by exploiting the sample weights provided by the Bank of Italy [9] this has the form of a price index:

$$\Delta p_{st} = \frac{\sum_i \Delta p_{sit} * w_{sit}}{pop_{st}}$$

in which pop_{st} is the number of firms operating in sector s.
As a validation exercise, I compare the sector prices obtained from the INVIND data with the official prices index provided by EUROSTAT. I obtain that the the two time series are highly correlated (almost 90% correlation in all sectors) and generally very close in levels as shown in Appendix C.

The dependent variable in my specification is the log of the variation in physical output Δq_{it} that relates to the output produced and sold and can be obtained using total sales (R_{it}) taking into account the log price variation:

[9] Precisely, at each firm within the sample is assigned a weighting factor (w_{sit}) that essentially indicates the number of the population that such firm represents. Given the stratified sample scheme used by the Bank of Italy, the sum of the weights in a certain layer (combination of sector and dimensional class) returns the numerosity of population of interest of that layer.

$$\Delta q_{it} = log\left(\frac{R_{it}}{P_{it}}\right) - log\left(\frac{R_{it-1}}{P_{it-1}}\right)$$
$$\Delta q_{it} = \Delta r_{it} - \Delta p_{it}$$

As for investments: the log of first difference of investment Δi_{it} is obtained as

$$\Delta i_{it} = i_{it} - i_{it-1} = log(I_{it}) - log(I_{it-1})$$

as well as first log differences of labour input wh_{it}:

$$\Delta l_{it} = l_{it} - l_{it-1} = log(wh_{it}) - log(wh_{it-1})$$

Normally, a production function includes the labour input in terms of number of workers, INVIND provides total hours of work which has some advantages as it takes into account overtimes hours and/or periods of absence from work.

As far as capital is concerned, I address the problem of including the "true utilized" input into the production function by exploiting two key variables in INVIND: percentage change in technical capacity and percentage of capital utilization. In particular, firms are asked to indicate the *percentage change in production capacity*[10]. I call the answer to this question the *TechCapVariation* and, since the variable of interest id the log variation in the installed capital stocks $\Delta\bar{k}_{it}$, it ca be easily obtained as

$$\Delta\bar{k}_{it} = \bar{k}_{it} - \bar{k}_{it-1} = log\left(\frac{TechCapVariation}{100} + 1\right)$$

This measure of capital variation has the advantage to be easily available without measurement errors typical of more classical capital measures based on book values or permanent inventory method.

Based on this variable, together with the availability of the *percentage utilization of the installed capacity* (u_{it})[11], the variation in the log utilized capital can be obtained as

[10]In the survey, it is well specified that "production capacity" has to be considered has the the maximum possible output obtainable with plant running at full capacity and that the "percentage change in productive capacity" has to computed considering solely the purchase and/or sale of plant and machinery and does not include any effects of split-offs, capital contributions, incorporations and sales of business activities.

[11]In the survey, again, it is well specified that utilization as to be computed as the ratio between utilized capital stocks and total installed capital stocks.

$$\Delta k_{it} = log\left(\frac{u_{it}}{100}\bar{K}_{it}\right) - log\left(\frac{u_{it-1}}{100}\bar{K}_{it}\right)$$
$$\Delta k_{it} = k_{it} - k_{it-1} = \bar{k}_{it} - \bar{k}_{it-1} - log\left(\frac{u_{it}}{100}\right) + log\left(\frac{u_{it-1}}{100}\right)$$

Referring to utilized capital instead of installed capital has two advantages: 1) it avoids to rely on the standard assumption of "full capacity utilization" which is clearly an extreme case; 2) utilized capital shows more variability with respect to installed capital and this provides a natural source of variability for the estimation of the production function coefficients. This genuine variability as one has to allow for a flexible set up as only in extreme cases firms would hit the constraint of the installed capital.

Table 1.2 shows summary statistics for the key variables of my empirical model: the variation across sectors is very evident for revenues (r) and the investment level (i). Statistics about the growth rate of real output (q)) show an average annual decline ranging from 4% in the Textile sector to 0.2% in the Metals sector. Price variation (Δp) is positive around 2% in all sectors with the exception of the Metal sector, that shows a lower price increase. It is interesting to note that the price variation is somewhat similar to the variation in real output, albeit smaller.

	Food	Textile	Chemicals	Minerals	Metals	Others
			Variables in level			
l	363,07	287.50	539.31	322.72	678.96	303.71
	(861.28)	(499.19)	(1055.27)	(468.64)	(2723.92)	(586.59)
r	169,209.80	63,722.17	537,127.20	72,634.85	181,212.30	85,239.05
	(423,762.60)	(138,109.40)	(391,4781)	(120,053.70)	(857,105.20)	(197,040.50)
i	5,579.55	1,930.44	11,783.67	6,090.26	9,011.55	3,821.30
	(15,016.41)	(5,125.86)	(4,7603.06)	(13,585.39)	(51,828.66)	(14,406.91)
			Variables in growth rate			
Δl	- 0.004	-0,24	-0,007	-0,023	-0.011	-0.010
	(0.15)	(0,18)	(0,15)	(0,15)	(0,019)	(0,15)
Δp	0.023	0,023	0,021	0,022	0.016	0,016
	(0.06)	(0,05)	(0,07)	(0,06)	(0.07)	(0,06)
Δq	- 0.014	-0,04	-0,014	-0,026	-0.002	0,023
	(0.20)	(0.19)	(0,18)	(0,19)	(0.25)	(0,16)
$\Delta \overline{k}$	0.050	0,023	0,044	0.039	0.047	0.046
	(0.12)	(0,11)	(0,09)	(0.19)	(0.12)	(0,11)
Δk	0.052	0,032	0,045	0.053	0.049	0,049
	(0.21)	(0,18)	(0,19)	(0.22)	(0.22)	(0,23)

Table 1.2: Summary statistics of the main variables by sectors

Figures reported are sample averages and standard errors are in parentheses.

1.5 Results

Table 1.3 reports estimates of the model in (1.13) by sectors. Estimates are obtained adding time-dummies in order to control for a time trend in productivity and demand. A fourth-degree polynomial is used to approximate the inverse investment function in (1.14). The *alpha*-coefficients in (1.13) are a non linear combination of the key parameters, so I carry out a bootstrap methodology to obtain proper standard errors. It should be stressed that all the estimates exhibit a high level of significance: this is not unusual in this framework as much of the literature gets similar results in terms of significance. In my work, as I explain below, the risk of producing "collinearity" is much reduced as the source of price information is not strictly related to the source of the information on productivity: a problem which might have affected some previous studies. I will further take up this point in my discussion below.

In all sectors, the estimated coefficient β_l is greater than the corresponding β_k:a result in line with previous studies. Textile sector exhibits the highest output elasticity with respect to capital and this is justified by the fact that this sector is one of the most capital intensive.
In four out of six sectors the estimated returns to scale are close to 1, precisely they range between 1.04 in the metal sector and 1.34 in textile sector. These values are higher than the results obtained by Pozzi and Schivardi (2012) who even obtained decreasing return to scale in all sectors, but they are similar to results by Levinsohn and Petrin (2003) and in line with the results by Martinho (2012) who finds slightly increasing return to scale in the manufacturing sector in Portugal.

In a sense it is important to exclude that the demand shocks pick up unexplained productivity shocks: if one obtains increasing returns to scale in the capital-intensive sectors, one is more confident that the share of growth due to the shape of the production function is "properly" accounted for. The only cases in which estimated returns to scale are decreasing are Food and Chemicals, in line with the results of Pozzi and Schivardi (2012). The Food sector is quite hard to model in general because the definition may vary a lot: in the INVIND survey this includes proper Food products, Beverages and Tobacco, hence making this sector more heterogeneous than in other studies carried out in different countries, my results are also in line with the ones obtained by Gervais, Bonroy, and Couture (2006).

The estimated demand elasticity ranges from -1.60 in the Chemical sector to -2.56 in the Mineral sector, Textile and Chemical exhibit the lowest elasticities. Before attempting a detailed comparison with the results by Pozzi and Schivardi (2012) it should be pointed out that they compute demand elasticities using the self-reported measure based on a cross-section of firms interviewed in 1996. Despite the fact that the survey presents a high rate of non-response on this item, they compute the average elasticity per sector and they assume that then σ-coefficients con be used across all the time period of the analysis. This methodology has a potential problem known as a the *Manski reflection problem* (Manski (1993)), i..e using the average of the self-reported prices as an explanatory variable induces collinearity. This might explain why the authors obtain estimates of the σ-values that are, in absolute terms, higher than my estimates: they range from -5.5 in the Metal sector to -4.5 in Textile sector, these values are particularly high if compared with previous studies based on other datasets, for example *vis-a-vis* estimates obtained for the US on the same sectors, which are around -2. Differences in estimates with the results of Pozzi and Schivardi are also due to the fact that I use the entire panel dataset.

	Food	Textile	Chemical	Mineral	Metal	Other
β_l	0.32***	0.81***	0.52***	0.75***	0.75***	0.78***
	(0.047)	(0.08)	(0.022)	(0.084)	(0.040)	(0.067)
β_k	0.11***	0.53***	0.20***	0.34***	0.29***	0.21***
	(0.030)	(0.069)	(0.077)	(0.084)	(0.038)	(0.068)
σ	-3.84	-1.87**	-1.60***	-2.43***	-2.56***	-2.00***
	(34.42)	(0.226)	(0.266)	(0.527)	(0.228)	(0.039)
R^2	0.08	0.27	0.15	0.27	0.25	0.22
Obs.	3180	3906	3228	1890	11629	2970

Table 1.3: Baseline model estimation results

Betas parameters and demand elasticity are obtained estimating equation (1.13) using as approximation of the control function in (1.14). Dependent variable is the growth rate of sales deflated with self-reported growth rate of price. Dependent variables are log difference in the numbers of worked hour, the log difference in the utilized capital and growth rate of sectorial quantities are obtained from non-seasonal adjusted real sales provided by Eurostat Control function is a complete fourth order polynomial in the growth rate of investments and growth rate of installed capital. Bootstrapped standard errors are reported in brackets. Significance levels: *10%, **5%, ***1%.

Table 1.4 shows a comparison of the results obtained in the complete model I propose with respect to: (i) a simple OLS model and (ii) an OP specification applied to first differences.

In general, my model specification generates higher coefficients than if using the OLS methodology or the OP methodology, a similar order of magnitude is obtained by Van Beveren (2012).

In a standard demand and supply framework inputs and output are positively correlated whilst output and prices are negatively correlated; as a consequence, there exists a negative correlation between inputs and firm-level prices resulting in a negative bias for input coefficients estimated through OLS and OP.

Comparing OLS and OP estimates: labour coefficients are lower compared to the corresponding OLS results, while the estimate of the capital coefficient is higher. The difference between the OLS estimates and the more flexible estimate is in line with what expected from the theoretical setup. To be more specific, if firms make input choices according to a certain expectation about productivity shocks that are serially correlated, a positive productivity shock will lead to an increase in the conditional demand of the variable input, introducing an upward bias in the estimate of the labour coefficient β_l.
On the other hand, Levinsohn and Petrin (2003) show that, in a two-input production function, the OLS methodology delivers downward biased parameter estimates for the capital coefficient, as capital is correlated with labour.

My model makes use of real output growth rate obtained through firm-level price variation: since this is not the typical variable used in the literature, I carry out a robustness check. I run the same model using the sector price deflator provided by Eurostat. Moreover, I run the model using also sector quantities which have been seasonally adjusted by Eurostat. Table (5) shows that the estimated coefficients are rather stable across the different specifications.

A further set of results that I can derive from the estimated parameters in Table 1.3, is idiosyncratic demand shocks and productivity shocks, using expressions (1.15) and (1.16).

Table (1.6) shows summary statistics for the estimated shocks: the average growth rates in productivity for the Food, Textile and Chemical sectors are negative while they are positive for the other sectors. However, average values are around zero showing a trend of stagnant productivity for Italy during the sample period, as also documented by Hassan and Ottaviano (2013) and Calligaris, Del Gatto, Hassan, Ottaviano, Schivardi, et al. (2016).

The distribution of the two shocks is fairly "symmetric" but demand shocks growth rates are more disperse than the shocks related to productivity and, overall, they also show higher values. This discussion brings me back to the issue of "collinearity" generated by the correlation between changes in inputs and the shocks: the use of external information, such as the Eurostat prices, while being less precise, partly removes the above risk: in this sense the robustness check supports my results.

	(1)	(2)	(3)		(1)	(2)	(3)
		OLS	**OP**			**OLS**	**OP**
	Food sector				**Textile sector**		
β_l	0.32***	0.29***	0.25***	β_l	0.81***	0.36***	0.38***
	(0.047)	(0.041)	(0.026)		(0.088)	(0.049)	(0.018)
β_k	0.11***	0.11***	0.09***	β_k	0.53***	0.25***	0.29***
	(0.030)	(0.027)	(0.020)		(0.069)	(0.054)	(0.019)
σ	-3.84***			σ	1.87***		
	(34.42)				(0.226)		
R^2	0.08	0.07	0.10	R^2	0.27	0.28	0.26
Obs.	3180	3180	3180	Obs.	3906	3906	3906
	Chemical sector				**Mineral sector**		
β_l	0.52***	0.49***	0.49***	β_l	0.75***	0.40***	0.40***
	(0.022)	(0.056)	(0.022)		(0.084)	(0.048)	(0.030)
β_k	0.20***	0.09***	0.09***	β_k	0.34***	0.20***	0.24***
	(0.077)	(0.025)	(0.015)		(0.084)	(0.035)	(0.023)
σ	-1.60***			σ	-2.43***		
	(0.266)				(0.527)		
R^2	0.15	0.20	0.17	R^2	0.27	0.26	0.22
Obs.	3228	3228	3228	Obs.	1890	1890	1890
	Metal sector				**Other sector**		
β_l	0.75***	0.47***	0.48***	β_l	0.78***	0.38***	0.42***
	(0.040)	(0.026)	(0.013)		(0.067)	(0.041)	(0.020)
β_k	0.29***	0.22***	0.23***	β_k	0.21***	0.12***	0.14***
	(0.038)	(0.019)	(0.012)		(0.068)	(0.023)	(0.015)
σ	-2.56***			σ	-2.00***		
	(0.228)				(0.039)		
R^2	0.25	0.28	0.25	R^2	0.22	0.24	0.22
Obs.	11629	11629	11629	Obs.	2970	2970	2970

Table 1.4: Comparison of baseline model estimates with estimated obtained from OLS and OP method

Betas parameters and demand elasticity in columns (1) are obtained exactly as in in Table (4). Parameters in columns (2) are obtained applying a simply OLS to equation (4) while the ones in columns (3) are obtained applying OP estimator to the same equation (4) with a fourth degree polynomial as control function.

	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
	q_{st} NSA p_{it} INV	q_{st} NSA p_{st} EUR	q_{st} CA p_{it} INV	q_{st} CA p_{st} EUR		$q_{st}NSA$ p_{it} INV	q_{st} NSA p_{st} EUR	q_{st} CA p_{it} INV	$q_{st}CA$ p_{st} EUR
		Food sector					**Textile sector**		
β_l	0.32***	0.34***	0.34***	0.48***	β_l	0.81***	0.78***	0.77***	0.77***
	(0.047)	(0.062)	(0.051)	(0.087)		(0.088)	(0.069)	(0.084)	(0.068)
β_k	0.11***	0.11***	0.11***	0.16***	β_k	0.53***	0.57***	0.50***	0.57***
	(0.030)	(0.037)	(0.032)	(0.052)		(0.069)	(0.096)	(0.066)	(0.094)
σ	-3.84	-2.51	-3.144	-1.74	σ	-1.87***	-1.96***	-1.95***	-2.00***
	(34.422)	(12.77)	(78.122)	(9.651)		(0.226)	(0.294)	(0.239)	(0.313)
R^2	0.08	0.07	0.08	0.07	R^2	0.27	0.27	0.27	0.27
Obs.	3180	2435	3180	2435	Obs.	3906	2366	3906	2366
		Chemical sector					**Mineral sector**		
β_l	0.52***	0.54***	0.55***	0.48***	β_l	0.75***	0.79***	0.73***	0.40***
	(0.022)	(0.042)	(0.053)	(0.072)		(0.084)	(0.117)	(0.082)	(0.056)
β_k	0.20***	0.22***	0.23***	0.18***	β_k	0.34***	0.30***	0.34***	0.24***
	(0.077)	(0.047)	(0.051)	(0.021)		(0.084)	(0.097)	(0.093)	(0.042)
σ	-1.60***	-1.18***	-1.65***	-1.70***	σ	-2.43***	-1.88***	-2.48***	-2.50***
	(0.226)	(0.175)	(0.235)	(0.154)		(0.576)	(0.337)	(0.600)	(0.256)
R^2	0.15	0.14	0.15	0.13	R^2	0.27	0.22	0.27	0.20
Obs.	3228	1940	3180	1940	Obs.	1890	1162	1890	1162
		Metal sector					**Other sector**		
β_l	0.75***	0.74***	0.74***	0.72***	β_l	0.78***	0.77***	0.77***	0.67***
	(0.040)	(0.052)	(0.062)	(0.087)		(0.088)	(0.067)	(0.089)	(0.084)
β_k	0.29***	0.28***	0.28***	0.25***	β_k	0.21***	0.19***	0.20***	0.24***
	(0.038)	(0.039)	(0.052)	(0.057)		(0.068)	(0.068)	(0.056)	(0.072)
σ	-2.56***	-2.57***	-2.55***	-2.49***	σ	-2.00***	-1.97***	-1.98***	-2.07***
	(0.228)	(0.234)	(0.289)	(0.381)		(0.226)	(0.236)	(0.219)	(0.2313)
R^2	0.25	0.24	0.24	0.23	R^2	0.22	0.21	0.21	0.20
Obs.	11629	8342	11629	8342	Obs.	2970	1789	2970	1789

Table 1.5: Robustness checks

Betas parameters and demand elasticity in columns (1) are obtained exactly as in in Table (4). Other columns differs for the deflator used to obtained the dependent variable and for the type of sectoral growth rate in real sales. In particular, q_{st} NSA and q_{st} CA are respectively the non-seasonal adjusted and the calendar adjusted growth rate of real sales while p_{it} INV and p_{st} EUR are the firm-specific deflator and the sectorial deflator provided by Eurostata$_{st}$ CA in columns (2) dependent variable is the real growth rate of sales obtained using as deflator sectorial growth rate of prices provide by EUROSTAT.

$\hat{\Delta\psi}$	**5th**	**25th**	**50th**	**75th**	**95th**	**mean**	**sd**
Food	-2.33	-0.81	-0.02	0.78	2.35	-0.018	1.39
Textile	-2.15	-0.79	-0.01	0.81	2.21	-0.019	1.40
Chemical	-1.99	-0.98	-0.01	1.02	2.03	-0.021	1.38
Mineral	-2.32	-0.84	0.01	0.92	2.47	0.037	1.43
Metal	-3.05	-1.40	0.03	1.32	2.99	0.014	1.37
Other	-4.03	-2.18	0.04	1.97	3.98	0.017	1.52
$\hat{\Delta\omega}$	**5th**	**25th**	**50th**	**75th**	**95th**	**mean**	**sd**
Food	-0.62	-0.19	0.04	0.27	0.74	0.046	0.40
Textile	-6.18	-4.14	-0.20	3.98	6.01	0.052	4.12
Chemical	-4.57	-1.98	-0.09	2.23	4.98	0.032	3.82
Mineral	-5.61	-2.10	-0.17	1.38	5.34	-0.15	3.27
Metal	-4.72	-2.32	-0.09	2.00	5.02	-0.036	3.17
Other	-6.18	-3.15	-0.10	3.20	6.25	-0.054	4.18

Table 1.6: Summary Statistics for $\hat{\Delta\psi}$ and $\hat{\Delta\omega}$

$\hat{\Delta\psi}$ and $\hat{\Delta\omega}$ are computed respectively as equations (1.15) and (1.16). Main percentiles, mean and standard deviations are reported by sectors.

	work hours	employment	hiring	separation	utilized capital	invest. rate
$\hat{\Delta\omega}_{it}$	0.018	0.084***	0.076***	-0.007	0.007	0.10***
	(0.019)	(0.018)	(0.018)	(0.018)	(0.200)	(0.020)
$\hat{\Delta\psi}_{it}$	0.252***	0.183***	0.063***	-0.018**	0.243***	0.028*
	(0.023)	(0.008)	(0.010)	(0.009)	(0.018)	(0.019)
R^2	0.10	0.12	0.15	0.07	0.05	0.09

Table 1.7: Productivity and demand shocks effect on firm-level outcomes

OLS estimation of equation (17). Dependent variables are for each specification the growth rate in worked hours, number of employees, hiring, separation, utilized capital and investment rate. Main independent variables are always $\hat{\Delta\psi}$ and $\hat{\Delta\omega}$ computed respectively as equations (1.15) and (1.16). Each specification contains a complete set of time, sectorial and geographical dummies. Robust standard errors are reported in brackets. Significance levels: *10%, **5%, ***1%.

My analysis, finally, assesses the impact of these two kind of shocks on the main firm-level outcomes, in particular I will focus the attention on hours of work, employment in terms of number of employees, hiring, firing, utilized capital and investment rate. I will do this by simply estimating by OLS the following linear model.

$$\Delta y_{it} = a\Delta\hat{\psi}_{it} + b\Delta\hat{\omega}_{it} + cX_{it} + e_{it} \tag{1.18}$$

in which (Δy_{it}) is the growth rate of the variable of interest and X_{it} is a complete set of time, sector and geographical dummies.

Table (1.8) shows that demand shocks have a significant effect on all the variables under investigation and they have a great positive impact on variable inputs in the short run, such as hours of work and capital utilization.
Idiosyncratic demand shocks also display a positive effect on "long term" factors, like employment and investment: a substantially higher impact on the labour input than the effect derived by the corresponding productivity shocks. As I already discussed, the fact that I use a more general model for the demand elasticity leads to results that are different from the ones obtained by Pozzi and Schivardi (2012) not only in terms of coefficients of demand and production function, but also in terms of the effect of different shocks on firm-level outcomes.

For example, an important difference in the implications is as follows: I show a differential impact of productivity and demand shocks on employment (demand shocks have a greater impact on employment with respect to productivity shocks) while Pozzi and Schivardi (2012) obtain the same effect, whether coming from demand shocks or from productivity shocks. My result is in line with Carlsson, Messina, and Nordström Skans (2014) who make use of a structural vector auto-regressive model to disentangle the effects of the two shocks.
Also, Carlsson, Messina, and Nordström Skans (2014) confirm another interesting results of my study: the positive effect of demand shocks on employment works through both an increase in hiring and a slightly decrease in separations or layouts. This is an outcome of the model which did not emerge from previous studies and it helps understanding the mechanisms through which shocks feed through the decision process of the firm.

On the other hand, productivity shocks have a positive effect on investments, that is greater in magnitude of its effect on employment. Not only; the only part of labour demand which seems affected by productivity shocks is hiring. Taken together, I find that both demand shocks and productivity shocks increases investment, but the productivity effect is much stronger.

Although my results differ from the ones obtained by Pozzi and Schivardi (2012), as they find that the impact of productivity shocks on investment is half the impact of the demand shocks, my prediction are consistent with the ones obtained in a fully blown simulation framework by Foster, Haltiwanger, and Syverson (2008) and Roberts, Xu, Fan, and Zhang (2012). Moreover, also Kumar and Zhang (2016), exploiting the variation of inventory to isolate demand shocks, obtain that productivity shocks are more important to determinate investment with respect to demand shocks.

It is hard to conclude what role has played my alternative specification in generating results which are different from Pozzi and Schivardi, and which elements exactly generate these differences because of the complex nature of the problem and of the shocks , however, I find it reassuring that the results of my study are coherent with the ones obtained by these authors.

1.6 Conclusion

In this chapter, I have followed the stream of the literature that looks at productivity as one of the main determinants of firm's growth. I extended the standard approach to the estimate of the production function by allowing for demand shocks to be a source of firm's heterogeneity: demand shocks interact with productivity shocks to affect the observable outcomes such as the revenue of the firm.

The inclusion of demand shocks in the production function has as a clear advantage as neglecting this source of heterogeneity would lead to estimates of the effect of productivity, which are in fact a mixture of productivity and demand effects, hence generating a standard identification problem.

The model and the estimation methodology that I propose are close to the work of Pozzi and Schivardi (2012) and De Loecker (2011) and are based on a CES demand function and on a Cobb-Douglas production function and, under the assumption that demand and productivity shocks follow a Markov dynamic process, I can disentangle demand and productivity shocks by using an extend version of the control function approach proposed by Olley and Pakes (1992). The framework that I propose can be used in any case in which one needs to consistently estimate production function parameters and demand elasticity exploiting firm-level data, as long as it containing information on firm-level price information.

The novelty of my approach is that it is a comprehensive and parsimonious framework that, with less data-requirement with respect to the few existing methods, allows to recover production and demand function parameters solving endogeneity problem and relaxing scalar unobservable assumption.

I show that estimated coefficients through my framework are reliable inasmuch they "correct" biased OLS and OP estimation in the expected way. Moreover, they results in line with other studies that use econometric techniques to estimate demand-supply systems close to my framework for countries similar to Italy.

I used estimated demand and production function parameters to disentangle between idiosyncratic demand and productivity shocks and I studied the effect of these shocks on the main firm-level variable affecting growth rate of firms.

I show that investments are more impacted by productivity shocks that demand ones. Demand shocks, instead, have not only a positive impact on both employment and investment but that the impact on employment is greater than the one generated by productivity shocks. Interesting is the fact that this result occurs through labour adjustment (more hiring, as it is the case for a productivity shocks) but also through a reduction in firings. These results may suggest that if policy makers wish to increase the employment rate they should operate in the perspective of stimulating demand instead of promoting supply side policies; on the other hand, if the objective is to stimulate investments, promoting innovation and improving efficiency are the most appropriate tools, because productivity shocks have a stronger impact on investments with respect to demand shocks.

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Appendix

1.A INVIND dataset features

The data used in this study come from the Inquiry into Investment of Manufactoring firms ("Indagine sugli investimenti della imprese manifatturiere", henceforth, INVIND), a survey collected every year since 1984 by the Bank of Italy. This survey contains a very rich set of information about industrial and service firms: biographic information, employment, investment (realized and projected), turnover, technical capacity, debt and credits and so on.

The survey reference population is stratified and, from each layer, a sample of firms is randomly extracted (stratified sampling scheme in one step). Stratification is made by combination of activity sector, class size (in terms of employees) and regional location of the headquarters administrative firm.

The sample is a panel: firms detected in a certain year are always contacted in the following year unless they are no longer part of the population of interest. If a company is no longer available to answer the questionnaire, another one similar in term of economic activity and size class replaces it. A firm is considered out from the reference population in case of liquidation or bankruptcy, merger or because the firm stop to belong to the sector or class size classes being surveyed.

Until 1998 INVIND was limited to firms in the manufacturing sector (ATECO section D) with 50 or more employees. Starting from 1999, the reference universe has been expanded to the entire industry, excluding construction, integrating the sample with firms operating in the Ateco subsection DF (oil refineries, treatment of fuel) and section C (mining) and E (energy electricity, gas and water). Starting from 2001 the survey has been extended to firms with 20-49 employees. Since 2002 the survey has been further extended to companies operating in the private non-financial services with 20 or more employees.

Although the basic structure of the survey has been adopted during the year in order to allow the construction of time series information on numerous variables, small changes have been introduced in particular years of the survey in order to introduce new variables. In

order to exploit all the information I need to apply the model and the strategy explained in the previous section, I select big industries (more that 50 employees) since 1988 for general applications.
Furthermore, I drop all the observations belonging to the non-manufacturing sector (almost the 3% of the initial sample) because they started to be investigated only in 1998 and they constitute a little and too much heterogeneous group. I finally rely on an unbalanced panel of 5314 firms observed for 27 years for a total of 38653 firm-year observations.
I rely on the sectorial division provided by the same Bank of Italy and it is based on aggregation of classes according to two-digit ATECO 2007 classification. Precisely:

- *"Food"*: food products, beverages and tobacco (ATECO 10,11 and 12);
- *"Textile"*: textile industries, clothing, leather and shoes (ATECO 13, 14 and 15);
- *"Chemicals"*: manufacture of coke, chemical industry, rubber and plastic (ATECO19, 20, 21 and 22);
- *"Minerals"*: industry of non-metallic minerals (ATECO 23);
- *"Metals"*: metals industry (ATECO 24, 25, 26, 27, 28, 29, 30 and 33);
- *"Others"*: wood industries, furniture, paper and printing (ATECO 16, 17, 18, 31 and 32).

Year	**Sam.**	**Pop.**	**%**	**Year**	**Sam.**	**Pop.**	**%**	**Year**	**Sam.**	**Pop.**	**%**
1988	1.039	12.025	8,64%	1997	1,002	11.792	8,50%	2006	1.838	11.574	15,88%
1989	1.053	11.883	8,86%	1998	998	11.609	8,60%	2007	1.783	11.432	16,60%
1990	1.071	11.739	9,12%	1999	1.107	11.502	9,62%	2008	1.752	11.168	15,67%
1991	1.027	12.041	8,53%	2000	1.428	11.798	12,10%	2009	1.706	10.652	16,02%
1992	993	11.658	8,52%	2001	1.713	12.389	13,97%	2010	1.666	10.119	16.46%
1993	994	11.185	8,89%	2002	1.797	17.509	10,26%	2011	1.748	10.119	17,27%
1994	953	11.037	8,63%	2003	1.848	11.978	15,42%	2012	1.747	9.882	17,68%
1995	996	10.880	9,15%	2004	1.861	11.677	15,94%	2013	1.780	-	-
1996	1.060	11.411	9,29%	2005	1.890	11.516	16,41%	2014	1.803	-	-

Table 1.A1: Number of firms in the sample for each year and corresponding reference population

For each year, the column "sample" contains the number of manufacturing firms surveyed in that year, the column "population" contains the numbers of firms of the reference population (source: Bank of Italy: "Indagine sulle imprese industriali e dei servizi. Disegno campionario e metodi utilizzati" February 2016), column "%" the percentage of firms in the sample with respect to reference population

1.B Descriptive attrition analysis details

Indicating with I_t the INVIND survey conducted in year t, a firm is considered "survived" if, observed in I_t, is observed also in the next I_{t+1}. Survival percentages are simply built as the number of survived firm over the total number of firms in the sample for each year.

				Food		Textile		Chemical		Mineral		Metal		Other	
Year	**Survived**	**%**	**Year**	**Survived**	**%**	**Survived**	**%**	**Survived**	**%**	**Survived**	**%**	**Survived**	**%**	**Survived**	**%**
1988	947	91.14	1988	92	92	180	91.83	114	90.47	81	92.04	396	90.20	84	99.33
1989	968	91.92	1989	89	89.90	177	88.50	120	93.75	91	95.78	404	92.87	87	90.62
1990	945	88.23	1990	86	91.49	176	87.13	119	89.47	82	82.82	398	88.64	84	89.36
1991	905	88.12	1991	75	82.42	171	90.00	117	87.31	77	86.51	386	89.35	79	86.81
1992	865	87.10	1992	74	85.06	170	84.57	117	89.31	70	86.41	353	87.16	81	92.04
1993	810	81.48	1993	80	91.95	164	84.10	106	80.91	67	84.81	318	77.37	75	82.41
1994	837	87.82	1994	83	87.37	175	91.14	103	83.73	64	84.21	339	89.44	73	82.95
1995	880	88.35	1995	84	88.42	181	90.50	112	86.15	59	81.94	362	88.07	82	9.318
1996	877	82.73	1996	85	83.33	176	85.02	107	76.97	59	84.28	361	82.60	89	84.76
1997	848	84.63	1997	80	83.33	162	82.23	98	84.48	56	87.5	362	84.57	90	89.11
1998	834	83.56	1998	84	87.50	154	83.24	89	80.18	59	83.09	369	85.21	79	77.45
1999	923	83.37	1999	93	78.81	164	83.24	118	84.89	65	86.66	387	82.86	96	86.48
2000	1194	83.61	2000	132	88	199	85.04	148	77.89	91	88.34	501	83.91	123	79.87
2001	1425	83.18	2001	157	82.63	246	83.95	164	80	109	89.34	589	82.60	160	84.21
2002	1434	79.79	2002	169	84.08	240	77.92	160	76.19	97	80.83	606	81.12	162	76.77
2003	1485	80.35	2003	175	78.12	225	78.12	167	78.03	107	84.25	651	82.30	160	78.43
2004	1519	81.62	2004	198	86.84	205	77.94	172	79.62	117	82.39	650	81.45	177	82.71
2005	1546	81.79	2005	207	81.81	198	77.64	179	81.36	116	84.05	662	82.	184	82.14
2006	1494	81.28	2006	180	75.63	187	78.24	179	84.03	104	83.2	659	82.16	185	83.71
2007	1433	80.37	2007	163	78.74	177	77.63	169	77.16	104	81.88	639	81.50	181	83.02
2008	1409	80.42	2008	168	77.78	174	81.69	165	81.28	92	74.79	622	79.94	188	85.84
2009	1367	80.12	2009	179	86.89	168	81.55	160	78.81	81	75	610	81.11	169	73.16
2010	1397	83.85	2010	190	85.97	161	80.90	160	82.90	86	81.90	640	85.44	160	80.40
2011	1437	82.20	2011	194	79.83	143	73.33	178	85.16	93	84.54	669	83.83	160	82.90
2012	1463	83.74	2012	205	89.13	144	81.81	184	83.25	87	78.37	678	83.80	165	82.50
2013	1503	84.43	2013	217	88.57	158	84.49	202	88.59	79	76.69	677	83.37	170	82.92

Table 1.B1: "Panel survived" firms in the INVIND sample by year and sector

	50-99		**100-199**		**200-499**		**500-999**		**1000+**	
Year	**Survived**	**%**	**Survived**	**%**	**Survived**	**%**	**Survived**	**%**	**Survived**	**%**
1988	166	85.12	204	96.22	264	93.62	159	87.84	154	91.12
1989	175	90.28	198	87.61	273	93.17	162	97.00	160	92.48
1990	174	85.714	197	89.14	277	90.52	144	85.20	153	88.95
1991	176	82.62	182	88.78	270	93.10	140	88.60	137	85.09
1992	163	81.90	201	88.93	242	85.51	127	88.19	132	93.61
1993	156	75.72	190	83.70	245	85.36	111	83.45	108	76.59
1994	184	84.01	187	88.20	258	89.27	104	89.65	104	88.88
1995	184	84.01	216	91.91	258	88.65	106	89.07	116	87.87
1996	170	79.81	227	85.34	257	83.44	111	81.61	112	81.75
1997	182	83.10	214	85.6	235	83.92	102	81.60	115	89.84
1998	187	82.01	217	86.45	235	85.76	94	80.34	101	78.90
1999	220	79.13	258	87.45	238	82.92	110	86.61	97	80.83
2000	336	84.00	331	82.75	288	83.24	129	82.69	110	87.30
2001	439	79.81	407	86.04	341	84.19	126	81.81	112	85.49
2002	437	74.06	435	83.97	327	80.54	122	80.26	113	86.26
2003	476	75.91	441	82.89	326	82.53	129	80.62	113	84.33
2004	511	79.34	446	81.38	325	81.86	119	85	118	89.39
2005	546	79.01	445	82.56	314	82.63	127	86.39	114	85.71
2006	542	78.55	411	82.53	308	80.83	127	86.39	106	86.88
2007	486	74.76	398	81.89	308	83.92	134	83.75	107	89.17
2008	469	76.63	411	82.03	309	81.96	122	82.43	98	85.96
2009	478	76.48	383	80.80	296	81.76	115	85.18	95	86.36
2010	463	78.60	394	83.65	332	90.71	120	86.33	88	87.12
2011	466	78.98	402	82.20	350	83.73	121	85.81	98	89.09
2012	504	81.81	408	85.00	340	84.57	119	85.00	92	84.40
2013	528	81.60	418	84.27	340	86.29	126	88.12	91	91.00

Table 1.B2: "Panel survived" firms in the INVIND sample by year and dimensional class

	NW		**NE**		**CEN**		**SOUTH**	
Year	**Survived**	%	**Survived**	%	**Survived**	%	**Survived**	%
1988	423	89.42	229	93.08	169	91.35	126	93.33
1989	426	90.06	237	92.57	174	95.60	131	92.25
1990	426	88.93	229	90.87	167	86.08	123	84.24
1991	425	89.85	209	85.65	153	87.93	118	86.76
1992	416	88.88	190	85.97	156	89.14	103	79.84
1993	384	80.84	196	84.84	147	83.52	83	74.10
1994	384	88.88	221	89.11	144	87.80	88	80.73
1995	401	88.13	226	90.76	156	88.13	97	84.34
1996	413	83.26	219	84.88	154	82.35	91	76.47
1997	392	85.58	205	82.00	152	86.36	99	83.89
1998	360	82.56	211	86.12	150	84.26	113	81.29
1999	371	83.37	217	84.76	159	87.36	176	78.57
2000	418	83.60	280	84.84	249	86.45	247	79.67
2001	428	84.41	330	83.96	327	84.49	340	79.81
2002	428	82.46	320	78.62	307	80.57	379	77.34
2003	440	83.17	328	77.54	318	79.89	399	80.12
2004	425	80.95	324	80.59	331	82.33	439	82.50
2005	427	84.89	333	78.90	344	83.90	442	79.63
2006	419	82.97	325	76.29	334	84.98	416	80.93
2007	412	82.73	306	79.48	319	80.15	396	78.88
2008	405	83.85	288	72.72	311	84.51	405	80.19
2009	404	81.28	268	77.01	290	78.16	405	82.65
2010	410	86.68	321	85.37	305	85.91	361	78.13
2011	403	80.43	336	78.13	330	85.93	368	84.98
2012	389	82.41	338	78.60	341	86.54	395	87.58
2013	383	83.26	352	83.41	395	86.81	373	84.19

Table 1.B3: "Panel survived" firms in the INVIND sample by year and geographical area

1.C Price variable validation

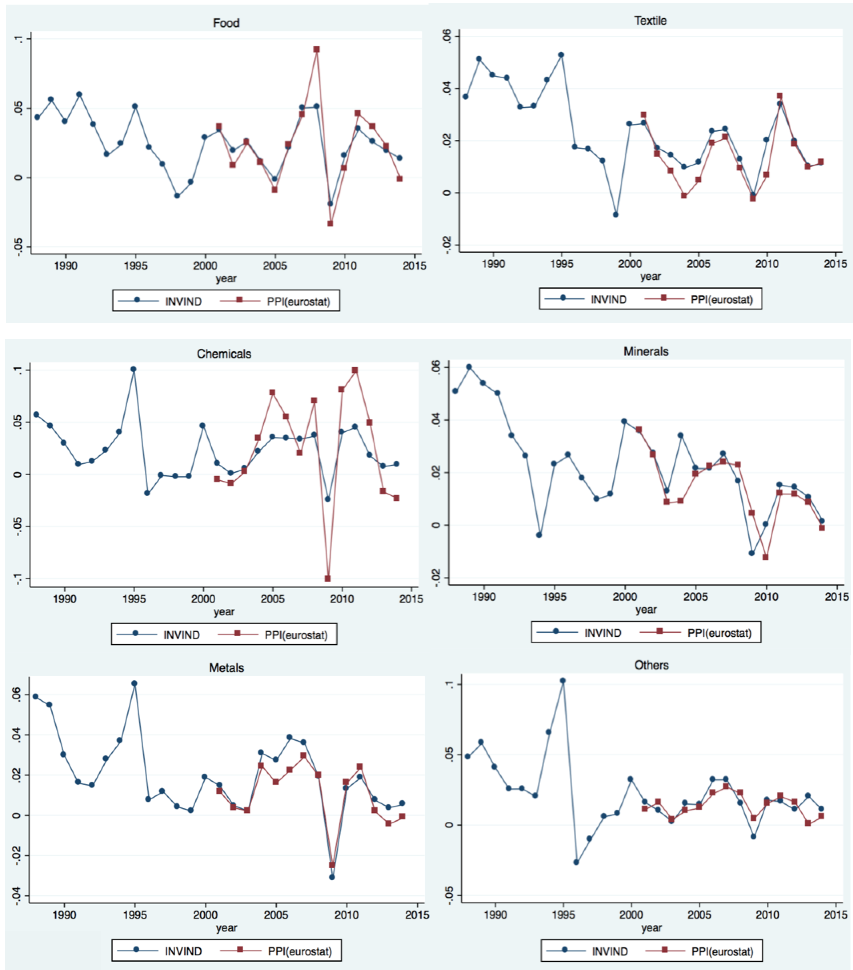

Figure 1.C1: Comparison by sector between the INVIND price index (computed as the average of firm-reported prices using sample weights provided by the Bank of Italy) and the Producer Price Index (PPI) provided by EUROSTAR.

Chapter 2

Firms' Expectations and Uncertainty: Evidence from Micro Data

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Abstract

Firms expectations and uncertainty about future business conditions are some of the main drivers of the firm-level decisions concerning investment, employment and capacity utilization. In the empirical literature, there are few investigations on the expectations formation mechanisms for the firms. Also, there is no general consensus on the measure of uncertainty of the expectations. Exploiting the rich information contained a survey on manufacturing Italian firms collected yearly by the Bank of Italy, this paper aims to enrich this stream of literature. We present some new stylized fact about the firm expectations' formation process and a measure of self-reported uncertainty. We propose two new firm-specific uncertainty measures based on the of forecast error. Then, we construct micro-founded macro uncertainty measures and compare them with the standard measures used in the literature.

2.1 Introduction

Decision makers are asked to make choices without perfect information almost all the time. In particular, at firm-level, the existence of adjustment costs put firms into the situation to decide how much to produce and/or the quantity of input to use before than certain market conditions realize. As a consequence, firms' expectation and uncertainty regarding their own future business conditions are important determinants of investment and hiring decisions.

The empirical stream of literature that address the question: "in which way expectations and uncertainty affect the main firm-level decision?" is huge and mainly focused on the effect that uncertainty has on investment since economic theory provides ambiguous results about the relationship between those two variables.

At the macro level, relatively recent works as Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), suggest that uncertainty is an important factor affecting economic activity in general with negative impact on investment and reallocation of capital and labour.

At micro level, the basic theory by Abel (1983) and Abel, Dixit, Eberly, and Pindyck (1996) studies the effect of uncertainty (referred to a increase in the variance of the distribution of the future rate of returns of a project) on investment in a call and put option framework generating an ambiguous effect of uncertainty on investment.

This, clearly, opens the door for empirical modeling that is, moreover, motivated by the fact that a clear understanding of the uncertainty effects on the firm-level outcomes is essential because decisions are taken at the micro-level and it is at this level that uncertainty play a key role. That is why, sectorial and aggregate studies, in general, tend to hide firms' heterogeneity due to the fact that are based on the classical assumption of "representative agents".

Despite its importance, existing micro-level empirical literature is scant and with contrasting and not comparable results. One particular feature is that in each study, according to the availability, different measures of uncertainty are used: we argue that a deep discussion around the measures of uncertainty is key to the development of this stream of literature.

Uncertainty is unobservable and there is no general consensus on how to estimate it. The huge variety of macro-uncertainty proxies makes empirical results not easily comparable and there are few attempts to estimate firm-specific and time-varying uncertainty [1].

[1] In next section of this chapter we are going to deeply analyze exiting literature that face the problem of estimate uncertainty and link it to the main firm-level outcomes

In this sense, the main contribution of this paper is to address the measurement problem of uncertainty proposing two different firm-specific and time-varying measures based on the concept of forecast error.

In doing this, we exploit rich information contained into the INVIND dataset, a survey on Italian Manufacturing firms provided by the Bank of Italy. Among the others, this dataset contains a huge number of variables regarding firm self-reported quantitative expectations about employment, investments, capacity utilization, growth rate of prices and growth rate of real sales.

In particular, we will mainly focus on two variables: i) the expectation about the growth rate for real sales and ii) the self-reported measure of uncertainty about the future growth rate of real sales. The motivation of this choice is that, being growth rate of real sales the results of the equilibrium between supply and demand, at the firm-level, expectations about future growth rate of real sales contains expected shocks from the production side as well as from the demand side. Moreover, according to the previous intuition we can read the available self-reported measure of uncertainty as the perceived variability of a convolution of both demand and productivity shocks. In stating this, even if we do not directly refer to Total Factor Productivity of Revenues (TFPR), we refer to the stream of literature to which demand and supply shocks contained in any measure of sales or value added are isomorphic as shown in a seminal work by Hsieh and Klenow (2009) [2]. We make this intuition more explicit through a basic model in which, under irreversibility of production inputs, uncertainty about future sales contains uncertainty about production and demand factors. One result of our simple model confirms the intuition according to which both first and second moment of the expected distribution of the growth rate of sales affect actual choices of firms in term of output (and as a consequence, given whatever technology, in terms of input to use)[3].

The availability of the self-reported measure of uncertainty, together with quantitative expectations, allows us to partially solve the usual problem concerning the unobservability of uncertainty and study, through simple econometric exercises, which is the behaviour of the uncertainty that we have in the data (path-dependence, correlation with forecast error and relationship with aggregate uncertainty) and which is the firms' expectation formation process.

This preliminary analysis allows us to construct valid indicators of uncertainty that, exploiting a time-series approach, can be computed even in less rich datasets because they are computable also in absence of self-reported data about expectations. We will show how

[2]Asker, Collar-Wexler and De Loecker (2013) use the same approach to investigate the role of dynamic production input in shaping the dispersion of capital misallocation

[3]A complete version of the model can be find in Appendix A

proposed measures of uncertainty, being built through empirical evidences found in the data, are correlated with the self-report measure more than other measure used in the literature.

Finally, we argue that the preliminary analysis about firms' expectation formation process and uncertainty behavior is not only useful to build our new measure of uncertainty, but it is interesting *per sè* and goes in the direction to offer new stylized fact that can contribute to relatively new stream of literature focused on "how firms create their expectations"[4].

Results by Coibion, Gorodnichenko, and Kumar (2015) suggest that the degree of inattention shown by firms in forecasting future inflation rate is lowers the higher is the importance of inflation in the determination of their business conditions.

This suggests that if firms have limited abilities to process information or, alternatively, if collecting information is a costly process, they should focus on information that are crucial for their own business [5]. Despite this, the empirical evidence on how firms create expectations about their own future outcomes and market conditions and in which way these expectations affect the main firm-level decision is pretty scant.

Bachmann, Elstner, and Sims (2013) and Buchheim and Link (2016) are, exploiting the database IFO - Business Climate Survey, obtain interesting results on how firms create qualitative expectations[6], but, at the best of our knowledge, we are the first to offer an analysis of quantitative expectations and self-reported uncertainty.

The paper is structured as follows: in Section (2.2) we will provide an analysis of the existing literature concerning different measures of uncertainty and their effect on the main firm-level outcome variable; in Section (2.3) we will explain the characteristics of our

[4]Recent literature has focused his attention on how firms create expectations about macro variables (e.g inflations, stock market returns or total output) providing evidence of poor ability of firms in creating accurate expectations. For example, Ben-David, Graham, and Harvey (2013) find that managers are systematically optimistic and miscalibrated (i.e. they tend to overestimate the mean and to underestimate the range of potential outcome) in forecasting about stock market return.
Almost in the same fashion, Coibion, Gorodnichenko, and Kumar (2015) point out a constant inattention of firms in forecasting inflation: the disagreement among firms about the future inflation rate is always higher with respect to the one computed for professional forecasters.

[5]This could be read as an implication of the rational inattention theory proposed by Sims (2003).

[6]The IFO dataset is a panel containing monthly firm-level expectations data in the form of qualitative information (i.e. expected increase, decrease or no change) about certain variables such as general business conditions, production, employment and demand. We argue that, despite the fact that this dataset has good features as the high frequency of the data, qualitative expectations are not suitable studying the expectation formation process because even if the sign of the expectation and the sign of the realization is the same, they can differ a lot in level and this difference can significantly affect firm-level choices. Moreover, with qualitative expectations, it is impossible to capture the level of confidence of firms in their beliefs.

dataset and the way in which we build the key variables for our analysis; Section (2.4) will be dedicated to the analysis of firm-level expectation and self-reported uncertainty measure and it will be the basis to construct our new measure of uncertainty that we will present in Section (2.5) together with the estimation strategy and the comparison with other measures. Conclusions can be find in Section (2.6).

2.2 The state of the art

As anticipated in previous section, there is a huge amount of macro-uncertainty proxies. One of the most used is the Economic Policy Uncertainty (henceforth EPU) proposed by Baker, Bloom, and Davis (2016). EPU is based on frequency counts of newspaper articles containing the words uncertainty or uncertain, economic or economy, and one or more policy-related terms.

Rossi and Sekhposyan (2015) proposed a proxy based on an ex-post comparison of the ex-ante forecast for GDP by a pool of professional forecasters and the unconditional likelihood of the observed outcome while Jurado, Ludvigson, and Ng (2015) proposed a measures of uncertainty based on the volatility of the forecast errors resulting from optimal predictions based on econometric models that exploits a huge set of macroeconomic information.

Then we have, volatility measures extracted by GARCH model on GDP proposed by Bloom (2009) plus lots of finance-based measures.

Skipping to the micro-level, Bloom (2014) describes a variety of uncertainty measures distinguishing macro and firm-level uncertainty. He relies on a concept of uncertainty that is more related to cross-sectional variation (i.e. dispersion in different measure of economic growth especially GDP). His approach is to derive micro-founded time-variant uncertainty starting from firm-level information. Starting from the work of Bloom (2014), the simple cross-sectional dispersion of the growth rate of firms is the most used (and abused) measure in the applied economics field. Assuming g_{it} the growth rate of firm i in period t then

$$(\sigma^2_{CS})_t = \sum_{i=1}^{N} [g_{it} - \overline{g_t}]^2 \tag{2.1}$$

in which $\overline{g_t}$ is the sample mean, is a natural proxy for the variance of the ex-ante distribution. The reason why $(\sigma^2_{CS})_t$ can be thought as a micro-founded uncertainty measure is that it tends to filter pure idiosyncratic shocks and, as a consequence, is a proxy for common aggregate fluctuations. The main weakness of this measure is that it tends to overestimate uncertainty if firms are heterogeneous and face different expected business conditions.

In Bloom et al. (2014) uncertainty is the cross-sectional dispersion of the TFPR computed as the residual e_i from the following model $Y_{it} = A_t z_{it} f(k_{it}; l_{it})$ with $z_{it} = \rho z_{it-1} + \mu_{it} +_t + e_i$. The concern linked to this measure is that e_i is a forecast error from a model rather than a shock to the economic agent.

Discontinuity Index on firms' qualitative expectations is used by Fuss and Vermeulen (2008) and Bachmann, Elstner, and Sims (2013) and it is computed as follow

$$(\sigma^2_{DI})_t = \sqrt{Frac^+_t + Frac^-_t - (Frac^+_t - Frac^-_t)^2} \tag{2.2}$$

in which $Frac^+_t$ ($Frac^-_t$) is the weighted fraction of firms in the cross-section declaring to expect an increase (decrease) in production. Even if this index is based on self-reported expectations, it provides no possibility to build a firm-level measure of uncertainty.

However, using this index, Fuss and Vermeulen (2008) show that also for a panel of manufacturing Belgian firms planned and realized investment are curbed by demand uncertainty while they are not influenced by price uncertainty. Furthermore, firms tend not to change plans: there is very little variation between planned and realized investment. Exploiting the availability of qualitative data about firm expectation on demand and price variation (firms are asked if the expect an increase, a decrease or no change in both demand and price), the authors estimate demand and price uncertainty as the variance of expectation over sector following a disconformity index of survey approach.
In the same fashion, Bachmann, Elstner, and Sims (2013) compute discontinuity index on German and U.S micro-data finding that the negative impact of uncertainty on investment is stronger in Germany but more persistent in the U.S. This difference could reflect stronger capital irreversibility in the former case and a larger impact of financial frictions in the latter.

A similar result is obtained by Guiso and Parigi (1999) that, from their cross-sectional analysis on Italian manufacturing firms, find that the negative effect of uncertainty on investment is exacerbated when capital expenses are more irreversible and when firms have greater market power. The authors use one specific year of the INVIND survey in which the respondents provide their subjective probability distribution of their own demand changes. Thus, they are able to construct firm-specific measures of future demand growth variance. Although ideal, their measure of uncertainty is based on a huge data requirement that is not available in the usual surveys.

Bontempi, Golinelli, and Parigi (2010) and Bond, Rodano, and Serrano-Velarde (2015)

use the same self-report measure of uncertainty that we are going to use as a benchmark in this chapter to study the effect of the uncertainty on investment in the Italian manufacturing sector. In these papers, a deep analysis of self-reported measure is missing and moreover, they obtain contrasting results.
In particular, Bontempi, Golinelli, and Parigi (2010) confirm Guiso and Parigi (1999) results by exploiting panel of Italian manufacturing firms for the period 1996-2004. They find that the negative effect of uncertainty on investment plans is lower for firms that can employ a more flexible labour input. On the contrary, Bond, Rodano, and Serrano-Velarde (2015) find that high uncertainty has a not significant role in explaining decreasing investment dynamics during the crisis because low investments are basically due to low expected growth rate of real sales[7].

Until now, we focused our attention on the uncertainty measures and empirical results obtain by the literature that explores the relationship between uncertainty and investment[8], however uncertainty can affect other firm-level outcomes like capacity utilization and employment.

Concerning the relationship between uncertainty and investment/capacity utilization, according to Pindyck (1990) and Maskin (1999), leading firms can use excess capacity to deter entry. The excess capacity has to be higher when demand is more uncertain. Moreover, uncertainty produce an option value in procrastinating investment ('wait and see effect') due to irreversibility.
The empirical literature studying the uncertainty-capacity utilization link tends to focus only in particular sectors.

Ambrose, Diop, and Yoshida (2016) empirically corroborate this theoretical results. They study investment in real estate finding that high level of real estate are positive correlated with industry concentration and negatively related to demand uncertainty. The effect of demand uncertainty, measured as dispersion of real sales realized over time by the same firm, on the level of investments is based on the possibility to experience large negative demand shocks that increases the probability to face high losses[9]. Focusing instead on the effect of uncertainty on employment, we're in presence of an absence of a precise theory but Bloom, Bond, and Van Reenen (2007) *"concerning the behavior of labor demand, the existence of labor hiring and firing costs would imply that higher uncertainty would also make employment responses to shocks more cautious"*.

[7] A similar result is obtained by Leahy and Whited (1996).

[8] For a complete, even if not so recent literature review on the topic, refer to Carruth, Dickerson, and Henley (2000)

[9] Moreover, Bell and Campa (1997) find no effect of demand uncertainty on capacity utilization in chemical industry while Escobari and Lee (2014) find that demand uncertainty has a negative effect on capacity utilization in US airline industry.

Also from an empirical point of view the evidence on this particular link are almost non-existing unless the recent work by Ghosal and Ye (2015) finding that higher macro uncertainty (measured in different ways) has a negative impact on employment growth for smaller firms while the impact is null for bigger businesses.
From this analysis of the existing literature, it is clear that many economists focus on aggregate uncertainty relying on the hypothesis that every firms is subject to the same probability distribution about business conditions and, as a consequence, to the same level of uncertainty.
This assumption is far from be straightforward (for example, because of all the issue related to the well-known aggregation problem) and limits the possibilities to estimate time-varying firm-level uncertainty.
This means that there is scope for further work aimed at proposed new measures of uncertainty that overcome previous limitation. This paper moves exactly in this direction: assuming firms heterogeneity, and having on hand key results about firms expectation formation process and uncertainty behavior, we will propose two measures of time-varying firm-level uncertainty.

Before moving to the point, it is worthy to focus on some basic features of our dataset followed by the empirical analysis of expectations and self-reported uncertainty: these results will act as a basis on which own uncertainty measures are built on.

2.3 Data and Variable Definition

The data used in this study come from the Inquiry into Investment of Manufactoring firms ("Indagine sugli investimenti della imprese manifatturiere", henceforth, INVIND), a survey collected every year since 1984 by the Bank of Italy.

This survey contains a very rich set of information about industrial and service firms: biographic information, employment, investment, turnover, technical capacity, debt and credits and so on. A feature that makes this dataset particularly suitable for out purposes is that lots of the variables are available as realized values and as expectation for next year.

In order to fully exploit information in INVIND, we select big industries (more that 50 employees) from 1996 to 2016 observed at least for two-consecutive years. Furthermore, I drop all the observations belonging to the non-manufacturing sector (almost the 3% of the initial sample) because they started to be investigated only in 1998 and they constitute a little and too much heterogeneous group. We rely on an unbalanced panel of 17194 observations (2620 firms and 20 years) and the sample composition is essentially unaffected with respect to the original sample[10].

In INVIND realized total sales (in thousand of euros) at firm-level current prices are available.

Let's call this variable $S_{it} = P_{it} * Y_{it}$ in which P_{it} and Y_{it} are respectively the average price and the amount of total real sales realized in time t by firm i. Moreover, firm are asked to compute percentage change in the total nominal sales $((s_{it}))$ with respect to last year as $(\frac{S_{it}}{S_{it-1}} - 1) * 100$.

Firm-level price information is only available in percentage term. Precisely, firms are asked the average percentage growth rate in prices of good and/or services sold. We refer to this variable as p_{it}.

These information allows us to compute one of the key variable for this analysis, the realized rate of growth in real sales as:

$$g_{it} = s_{it} - p_{it}$$

In the survey, firms are asked to give a forecast for total nominal sales expected for next year and to compute the expected growth rate of nominal sales with respect to today realized sales. We refer to this as $E_[s_{it+1}|I_{it}^F]$ in which I_{it}^F is the information set available to the firm in the moment in which it creates the expectation.

Then, firms are asked to give a forecast for the expected average percentage change of prices for next year $(E[p_{it+1}|I_{it}^F])$. Afterwards, the survey requires to compute the expected percentage change in real sales as the difference between expected growth rate of nominal sales and expected average percentage change of prices. In our notation it's

$$E[g_{it+1}|I_{it}^F] = E[s_{it+1}|I_{it}^F] - E[p_{it+1}|I_{it}^F]$$

So, according to this definition, $E[g_{it+1}|I_{it}^F]$, in a given year, represents the rate of real sales, net of the growth rate of prices, that the firm expected at the end of year t for the year $t+1$. At the end, firms are asked to *"give a range, i.e. a forecast of minimum and maximum rate of growth of sales adjusted for changes in prices"*. We can imagine that when firms answer this question each of them has 'in mind' a distribution of possible future realization of g_{it+1}. As a natural consequence, even if this distribution is unknown we can recover quantile-based proxies for this distribution assuming that minimum and maximum rate of growth of real sales provided by the firms are respectively the minimum (m_{it}) and the maximum (M_{it}) quantile of this unknown distribution.

Under this assumption, we can recover our proxy for the dispersion of the distribution of

[10]More detailed information about panel structure, sample composition as well as descriptive statistics of the main variable that we are presenting in this section can be found in Appendix B.

the expected growth rate of real sales, i.e. our self-reported uncertainty measure as [11]

$$R_{it} = (M_{it} - m_{it})^2$$

Finally, we can define forecast error for the growth rate for the real sales as

$$FE_{it} = g_{it} - E[g_{it}|I^F_{it-1}]$$

In what follows we will focus on the study of some stylized fact about $E[g_{it}|I^F_{it-1}$, FE_{it} and R_{it}. This analysis will be our basis for the construction of the the new measures of uncertainty.

2.4 Some New Stylized Fact

We start this section proposing an analysis and some empirical evidence on firm-level expectation about growth rate of real sales. In particular, we want to answer at a precise question that is *"How firms create their expectations?"*. Then, we will move to an analysis focused of the self-reported measure of uncertainty aimed to discover if into this measure it is possible to find some path-dependency behaviour and how this measure is correlated to the forecast error.

Before answering the question about firms-level expectation formation process, we will go through a descriptive analysis.

Figure 2.41 (a) represents the median across years of out expectation variable $E[g_{it+1}]$. The expected growth of real real sales evidently fell in 2008. From an average of 2.7% during pre-crisis period, it fell to -5% in 2008. Despite the fact that it rebounded up starting from 2009 it never fully recovered to its pre-crisis median level remaining around an average 1.8%.

These figures do not concern just the median expectation time series but, looking at figure 2.41 (b), it is clear that the permanent drop in the level of expected real sales at the beginning of the financial crisis is translated in a permanent drop the realized real sales. Moreover the variability shown by the time series of the realized median values is more

[11] We use range as benchmark uncertainty proxy not only because it can be computed very immediately but also because it has been used to assess the effect of uncertainty on investment by Bontempi, Golinelli, and Parigi (2010) and Bond, Rodano, and Serrano-Velarde (2015). This choice will make our result more comparable with this literature. We are also aware that other stream of literature, with similar data rely on the assumption of a triangular distribution and exploit information about expected value, minimun and maximum to compute the second moment

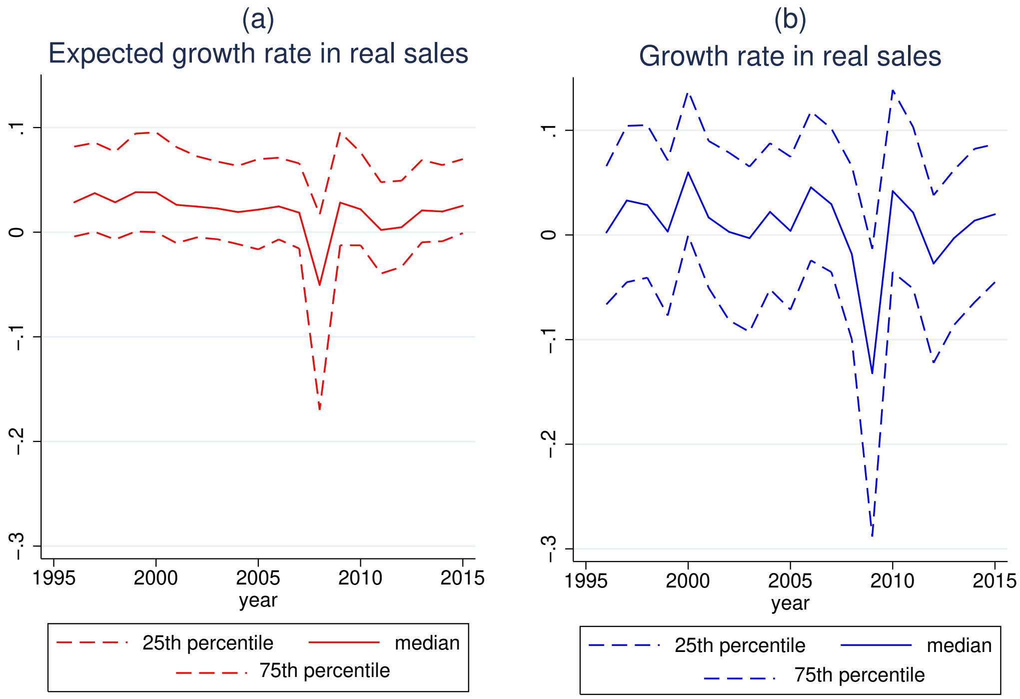

Figure 2.41: Panel (a): median, 25^{th} and 75^{th} of $E_t[g_{it+1}|I^F_{it}]$ by year. Panel (b): median, 25^{th} and 75^{th} of g_{it} by year.

accentuated with respect to the one of the median expected values. Indeed, from an average of 1.8% for the period 1995-2008, the growth rate of real sales fell to -13% in 2009.

The huge difference between the expected decline in the growth rate of real sales in 2008 (-5%) and the realized one in 2009 (-13%) is just an example of a feature that is repeated along every year of the analysis: the time series of median $E[g_{it+1}|I^F_{it}]$ is clearly smoother with respect to the one of median g_{it}. Firms seem to be prudent in the sense that, on average, they tend to underestimate positive growth rate and to overestimate negative growth rate. Otherwise, one can interpret this as the attitude to be optimistic (over-confidence) in forecasting negative picks and be pessimistic (under-confidence) in forecasting positive picks.

Despite this systematically negative bias of the forecast with respect to realized value (more evident looking at the time-series of the median forecast error in figure 2.42), it seems that the expectation ca be used to partially predict the realized values.

Now, in order to address the question *"How firms create their expectations?"* and understand which kind of information firms use to create their own expectations, we need to understand if firms expectations reflect just aggregate shocks affecting the entire

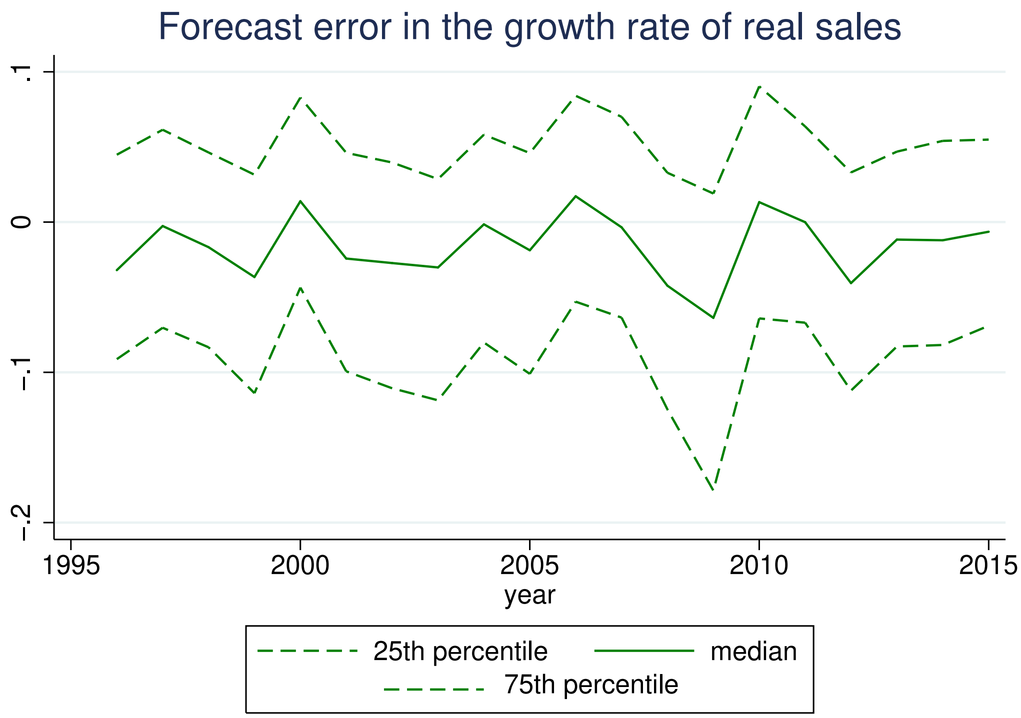

Figure 2.42: Median, 25^{th} and 75^{th} of the forecast error in the growth rate in real sales defined as $g_{it} - E_{t-1}[g_{it}|I^F_{it-1}]$.

industry (or entire economy) or if they do reflect also idiosyncratic shocks strictly related to firm specific conditions? Answering this question is important because it allows to disentangle the source of heterogeneity in firms expectations, i.e. if this heterogeneity is primarily due to different idiosyncratic conditions of firms or if it is mainly due to aggregate (at both entire economy or sector level) shocks.

In order to ask this question, we estimate the following model

$$E[g_{it+1}|I^F_{it}] = (\alpha_i) + \beta_1 g_{it} + \beta_2 g_{it-1} + \alpha_1 size_{it} + \alpha_2 age_{it} + d_t + d_s + \nu_{it} \tag{2.3}$$

in which α_i, d_t and d_s and are respectively firm-specific, time and sector fixed effects.

Table (2.41) shows that realized values of g_{it} are still significant in explaining some part of the variability of $E[g_{it+1}|I^F_{it}$ even after controlling for aggregate and sectorial common conditions. The fact that the estimated β_2 is not significant can be interpreted as the evidence that, in order to create expectation firms look at the growth rate realized in the period in which they form the forecast for the future and they do not focus in past

$E[g_{it+1}\|I_{it}^F]$	(1)	(2)	(3)	(4)	(5)
g_{it}	-0.20***	-0.11**	-0.11****	-0.08***	-0.08***
	(0.015)	(0.006)	(0.005)	(0.006)	(0.005)
g_{it-1}					-0.01
					(0.013)
$size_{it}$			0.00	0.00	
			(0.956)	(0.856)	
age_{it}			0.00	0.00	
			(0.218)	(0.324)	
d_t		Yes	Yes		
d_s		Yes	Yes		
$d_s * d_t$				Yes	Yes
Obs.	17194	17194	17148	17148	13861
R^2	0.12	0.28	0.28	0.30	0.29

Table 2.41: How firms create expectations:
Panel Fixed Effect Estimation model (1)

d_t are year time dummies while d_s are sector dummies according the sectorial division available in the data and explained in section (2.3). Robust standard errors. Level of significance: * $p < 0.10$, ** $p < 0.05$ and $p < 0.01$

realizations.

We conclude our analysis about firms' expectation answering the question: do expectations respond to the availability of new information concerning future business conditions or more simply, firms use only the past realized value of sales to create expectation?

$$E[g_{it+1}|I_{it}^F] = \beta_1 g_{it} + \beta_2 g_{it+1} + \alpha_1 size_{it} + \alpha_2 age_{it} + d_t + d_s + \nu_{it} \tag{2.4}$$

In equation (2.4) g_{it+1} is used as a proxy for information about future available for the firm in time t. If β_2 will be significant despite the fact the in the same equation we control for current realized value of the growth rate of net sales as well as time and sector effect, it will mean that firms incorporate some information about future available in t that is not captured by their current conditions. In adopting this methodology we partially follow the work by Buchheim and Link (2016)

Estimated coefficient in Table (2.42) shows that, heterogeneity in expectation formation process is also evident into the fact that firms' expectations strongly capture idiosyncratic component in their ex-post realized values of the growth rate of sales (g_{it+1}) that is independent from economy and sectorial conditions. If firms' expectations were mainly

$E[g_{it+1}\|I^F_{it}]$	(1)	(2)	(3)	(4)
g_{it}	-0.20***	-0.04**	-0.04****	-0.04***
	(0.015)	(0.005)	(0.005)	(0.006)
g_{it+1}		0.33**	0.34***	0.34***
		(0.004)	(0.005)	(0.005)
$size_{it}$			0.00	0.00
			(0.001)	(0.001)
age_{it}			0.00	0.00
			(0.002)	(0.003)
d_t		Yes	Yes	
d_s		Yes	Yes	
$d_s * d_t$				Yes
Obs.	17194	14643	14532	14532
R^2	0.12	0.30	0.31	0.31

Table 2.42: How firms create expectations: Panel Fixed Effect Estimation model (2)

d_t are year time dummies while d_s are sector dummies according the sectorial division available in the data and explained in section (2.3). Robust standard errors. Level of significance: * $p < 0.10$, ** $p < 0.05$ and $p < 0.01$

reflecting a common view about future condition, then time and sectorial dummies would capture almost all the variability of the dependent variable and g_{it} would not be correlate with $E[g_{it+1}|I^F_{it}]$ after controlling for these factors. Our results (column (4) of table (2.42), instead, suggest that results in suggest that in order to create expectations firms use some piece of information that is not contained into realized value or common time-sector characteristics and that this piece of information is more important to in the determination of expectation with respect to realized values (estimated β_2 in equation 2.4 is positive and greater with respect to β_1).

Moving to the study of uncertainty behavior, figure (2.43) shows a substantial increase in uncertainty in 2008. The measure of uncertainty increases from an average around 0.07 for the pre-crisis period to a little bit more than 0.10 in 2008. Even if it falls back close to his original average in the pre-crises period, it rest more volatile than before. Our measure of uncertainty follows a countercyclicality property highlighted by Bloom (2009): uncertainty is higher during crises period instead is lower in "normal times".

The availability of this measure allows us to analyze if there is same path-dependency or if self-reported uncertainty is only related to aggregate and sectorial conditions. We test

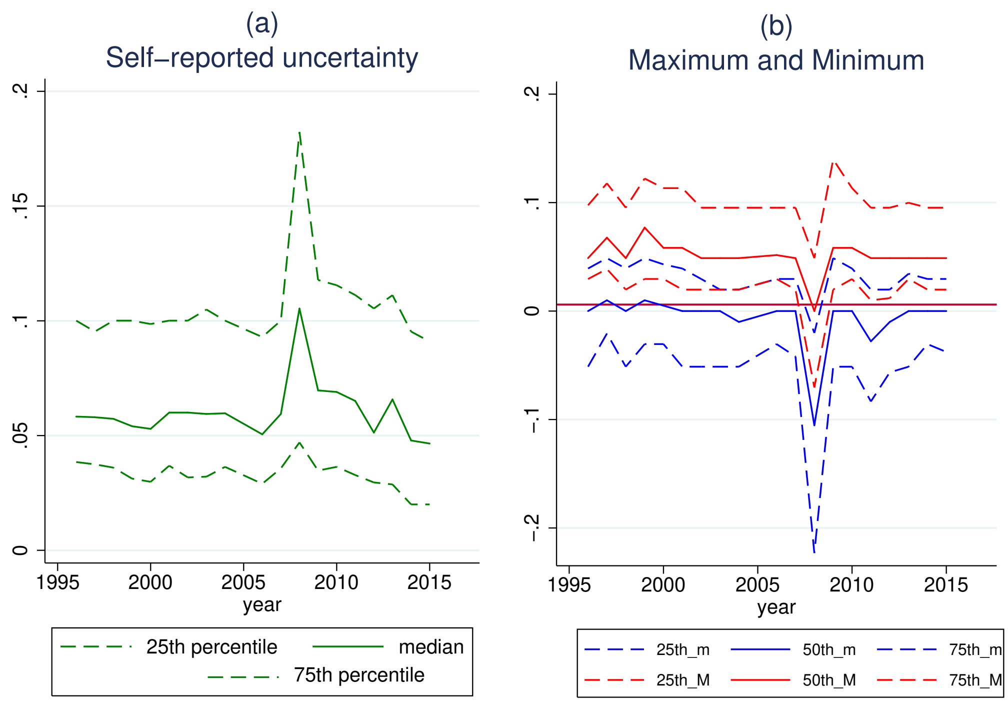

Figure 2.43: Panel (a): median, 25^{th} and 75^{th} of R_{it} by year. Panel (b): median, 25^{th} and 75^{th} of m_{it} and M_{it} by year.

this by estimating the following regression:

$$R_{it+1} = \beta_1 R_{it} + \beta_2 R_{it1} + \alpha_1 size_{it} + \alpha_2 age_{it} + d_t + d_s + \nu_{it} \tag{2.5}$$

Results in table (2.43) suggest that uncertainty has a first degree path dependency even after controlling for aggregate and section common condition. This means that each firms is subject to some idiosyncratic uncertainty that is not explainable just using common pattern. Interesting is that uncertainty depends from the uncertainty reported in the previous year but it's not related to firm characteristics such dimension in term of number of employees and age.

Finally, we want to assess if the forecast error is related to uncertainty. We answer this question by estimating the following equation:

$$|FE_{it}| = \beta_1 R_{it-1} + \alpha_1 size_{it} + \alpha_2 age_{it} + d_t + d_s + \nu_{it} \tag{2.6}$$

We obtain that forecast error, regardless of the sign, is strictly correlated with uncertainty one period ahead: uncertainty today implies an higher probability to end up in

R_{it+1}	(1)	(2)	(3)	(4)
R_{it}	0.14***	0.11**	0.11****	0.27***
	(0.008)	(0.009)	(0.009)	(0.056)
R_{it-1}				0.06
				(0.225)
l_{it}			0.00	0.00
			(0.000)	(0.000)
age_{it}			0.00	0.00
			(0.000)	(0.000)
d_t		Yes	Yes	
d_s		Yes	Yes	
$d_s * d_t$				Yes
Obs.	7160	7160	7149	4294
R^2	0.03	0.13	0.13	0.16

Table 2.43: Uncertainty Serial Correlation:
Panel Fixed Effect Estimation model (3)

d_t are year time dummies while d_s are sector dummies according the sectorial division available in the data and explained in section (2.3). Robust standard errors. Level of significance: * $p < 0.10$, ** $p < 0.05$ and $p < 0.01$

$\|FE_{it}\|$	(1)	(2)	(3)	(4)
R_{it-1}	7.33***	4.11**	4.10***	4.07***
	(0.599)	(0.559)	(0.557)	(0.056)
$size_{it}$			0.00	0.00
			(0.00)	(0.000)
age_{it}			0.01	0.00
			(0.001)	(0.000)
d_t		Yes	Yes	
d_s		Yes	Yes	
$d_s * d_t$				Yes
Obs.	9537	9343	9343	9343
R^2	0.02	0.20	0.20	0.21

Table 2.44: Forecast Error - Uncertainty Relatioship:
Panel Fixed Effect Estimation model (4)

d_t are year time dummies while d_s are sector dummies according the sectorial division available in the data and explained in section (2.3). Robust standard errors. Level of significance: * $p < 0.10$, ** $p < 0.05$ and $p < 0.01$

a growth rate of real sales different with respect to the forecast one.

Summarizing, we obtain that self-reported uncertainty show a first-degree path dependency at firm-level and that it is positively correlated to the forecast error.
We also obtained that firms, in order to create expectations about future rate of growth of real sales, firms use information about realized growth rate (they don't use previous information concerning realized values one or more period ahead) plus some information about future business condition not available for the econometrician in the data. This means that the information set available for firms is greater with respect to the one available in the data and, as a consequence, that one of the best possible way to isolate firm-level shocks is taking into account firm level expectations.

For the same reason, self-reported measures results as the best way to measure time-varying firm-level uncertainty but, we aware of the fact that such kind of measures are usually not available in the most common micro-panel. That is the main reason way we are going to exploit evidence about firms expectations, self-reported uncertainty and forecast error to build two measures that are computable even in less rich database.

2.5 New uncertainty measures

2.5.1 Definition and Estimation Strategy

The two measures of firm-level and time-varying uncertainty that we propose are

- **Opinion-based uncertainty**: estimable just using expectations and realized values (available in some of data-sets).
- **Model-based uncertainty**: estimable even in the absence of data about expectations.

The definition of both measure starts from a common one, uncertainty is the variability of the g_{it} variable after removing predictable component. Our main point is that uncertainty is not the simple dispersion of g_{it}, uncertainty does not concern the forecastable component and it is related to variation around an expected value by the agent taking the decision. [12]

[12]This measure can be seen as an application at the micro-level of the uncertainty measure proposed by Jurado, Ludvigson, and Ng (2015) in a macro context. For the sake of precision, (2.7) corresponds to uncertainty index used by Jurado, Ludvigson, and Ng (2015) evaluate for a single period ahead. Using their notation, we consider just the case in which $h = 1$.

$$\sigma_{it}^2 = E[(g_{it} - E[g_{it}|I_{it-1}^F])^2|I_{it-1}] \tag{2.7}$$

According to this definition σ_{it}^2 is the conditional variance in which the usual mean is replaced with the expectation taken with respect to information set available to firm i at time $t-1$. This definition is fully coherent with the uncertainty measure available in our dataset, i.e. a proxy of the dispersion of possible future realization of g_{it} around the point expectation around the point expectation for the same variable. Moreover, this definition allows the uncertainty measure to be higher the higher is the squared of the forecast error as we obtained from the empirical evidence analysis. We obtain our two measure of uncertainty by considering different options for $E[g_{it}|I_{it-1}^F]$.

If information about point expectation is available, one can use the opinion-based uncertainty $(\sigma_{OB}^2)_{it}$

$$(\sigma_{OB}^2)_{it} = E[[g_{it} - E(g_{it}|I_{it-1}^F)]^2|_{it-1}^F] \tag{2.8}$$

This measure con be easily computed modeling the forecast error as a GARCH(1;1) process

$$\begin{gathered} g_{it} - E_{t-1}[g_{it}] = \sigma_{it}\epsilon_{it} \quad where \quad \epsilon_{it} \sim NID(0;1) \\ \sigma_{it}^2 = \alpha_\sigma + \gamma_1\mu_{it-1}^2 + \delta_1\sigma_{it-1}^2 \end{gathered} \tag{2.9}$$

We define the model-based uncertainty measure as

$$(\sigma_{MB}^2)_{it} = E[[g_{it} - E[g_{it}|I_{it-1}^D]]^2|I_{it-1}^D] \tag{2.10}$$

This measure con be computed modeling the expectation as a ARMA(1;1) and, consecutively, modeling the the forecast error with respect to the value predicted by the ARMA model as a GARCH(1;1) process exactly as in the previous case

$$\begin{gathered} g_{it} = \phi g_{it-1} + \theta\mu_{it-1} + \mu_{it} \quad \forall \quad i = 1, ..., N \quad and \quad t = 1, ..., T_i \\ \mu_{it} = \sigma_{it}\epsilon_{it} \quad where \quad \epsilon_{it} \sim NID(0;1) \\ \sigma_{it}^2 = \alpha_\sigma + \gamma_1\mu_{it-1}^2 + \delta_1\sigma_{it-1}^2 \end{gathered} \tag{2.11}$$

Model-based uncertainty has the clear advantage to be computable for whatever firm-level due to the fact no data on expectations are required. On top of this, model-based uncertainty suffers of two main disadvantages with respect to the opinion-based one: first: $I_{it-1}^D \subset I_{it-1}^F$ one can use the information set available to the econometricians that is surely a subset of the one available for the firms [13]; second, this measure shows a clear specification dependence. Our choice to model the mean equation as an ARMA(1;1) and the variance equation as a GARCH(1;1), firstly comes from the obtained results in previous section but it has been validated by estimation and rejection of other specifications.

Before moving to the estimation and to the results, it is worthy to highlight that the measure that we are proposing have the same interpretation that we give to the range using our simple model: indeed, they are measures of total uncertainty in the sense that it's the variability of the convolution among demand and supply shocks. The reason why we do not try disentangle between demand side and production side shocks is twofold: first, in order to disentangle the two types of shocks one need to build a structural model relying on very strong assumptions; second, obtaining measures that contain any kind of shocks (e.g. such as change in consumers taste, change in the mark-up, change in firm-level efficiency, change in input costs and so on) will allow us to obtain measures comparable with the the self-reported measure that we have in the data. [14]. Moreover, our measures of uncertainty are built on the basis of the micro-evidence regarding the various relationship that we found in the previous section concerning expectation, forecast error and uncertainty. Precisely our measure are coherent with the fact that a) firms, in order to create expectations, use information contained in realized value (not other lags); b) they have a greater information set concerning future business conditions, with respect to which available in the data; c) today uncertainty depends on one period ahead uncertainty; d) forecast error are strictly correlated with uncertainty one period ahead.

In order to estimate model-based uncertainty in (6) using model (2.11) we rely on a PANEL-GARCH approach proposed by Cermeño and Grier (2001) as an extension of the well-known GARCH model thought for time-series and proposed in the seminal works by Engle (1982) and Bollerslev (1986).

One of the main advantages of the panel-garch approach is that it allows to directly estimate time-varying and observation-varying volatility exploiting both the cross-sectional

[13] In estimating (2.10) an omitted-information bias may arise if firms have more information with respect to the information available for the econometricians in the data. Jurado, Ludvigson, and Ng (2015) solve this problem in a macro context using hundreds of variable in order to have a data-based information set spanning as much as possible the information set available to the agents. Clearly this solution is not plausible in a micro context in with surveys provide limited information for each of the interviewed firm

[14] Even if we do not directly refer to Total Factor Productivity of Revenues (TFPR) our approach is close to the stream of litearture according to which demand and supply shocks are isomorphic as shown in a seminal work by Hsieh and Klenow (2009) Moreover, Asker, Collar-Wexler and De Loecker (2013) use the same approach to investigate the role of dynamic production input in shaping the dispersion of capital misallocation

and the time dimension of the data by pooling the parameters to estimate. When one is in front of a micro-panel dataset the multivariate GARCH proposed by Bollerslev, Engle, and Wooldridge (1988) is not suitable because in micro contest, unlike macro contest, single unit rarely produce long time series of data. Switching from a single long time series to several pooled shorter time series, significantly reduce the efficiency of the OLS estimator: heteroskedasticity is more probable. As a consequence, panel GARCH not only allows to estimate time and observation varying volatility but it leads to an efficiency gain with respect to OLS. The model we estimate is an extension of Cermeño and Grier (2001). The extension goes in two directions: first, we allows for MA effect together with AR effect in the mean equation; second, we consider an unbalanced panel (in the formal presentation that follows T_i is the maximum number of consecutive periods in which we observe the firm i.) [15]

Under the assumption of cross sectional independence, the conditional normal density for model (2.11) is

$$f(g_{it}|;\alpha_\sigma;\gamma_1;\delta_1) = (2\pi\sigma_{it}^2)^{\frac{1}{2}} exp - \frac{(g_{it} - \phi g_{it-1} - \theta\mu_{it-1})^2}{2\sigma_{it}^2} \tag{2.12}$$

We obtain estimates of the key parameters by maximize the following maximum likelihood

$$L = -\frac{NT}{2} ln(2\pi) - \frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T_i} ln\sigma_{it}^2 - \frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\frac{(g_{it} - \phi g_{it-1} - \theta\mu_{it-1})^2}{\sigma_{it}^2} \tag{2.13}$$

where $T = \sum_{i=1}^{N} T_i$ and, as a consequence the term NT is the total number of cross-sectional and time-varying observations.

In order to estimate opinion-based uncertainty in (2.10) using model (2.9) we rely on a simplified version of the Cermeno Panel-Garch.

Note that the choice of the AR(1) and GARCH(1) component comes directly from the previous empirical evidence. The choice instead of the MA(1) and ARCH(1) component comes from the fact that, being the Panel-Garch model subject to particularly model specification sensibility, we need to specify the model in the way that better fit the data.

[15] Maximum likelihood estimator is more efficient with respect to simple OLS in case of heteroschedasticity and it allows to recover the parameters of both conditional mean and conditional variance equation. Note that if $\delta_1 = 0$ the model is a PANEL-ARCH while if $\delta_1 = \gamma_1 = 0$ the model is a straightforward MLE with homoschedasticity.

	$(\sigma^2_{MB})_{it}$	$(\sigma^2_{OB})_{it}$
ϕ	-0.49***	
	(0.132)	
θ	0.54***	
	(0.128)	
γ	0.37***	0.31***
	(0.005)	(0.005)
δ	0.56***	0.60***
	(0.008)	(0.006)
α	0.01***	0.01***
	(0.001)	(0.001)
Obs	17194	17194
L-L	4961.88	6926.11

Table 2.51: Estimated parameters of the GARCH models

The first column contains of the GARCH model containing the mean equation in order to estimate the Model-Based uncertainty. Column (2) contains estimated parameters of the GARCH model without mean equation in order to estimate Opinion-Based uncertainty. Standard errors are reported in brackets. Level of significance: * $p < 0.10$, ** $p < 0.05$ and $p < 0.01$

2.5.2 Results

Table (2.51) shows parameters of the GARCH models in order to obtain $(\sigma^2_{MB})_{it}$ and $(\sigma^2_{OB})_{it}$ Given the representativeness of our sample of firms, we are able to build aggregate time-variant uncertainty starting from the firm-level uncertainty measures in the following way:

$$(\sigma^2_{kB})_t = \sum_{i=1}^{N_t} \omega_{it} (\sigma^2_{kB})_{it} \quad \forall \quad k = M; O$$

where N_t is the number of firms observed in year t and ω_{it} are sample weights.

Figure (2.51) shows estimated average opinion and model based uncertainty by sector and in the last panel there is the average across the all sample. As expected model-based uncertainty tends to overestimate uncertainty with respect to the opinion-based one and the pattern does not shows particular sectorial differences.Moreover our measures preserve the countercyclicality characteristic of other measures of uncertainty: picks of high uncertainty are particularly evident during crisis.

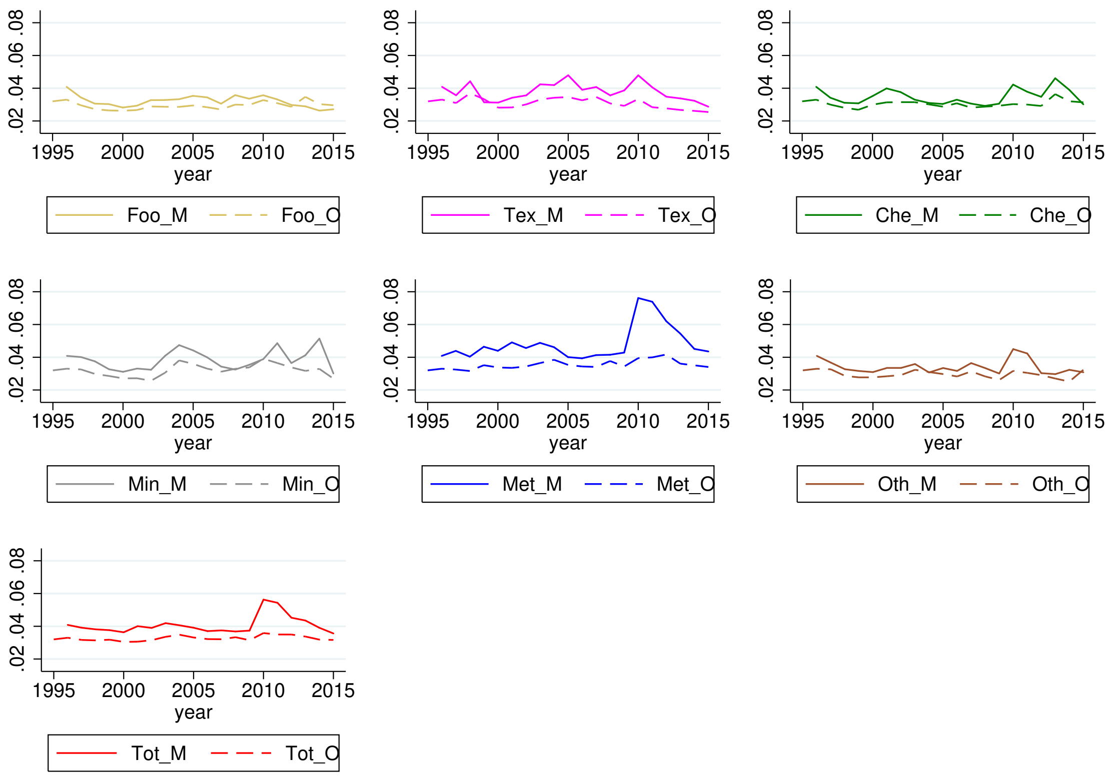

Figure 2.51: Comparison between estimated $(\sigma^2_{MB})_t$ and $(\sigma^2_{OB})_t$ on average by sectors

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2.5.3 Comparison with other uncertainty measures

We now compare our measures of uncertainty to other uncertainty measure used in the literature. We first compare them to cross-sectional standard deviation in firm-level growth rate of sales $(\sigma^2_{CS})_t$ proposed by Bloom (2014). Figure (2.52) shows exactly what we argue at the beginning: cross-sectional measure tend not only to overestimate uncertainty in level but it exhibits an excess variability due to the fact that, by construction, it reflects a range a reasons for cross-sectional differences in growth rates among firms besides firm-specific shocks. $(\sigma^2_{CS})_t$ can be seen as a measures that contains heterogeneity elements that are not directly linked to uncertainty.

Table (2.52) shows that how our measure are more correlated to the self-declared measure of uncertainty (0.65 and 0.54 respectively for model-based and opinion based uncertainty measure) with respect to the cross-sectional one.

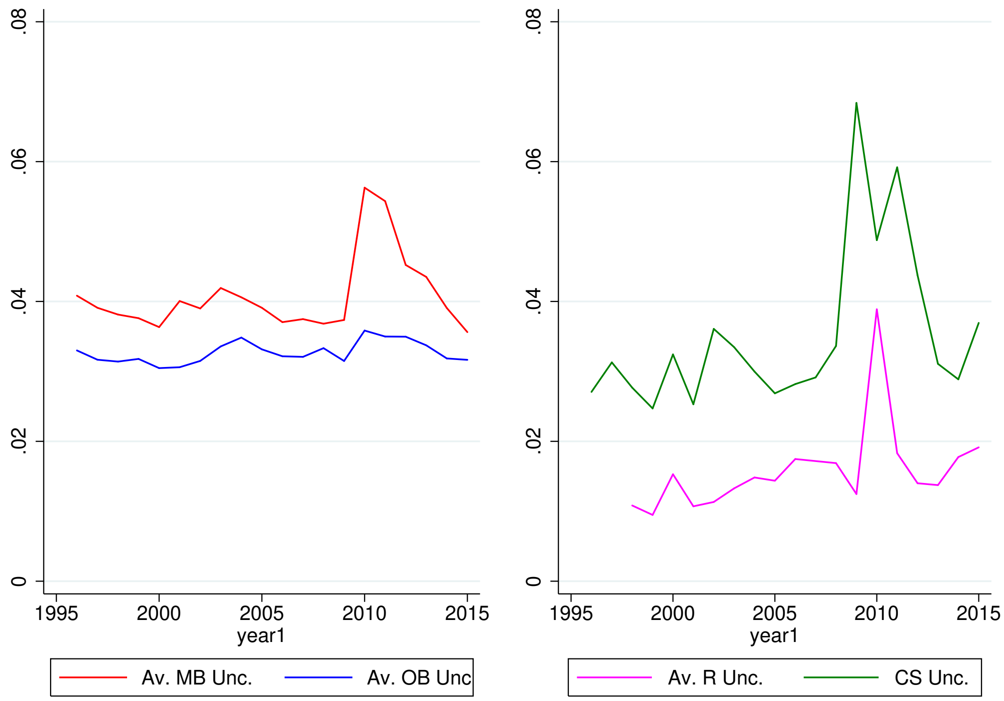

Figure 2.52: In the first graph, the average of the uncertainty measures build in this paper (AU_{it}^{mb} and AU_{it}^{ob}). In the second graph, Av. R Unc is the average of the range. while CS Unc. is the cross sectional variance of the rate of growth of real sales.

	$(\sigma^2_{MB})_t$	$(\sigma^2_{OB})_t$	R_t	$(\sigma^2_{CS})_t$	EPU	MU
$(\sigma^2_{MB})_t$	1					
$(\sigma^2_{OB})_t$	0.77	1				
R_t	0.65	0.54	1			
$(\sigma^2_{CS})_t$	0.48	0.33	0.31	1		
EPU	0.58	0.40	0.08	0.32	1	
MU	0.20	0.10	0.39	0.42	-0.20	1

Table 2.52: Correlation among different measures of uncertainty

$(\sigma^2_{MB})_t$ and $(\sigma^2_{OB})_t$ are respectively the Model -Based and the Opinion-Based that we propose. R_t is our benchmark uncertainty measure self-declared by the firm. $(\sigma^2_{CS})_t$ is the Bloom uncertainty measure. EPU is the Economic Policy Uncertainty by Baker et al. (2016). Data are available in http://www.policyuncertainty.com MU is the Macroeconomic Uncertainty Index by Rossi and Sekhposyan (2015). Data are available in http://www.tateviksekhposyan.org/

2.6 Conclusions and further extensions

The existence of adjustment costs put firms into the situation to decide how much to produce and/or the quantity of input to use before than certain market conditions realize. In such environment, firms' expectation regarding their own future business conditions are important determinants of investment and hiring decisions.

The first contribution of this paper is studying the firms' expectation formation process using non-qualitative expectation data about future growth rate of real sales contained in INVIND, a panel dataset of Italian manufacturing firms provided by the Bank of Italy.

Our results suggest that, despite the fact that expectations seem to be systematically biased through prudent behavior (on average they tend to be over-confident in forecasting negative picks and under-confident in forecasting positive ones), expectations can be used as a good indicator to forecast future values of the growth rate of sales.

This is confirmed by the result of our panel FE estimations: firms in order to create expectations use not only realized idiosyncratic value of the realized growth rate of real sales (not other lags) but they use a series of information about future business condition that are not available for the econometrician, in fact expectations are more correlated with future realized values than with past ones.

Then, we exploit the availability of a self-reported measure of uncertainty in our data to figure out important feature about the uncertainty perceived by the single firm. We obtain that, after controlling for time and sectorial effects, uncertainty tends to show a one lag path dependence (at firm-level uncertainty today depends from yesterday uncertainty). Moreover, we find that forecast error are strictly correlated with uncertainty one period ahead.

With these results on hand, we build two different measures of time-varying firm-level uncertainty: the opinion-based uncertainty that can be computed having access to data containing firms' expectations and the model-based uncertainty that need just realized values in order to be computed.

MB uncertainty tends to overestimate uncertainty with respect to OB ones but both countercyclical and positive correlated with other measure of uncertainty. Moreover, the measures of uncertainty that we propose are more correlated with the self-reported measure that is available in our data than other measure usually used in the literature. with respect to other measures.

In further research, we are planning to investigate the effect of the OB and MB uncertainty, together with the expectation, to the firm-level outcomes in order to enrich the stream of literature that analyze the effect of uncertainty on investments, employment and capacity utilization.

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Appendix

2.A A basic model

Each firm i in each period t faces the following profit maximization problem

$$\operatorname*{Max}_{Y_t} \quad Y_t P_t - c(Y_t)$$

in which Y_t is the quantity to be produced; P_t is the price set by the same firm and $c(Y_t)$ is a general cost function.

Let's assume that price is fix and normalized to 1. Now we introduce 'total irreversibility' in the sense that firm has to decide in period t the quantity that it will sell in period t+1. Note that this assumption is equivalent to the classical irreversibility of investment and for high adjustment costs for employment, i.e. in any case in which firm has to decide the amount of input factor one period ahed with respect to the utilization period. Moreover, we assume that the demand in t+1 will be

$$D_{t+1} = \overline{D} + \epsilon_{t+1}$$

in which $\overline{D}$ can be interpreted as the expectation that firm has about future demand and ϵ_{t+1} is a zero-mean random shock.

Under the previous assumptions, the maximization problem becomes

$$\operatorname*{Max}_{Y_t} \quad E_t[min(Y_t; D_{t+1})] - c(Y_t)$$

that is equivalent to

$$\operatorname*{Max}_{Y_t} \quad E_t[min[(Y_{it} - \overline{D}); \epsilon_{t+1}] + \overline{D} - c(Y_t)$$

and as a consequence to

$$\operatorname*{Max}_{Y_t} \quad \int_{\underline{\epsilon}}^{Y_t - \overline{D}} \epsilon f(\epsilon) d\epsilon \quad + \int_{Y_t - \overline{D}}^{\overline{\epsilon}} (Y_t - \overline{D}) f(\epsilon) d\epsilon \quad + \overline{D} - c(Y_t)$$

The solution of the maximization problem is

$$1 - F_{\epsilon}(Y_t - \overline{D}) = c'(Y_t)$$

in which F_{ϵ} is the cumulative density function of ϵ. Note that this can be read as a classical equality between marginal revenue and marginal cost. But in this model marginal revenue in the optimal quantity Y_{it} are probabilistic and realizable just in the case in which the demand shock in sufficiently large to allow to sell all the produced quantity. Moreover, the distribution of the demand shocks (we can allow also for skewed distribution) affect the optimal choice. Let's make this point more clear assuming that

$$\epsilon_{t+1} = \sigma_t^D \eta_{t+1}$$

in which σ_t^D is the uncertainty of the future demand (this parameter is known to the firm) and η_{t+1} is a shock with unitary variance whatever distributed.
The final results is

$$Y_t = \overline{D} + \sigma_t^D F_{\eta}^{-1}(1 - c'(Y_t))$$

Production today (and, as a consequence, the level of input utilized) depends from both expectation and uncertainty about future level of demand.
Taking the total differential al the optimality condition written in the following way

$$1 -_{\eta} (Y_t - \overline{D}) - c'(Y_t) = 0$$

we obtain

$$-F_{\eta}(Y_{it} - \overline{D})d\sigma + [-\sigma \frac{\partial}{\partial Y_{it}} F_{\eta}(Y_{it} - \overline{D}) - c''(Y_{it})]dY_{it} = 0$$

rearranging

$$\frac{dY_t}{d\sigma} = -\frac{F_{\eta}(Y_{it} - \overline{D})}{\sigma \frac{\partial}{\partial Y_{it}} F_{\eta}(Y_{it} - \overline{D}) + c''(Y_t)}$$

The effect of the uncertainty on Y_t is negative. Just note that the denominator cannot be negative because the S.O.C $-c''(Y_t) - \sigma \frac{\partial}{\partial Y_{it}} F_{\eta}(Y_{it} - \overline{D}) < 0$ must be satisfied.
We can extend the model introducing productivity shocks in the same way

$$Y_{t+1} = Y_t + \xi_{t+1}$$

Indeed allowing for the fact that the quantity that a firm can produce tomorrow depends from the choice about the production capacity that firms made one period ahead plus a productivity shock. If $\xi_{t+1} > 0$ firm is more efficient in the sense that is able to produce

more even facing the same cost related to the productive capacity set in t instead if $\xi_{t+1} < 0$ firm is less efficient in the sense that is able to produce less even facing the same cost related to the productive capacity set in t. Note how this specification correspond to an usual production function in which all input are pre-determined but it has the advantage to be simply treatable.
Under the previous assumptions, the maximization problem becomes

$$\underset{Y_t}{\text{Max}} \quad E_t[min(Y_{t+1}; D_{t+1})] - c(Y_t)$$

that is equivalent to

$$\underset{Y_t}{\text{Max}} \quad E_t[min[(Y_{it} - \overline{D}); (\epsilon_{t+1} - \xi_{t+1})] + \overline{D} - E_t[\xi_{t+1}] - c(Y_t)$$

The solution of the maximization problem will depends on the feature of the convolution of the two shocks that we can write as

$$\epsilon_{t+1} - \xi_{t+1} = \sigma_t \nu_{t+1}$$

in which σ_t is the uncertainty of the future demand and productivity (this parameter is known to the firm) and ν_{t+1} is a shock with unitary variance whatever distributed. The final results is

$$Y_t = \overline{D} + \sigma_t F_\nu^{-1}(1 - c'(Y_t))$$

All the consideration that we made before are valid also in this case. We build a super simple model in which expectations about the realization of future demand and productivity shock and its uncertainty affect current choices of productivity capacity (we do not distinguish between different inputs). Uncertainty about the convolution of the shocks will affect input utilization in a negative way (at least in this preliminary version of the model!). We do not rely on any assumption on the distribution so also asymmetric distribution are allowed and skewness can affect the results. The measure of uncertainty that we'll extrapolate directly from our dataset is a proxy of this variance (σ). Moreover, total real sales are the result of an equilibrium determined by both supply and demand shocks. At this step, we do not try to disentangle between demand and productivity shocks relying on the seminal work of Hopenhayn and Rogerson (1993): at micro level productivity shocks are isomorphic to shocks shifting the demand curve.
Expectation about future realization of sales contain expectation of the realization of both type of shocks. In the same fashion, our measure uncertainty can be interpret as a measure containing the expected variability of demand and productivity shocks. Expectation and

uncertainty about future realization of sales are important determinant of current choices of employment and investment. This last effect is higher, the higher is the level of irreversibility and adjustment cost.

2.B INVIND dataset features

The data used in this study come from the Inquiry into Investment of Manufactoring firms ("Indagine sugli investimenti della imprese manifatturiere", henceforth, INVIND), a survey collected every year since 1984 by the Bank of Italy. This survey contains a very rich set of information about industrial and service firms: biographic information, employment, investment (realized and projected), turnover, technical capacity, debt and credits and so on.

The survey reference population is stratified and, from each layer, a sample of firms is randomly extracted (stratified sampling scheme in one step). Stratification is made by combination of activity sector, class size (in terms of employees) and regional location of the headquarters administrative firm.

The sample is a panel: firms detected in a certain year are always contacted in the following year unless they are no longer part of the population of interest. If a company is no longer available to answer the questionnaire, another one similar in term of economic activity and size class replaces it. A firm is considered out from the reference population in case of liquidation or bankruptcy, merger or because the firm stop to belong to the sector or class size classes being surveyed.

Until 1998 INVIND was limited to firms in the manufacturing sector (ATECO section D) with 50 or more employees. Starting from 1999, the reference universe has been expanded to the entire industry, excluding construction, integrating the sample with firms operating in the Ateco subsection DF (oil refineries, treatment of fuel) and section C (mining) and E (energy electricity, gas and water). Starting from 2001 the survey has been extended to firms with 20-49 employees. Since 2002 the survey has been further extended to companies operating in the private non-financial services with 20 or more employees.

Although the basic structure of the survey has been adopted during the year in order to allow the construction of time series information on numerous variables, small changes have been introduced in particular years of the survey in order to introduce new variables.

Year	Sam.	Pop.	%	Year	Sam.	Pop.	%	Year	Sam.	Pop.	%
1988	1.039	12.025	8,64%	1997	1,002	11.792	8,50%	2006	1.838	11.574	15,88%
1989	1.053	11.883	8,86%	1998	998	11.609	8,60%	2007	1.783	11.432	16,60%
1990	1.071	11.739	9,12%	1999	1.107	11.502	9,62%	2008	1.752	11.168	15,67%
1991	1.027	12.041	8,53%	2000	1.428	11.798	12,10%	2009	1.706	10.652	16,02%
1992	993	11.658	8,52%	2001	1.713	12.389	13,97%	2010	1.666	10.119	16.46%
1993	994	11.185	8,89%	2002	1.797	17.509	10,26%	2011	1.748	10.119	17,27%
1994	953	11.037	8,63%	2003	1.848	11.978	15,42%	2012	1.747	9.882	17,68%
1995	996	10.880	9,15%	2004	1.861	11.677	15,94%	2013	1.780	-	-
1996	1.060	11.411	9,29%	2005	1.890	11.516	16,41%	2014	1.803	-	-

Table 2.B1: Number of firms in the sample for each year and corresponding reference population

For each year, the column "sample" contains the number of manufacturing firms surveyed in that year, the column "population" contains the numbers of firms of the reference population (source: Bank of Italy: "Indagine sulle imprese industriali e dei servizi. Disegno campionario e metodi utilizzati" February 2016), column "%" the percentage of firms in the sample with respect to reference population

We rely on the sectorial division provided by the same Bank of Italy and it is based on aggregation of classes according to two-digit ATECO 2007 classification. Precisely:

- *"Food"*: food products, beverages and tobacco (ATECO 10,11 and 12);
- *"Textile"*: textile industries, clothing, leather and shoes (ATECO 13, 14 and 15);
- *"Chemicals"*: manufacture of coke, chemical industry, rubber and plastic (ATECO19, 20, 21 and 22);
- *"Minerals"*: industry of non-metallic minerals (ATECO 23);
- *"Metals"*: metals industry (ATECO 24, 25, 26, 27, 28, 29, 30 and 33);
- *"Others"*: wood industries, furniture, paper and printing (ATECO 16, 17, 18, 31 and 32).

Table (2.B2) shows that, into our selected sample, most of the observations in the sample belong to the metals sector (42%) followed by the food sector (12%) while the rest are almost equally distributed among the other sectors. Furthermore, as expected, most of the firms are located in the North-West and North-East and, looking at the class size

Year	Freq.
1996	524
1997	678
1998	694
1999	694
2000	733
2001	952
2002	1102
2003	1055
2004	1044
2005	1018
2006	1007
2007	1002
2008	935
2009	904
2010	845
2011	865
2012	826
2013	831
2014	805
2015	680
Tot.	17194

Sector	%
Food	12.77%
Textile	14.93%
Chemicals	11.16%
Minerals	7.67%
Metals	41.57%
Others	11.90%

Geo.Area	%
NW	28.71%
NE	23.39%
CEN	22.61%
SOUTH	25.29%

Dim. Class	%
50-99	31.84%
100-199	29.30%
200-499	23.54%
500-999	9.00%
1000+	6.32%

Table 2.B2: Composition of the selected sub-sample

classification, most of the firms have from 50 to 99 employees.

Any information in INVIND is self-reported by firm and this may rise some concern about the credibility of this variable but Bank of Italy declares that the survey is carried out by professional interviewers that tend to establish long term relations with firms' manager and investigate in case of non-coherent answers ask a revision to the firm. Moreover, Bank of Italy relies on price variable, together with lots of INVIND information for its official reports.

We conclude this section with some descriptive statistics for the main variables of our analysis.

	p5	p25	p50	p75	p95	mean	sd	skw	kur	obs
g_{it}	-0.28	-0.07	0.01	0.09	0.26	0.01	0.19	-1.26	33.13	17194
$E[g_{it}\|I^F_{it-1}]$	-0.16	-0.02	0.02	0.07	0.21	0.02	0.15	0.02	56.35	17194
g_{it}-$E[g_{it}\|I^F_{it-1}]$	-0.28	-0.09	-0.01	0.05	0.20	-0.03	0.17	-1.28	25.94	17194
p_{it}	-0.05	0.00	0.01	0.03	0.10	0.02	0.06	-1.55	46.02	17194
$E[p_{it}\|I^F_{it-1}]$	-0.04	0.00	0.01	0.03	0.08	0.02	0.04	-0.93	38.82	17194
p_{it}-$E[p_{it}\|I^F_{it-1}]$	-0.07	-0.01	0.00	0.01	0.06	0.00	0.05	-1.21	73.31	17194
m_{it}	-0.20	-0.05	0.00	0.03	0.14	-0.01	0.13	-2.17	43.42	11459
M_{it}	-0.05	0.02	0.05	0.09	0.24	0.07	0.12	-0.56	76.70	11479
R_{it}	0.01	0.03	0.06	0.10	0.23	0.08	0.09	4.85	57.00	11382
R^2_{it}	0.00	0.00	0.01	0.01	0.05	0.02	0.07	37.13	225.77	11382
age_{it}	8	20	33	48	94	38.72	27.46	1.95	9.11	17148
$size_{it}$	54	85	147	316	1190	379	1279	28.14	1205	17194

Table 2.B3: Descriptive Statistics

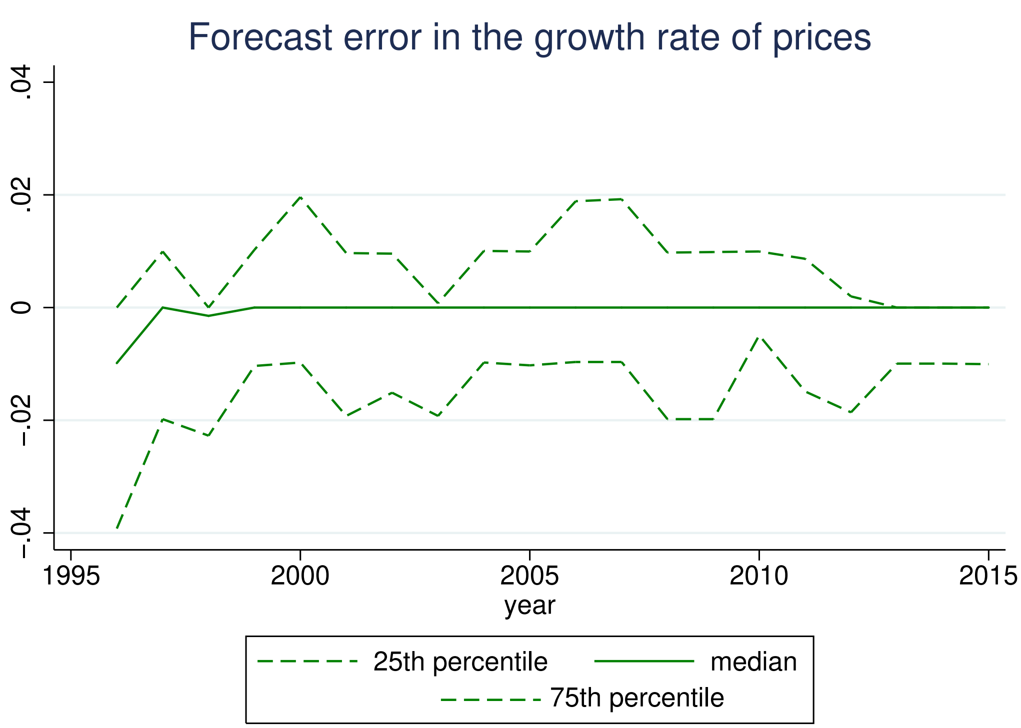
2.C Expectations on growth rate of price

On average firms tend to well forecast prices and the great part of the forecast mistakes regards "quantities" produced and sold.

Time-series of median $E_t[P_{t-1}]$ seems to be an almost perfect predictor for the time-series of P_{t+1}.

Absence of bias in the forecast error: price-setting behavior and/or awareness of future competitive environment.


Growth rate in prices
Expected growth rate in prices
.05
.025
0
−.025
−.05
1995
2000
2005
2010
2015
year
25th percentile
median
75th percentile


Forecast error in the growth rate of prices
.04
.02
0
−.02
−.04
1995
2000
2005
2010
2015
year
25th percentile
median
75th percentile

Chapter 3

Unraveling the determinants of capacity utilization: expectations, uncertainty and market power

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Abstract

According to the European Commission low capacity utilization rates are the main indicator of the low level of investment of manufacturing firms observed in Italy during the crisis. A reduced capacity utilization is typically related to low output growth or even stagnant output, together with inefficient levels of activities of the firm. An adequate level of capacity utilization should stimulate firm's growth and in turn improve firm's performance. The challenge is to specify an economic model which is capable of distinguishing between factors which are exogenous and might affect production and pricing decisions in a similar fashion to actions dictated by strategic consideration. This chapter studies the determinants of capacity utilization by firms by making use of a rich micro-dataset in the form of a panel of Italian manufacturing firms. We find that capacity utilization is negatively affected by the uncertainty faced by the firm, but interesting differences emerge for different sectors and industries. We argue that firms with "high market power" tend to exhibit higher rates of capacity utilization.

3.1 Motivation

Capacity utilization is normally defined as the level of output actually produced, given the capital stock, versus the potential output which could be produced with the same stock of capital: this ratio is expressed in terms of an utilization index varying between zero and one. The economic literature has widely discussed the dimensions of the decisions taken by the firm as the level of inputs to be employed, the level of production as well as the entry/exit decision. However, the choice of capacity utilization is often neglected in economic models and yet could be an important element of firm's health and firm's performance. In fact, the degree of capacity utilization is commonly viewed as an *ex post* equilibrium outcome, combining the potential supply of the firm with actual demand facing the firm: in this line of reasoning it is hard for researchers to identify the determinants of the capacity utilization decision. Furthermore attention has been devoted to the cost of capital and to constraints that may come from the financial institutions as the main sources of rigidity for investment the decision, but this line of argument neglects the fact that may optimally decide to produce below full capacity

Theoretical and empirical studies, that do include the role of capacity utilization, focus on the dynamic features of firm's behaviour or even on their strategic considerations, because standard models may fail to capture the multiple roles that capacity utilization performs. In this landscape, few empirical studies focus on capacity utilization, also due to the lack of data.

According to the European Commission[1] insufficient demand prospects and low capacity utilization are the most important factors associated to low investment in manufacturing in Italy in the year 2014. This survey indicates that there is still a large degree of inefficiency which is unresolved and thus investments are projected to stay low for several years in the future.

In order to provide a complete view of the various approaches adopted in the literature for the investigation of capacity utilization, is important to recall the related concept of "excess capacity". This idea considers a benchmark situation when there is full capacity utilization and the index of capacity utilization is equal to one: when the used capacity is below the limit there exists excess capacity. A number of implications follow: firms operating close to full capacity are more likely to invest in additional capital and/or employ more workers in order to increase their output, and they may also be more likely to decrease the prices of their output. In contrast, when capacity utilization is low (the index is much below one) firms can increase output by more intensively using the labour input and of course capital, hence reducing the excess capacity.

[1] European Commission Investment Survey

The policy implications derived from the standard approach to the behaviour of the firm focused on stimulating investments as the *panacea* to promote growth, but this policy could be ineffective if there is an existing excess capacity or if they are directed to the forms of capital that are more likely to be "stored". If the excess capacity is a standard behavior, expansionary policies are doomed to fail and in turn they may even lead to low levels of competitiveness.

In this chapter, we focus on two main factors that affect the capacity utilization rate (and excess capacity) and which have been partly neglected in the literature.

Firstly, firms take decisions under uncertainty: they decide how much to invest and how many workers to hire before the realization of relevant shocks, but it should be stressed that these choices may also exhibit a certain degree of irreversibility. Typically investment decisions are irreversible, but in many cases even hiring and firing decisions when the firm is operating in union-covered sectors may be quite irreversible (Bertola (2000)). If there is uncertainty about productivity and demand, having excess capacity may be a buffer for firms that can thus respond to shocks. In other words, capital utilization is easily adjusted in the short-run, with relatively low adjustment costs, while capital stock is adjusted only in the long-run with relatively high adjustment costs.

Second, in imperfectly competitive markets, excess capacity may represent a barrier to new entrants, because it represents a commitment device to flood the market with products at lower prices, leading the entrant firm to make negligible profits.

The theoretical literature has strongly emphasized these two aspects, starting from the seminal work by Spence (1977), who recognized that in a non-perfectly competitive framework limit pricing becomes a credible deterrence strategy when the incumbent firm is able to make an ex ante and irrevocable investment in production capacity. The excess capacity allows firms to expand output and reduce price when entry is threatened, thereby reducing the potential profits of the new entrant, who will operates in the residual zero demand curve. Following this line, Dixit (1980) offered a complete model in which such strategic behavior emerges as a sub-game perfect equilibrium.

Turning to the empirical implications of these models Pindyck (1990), Dixit and Pindyck (1994) and Maskin (1999) show that leading firms need to employ a larger amount of capital to deter entry when demand is more uncertain. Moreover, there is an option value in procrastinating investment when managers have concerns about the durability of any observed sustained demand: since investments have an irreversible nature, waiting may be valuable as additional time provides managers with the option to collect more information and reduce the down-side risk of the investment. The contribution of Lieberman (1987) can be seen as a first attempt at testing the theoretical predictions by Spence and Dixit. He examines excess capacity barriers to entry and investment dynamics in chemical products industries: his results show that, in contrast with the predictions of the theory, holding excess capacity as entry barriers is not very common in practice. In fact, incumbents rarely build excess capacity in the effort to deter entry (pre-empting behaviour) and, in general, entrants and incumbents exhibit similar investment behavior. Nevertheless, significant excess capacity is held by firms in order to accommodate demand shocks and investment variability.

The work by Ambrose et al. (2016) corroborates the results by Pindyck and Maskin by studying investments in real estate. Ambrose et al. find that high level of capital in the form of real estate are positively related with industry concentration and negatively related with demand uncertainty. The central point of the paper is that investments in strategic corporate capital have a stronger entry-deterrence effect when uncertainty is modest, as in this case investments represent a convincing signal of the firm's commitment to increase production. Uncertainty in the demand schedule faced by the firm is a confounding factor, because there are competing effects implied by fluctuations in demand. On the one hand, the the effect of demand uncertainty on the level of investments is related to the probability of experiencing negative (large) shocks that generate high losses and therefore make the investment less appealing. On the other hand, uncertainty about demand has also effects on the degree of competition (and concentration) for the the industry at large, because higher uncertainty is related to a higher probability of experiencing a large positive demand shock, that in turn encourages entry of new firms. The net effect for each firm is not clear ex ante.

This chapter provides new evidence on the role of excess capacity, trying to disentangle the strategic motive of holding excess capacity from the "buffer stock" motive, due to uncertainty in demand and productivity. The empirical literature on these issues is very limited, mostly due to the intrinsic difficulty of generating reliable measures of excess capacity. Indeed, much of the existing literature on capital utilization focuses on specific sectors or industries, for which measures of capacity utilization are more readily available. As an example, Bell and Campa (1997) study the chemical processing industry and find that volatility in product demand has no effect on capacity utilization, while Hubbard (2003) shows that the use of on-board computers reduces demand uncertainty, raises capacity utilization and thus productivity in the trucking industry. A paper which is particularly relevant by Escobari and Lee (2014) investigates the relationship between demand uncertainty and capacity utilization in the US airline industry: the authors present a simple theoretical model, supported by panel data estimates, and show that an increase in the standard deviation of unexpected demand (demand shocks) has a strong negative effect on capacity utilization.

We are aware that the role of excess capital as entry deterrent is likely to be found in a

very limited number of industries and that this justifies empirical studies cried out for specific sectors of the economy[2], but, concerning the relationship between capacity utilization and uncertainty, we argue that these "case-studies" show the difficulty to generate homogeneous measures of capacity utilization across all sectors. The availability of an homogeneous measure of capacity utilization will allow us to partly overcome this limitation, studying how uncertainty affects capacity utilization in both the overall Italian Manufacturing industry and into the single sectors. In doing this, it is impossible not to consider strategic behaviour as a variable that may affects capacity utilization.
Our simple model will allow to gain a better understanding of the determinants of capacity utilization across and within sectors that, as we will see later, can be the basis for further research in both empirical and economic policy terms.

The rest of the chapter is organized as follows: in Section (3.2) we present the model and argue that this represents a novel approach to the literature; in Section (3.3) and (3.4) we present the basic features of the dataset that is used in the empirical application along with the definition of the relevant variables. Section (3.5) provides a thorough discussion of the set up of the model while Section (3.6) presents the results . We provide some concluding remarks in Section (3.7).

3.2 The INVIND data and the measures of capacity utilization

The aim of this chapter is to gain a better understanding of the different factors affecting capacity utilization and the role played by capacity utilization in the decisions of the firm. We propose a common set up to consider jointly expectations by firms and their exposure to demand uncertainty as well as the role of market power as determinants of capacity utilization rates.

We exploit detailed information provided by the sample of the Inquiry into Investment of Manufacturing Firms ('Indagine sugli investimenti delle imprese manifatturiere', henceforth INVIND), a survey collected in the form of a panel every year since 1984 by the Bank of Italy. This survey contains a very rich set of information about Italian industrial firms, in particular it contains information on the level of installed technical capacity and

[2] For example, Mathis and Koscianski (1997) found that excess capacity appears to diminish the probability of firm entry into the US titanium industry while Cookson (2017), studying the American casino industry, found that investments with deterrence objective are more likely especially when new entrants are facing also significant other barriers to entry.

the utilization rate, measures of output and inputs, plus prices.

The key variable is a self-reported measure of capacity utilization, which allows us to make use of a homogeneous measure of capacity utilization for all the sectors covered by the survey. This feature overcomes one of the major problems faced by previous studies which had to impute the degree of capital utilization at the industry/sector level or, at the other extreme, rely on a narrow industrial sector where capacity utilization could be measured in a direct way.

The INVIND questionnaire provides a detailed explanation of the "rate of capacity utilization", precisely firms are ask

What is the percentage ratio between the production effectively realized and the maximum production you could achieve?

so that the basic definition is the same for all firms and we are not facing the obvious measurement problem based on filtering techniques as highlight by Ray (2013). Moreover, our study can provide some insight also the macro-level in order to to better describe the dynamics of capital utilization and of the output gap (Crosilla et al. (2014)).

Another key characteristic of this dataset is that for important variable concerning expectations are available, in particular we will focus on expectation about future rate of real sales and uncertainty about that. At the best of our knowledge we are the first to consider expectation as a determinant of capacity utilization rate and even if there are some other works linking uncertainty and capacity utilization, our measure of uncertainty owns the advantage to be firm-time-variant, so it express variability in aggregate and idiosyncratic shocks at which firms are subject to.

The INVIND survey contains a very rich set of information about industrial and service firms: standard descriptive variables, the level of employment, the level of investments (realized and projected), turnover, technical capacity, capacity utilization etc. The sampling frame is such that the reference population of industrial firms is stratified and, from each stratum, a sample of firms is randomly selected. Stratification is based on a combination of sector of activity, class size (in terms of number of employees) and regional location of the headquarters of the firm.

The resulting panel, covering twenty years, is unbalanced: it is generated starting from a first contact with the firm, once selected the firms is contacted again in the following year and in all the subsequent years, unless they loose eligibility. If a firm is no longer willing to participate, it is replaced by a similar one in terms of economic activity and size class. It is important to stress that a firm is regarded as non-eligible (it is not part of the reference population) in case of liquidation or bankruptcy, in case of merger or because the firm is no longer eligible in terms of sector or class size. This selection mechanism suggests particular care in analyzing the data as the final sample could be affected by non random attrition. Until 1998 INVIND was limited to firms in the manufacturing sector (classification ATECO section D)[3] having fifty or more employees, while as from 1999, the sampling frame has been expanded to the entire industrial sector (excluding building and construction) thus enlarging the sample to include firms operating in the sector of oil refineries, fuels etc...(Ateco subsection DF) and mining and energy electricity, gas and water (ATECO E). As from 2001 the survey has been extended to firms which employ 20-49 workers and then further extended to firms operating in the private non-financial services with 20 or more employees.

Although the basic structure of the survey has been kept basically constant during the years, several small changes have been introduced in particular years, basically just introducing new variables. During the years the number of firms in the sample has grown with the aim to make the survey more representative of the entire population of Italian firms Table (3.21)).

Year	**Sam.**	**Pop.**	**%**	**Year**	**Sam.**	**Pop.**	**%**	**Year**	**Sam.**	**Pop.**	**%**
1988	1.039	12.025	8,64%	1997	1,002	11.792	8,50%	2006	1.838	11.574	15,88%
1989	1.053	11.883	8,86%	1998	998	11.609	8,60%	2007	1.783	11.432	16,60%
1990	1.071	11.739	9,12%	1999	1.107	11.502	9,62%	2008	1.752	11.168	15,67%
1991	1.027	12.041	8,53%	2000	1.428	11.798	12,10%	2009	1.706	10.652	16,02%
1992	993	11.658	8,52%	2001	1.713	12.389	13,97%	2010	1.666	10.119	16.46%
1993	994	11.185	8,89%	2002	1.797	17.509	10,26%	2011	1.748	10.119	17,27%
1994	953	11.037	8,63%	2003	1.848	11.978	15,42%	2012	1.747	9.882	17,68%
1995	996	10.880	9,15%	2004	1.861	11.677	15,94%	2013	1.780	-	-
1996	1.060	11.411	9,29%	2005	1.890	11.516	16,41%	2014	1.803	-	-

Table 3.21: Number of firms in the sample for each year and corresponding reference population

For each year, the column "sample" contains the number of manufacturing firms surveyed in that year, the column "population" contains the numbers of firms of the reference population (source: Bank of Italy: "Indagine sulle imprese industriali e dei servizi. Disegno campionario e metodi utilizzati" February 2016), column "%" the percentage of firms in the sample with respect to reference population

In our study we select only firms with fifty employees or more and we restrict the time-window to the years 1996 to 2016. A firm (observation) is part of our sample if

[3]The ATECO code is a code assigned to the firm in order to uniquely identify the sector of activity

observed for at least two consecutive years, in fact some crucial information about uncertainty can be inferred only for this group of firms [4]. We dropped observations belonging to the non-manufacturing sector (almost 3% of the initial sample) because they became part of the survey only in 1998.

The sample selection generates an unbalanced panel of 17194 observations (2620 firms over 20 years) where on average a firm is observed for six years. The final estimation sample essentially reflects the same characteristics and composition of the original initial sample, but one relevant issue in this chapter is obviously the nature of attrition, which may produce over-representation of some types of firms vis-a-vis other firms. Although firms are replaced by "sister firms" as they exit the panel, the reasons of panel drop-outs may be related to the variables of interest, if for example firms decide not to participate, or if they went bankrupt or in liquidation. Unfortunately INVID does not entail a follow-up question for "reason of exit from the survey" or an interviewer remark on this point, which limits our possibilities to directly control for non-random attrition.

A useful way to organize the data is to rely on the classification by sectors provided by the Bank of Italy, which is based on the aggregation of the two-digit ATECO codes. This gives:

- *"Food"*: food products, beverages and tobacco (ATECO 10,11 and 12);
- *"Textile"*: textile industries, clothing, leather and shoes (ATECO 13, 14 and 15);
- *"Chemicals"*: manufacture of coke, chemical industry, rubber and plastic (ATECO 19, 20, 21 and 22);
- *"Minerals"*: industry of non-metallic minerals (ATECO 23);
- *"Metals"*: metals industry (ATECO 24, 25, 26, 27, 28, 29, 30 and 33);
- *"Others"*: wood industries, furniture, paper and printing (ATECO 16, 17, 18, 31 and 32).

In order to document the nature of the final sample we provide descriptive evidence according to which the attrition rate is high (about 20% per year), but it does not appear to systematically change by sector, size or geographical area.

Table (3.22) shows that the final estimation sample is, on average, equally distributed across the years. The attrition is not particularly evident and, particularly for our purposes, it is not too different in the periods which could correspond to the crisis years when it could be more likely to drop out of the sample (say the years 2007-2009).

[4] the survey for the small firms does not provide the question about uncertainty

Year	**Freq.**
1996	523
1997	564
1998	598
1999	585
2000	647
2001	789
2002	761
2003	810
2004	879
2005	856
2006	873
2007	896
2008	819
2009	765
2010	754
2011	397
2012	452
2013	458
2014	559
2015	687
2016	776
Tot.	14448

Sector	**%**
Food	12.77%
Textile	14.93%
Chemicals	11.16%
Minerals	7.67%
Metals	41.57%
Others	11.90%

Geo.Area	**%**
NW	28.71%
NE	23.39%
CEN	22.61%
SOUTH	25.29%

Dim. Class	**%**
50-99	31.84%
100-199	29.30%
200-499	23.54%
500-999	9.00%
1000+	6.32%

Table 3.22: Composition of the selected sub-sample

Completely in line with the Italian industrial landscape, in our sample the bulk of the firms belongs to the metal sectors, followed by the firms belonging to the textile sector. Firms are mostly located in the North-West geographical area of Italy. In terms of size, firms with a number of employees between 50 and 199 are the modal case.

Another source of concern is due to the self-reported nature of the information contained in INVIND, which like any other survey elicits the information through interviews. However the quality of the data is guaranteed by several points: (i) the survey is carried out by professional interviewers who have established long-term relations with the firm's managers, (ii) the Bank of Italy carries out a close monitoring of the results "in real time" so that any anomaly immediately prompts a "recontact" action with the manager, (iii) the Bank of Italy relies on the INVIND information for its official reports so that there exists also an ex post validity check being carried out. A good reference on this point is the work of Pozzi and Schivardi (2016) who compare the INVIND dataset with official balance-sheets recorded from other sources and find a high level of correspondence.

3.3 The model and the available data

The aim of this chapter is to model capacity utilization taking into account both the uncertainty facing the firm and the role of market power.

The motivation of our work can be described by making use of a typical investment function derived from profit maximization:

$$Max_{\{K_{it};L_{it}\}}\ P_{it}Q_{it} - p_K K_{it} - p_L L_{it}$$

where p_K and p_L are utilization costs of capital and labour, respectively. It is useful to refer to the derivation proposed by Pozzi and Schivardi (2016) in terms of shocks to productivity and shocks of the demand faced by firms. By substituting a Cobb Douglas production function

$$Q_{it} = A_{it}{L_{it}}^{\beta_l}{K_{it}}^{\beta_k} \tag{3.1}$$

and by defining an investment function $i_{it} = f(k_{it};\omega_{it})$ with $\frac{\partial i_{it}(\cdot)}{\partial \omega_{it}} > 0$, which under fairly general conditions is invertible, one gets the productivity shock:

$$\omega_{it} = f^{-1}(i_{it};k_{it}) \tag{3.2}$$

By considering then a demand function in terms of firm-level prices and in terms of a firm-specific shock ψ

$$Q_{it} = Q_{st}(\frac{P_{it}}{P_{st}})^{\sigma} exp(\psi_{it}) \tag{3.3}$$

after applying a log-trasnformation one has a reduced form:

$$\begin{aligned} q^*_{it} &= c_q + \frac{\sigma}{\theta}\omega_{it} + \frac{\beta_l+\beta_k}{\theta}\psi_{it} \\ p^*_{it} &= c_p - \frac{1}{\theta}\omega_{it} + \frac{1-\beta_l-\beta_k}{\theta}\psi_{it} \\ x^*_{it} &= c_x + \frac{\sigma-1}{\theta}\omega_{it} + \frac{1}{\theta}\psi_{it} \end{aligned}$$

in which $\theta = \beta_l + \beta_k + \sigma(1-\beta_l-\beta_k)$, $x = k;l$ and c_q, c_p and c_x are constants. In particular the latter expression represents the demand for inputs as a function of the shocks alone.

It is important in this context to consider the role of capital and investment: we distinguish between used capital K,such that if the rate of utilization is $0 \leq u_{it} \leq 1$ and the installed level of the capital stock is $\bar{K}_{it}$, then $K_{it} = u_{it}\bar{K}_{it}$.

The above model assumes that firms do not operate at full capacity, i.e. the installed capital is not a constraint

$$\bar{K}_{it} \leq c_k + \frac{\sigma - 1}{\theta}\omega_{it} + \frac{1}{\theta}\psi_{it}$$

If we define B the threshold:

$$B_{it} = c_k + \frac{\sigma - 1}{\theta}\omega_{it} + \frac{1}{\theta}\psi_{it} \tag{3.4}$$

then if firms do hit the capital constraint the whole system has to be re-written, as proposed by Pozzi and Schivardi, by taking into account that capital is fixed at $\bar{K}_{it}$. In this latter case the returns to scale are automatically reduced by a factor β_k, so that the parameter θ becomes smaller. This result is saying that the firm has a different response to shocks that it would be the case in the unconstrained case.

This set up provides the intuition of how firms may decide to respond to shocks by considering that they set a proxy for the threshold, say $\tilde{B_{it}}$, whereby the capital constraint would be "almost binding". Once they hit this threshold they would be forced to consider expanding the capital stock in order to expand production. The threshold itself is endogenously determined (based on the capital installed) and it also depends on the parameters of the model as in equation (4) above. In this paper we want to get a better grasp of how the latent variable $\tilde{B_{it}}$ affects the choices of firms: this might help the identification of a strategic behaviour versus a simple response to the shocks. In fact when the firms hits the threshold it is constrained and it has a reduced leverage in using its market power. In order to do so we model capacity utilization so that we can exploit the information on uncertainty facing the firm as well as the role of market power. The key variable is a self-reported measure of capacity utilization, which relates both to the technology of the firm and to the strategic decisions of the firm. In this section we present a set of definitions of the variables we can measure in INVIND and which allow us to build an estimable set of equations capturing the different routes through which capacity utilization may be determined.

Capacity Utilization Variables

In the INVIND survey firms are asked to report the percentage change in productive capacity. The questionnaire makes clear that productive capacity is the maximum possible output obtainable given that the current plants are running at full capacity and that the reported percentage change must depend solely on the purchase and/or sale of plant and machinery and on the plant ceased operating during the year. One way to specify the behaviour of firms which exploits the information provided by the survey is to describe the log-variation in firm's potential output as [5]

$$\Delta pc_{it} = log(PC_{it}) - log(PC_{it-1}) = log\Big(\frac{\%productive capacity}{100} - 1\Big)$$

We define the utilization rate (ur_{it}) as the percentage of utilized capacity utilization directly available in INVIND. Firms answer reporting the percentage ratio between actual production and maximum possible output.

Given that the utilized capacity is equal to the utilized percentage of the total productive capacity ($UPC_{it} = ur_{it} * PC_{it}$), using the previous expressions, we obtain the log rate of growth of the utilized capacity as

$$\Delta upc_{it} = log(UPC_{it}) - log(UPC_{it-1}) = \Delta pc_{it} + log(ur_{it}) - log(ur_{it-1})$$

Given the objectives of this chapter, it is useful to think of ur_{it} as the dependent variable, i.e. the relevant decision of the firm. It is also useful to recall that this measure provides a series of advantages: it allows the researcher to avoid the measurement problem, which affects most empirical studies as it is is elicited directly from the firm, it is also a homogeneous measure across sectors so that we can exploit cross-sectorial variation.

Expectations and Uncertainty Variables

In the INVIND survey the variable "realized total sales" (in thousand of euros) and current prices of the product are available. If we define the variable "sales" as $S_{it} = P_{it} * Y_{it}$, where P_{it} and Y_{it} are the average price and the amount of total real sales realized at time t by firm i, respectively. Moreover, firm are asked to report the percentage change in the total nominal sales (s_{it}) with respect to the previous year. That is $(\frac{S_{it}}{S_{it-1}} - 1) * 100$. Firm-level price information is available only in percentage terms: firms are asked to report the average percentage growth rate in prices of goods and/or services sold. We refer to this variable as

[5] All the following variables expressed in percentage points are transformed in log-variations in the same way.

p_{it}. We can then compute one key variable: the realized rate of growth in real sales:

$$g_{it} = s_{it} - p_{it}$$

The important novelty of this chapter when comparing with the previous papers, is that firms are also asked to provide a forecast of total nominal sales expected for next year and to provide the expected growth rate of nominal sales with respect to current realized sales, we refer to this as $E_t[s_{it+1}]$. Furthermore firms are asked to give a forecast for the expected average percentage change of prices for next year ($E[p_{it+1}|I_{it}^F]$), plus the expected percentage change in real sales as the difference between expected growth rate of nominal sales and expected average percentage change of prices. In our notation this is

$$E_t[g_{it+1}] = E_t[s_{it+1}] - E_t[p_{it+1}]$$

These two variable can be used to generate a forecast error defined as

$$err_{it} = g_{it} - E_{t-1}[g_{it}]$$

Interesting enough, firms are also asked to *"give a range, i.e. a forecast of minimum and maximum rate of growth of sales adjusted for changes in prices"*. We argue that, when faced with this question, each firm forms expectations having 'in mind' a distribution of possible future realization of g_{it+1}. Even if this distribution is unknown to us, we can recover quantile-based proxies for this distribution assuming that the minimum and the maximum rate of growth of real sales provided by the firms are respectively the minimum (m_{it}) and the maximum (M_{it}) quantile of the unknown distribution.

Under this assumption, we can recover a self-reported uncertainty measure

$$UNC_{it} = M_{it} - m_{it}$$

Our measure of uncertainty has a series of advantages. The first one is that it allows to evaluate perceived uncertainty by each firm in every year, this is an important feature of the model because we have a direct measure of a time-variant idiosyncratic shock. A second feature of the data is that, if the growth rate of real sales represents the result of the equilibrium outcome, firm's expectations about future growth rate of real sales embed both expected shocks from the production side as well as shock from the demand side. As a consequence, our measure of uncertainty can be read as the perceived variability, i.e. some function of both demand and productivity shocks.

Market Power Variables

One way to think about market power is to consider the ability of a firm to raise the market price of a good or service over marginal cost. In order to measure this actions, or at least infer these actions, one needs data about prices of sold goods and about cost functions. Unfortunately, INVIND does not contain information about costs, which prevents us from applying a direct a measure of the "mark-up". However, we can use a proxy of market power based on profits: we rely on the simple intuition that a firm can exert significant market power, its prices should exceed marginal costs and the firm should make profits.

In INVIND, firms are asked to describe the margins ("risultato operativo") realized during the year and they can choose between five options: large profit, small profit, broad balance, small loss or large loss. We therefore generate five dummy variables $dum{-}pro1$ to $dum{-}pro5$ in order to classify firms according to the level of profits that they report: firms for which $dum - pro1 = 1$ are the ones answering large profit, firms for which $dum - pro2 = 1$ are the ones answering small profit and so on. We argue that profits dummies generated in this way are a good proxy for market power and also they allow us to overcome the usual problem of estimating market power through the Herfindahl-Hirschman Index (HHI) which relies heavily on the definition and the boundaries of the market. We assume that each firm faces a given market and that the profits that it realizes are proportional to the market power that it has in that market.

In order to provide further evidence on the quality of the data, particularly for the variables of interest, the recorded productive capacity and utilization rate have been analyzed by Locatelli et al. (2016) who compare data from INVIND with the official data collected by ISTAT, used for the official reports by the European Central Bank: they also find high conformity as shown in Figure (3.31).

Table (3.31) contains descriptive statistics for the variables of interest, plus information about the "age" of the firm and the size in terms of number of employees. Two important features are worth discussing: (i) the average utilization rate is around 80%, (ii) there exists important variability in the utilization rate, particularly across sectors, to the point that a few firms report operating close to total utilization (3.32)). The former result suggests that operating under the limit of full utilization is an explicit decision of the firm, while the latter seems to suggest that different sectors have different technical and/or strategic considerations in choosing the level of utilization (look at Table (3.32)).

Sectorial differences in utilization rates are also evident if we analyze the average temporal trend by sector. Table (3.33) shows that the general trend is negative especially due to the fact that after the drop during the crises the utilization rate does not go back to its original average. This is very evident in all sectors with the exceptions of the Food one that seems to be pretty stable.

	p5	p25	p50	p75	p95	mean	sd	skw	kur
Δpc_{it}	-0.040	0	0.009	0.058	0.182	0.037	0.100	0.565	41.7
ur_{it}	0.35	0.7	0.8	0.9	0.98	0.79	0.136	-1.163	5.638
Δupc_{it}	-0.267	-0.022	0.019	0.103	0.316	0.031	0.246	-1.81	76.05
g_{it}	-0.28	-0.07	0.01	0.09	0.26	0.01	0.19	-1.26	33.13
$E[g_{it}]$	-0.16	-0.02	0.02	0.07	0.21	0.02	0.15	0.02	56.35
FE_{it}	-0.28	-0.09	-0.01	0.05	0.20	-0.03	0.17	-1.28	25.94
UNC_{it}	0.01	0.03	0.06	0.10	0.23	0.08	0.09	4.85	57.00
age_{it}	8	20	33	48	94	38.72	27.46	1.95	9.11
$size_{it}$	54	85	147	316	1190	379	1279	28.14	1205

Table 3.31: Descriptive Statistics

	Food	Textile	Chemical	Mineral	Metal	Other
Δpc	0.047	0.017	0.039	0.031	0.041	0.041
	(0.099)	(0.104)	(0.087)	(0.112)	(0.101)	(0.098)
	-0.69 1.10	-2.30 0.70	-0.69 0.69	-0.75 0.69	-1.20 0.72	-0.69 0.72
ur	0.78	0.81	0.77	0.78	0.79	0.80
	(0.135)	(0.131)	(0.145)	(0.151)	(0.133)	(0.126)
	0.01 1	0.07 1	0.1 1	0.3 1	0.3 1	0.09 1
Δupc	0.045	0.047	0.029	0.012	0.036	0.039
	(0.220)	(0.229)	(0.246)	(0.277)	(0.238)	(0.203)
	-4.52 1.87	-4.61 1.47	-4.37 2.15	-2.99 1.95	-3.42 3.71	-2.07 2.23
$M_{it} - m_{it}$	0.071	0.083	0.079	0.085	0.097	0.081
	(0.361)	(0.086)	(0.111)	(0.0781)	(0.114)	(0.097)
	0 14.95	0 1.58	0 3.21	0 0.9	0 2.63	0 2.19
g_{it}-E[g_{it}]	-0.020	-0.036	-0.017	-0.025	-0.024	-0.029
	(0.140)	(0.162)	(0.141)	(0.162)	(0.185)	(0.148)
	-2.19 1	-2.18 1.24	-0.94 1.17	1.25 1.20	-1.25 2.23	-1.34 1.61
Obs.	1,747	2163	1633	1030	5909	1677

Table 3.32: Descriptives Statistics by sector

For each variable and sector, we report sample mean and standard deviation between brackets. In the third line of each "box" minimum and maximum values are reported.

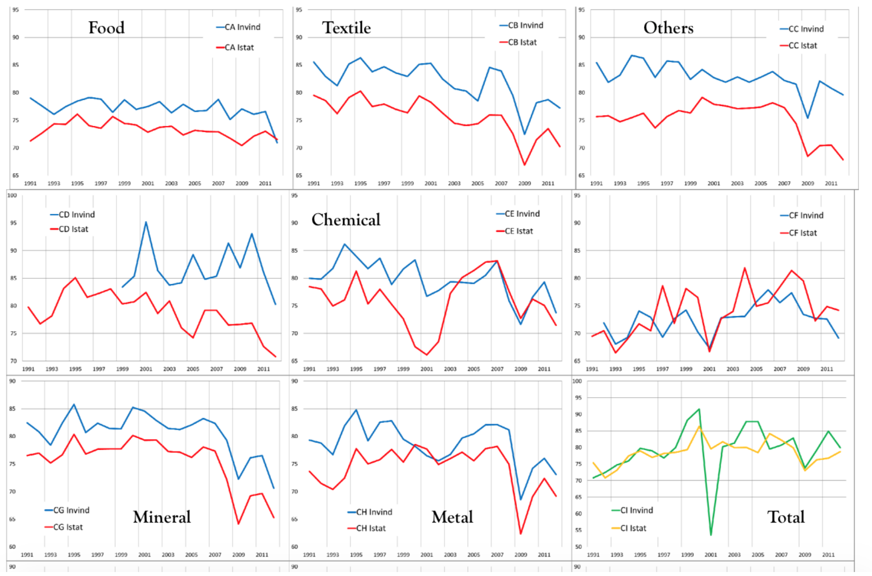

Figure 3.31: Average Utilization Rate by sector from INVIND and ISTAT data

Source: Locatelli, Monteforte, and Zevi (2016)

Thefact that after the crises firms do not recover the original level of capacity utilization seems to be directly translated to the investment in productive capacity. Figure (3.34) highlights a decrease in productive capacity growth rate during the crisis. After the crises there is a recovery but not to the original average.

Figure(3.33) shows that the general trend is negative, especially due to the fact that after the crises, when we observe a "natural" decline of the utilization rate, the utilization rate does not go back to the original trend.This is evident in the whole manufacturing industry in Italy, with the exceptions of the Food industry, that appears rather stable overtime.

The observation that,after the crises,firms do not restore the original level of capacity utilization, seems to point to a reduction in the investment in productive capacity. Figure(4) shows a decrease in the growth rate of productive capacity during the crisis which is not followed by a pattern of recovery.The other important player in our analysis is the uncertainty faced by firms: Figure (3.35) shows the median percentage variation of the uncertainty variable, defined as uncertainty about the growth rate of real sale, over the sample period. A substantial increase in uncertainty is observed just within a few years: the average percentage variation increases from about 0.07 percentage points for the pre-crisis period to just about 0.10 percent in 2008, it goes back to 0.05 percentage points in 2011. Interesting to note that, even if the central moment of the uncertainty measures reverts to the general pre-crisis values,

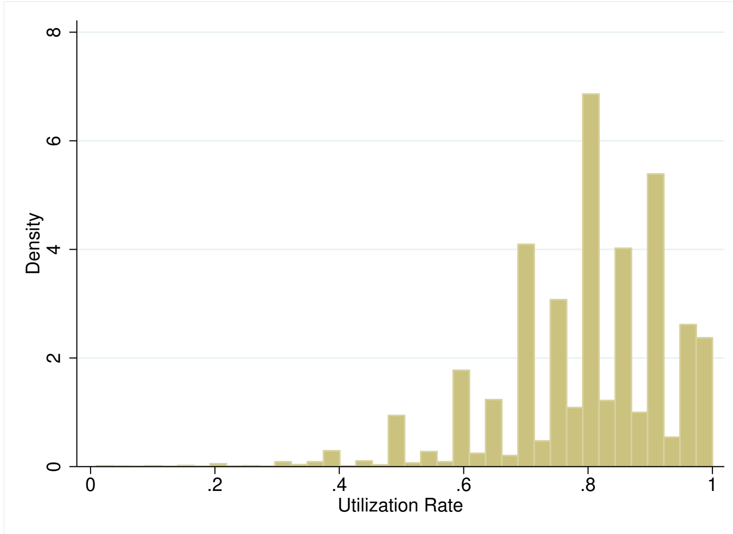

Figure 3.32: Utilization Rate sample distribution

volatility stays high throughout the sample period: it could be argued that uncertainty exhibits a counter-cyclical pattern,as also discussed by Bloom(2009).
A comparison between Figure (3.34) and Figure (3.35) also suggests that uncertainty and productive capacity growth are negatively correlated, although the different scale adopted for the two variables is somewhat blurring the results which do require a more careful econometric methodology.

Turning the attention to the rate of capacity utilization, prima facie evidence suggests a negative correlation between the utilization rate and the uncertainty measure (Figure(3.37)): lower utilization rate seems to be associated with high level of uncertainty about the future as directly reported by firms. This is an interesting correlation as it lends support to the commonly held view that uncertainty has a strong impact on the decision of the firm, which tends to stretch the use of capacity when the outlook is a stable one.

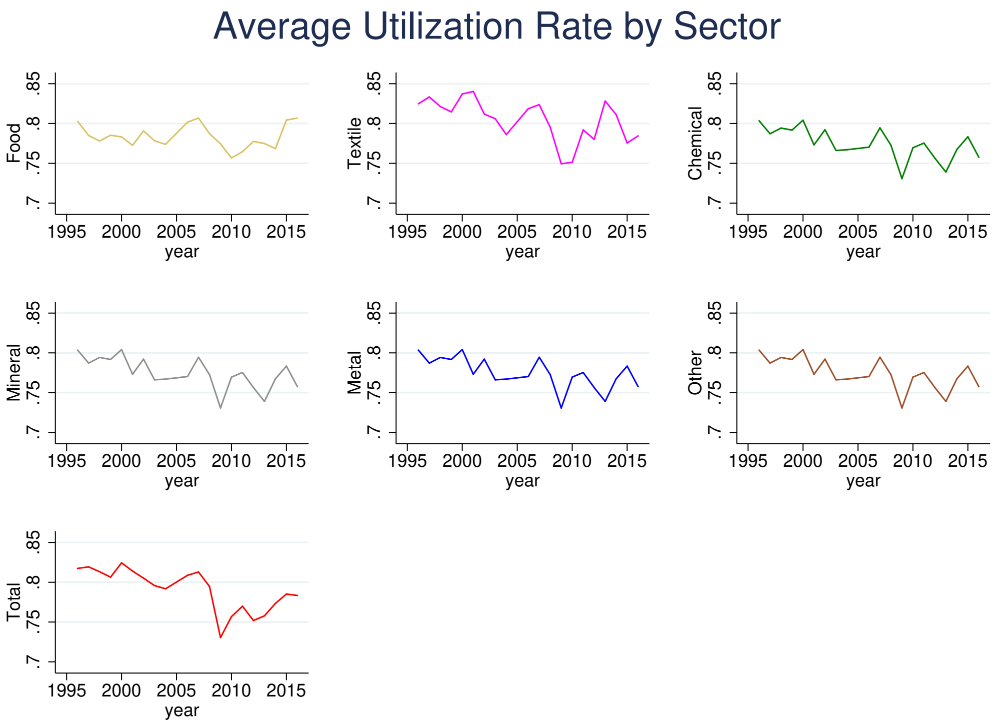

Figure 3.33

	Freq.	Percent
Large Profit	3042	21.00
Small Profit	6810	47.00
Broad Balance	1883	13.00
Small Loss	1594	11.00
Large Loss	1159	8.00
Total	14488	100.00

Table 3.33: Sample distribution by Market Power Level

Analyzing the utilization rate according to different level of self-reported profits,it seems that firms characterized by“higher market power” are also using an higher percentage of the installed capital: Figure(8) shows that firms characterized by higher levels of market power systematically exhibit higher levels of the capacity utilization rate.

	Large Profit	Small Profit	Broad Balance	Small Loss	Large Loss
ur_{it}	0.82	0.79	0.76	0.74	0.69
	(0.127)	(0.128)	(0.138)	(0.151)	(0.180)
Δpc_{it}	0.052	0.051	0.043	0.036	0.012
	(0.095)	(0.111)	(0.133)	(0.115)	(0.158)
Δupc_{it}	0.053	0.047	0.028	-0.007	- 0.046
	(0.199)	(0.236)	(0.226)	(0.281)	(0.365)
Obs	3042	6810	1883	1594	1159

Table 3.34: Descriptives Statistics by Market Power Level

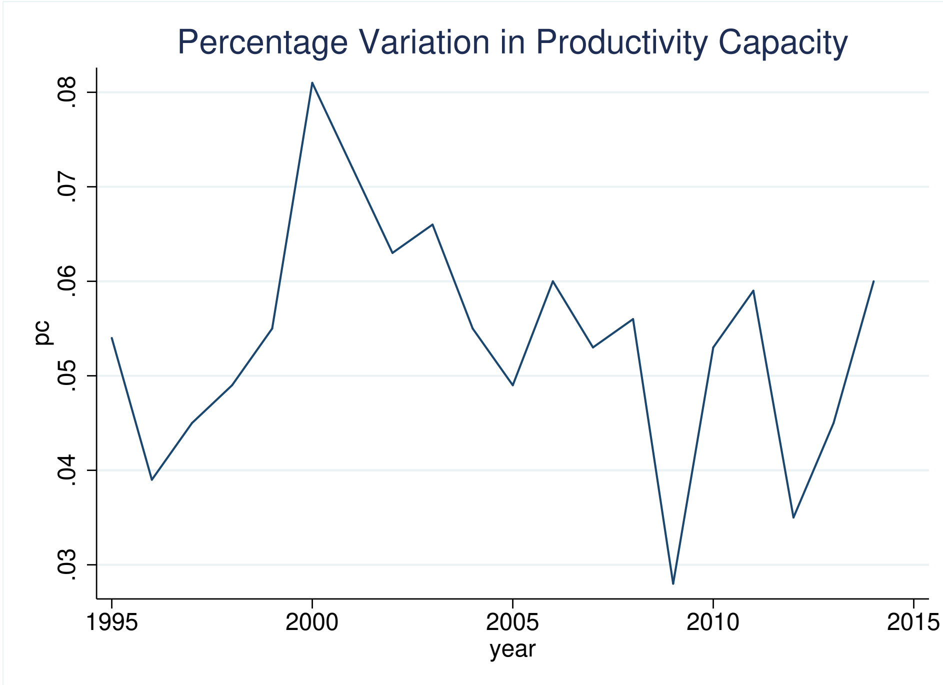

Figure 3.34: Average percentage variation on productive capacity
(mean of Δpc_{it} by year)

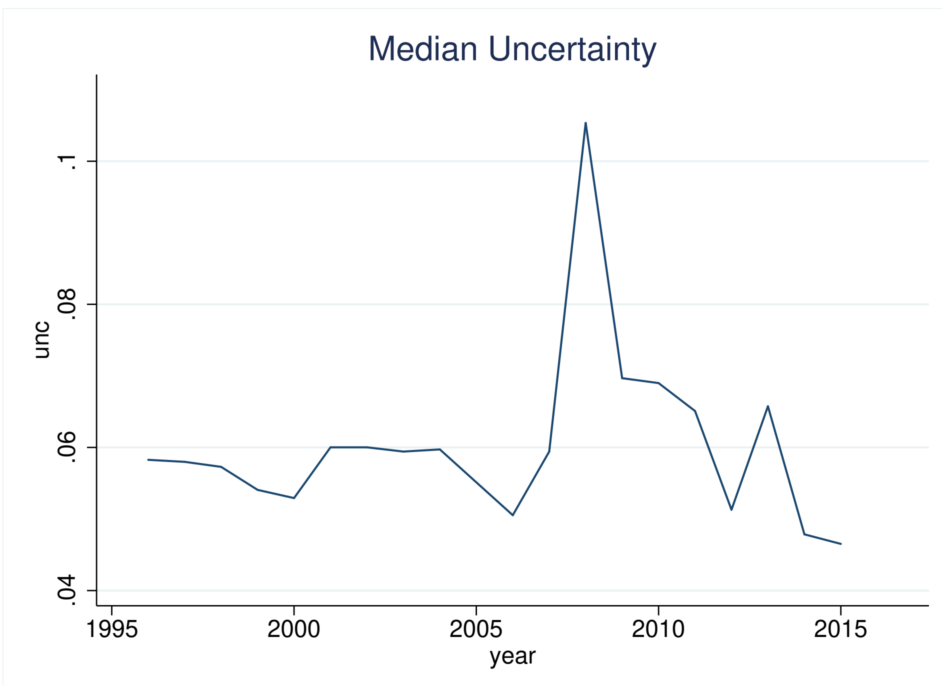

Figure 3.35: Median uncertainty
(median of UNC_{it} by year)

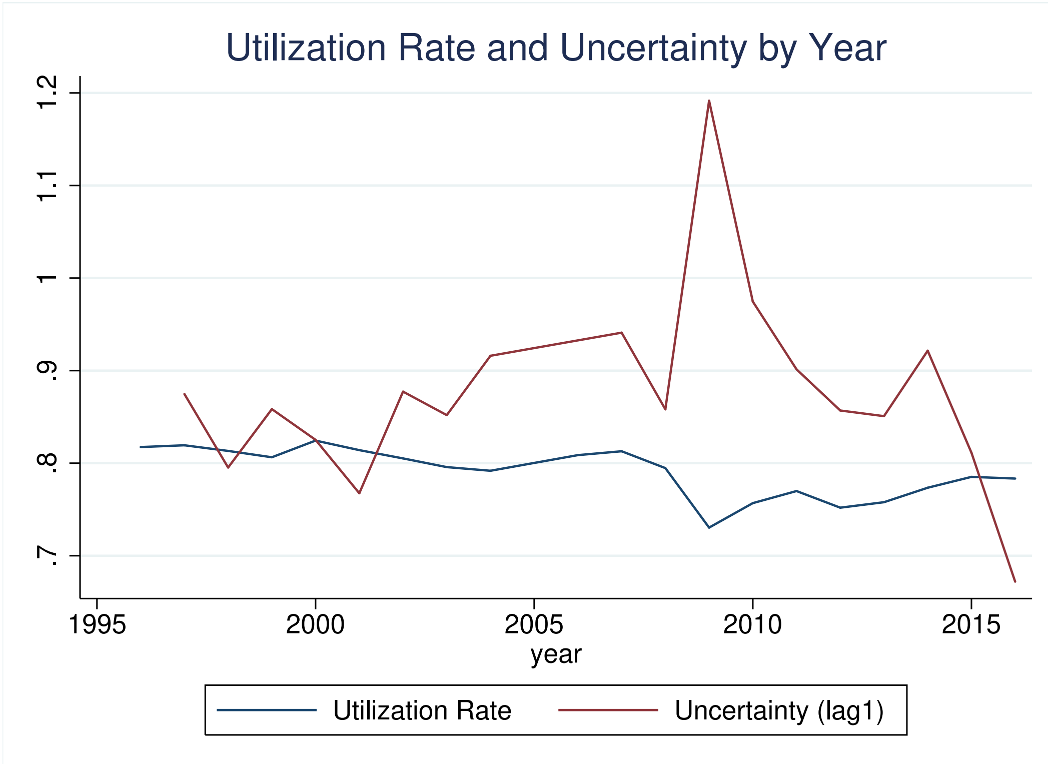

Figure 3.36

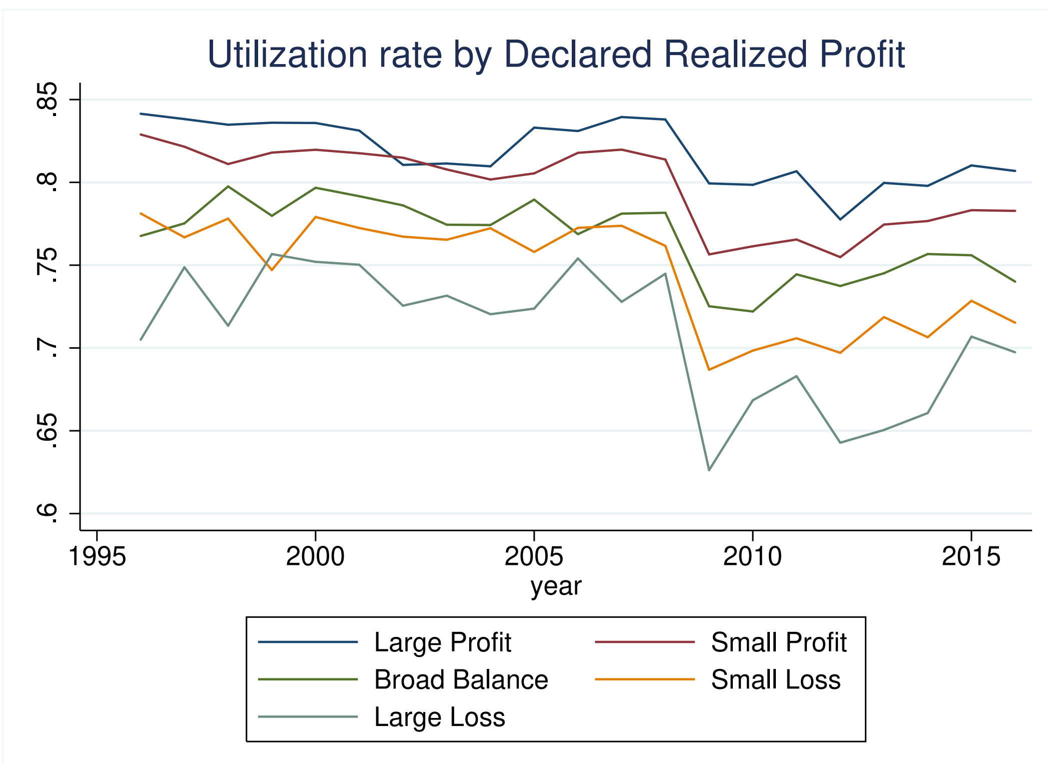

Figure 3.37

3.4 Econometric Specification and Results

The descriptive analysis presented in the previous section highlights two main points: high uncertainty about future growth rate of real sales leads to lower utilization rates and firms characterized by high levels of market power (large profits) are the ones which exhibit high utilization rates. Sectorial differences in utilization rates are also evident if we analyze the average time-trend by sector. In the light of these considerations we present an econometric specification which attempts to use the information provided in INVIND to separate the different reasons of the capacity utilization decision by firms. Given the panel nature of the data we implement a Fixed Effect estimation methodology, using as dependent variable directly the self-reported rate of capacity utilization.

The above considerations suggest that the main drivers and the main trade-offs of our model are: (i) high uncertainty about future growth rate of real sales is associated to lower utilization rates and (ii) firms characterized by high market power (large profits) exhibit higher utilization rates with respect to the rest.

Hence we propose the following specification:

$$ur_{it} = \beta_1 err_{it} + \beta_2 UNC_{it-1} + \beta_3 err_{it} UNC_{it-1} + \beta_4 dum - pro_{it} + \gamma X_{it} + \tau_i + \tau_t + \epsilon_{it} \quad (3.5)$$

In order to evaluate the effect of the expectation and uncertainty in the determination of the utilization rate of capacity, we use the measure of uncertainty UNC defined above, together with the forecast error. The intuition is that the capacity utilization rate is a short-run decision that firms take in order to face shocks and therefore there must be an ex post correlation with the forecast error which captures the unexpected part of the shocks. Concerning the sign of β_2 this is ambiguous because, on the one hand the theory suggests that a high level of uncertainty should be related to a high level of investment in productive capacity, so that the firm is well equipped to face productivity and demand shocks, but, on the other hand, if investment in capacity are highly irreversible, high uncertainty can curb investment because as a result of a wait-and see strategy. We expect that positive forecast errors (unexpected positive shock in the real growth rate of sales) should affect positively the utilization rate and that this effect is exacerbated by uncertainty. In the equation specification (1) we expect the sign of the interaction term to be dominated by the sign of the β_2: if uncertainty has a negative effect on the growth rate of productive capacity it should have a positive effect on the utilization rate if interacted with a positive forecast error.

As for the effects of market power and excess capacity, according to the theoretical predictions, the sign of β_4 should be negative : firms characterized by market power should exhibit lower rate of capacity utilization due to the fact that unused capacity is the key element to preserve low level of competition. A positive β_4 could instead indicate a modest or even absent strategic behavior by firms. In such a case firms with high market power are able to obtain high profits also thanks to the ability to use capacity and reduce slacks. Table (3.41) presents the estimated coefficients of our estimates carried out by making use of a Fixed Effect estimator: these are quite stable, even when controlling for a complete set of firms characteristics as well as for a time trend. The main result is that the correlation between the capacity utilization rate and the lagged values of uncertainty is negative and very strong: firms which face high uncertainty today tend to exhibit low levels of capacity utilization tomorrow. This confirms the intuition that firms can use excess capacity in order to face uncertainty both from the demand side and from the production side. Capacity utilization does not seem to strongly depend on the unexpected shocks: the forecast error and its interaction are not significant. This can be interpreted as a signal of the fact that, even if in general capacity utilization is a "short run decision", firms do not adjust capacity utilization, probably because of adjustment costs. Note that we tried specifications using lags of the forecast error which delivered the same result. As for market power, firms with high level of profits (our proxy for market power) exhibit high level of capacity utilization: excess capacity does not seem to be the route through which firms are able to maintain low levels of competition and high profits. In other words, the evidence points to a lack of strategic behavior so that high profits are obtained by those firms which are able to operate close to full capacity.

Table (3.42) contains the estimated coefficients for the same model where we split the sample by sectors. If on the one hand the relationship between market power (in terms of profits) and capacity utilization is homogeneous across sectors, on the other hand the relationship between uncertainty and capacity utilization is very strong for the textile sector, significant but weak in the food sector and not significant for the other sectors. A prima facie explanation is that these sectors are more inclined to respond to shocks than the other sectors, however this result deserves further investigation which we plan to carry out in future research.

	(1)	(2)	(3)
α	0.72***	0.623***	0.608***
	(0.011)	(0.017)	(0.019)
err_{it}	-0.003	-0.001	-0.002
	(0.003)	(0.003)	(0.003)
UNC_{it-1}	-13.541***	-12.520***	-13.254**
	(3.578)	(3.568)	(3.578)
$err_{it} * UNC_{it-1}$	1.771	0.704	0.486
	(2.603)	(2.586)	(2.587)
$dum - pro1$	0.129***	0.117***	0.115***
	(0.012)	(0.012)	(0.012)
$dum - pro2$	0.111***	0.101***	0.100***
	(0.011)	(0.011)	(0.011)
$dum - pro3$	0.076***	0.065***	0.065***
	(0.013)	(0.012)	(0.013)
$dum - pro4$	0.057***	0.046**	0.045***
	(0.011)	(0.013)	(0.013)
X_{it}	no	no	yes
$dum - time$	no	yes	yes
Obs	14448	14448	14448

Table 3.41: Estimated coefficients model (1)

	Food	Textile	Chemical	Mineral	Metal	Other
α	0.71***	0.67***	0.73***	0.69***	0.72***	0.74***
	(25.50)	(25.89)	(23.85)	(25.92)	(30.21)	(26.95)
err_{it}	-0.005	-0.014*	0.003	0.008	-0.003	-0.0115
	(-0.72)	(-1.92)	(0.36)	(1.19)	(-0.44)	(-1.50)
UNC_{it-1}	-17.56*	-19.50**	-14.10	-0.25	-13.73	-11.48
	(-1.72)	(-2.42)	(-1.48)	(-0.03)	(-1.54)	(-1.23)
$err_{it} * UNC_{it-1}$	7.866	4.912	-2.395	-7.776	3.625	4.470
	(1.04)	(0.80)	(-0.40)	(-1.26)	(0.52)	(0.62)
$dum - pro1$	0.115***	0.174***	0.115***	0.141***	0.125***	0.101***
	(3.77)	(6.11)	(3.53)	(5.04)	(4.68)	(3.50)
$dum - pro2$	0.122***	0.161***	0.0851***	0.119***	0.0998***	0.0851***
	(4.35)	(5.94)	(2.83)	(4.41)	(4.04)	(3.11)
$dum - pro3$	0.0932***	0.131***	0.0638*	0.0947***	0.0506*	0.0380
	(2.85)	(4.25)	(1.82)	(3.12)	(1.81)	(1.21)
$dum - pro4$	0.0521	0.141***	0.00927	0.0694**	0.0430	0.0312
	(1.62)	(4.27)	(0.26)	(2.26)	(1.42)	(0.97)

Table 3.42: Estimated coefficients model (1): sample split by sector

3.5 Conclusions and further extensions

Capacity utilization by firms is an important indicator of the strength of demand and possibility of their growth prospects. Indeed policies aimed at increasing capacity utilization seem to have a positive effect on reducing the excess capacity and even stimulating new investments.

In this chapter we trey to understand which are the determinants of the decision of capacity utilization by firms. To do so we make use of self-reported capacity utilization rate provided by a the INVIND Surevy carried out by the Bank of Italy. We analyze a panel of Italian manufacturing firms and exploit the unique information provided by the survey on a number of characteristics, choices made by the firms and their expectations. We find that low levels of capacity utilization are strongly associated with high level of uncertainty (one period ahead) and that firms characterized by higher levels of profits tends to exhibit high utilization rates.

Even if we do not find a significant role for expectations in term of the forecast error, our results suggest that excess capacity is a powerful tool for firms in order for them to face shocks both from the demand side and the productivity side. Another notable result of our analysis is that we deviate from the theoretical predictions of the Spence model and the Dixit model, more in line with the empirical findings of Lieberman (1987): firms do not seem to use excess capacity to deter entrance, but rather high market power (in our data high profits) are obtained by firms that operate close to full capacity. Hence the uncertainty explanation seems to dominate the scene. When we carry out estimates at the sector level, we find that capacity utilization is positively correlated to high profits in a homogeneous way across sectors, but this relationship is strong in the food sector and in the textile sector, while it is non significant in the other sectors. The latter is a very interesting result which deserves further investigation.

Despite the fact that we found high level of negative correlation between uncertainty and capacity utilization, our specification does not allow to discover the channel through which this relationship works. Specifically, it could be a direct effect: uncertainty (especially from the demand side) can reduce probability to sell products and, as a consequence firms use less capacity utilization to avoid overproduction but also an indirect one: the relationship works through the effect of uncertainty on investment.

We are going to investigate this by enriching our model using a threshold investment model that will allow us to identify firms that answer to shocks considering uncertainty and cost of capital. We are going to rely to the stream of literature that since Guiso and Parigi (1999) and Bontempi et al. (2010) until Melolinna et al. (2018) studies the effect of uncertainty on investment and we are going to relate it to capacity utilization.

Moreover, we are planning to enrich our work with additional information on the fiscal advantages enjoyed by firms, this is a new piece of information that we just obtained from the Survey INVIND (also self-reported), which would allow us to gain a better understanding of the profits variable. This will provide further evidence as to weather firms use excess capacity in order to smooth production in the face of shocks.

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