UNIVERSITY OF TRENTO

SCHOOL OF SOCIAL SCIENCES
PHD PROGRAM IN ECONOMICS AND MANAGEMENT

DOCTORAL THESIS

INNOVATION, MANAGEMENT AND PUBLIC POLICIES:

Three Essays on Firm Productivity and Efficiency Analysis

A DISSERTATION SUBMITTED TO THE DOCTORAL SCHOOL
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY (PHD)
IN ECONOMICS AND MANAGEMENT

Author:
Enrico Tundis

Supervisor:
Prof. Enrico Zaninotto

Co-Supervisor:
Prof. Roberto Gabriele

April 2014

SUPERVISOR:

Prof. Enrico Zaninotto
University of Trento

CO-SUPERVISOR:

Prof. Roberto Gabriele
University of Trento

DOCTORAL COMMITTEE:

Prof. Stefano Azzali
University of Parma

Prof. Flavio Bazzana
University of Trento

Prof. Howard Gospel
King's College London

Prof. Enrico Rettore
University of Padova

Acknowledgements

First and foremost, I am grateful to my supervisor, Enrico Zaninotto. He encouraged me since the beginning of my PhD and provided essential advices and insightful discussions about my research throughout the years. He always allowed me the freedom and independence to pursue the final goal of the thesis. I would also like to express my gratitude to Roberto Gabriele for his advice and knowledge and many suggestions that substantially improved the quality of my work. I am indebted with them. Special thanks are due to Marco Corsino for his support.

I would also like to thank the examiners Cinzia Daraio, Guido Pellegrini and Marco Zamarian for their useful suggestions which added value to my work. Thanks also go to Giuseppe Espa, Giovanna Fambri, Diego Giuliani, Cristina Mirabella, Enrico Rettore, Antonio Schizzerotto, Sandro Trento, researchers at FBK-IRVAPP, and the members of the Stein Lab at University of Trento. Warm thanks to my colleagues, in particular: Elena Feltrinelli, Selda Kao, Lucia Leonardi and V. Ragupathty.

Lastly, thanks to Gaetana for her patience and unconditional love. This thesis is dedicated to my family.

The author acknowledges the Caritro Foundation for financial support and the PaT-Ufficio Statistica for providing access to data on hotels.

Contents

1 Introduction

Productivity, i.e., the efficiency with which nations, industries and firms use resources to achieve economically valuable results, is perhaps the most important measure available to policy-makers to gauge the health of an economic system (Economist, 2009). In view of its importance for the prosperity of nations, theoretical contributions after the seminal work of Solow (1957) have devoted much effort to identifying what lies behind productivity differentials and growth rates. Likewise, empirically oriented studies promoted by international organisations have addressed methodological issues on productivity measurement and comparison across nations and over time (e.g., O'Mahony and Timmer, 2009).

Early empirical explorations based on country- or industry-level data relied on representative firm paradigms. However, the increasing availability of firm-level data has provided robust evidence for the existence and persistence of wide productivity differentials among firms (Nelson, 1981; Bartelsman and Doms, 2000; Dosi et al., 2010). In the past few decades, applied research has found that factors such as differences in technology and innovation effort (Brynjolfsson and Hitt, 2000) and management practices (Bloom and Van Reenen, 2007), the quality of labour employed (Fox and Smeets, 2010), international trade (Melitz, 2003) and location (Rosenthal and Strange, 2004) all play a role in explaining firm productivity heterogeneity, although what determines firm productivity differentials is far from being clearly understood (Syverson, 2011). In particular, questions regarding what supports such wide heterogeneity, which factors matter most, whether factors influencing productivity can be controlled by firms or are purely external products of the operating environment (Syverson, 2011) and which policies can be used to boost productivity growth (Bartelsman, 2010) are all of primary importance.

These issues are even more critical in the services sector. Taken as a whole, the services sector accounts for over two-thirds of value added in advanced economies (OECD, 2005). Recent studies emphasise the importance of services in the productivity growth of countries. For instance, Van Ark et al. (2008) analysed the industry-level productivity growth of Europe and the United States and concluded that the major factor causing the divergence of aggregate-level productivity between them is the different productivity of the services sector. That of local services (e.g., transport, hotels) is in fact increasingly viewed as a problem, since it explains most of this productivity gap (McKinsey Global Institute, 2010).

There is still little knowledge on firm-level productivity in the services sector, although pioneering studies have suggested that firm productivity dispersion is even greater in this sector than in manufacturing (Oulton, 1998; Faggio et al., 2010). The most obvious reasons are that in services, and personal services in particular, firms generally face huge differences in demand (Morikawa, 2012), are greatly affected by location (Morikawa, 2011) and have access to diverse externalities. The extension of the debate to the tourist sector is a substantial one, as it has immediate practical consequences on tourism policies. This sector is of increasing importance for countries like Italy, in which the current economic crisis has fuelled a debate on the sustainability of a model of economic development focusing largely on manufacturing. Tourism is characterised by the simultaneous occurrence of production and consumption, and productivity thus mainly depends on demand conditions and location factors, generally beyond the control of single firms. In this respect, two critical questions are whether there is a role for public policies aimed at strengthening the sector in the face of increasing competitive pressure, and whether interventions should focus more on external than firm factors - for instance, by reinforcing destination management - or whether they should aim at improving the internal features of tourist firms.

This thesis contributes to the empirical literature on firm productivity with three core papers. The first re-examines the slowdown in productivity in Italian manufacturing by studying the link between innovation, imitation and human capital, which sustained wide heterogeneity of firm productivity behind the aggregate flat productivity trend. The second paper extends analysis to the services sector, in particular to tourism. At a very disaggregated level, it identifies the various sources of differences in productive efficiency of hotels stemming from entrepreneurial and managerial factors, and external to firm factors. The third paper examines the effect of public policy in tourism. A methodological advance is proposed by defining an econometric framework, which allows us to identify and estimate not only the direct but also the indirect effects which public policies may have on hotel performance, in a dynamic treatment setting.

The thesis is structured as follows. In the rest of this introductory chapter, we first define productivity and efficiency and discuss the main difficulties involved in their measurement (section 1.1). Section 1.2 presents an overview of the literature on the factors determining firm productivity and its evolution, with particular emphasis on those factors which are of main interest in this thesis. Section 1.3 discusses the role which policy-makers may play in boosting firm productivity growth. Section 1.4 addresses the links with the three papers (Chapters 2, 3 and 4), which represent the main contribution of this thesis. Chapter 5 concludes, with a general summary of the main findings and their implications.

1.1 Efficiency and productivity: definition and measurement issues

Productivity is the measure of the ability with which a production system transforms input into output. The literature uses two basic types of productivity measures, single-factor and multi-factor.

Single-factor measures involve one particular input. Labour productivity, i.e., the ratio of output (either total sales or value added) over the number of employees or number of worked hours, is the most widely used proxy of single-factor productivity at several levels of analysis, as it is the unit of measure which best reflects the competitiveness of an economic sector or country, but does not require any assumption regarding the relationship between input and output. However, single-factor measures have the disadvantage of being affected by the intensity of use of the excluded inputs. Multi-factor or Total Factor Productivity (TFP) indexes overcome the limitations of single-factor measures in that they involve multiple inputs. TFP is a residual, and is the unexplained part of the variation of output after variations in inputs have been taken into account.

The concept of efficiency is closely related to that of productivity, and is frequently used as a synonym to indicate the performance of a production unit (country, region or firm). In fact, from the theoretical point of view, productivity and efficiency are separate concepts. Productivity is defined as the ratio of the outputs of a production process to its inputs; efficiency refers to the comparison between observed and *optimal* outputs and inputs (Fried, Lovell and Schmidt, 2008). Therefore, efficiency measurement requires the existence of a benchmark. Firms operate inefficiently for two reasons: either, given input prices, firms fail to allocate resources in the most efficient manner (allocative inefficiency) or, given their optimal allocation), they are unable to exploit their resources (technical inefficiency). In other words, even if two firms have the same resource allocation, one firm may produce less output than the other.

Section 1.1.1. examines the key issues in the measurement of efficiency and productivity.

1.1.1 Measuring productivity and efficiency

For a formal description of productivity and efficiency measurement, let us consider a production unit which employs an array of inputs to achieve a single output. The production process of the *i-th* unit at time *t* can be formalised as a function:

$$Y_{it} = A_{it} F\left(X_{it}\right) \qquad \textbf{Eq. 1.1}$$

where Y_{it} is the amount of output, X_{it} is a vector of inputs, and A_{it} represents the productivity index. In particular, A_{it} is a measure of Multi-factor or TFP:

$$A_{it} = TFP_{it} = \frac{Y_{it}}{F\left(\mathrm{X}_{it}\right)} \qquad \textbf{Eq. 1.2}$$

Single-factor productivity measures are obtained as a special case when X_{it} is a scalar, for instance, a measure of labour use.

Productivity is a relative concept (Van Biesebroeck, 2007). In the production function framework, a measure of productivity can be obtained in a given period of time t, considering the mean value of productivity obtained by N units in the observed sample:

$$TFP_{it} = \frac{A_{it}}{\sum_{j=1}^{N} A_{jt}} \qquad \textbf{Eq. 1.3}$$

A measure of productivity growth can also be obtained by considering a given unit at two different times:

$$\Delta TFP_{it,t+1} = \frac{A_{it+1}}{A_{it}} \qquad \textbf{Eq. 1.4}$$

Production unit i may be inefficient, i.e., its observed output at time t may be lower than the maximum potential output obtainable, given the input. Therefore, we have:

$$Y_{\mathrm{it}} \leq A_{\mathrm{it}} F(\mathrm{X}_{\mathrm{it}}) \qquad \textbf{Eq. 1.5}$$

Introducing a parameter which measures the level of technical efficiency in Eq. 1.1, we obtain:

$$Y_{\mathrm{it}} = A_{\mathrm{it}} F(\mathrm{X}_{\mathrm{it}}) \cdot TeEff\,(X_{it}, Y_{it}) \qquad \textbf{Eq. 1.6}$$

where $TeEff\,(X_{it}, Y_{it}) \leq 1$ is the level of technical efficiency of unit I. After accounting for technical inefficiency, the productivity growth of a given unit between two time-points is clearly composed of two parts: one accounting for technological changes and the other for changes in the efficiency with which technologies are exploited. Formally, we therefore have:

$$\Delta TFP_{it,t+1} = \frac{A_{i,t+1}}{A_{i,t}} \frac{TeEff(X_{i,t+1}, Y_{i,t+1})}{TeEeff(X_{i,t}, Y_{i,t})} = \frac{Y_{i,t+1}/F(X_{i,t+1})}{Y_{i,t}/F(X_{i,t})} \frac{TeEff(X_{i,t+1}, Y_{i,t+1})}{TeEeff(X_{i,t}, Y_{i,t})} \qquad \textbf{Eq. 1.7}$$

Alternative measures of productivity can be obtained, the differences in which depend on how $F(X_{it})$ is calculated (Del Gatto et al. 2010; Van Biesenbroek, 2007). The literature refers to three families of methods: index numbers; econometric estimation of the average relationship between inputs and outputs; and frontier estimation based on either parametric or non-parametric techniques.

Index numbers (Caves, 1982; Diewert, 1976) are the basis for growth accounting and are widely used in comparisons of productivity growth across nations. Econometric estimation comprises semi-parametric methods (Olley and Pakes, 1996; Levinsohn and Petrin, 2003) and Generalized Methods of Moment (GMM) (Blundell and Bond, 2000).

In the frontier framework, efficiency and productivity are functions of distances from the production frontier. Estimates are obtained by an econometric stochastic frontier approach (Battese and Coelli, 1992; Greene, 2008): distributional assumptions of the unknown productivity component separate it from random error. A second method of frontier estimation is non-parametric (Daraio and Simar, 2007; Simar and Wilson, 2008, 2013). Among non-parametric estimators, Data Envelopment Analysis (Charnes et al., 1978; Banker et al., 1984; Thanassoulis et al., 2008) is an estimator based on piecewise construction of a convex production frontier from a set of observations, without any assumptions regarding its functional form, which shows good statistical properties (see Simar and Wilson, 2008, 2013).

The choice of relying on parametric versus non-parametric estimation is a matter of debate. As noted by Simar and Wilson (2008) "a parametric form for the production function allows easier, perhaps richer, economic interpretation and is often easier to estimate. But the parametric specification must be a reasonable approximation of the underlying true model". Non-parametric estimation does seem to be more appropriate in the case of services, where the assumption of a stable relationship between input and output (i.e., a well-defined production function) seems even more unlikely. However, non-parametric approaches have their drawbacks. In particular, the DEA estimator faces the so-called "curse of dimensionality", as the rate of convergence of the estimator is much slower than in the case of parametric estimation, depending on the numbers of observations and inputs and outputs taken into account (the dimensionality of the problem). Second, DEA is sensitive to outliers, which may define an efficient frontier. Using large datasets and methods to detect outliers (e.g., Sampaio de Sousa and Stosic, 2005; Simar, 2003) does improve estimation, and bootstrap procedures are available which allow inferences to be made of DEA efficiency measures (Simar and Wilson, 1998). In addition, in the DEA framework, analysis of productivity dynamics and its decomposition is possible with the Malmquist index (Färe et al., 1992, 1994; Färe and Grosskopf, 1996).

Productivity (and efficiency) is a residual which explain variations in output, unrelated to observable variations in input. In this definition, outputs and inputs are assumed to be homogeneous and measured as physical quantities. Much of the literature typically measures output by revenue divided by an industry-level deflator. With a monetary instead of a physical quantity, output and productivity are influenced by within-industry price differences. On one hand, higher prices are associated with high-quality products, which in turn implies higher output and consequently higher productivity – this is particularly important in services in which revenue is preferred to physical quantity measures (Grönroos and Ojasalo, 2004). On the other hand, if prices also reflect idiosyncratic demand shifts or market power variations across firms, then high-productivity firms may not be particularly efficient from the technological viewpoint. This problem becomes less important when the observed firms are micro and small, i.e., they probably do not have the power to influence the equilibrium price of goods and services in the output market. In addition, when the analysis is framed within a longitudinal setting, in which comparisons are in terms of variations, the problem of comparisons among firms may even be reduced.

In this thesis, both single-factor and Total Factor Productivity measures are used. We decided to apply the more flexible non-parametric frontier estimation of TFP and efficiency indexes. The next section addresses the question of how to identify which factors influence productivity and efficiency in the non-parametric framework. These factors are neither inputs nor outputs, but they influence the ability with which firms transform inputs into outputs.

1.1.2 Explaining productivity and efficiency in the nonparametric frontier framework

The non-parametric literature on efficiency and productivity refers to factors which influence efficiency and productivity in an “environmental” or “contextual” sense. Researchers have proposed several approaches to measure the effects of these external variables on the production process (e.g., Fried et al. 1999; Daraio and Simar, 2007). The methods can be classified into distinct classes:

- The *separation approach,* based on the seminal work by Charnes et al. (1981), is directly applicable to dichotomous or categorical environmental variables. The impact of an environmental variable is estimated by stratifying the observed units analysed according to the value of the variable, and subsequently estimating efficiency within subsamples. Portela and Thanassoulis (2001) derived an efficiency decomposition approach by solving two DEA models. As a first step, they estimated within-group efficiency and then overall efficiency in the pooled dataset. A similar method is the metafrontier approach within the DEA framework (O'Donnel et al., 2008), in which a metafrontier is defined as the convex hull of the union of the group frontier. Information on the effects of external factors is then obtained by comparing efficiency, estimated by pooling all observation and efficiency values are obtained by examining only firms within each group.

- In the *one-stage approach* (e.g. Banker and Morey, 1986a,b), environmental variables are incorporated directly into the definition of the production possibility set (PPS) – the space of feasible input/output combinations - and then into the models. This approach requires prior knowledge of whether the environmental variable is an input or an output of the production process.
- In the *two-stage approach,* a type of envelopment estimator (mostly DEA estimators) is used to obtain efficiency scores, which are then regressed against the environmental variables. Although this approach, first introduced by Ray (1991), is now widely used, how the second-stage regression should be carried out is debated. Two different approaches have recently been proposed to overcome *ad hoc* strategies of analysis in the second-stage regression. Both approaches develop proper Data Generating Processes (DGP) which provide formal links of the first stage (in which efficiency scores are obtained) with the second stage (in which the regression analysis is performed). The former approach was proposed by Simar and Wilson (2007), who addressed several problems in order to obtain consistent estimation and inference in the second-stage regression, in which the DEA score is the dependent variable. First, DEA efficiency estimates are serially correlated, since perturbations of observations lying on the best-practice frontier cause changes in the efficiency scores of other observations. Second, since the explanatory variables are correlated with both inputs and outputs (otherwise there would be no need for a second-stage regression), these variables must also be correlated with the error term of the second-stage regression. In addition, since the efficiency scores are truncated at one by construction and not because of censoring, a censored (Tobit) regression is not the correct procedure to follow. Lastly, explanatory variables may affect efficiencies by means of two mechanisms: influencing the shape of the distribution of efficiencies, or affecting the support of input or output variables,

i.e., the set of production possibilities (Daraio et al., 2010). Simar and Wilson (2007) rationalised the two-stage approach by taking these problems into account and proposed using maximum likelihood (ML) estimators of truncated regression and smooth bootstrapping to improve inferences. The second approach, by Banker and Natarajan (2008), uses a DGP, in which the use of simple ordinary least-squares (OLS) or even Tobit estimation in the second-stage parametric regression is theoretically justified. Another view, the called "instrumentalist" view as defined by McDonald (2009), considers the DEA score as a descriptive measure of the relative distance of a unit to the *observed* best-practice frontier. In this approach, the DEA scores do not cause arise any particular concern in regression analysis, as they are treated like as any other dependent variable. Parameter estimation and inference in the second stage may be carried out with using appropriate, but standard procedures (Ramalho et al., 2010). Under this view, McDonald (2009) has argued strongly against a Tobit model, on the grounds that the DEA efficiency scores are not censored but can be seen to be as a special instances of fractional dependent variables. He recommends thea quasi-maximum likelihood estimation (QMLE) in the context of fractional data, but notes that the OLS procedure would provide a reasonable approximation.

- Also multi-stage (three- and four-stage) approaches have been proposed (Ruggiero, 1998; Fried et al., 1999; Muniz, 2002). Multi-stage models make it possible to consider both continuous and discrete environmental variables as well as potential slacks. However, models following this approach assume that the operational environment influence only efficiency distribution and, most importantly, inference is not possible (Daraio and Simar, 2007).
- Another class of models, the *conditional approach*, has recently been proposed (Cazals et al., 2002; Daraio and Simar, 2005, 2007b; Badin et al. 2012). It incorporates environmental variables into a conditional frontier, established in a probabilistic formulation of the production process. Daraio and Simar (2005) introduced this method and extended the framework to DEA models (Daraio and Simar, 2007b). The difficulty with this approach is that handling multivariate covariates and categorical and dummy variables is not easy.

1.2 Sources of firm productivity differentials: an overview

Given its importance for the prosperity of contemporaneous societies, research has devoted an enormous effort to understand the sources of differing level of efficiency and productivity.

The observed differences in productive efficiency can be a side effect of firm decision meant to achieve diverse objectives. Operations management researchers, for instance, have debated the significance of efficiency and slack – excess inputs for the same level of output (Bourgeois, 1981) – in generating competitive advantage (e.g., Adler et al., 2009). On the one hand, increasing levels of efficiency raise the possibility of internal frictions within a firm and reduce the firm's ability to create new knowledge and buffer against discontinuity in its supply chain. For instance, planning and budget decisions are usually made under uncertainty, slack in the form of excess use of resources may thus be useful as a buffer against uncertain demand and furthermore provides flexibility which facilitates the coordination of the internal working of the firm (see e.g. Cyert and March, 1963). What is not clear, however, is the level of slack firms have to choose with respect to their financial performance, mostly when competition increases. Following the economic literature (e.g., Leibenstein, 1966) the alternative view argues that slack resources imply sub-optimal resource utilization and thus reveal waste. Further, strategic management researchers have argued that resource efficiency is often characteristic of valuable and rare firm capabilities formed as a result of complex path dependencies (Peng et al., 2008), and thus enable competitive advantage (Teece et al., 1997).

Management studies and strategic research have used decomposition techniques to outline a strict relationship between productivity growth and enhanced financial performance, after controlling for a price recovery effect (Miller, 1984; Miller and Rao, 1989). Later contributions have extended the original framework allowing factors like product mix and capacity utilization to influence the ultimate financial performance of the firm. Drawing on these methods, applied research has shown how increasing productivity has counterbalanced a dramatic drop in prices and positively affected profitability in the US telecommunications industry (Banker et al., 1996). Likewise, productivity and in particular its technical change component, has been found to provide a large positive contribution to the operating profits of Spanish commercial bank sector in the early ‘90s (Griffel-Tatjé and Lovell, 1999).

According to Syverson (2011), the factors determining observed differences in firm productivity can be classified as either internal or external to firm factors. Although theoretically productivity and efficiency are different concepts, the empirical literature on what determines different levels and rates of growth of both measures shows a substantial overlap.

In the following, we discuss the role of explaining the productivity and efficiency heterogeneity of the main internal and external productivity drivers reported in the literature on firm productivity and efficiency.

1.2.1 Internal levers

Internal to the firm factors are within-firm factors, the “levers”, according to Syverson (2011), which firms can directly control and which can be activated to enhance firm productivity.

Empirical research has shown a positive relationship between a firm’s internal working and its productivity. That is, within-firm factors such as re-organisation of work-shifts, transfer of responsibility to teams, innovations in workplace organisation, and the use of incentives have been shown to be effective mechanisms for improving productivity at both firm (Huergo and Jaumandreu, 2004) and plant level (Ichniowski et al., 1997). Firm productivity appeared to be positively affected by the adoption of new technologies (Brynjholfsson and Hitt, 1996). There is also growing evidence which establishes significant links between returns to new technologies (i.e., Information and Communication Technologies (ICTs)) and the internal organisation of firms. In particular, the productivity gap between the US and Europe in the 1990s has been associated with two factors: firms in the US are organised in a way which allows them to be more flexible within their organisational structure and to use new technologies more effectively (Bloom et al., 2012).

Below, we discuss in more detail the three internal factors which are of primary importance in this thesis. First, we examine the effects of adopting innovation and technology to explain the evolution of productivity dispersion. Then we address the role of management as a driver of the productivity differential. Lastly, we introduce the role of human capital.

1.2.1.1 Technology, innovation and imitation

One reason for the heterogeneity of inter-firm productivity is that firms can use various production technologies. Empirical analyses have shown that even plants within the same narrowly defined industry may use quite different technologies. Indeed, these differences tend to persist over time and spatial differences are significant (e.g., Rigby and Essletzbichler 2006).

Technical change plays a central role in models explaining the evolution of productivity distribution. One strand of research considers the skill-biased nature of technological change (Acemoglu, 2002; Aghion, 2002). Technological change is skill-biased when changes in production technology favour skilled over unskilled workers by increasing their relative productivity and, as a consequence, their relative demand. Along these lines, Caselli (1999) associated the evolution of productivity dispersion across firms with the diverse rates of technology adoption across them. Those firms with more highly skilled workers tended to adopt new technologies faster. The difference in adoption rates thus led to increased dispersion of inter-firm labour productivity. Since new technologies allow capital to be re-allocated to its best use, TFP increases in firms which introduce a new technology, so TFP dispersion also rises. Dunne et al. (2004) in the US, Faggio et al. (2010) in the UK, and Ito and Lechevalier (2009) in Japan found evidence consistent with the technological explanation of productivity dispersion. Indeed, for effective enhancement of productivity, technical change must be accompanied by organisational change (Nelson, 1991) which affects the composition of the workforce (Piva et al. 2005) and may be an even more dramatic source of productivity dispersion across firms.

A more complex view of the impact of the role of technology acknowledges the interplay between innovation and imitation. Whereas innovation tends to increase the heterogeneity of production technologies in an industry, already available diffusion and imitation of technologies tend to reduce heterogeneity and dispersion of performance across firms.

Iwai (2000) presents the characterisation of innovation, imitation, in an evolutionary framework. Firms are associated with the various technologies available on the market, which in turn determine their productivity. Two processes drive the evolution of productivity dispersion: innovation, which is the result of an expensive and uncertain search for new technologies, and imitation, which results from the adoption of the best technologies already existing on the market. These two processes counterbalance each other and induce productivity differentials over time. Explaining these dynamics depends on two aspects. On one hand, innovation enlarges the set of available technologies, supporting firm heterogeneity; on the other hand, imitation of more productive techniques drives firms to become more homogeneous in technologies. Firms can always use the best technologies available on the market, ignoring the possibility that they often adopt less efficient ones. Consequently, this model can hardly explain the persistence of productivity differentials over time.

Very recently Konig et al. (2012) proposed a model based on technological advance driven by innovation, based on investment in Research and Development (R&D) combined with a process of imitation of external technological knowledge. These authors apply to firm level the distance-to-frontier framework inspired by growth models in the Schumpeterian tradition (e.g., Acemoglu et al., 2006), in which countries on the frontier engage in innovative activity and backward ones try to reach the frontier through imitation. The model theorises that firms close to the (industry) technological frontier innovate, driving movement of the productivity frontier; firms lagging behind the frontier, which choose to imitate, have different ability to assimilate and exploit existing technologies, i.e., different absorptive capacity (Cohen and Levinthal, 1990). Although firms can increase their absorptive capacity over time, they can only do so up to a certain point. This limited capacity of imitating new technologies is crucial in the model, as it allows productivity differentials among firms to persist.

The distance-to-frontier framework has also been applied at firm level in recent empirical studies which empirically shown the link between corporate strategy and distance to the technological frontier (e.g., Coad, 2011).

1.2.1.2 Managers and/or Managerial practices

From the economic viewpoint, there are various perspectives showing the link between management and firm productivity. According to Bloom et al. (2013), three perspectives can be used: management as design, management as production input, and what the above authors call "management as technology". Each leads to a different prediction about the potential relationship between the quality of managerial practices and the firm's performance.

In the design approach, management is viewed through the lens of the "contingency" paradigm (Woodward, 1958): heterogeneity derives from the adoption of various practices and is essentially linked to the different environments in which firms operate. Different management practices are chosen by firms to maximise their profits in not perfectly competitive markets. In this perspective, there are no correlations between management practices and either productivity or profitability; only correlations with the intensity of various factor inputs are expected.

Management may also be viewed as a factor of production, like labour or capital. In this case, there is a market price under which firms determine their optimal level of management input. As a result, differences in management practices are correlated with differences in productivity, but no correlation with profitability is expected. However, this perspective does not explain the fact that management decision-making has the power to influence the productivity of all the other factors of production. Syverson clarifies this point: "Managers are conductors of an input orchestra. They coordinate the application of labor, capital, and intermediate inputs. Just as a poor conductor can lead to a cacophony rather than a symphony, one might expect poor management to lead to discordant production operations" (Syverson, 2011, p. 336). This aspect therefore means that considering management simply as another production factor is problematic.

The large dispersion of firm productivity even in narrowly defined sectors has given rise to an alternative view, in which management also incorporates features resembling "hard" technologies (Bloom et al., 2013). Referring to the production function as a tool to represent the production process, management is no longer considered as a further argument of the function, but is now embodied in the productivity measure.

Management quality embedded in managers' talents translates into productivity - specifically TFP, because firms with better managers produce more output than other firms using the same amount and quality of inputs. Productivity improvements are thus transferable across workers and plants which are under the control of managers, and management quality is transferred between firms when managers move across firms. Empirical studies have shown that CEO attributes are significant predictors of relative R&D spending (Barker and Mueller, 2002) and that there is a “fixed effect” which CEOs bring with them when they move across firms (Bertrand and Schoar, 2003).

However, relying as it does essentially on the human capital of managers, this view does not explain why the productivity of a firm may persist over time, in spite of manager turnovers. An extension of this perspective is that management quality – specifically, that embedded in managerial practices, i.e., what managers do - is partially transferable even without management mobility (Bloom et al., 2013). As for technologies, genuine managerial innovations may arise (Birkinshaw et al., 2008). Managerial practices should resemble technology also in the process of adoption that characterises technological innovations. Therefore, models of technological diffusion (e.g. Hall and Khan, 2003; Geroski, 2000) should become important tools to understanding the spread of management practices. Management as technology predicts positive correlations between management and productivity and profitability.

Although there are fewer studies in the economic literature examining the adoption of management practices and its relationship with firm productivity, two factors do appear to be important predictors of the quality of management practice in a firm. More intense competition is positively correlated with best-practice management (Van Reenen, 2011). Bloom and Van Reenen (2007) have also shown that management practice scores are lower when firms are family-owned and primogeniture determines the current CEO’s succession. These two factors explain most of the cross-country differences in average management quality.

However, family ownership per se is not necessarily detrimental for efficiency and productivity. Research in this field has shown that firms run by family managers are likely to benefit from lower agency costs, since there is an alignment of interests and reduced information asymmetry between owners and managers if firms are both family-owned and managed (Chrisman et al., 2004; Gomez-Mejia et al., 2001). Family ties may eventually lead to higher efficiency, especially in small firms, in which low agency costs are also expected between managers and family members employed in firm operations (Herrero, 2011). Firm size is in fact an important indicator of administrative complexity, which encompasses the need for more complex control and monitoring systems. These factors elevate the skill requirements of managers and may reduce the advantage in terms of agency costs (Galbraith, 1995; Mintzberg, 1979). The practice of choosing top managers only among family members may be detrimental when firm size increases.

The open question is to understand whether is the managers' human capital - i.e., managers' talents, and what they know – or what managers do – i.e. managerial practices – that plays a role in increasing the productivity of a firm (Syverson, 2011).

1.2.1.3 Human capital

Firm productivity appears to be positively correlated with the personal characteristics of its workforce, for example, the education, training, and experience of its staff (Fox and Smeets, 2010). The role of human capital is closely related to the two internal factors discussed above: the effectiveness with which managers implement managerial practices, and the adoption and application of new technology. The education levels of workers and managers are correlated with high management scores (Bloom and Van Reenen, 2010). Highly educated managers are more likely to be aware of the benefits of modern management practices, and implementation of these practices may be easier when the workforce is more knowledgeable. Indeed, case studies and econometric analyses have emphasised the importance of complementarity between organisational practices, investments in new technologies, human capital, and the economic environment in which firms operate (Brynjholfsson and Hitt, 2000, Bresnahan et al., 2002; Tambe et al., 2012).

Labour flexibility practices can be a source of productivity and efficiency outcomes. Flexibility can be introduced through various channels. First, flexibility can be related to the responsiveness to external shocks. For instance, firms can adjust the amount of labour employed (i.e., numerical flexibility achieved by using fixed-term or part-time contracts and reducing working hours) or modulate the dynamics of wages in response to external shocks. An alternative way through which firms can achieve flexibility is related to the reorganization of the workforce by means of training and the development of multi-skilled employees. Schuler and Jackson (1987) linked human resource practices to the strategic posture of firms. In particular, human resource practices appear effective for achieving competitive advantage only where the firm emphasizes the importance of either quality enhancement or innovation within its strategy. In organizations pursuing a cost based strategy, the most logical approach would be to emphasize numerical flexibility and wage cost minimization. The effect of labour flexibility on firm productivity is however mixed. A rigid labour market may have a negative impact on aggregate productivity (Bassanini and Ernst, 2002; Scarpetta and Tressel, 2004). Other scholars suggest instead a negative relationship between increased labour flexibility and innovation and productivity at firm level (Arvanitis, 2005; Kleinknecht et al., 2006; Michie and Sheehan, 2001, 2003).

1.2.2 External factors

The effect of factors external to firms may not directly influence their productivity, but they can affect firms' incentives to apply productivity-enhancing actions. They can also influence the extent to which such efforts are successful at moving firms to a higher position within their industry productivity distribution (Syverson, 2011). In other words, the external environment may operate as a moderator of the potential productivity-enhancing effect of changes in the internal working of the firm by making it comparatively harder or easier for firms operating in various environments to reduce their distance to the production frontier.

1.2.2.1 Competition, internationalization and market conditions

A competitive environment affects the productivity level of firms. That is, the more competitive the markets in which a firm operates, the lower the dispersion of inter-firm productivity.

A highly competitive environment is expected to influence productivity distribution through two main mechanisms. First, higher competition affects the selection process of firms: a more competitive environment boosts re-allocation of market shares and resources to more productive firms (e.g., Foster et al., 2006), forcing poorly productive firms to leave the market. In the long term, this selection process gives rise to less productivity dispersion, higher average productivity, and a greater share of output produced by high-efficiency firms. The second mechanism works within a firm: heightened competition induces existing firms to undertake costly productivity-raising actions which they would not otherwise make (e.g., Schimitz, 2005). Which of the two mechanisms predominates and in what conditions is an open question (Syverson, 2011). However, the ability of markets to select more efficient firms appears to be in doubt, whereas most aggregate productivity dynamics appear to be driven by within-firm changes in existing firms (e.g., Bottazzi et al., 2010).

The relationship between competition and innovation in existing firms is probably not linear. In certain conditions, heightened competition can actually diminish a firm's incentives to make productivity-enhancing investments. The propensity to invest in new technologies and new production processes for incumbent firms close to the frontier is expected to increase as and when competition increases, but the incentive to innovate of firms far from the frontier is low, as their expected profits are reduced because their efficiency is too low to allow them to compete with more efficient firms (Aghion et al, 2005; Iacovone, 2012). However, empirical evidence is mixed. Konings and Vandenbussche (2007) find that decreased competition due to anti-dumping protection helps more laggard EU firms than efficient ones. In Czech and Russian industries, Sabirianova et al. (2005) found that increased competition raised the efficiency of foreign firms, which were assumed to be closer to the technological frontier, but had a negative effect on the productive efficiency of less efficient domestic firms. Conversely, Bernard et al. (2006) found no evidence of a different impact on firm productivity due to trade cost reduction in US manufacturing. Topalova (2004) also showed how trade liberalisation within Indian industries had similar productivity improvements in firms with both high and low productivity prior to the reform.

Closely related to the effect of competition is that of internationalisation on firm productivity. Greater exposure to international trade should be characterised by reduced productivity dispersion because of higher competition. Beyond the competition effect, globalisation may increase productivity dispersion because of the cumulative impact of two effects: firms' self-selection in exporting, and learning from exporting (see Wagner, 2007, 2012, for a review of empirical works). If these two potential effects reinforce each other, internationalisation may produce an increasing dispersion of productivity. The theoretical literature on heterogeneous firms and trade (e.g., Melitz, 2003) was inspired by these empirical findings (see Redding, 2011, for a review).

Demand-side explanations of the evolution of productivity have also been proposed. Syverson (2004) showed how low product substitutability prevents customers from changing from purchasing goods made by relatively less productive firms to ones made by relatively more productive ones. Thus, anything that increases product substitutability should have lower productivity dispersion. Demand-side factors play an important role in services. In tourism, demand is increasingly global, but the supply of tourism-related goods and services remains constrained to the place of consumption, making the problem of product substitutability crucial and closely related to location factors.

1.2.2.2 Location factors: agglomeration, urbanization and natural advantages

Understanding the implications of firms' performance of where economic activities are located has attracted the interest of scholars from the fields of both economics (Rosenthal and Strange, 2004; Puga, 2010) and management (McCann and Folta, 2008). What clearly emerges from both fields is that firms crucially interact with the local environment, and that either positive or negative externalities eventually emerge. Geographically proximate firms may draw benefits from supply-side as well as demand-side externalities (McCann and Folta, 2009).

Several studies have addressed the role of agglomeration in various sectors. In the hotel industry, for instance, Baum and Mezias (1992), Baum and Haveman (1997) and Baum and Ingram (1998) focused on the Manhattan hotel industry, Chung and Kalnins (2001) studied the Texas lodging industry, and Kalnins and Chung described the hotel industry as an economic sector in which "agglomeration benefits and resource spillovers likely play a role in location decisions" (Kalnins and Chung, 2004, p. 690).

Two general explanations associate performance with firm location. First, firms may benefit from positive externalities which accrue from agglomeration economies: they benefit by being located close to other firms. In this case, agglomeration generates benefits for two separate reasons, depending on whether the agglomeration consists of similar or diverse industrial activity. The best-known form of externality is the presence and scale of other companies in the same industry. Marshall (1920) identified three main supply-side benefits emerging from the concentration of a given industry in a region: knowledge spillovers between firms, labour market pooling, and input-output linkages. An example of substantial demand-related externality is the reduced search cost for customers stemming from the geographic proximity of firms. The spatial concentration of unrelated firms may benefit from urbanisation economies. These externalities derive from the geographic concentration of aggregate economic activities, as in cities. Firms benefit from urbanisation externalities because industrial diversity fosters fertilisation of ideas across industries (Jacobs, 1969). Supply and demand-side agglomeration differs in terms of composition, relationship complexity, and geographic scope (McCann and Folta, 2009). In particular, the type of relationship is less complex in demand-side agglomeration, in which the existence of relationships between firms is not a necessary condition for gain from geographic proximity. For instance, a group of hotels whose managers never speak to each other and who share no information among themselves still receive the benefits of demand-side agglomeration externalities (McCann and Folta, 2009). Thus, such agglomerations may exist even without interconnections among firms. In this case, the fact of being located close to each other is sufficient to allow gain from enhanced demand.

The second explanation regards externalities due to factors exogenous to economic actors, i.e., benefits which are not linked to the presence of other firms. Marshall (1920) argued that the chief explanation for industrial location was the unique physical condition of particular areas. Examples of factors which might attract firms to a particular area include unique raw materials, specialised workers, transportation facilities, and the capacity of a particular location to attract consumers. Ellison and Glaeser (1999) showed that the percentage of agglomeration predicted by natural advantage proxies is about 20%. However, these authors argued that, since the proxies they used were imperfect, the fraction of agglomeration which might be explained by natural advantages was probably larger. Exactly how much larger is unclear, but they conjectured that "at least half of observed geographic concentration is due to natural advantages" (Ellison and Glaeser, 1999, p. 316). Externalities stemming from natural advantages are very important for personal service firms. In particular, the attraction factors of the area in which firms operate, such as natural environmental features (beaches, scenic landscapes, or pleasant weather), or man-made features (historic, artistic and architectural attractions), or even more practical ones (such as good tourism facilities) can be very important demand-related sources of success in the tourist trade.

Lastly, it is still standard for economists to employ cluster-based methods in evaluating the geographic distribution of firms. These methods measure the spatial concentration of economic activity according to predefined geographic limits (administrative districts, city, regions, counties, etc.). Measures obtained with these methods introduce bias resulting from the quite arbitrary concept of space chosen. Distance-based methods, which definitely reduce bias by using a continuous approach to space in order to gauge geographic concentration of activities, have recently been introduced (Arbia and Espa, 1996; Marcon and Puech, 2003, 2010; Duranton and Overman 2005).

1.3 The role of the policy makers in stimulating firms productivity growth

For policy-makers, "the state of affairs of productivity research is frustrating, at best. The main question on the table seems fairly straightforward: which policies can be used to boost productivity (growth)?" (Bartelsman, 2010, p.1891). In order to improve aggregate productivity, government can influence many of the productivity drivers discussed above. Public interventions in economic activities take on various forms, ranging from regulatory interventions with no direct financial implications for the government's budget, to direct provision of funds (i.e., subsidies) to private firms (Buigues and Sekkat, 2011).

At first, policy-makers may influence the factors shaping the external environment in which firms operate. Many policy reforms have plausibly productivity-enhancing effects. For instance, policy-makers can change trade policy and market regulation design with implications on the competitive conditions, allowing the market to operate more effectively in selecting more efficient firms.

However, market failures represent an important hampering factor behind the functioning of markets. The traditional argument for subsidising particular kinds of investments is the possibility that there are divergences between private and social returns due to externalities (references). In th case of market failure, policy interventions targeted directly towards firms, such as subsidies, can accelerate technological progress, and therefore productivity.

There are different sources of technological change at firm level. On one hand, firms undertake in-house R&D. In this case, the argument on divergences between private and social returns is straightforward because, due to knowledge spillover, firms making R&D investments do not appropriate the entire gains originating from their innovative effort (Nelson, 1959). On the other hand, firms may incorporate new technological knowledge embodied in new machinery and equipment acquired in the market (Pellegrino et al., 2011). DeLong and Summers (1991) argued that even investments in equipment, as opposed to other kinds of fixed capital, may generate externalities and that private return from this kind of investment would be below social returns. This suggests the possibility of under-investment by market economies and scope for government intervention. However, a stronger rationale explaining lack of investment is inefficiency in the capital market. In fact, because of credit risk and information asymmetry, borrowers tend to set the price of money on above-optimal levels or to rationalise credits. Thus, in order to finance investments, firms tend to follow a hierarchical approach (Myers and Majluf, 1984): they first rely on internal sources and then turn to external ones (primarily debt, usually that with the lowest cost). Credit rationing is problematic, especially for small firms (see Carreira and Silva, 2010, for a review), since information asymmetry may be more severe in their case. Therefore, small businesses rely heavily on internal resources to finance growth (Carpenter and Petersen, 2002). As a result, they may not be able to raise the necessary amount of money to fulfill their investments when internal financial capital is not sufficient, and may postpone, partially reduce, or even abandon their growth objectives. The support of investments in physical capital plays an important role in tourism, since the productivity and competitiveness of tourist firms is influenced by investments which provide equipment and infrastructures and facilitate the introduction of new technologies (Blake at al., 2006).

Public subsidisation is effective when policy-makers can improve market outcomes. Although subsidies are seen as effective and highly acceptable policy instruments, their implementation may raise concern, due to governmental budget constraints. Indeed, what might be contended is the ability of policy-makers to provide effective private incentives to rectify market failures and to avoid the introduction of additional distortions to the economic system. Governments, in general, may not be able to substitute markets in processing decentralised information, and lobbying and corruption may further distort their decisions (Rodrik, 2007). Lastly, subsidies may improperly support firms which are more interested in subsidy-seeking than productive activities and which capture subsidies in the form of slackness or lack of effort, so that subsidies give rise to inefficiencies (Bergstrom, 2000).

1.4 The main contributions of the thesis

This thesis is composed of three core papers, the main contributions and results of which are summarized in the following sections.

1.4.1 First paper: A new look at the evolution of productivity of Italian firms.

The competitive environment faced by Italian firms has changed dramatically since the mid-1990s, mainly due to the increased competitiveness of new industrialising countries and the introduction of the euro. On the input side, Italian firms faced a sequence of labour reforms which introduced more flexible practices into the labour market. In this context, the Italian economy has witnessed slowed productivity, although the extensive heterogeneity of firms' behaviour in flat overall productivity growth seems to emerge from recent studies (Bugamelli et al., 2010; Dosi et al., 2012). In particular, a tendency towards "neo-dualism", in which dynamic firms coexist with less technologically progressive ones has emerged in terms of labour productivity dynamics (Dosi et al., 2012).

The first paper (Chapter 2) re-examines the Italian productivity slowdown. Instead of labour productivity, we analyse the TFP dynamics of a sample of Italian manufacturing single-plant firms in the period 1996-2006 by means of the distance-to-frontier framework (Acemoglu et al., 2006; Konig et al., 2012). Here, the interplay between technological advance driven by innovation combined with a process of imitation is essential, in order to explain inter-firm heterogeneity; the distance to the frontier operates as a moderator of this process.

In the first part of the paper, two separate components of TFP growth are distinguished. The first is technological progress associated with the movement of the best-practice production frontier of an industry, due to successful innovators. The second component is technical efficiency, which explains changes in firms' distance to the technological frontier over time. Both components are then further decomposed into subcomponents. We identify a clear-cut discontinuity after the adoption of the euro, highlighting the increasing gap between firms which contribute to technological advance and others whose performance worsened and which have moved away from the technological frontier.

The second part of the paper extends analysis of the causes of the increased dispersion of productivity. We classify firms into four types, according to their initial efficiency level (i.e., distance to the frontier) and productivity dynamics over time, and explore the hypothesis that the increased dispersion of productivity is due to the differing strategic adaptation of firms to external shocks. Firms belonging to the least dynamic group, i.e., those characterised by greater distance from the frontier and slower productivity growth, use labour of poorer quality and draw from the flexible labour market more extensively than other firms.

1.4.2 Second paper: The influence of managerial and location factor on hotel efficiency

The problem of which factors matter most in determining firm productivity is crucial for managers, for whom lack of knowledge of the relevant sources of efficiency differences over which they have control may hamper improved performance. Distinguishing these various sources is particularly interesting for research in services, where knowledge of what determines firms' differences in productivity is still limited.

The second paper (Chapter 3) contributes to the empirical literature on the determinants of firm productivity and efficiency by an in-depth exploration of the determinants of hotel productive efficiency. The production process of personal service firms, like hotels, is characterised by the simultaneous occurrence of production and consumption. This implies that these firms cannot use inventories to smooth production, so that productivity depends to a great extent on demand conditions, mainly due to different locations (Morikawa, 2011, 2012). For instance, Morikawa (2011) found significant economies of demand density for firms in the personal services industries, such as beauty salons, fitness clubs and movie theaters in Japan, where the TFP of firms increases by 7–15% when the population density of the municipality in which firms operate doubles.

We question the predominance of location factors by showing that other factors may also play important roles. We exploited a detailed and unique dataset of a large representative sample of hotels operating in the Trentino province (north-east Italy), obtained by integrating several data sources. We first isolated the component of inefficiency arising from location factors, linked to destination, by non-parametric metafrontier analysis. Differing destinations explain only part of the efficiency dispersion, which still remains ample within each destination. In the second step, we regressed inefficiency scores on a set of firm-level variables related to factors directly controllable by firms. We distinguished between factors related to manager/owner human capital and those related to management choices on investing behaviour, quality of management practices, hotel organisation, and family involvement in the hotel. Our results point to the significant impact of managerial choices and family involvement on hotel efficiency. The role played by owner/manager characteristics are less important. Our findings are confirmed even after controlling for fine-grained intra-destination location factors.

1.4.3 Third paper: Evaluating the effect of public capital subsidies on firm performance

In the third paper (Chapter 4) we studied the effect of policy intervention in the tourist sector. Tourism-related industries must increase their competitiveness by exploiting scarce resources in more efficient and more innovative ways in order to develop and market competitive products (OECD, 2008). Physical capital plays an important role in raising the productivity and competitiveness of tourism firms (Blake at al., 2006), and governments should play a role by stimulating and supporting this type of productivity-based growth (OECD, 2008).

Whether a policy is effective or not is a matter of ex-post evaluation. In this respect, it is crucial to set up evaluation models to identify and estimate not only the direct effects of policies on the performance of those firms supported by them, but also indirect effects, due to the externalities which public policies may generate, which eventually also influence non-supported firms. In this paper, several steps were followed in the construction of the econometric model and estimation, starting with standard assumptions, and addressing and overcoming empirical and methodological issues in each step. We assessed whether subsidies for investment in renewing hotel buildings, equipment and facilities are beneficial in terms of increased hotel performance. We also tested to what extent subsidies cause spillover on neighbours. In principle, spillovers, or more generally externalities, may be positive or negative. Externalities are positive if public support to renewing hotels not only increases its own performance, through enhanced quality and attractiveness, but also improves the quality and attractiveness of the neighbourhood in which the hotel is located. This will eventually be beneficial for all the other hotels in the same neighbourhood, and for the overall image of the destination. In this case, non-subsidised neighbours may add positive externalities to their production process and improve their performance. However, externalities may also be negative if the incentives offered by policies cause heightened competition. If hotels within a destination compete to become tourists' first choice, the support received by some hotels may negatively affect the performance of unsubsidised ones.

If these kinds of policies cause externalities, these effects cannot be disregarded. Examining both treated and control units in the eligible area should be the preferred strategy in order to achieve comparability among units. However, if policies generate externalities, the estimated effects are biased, as the presence of externalities violates the assumption of no interference (the SUTVA assumption in Rubin's causal framework) on which policy evaluation models are based.

The contribution of this work has both econometric and empirical applications. We propose a methodological advance by defining an econometric framework which can identify and estimate not only the direct effects of subsidies on hotel performance, but also the indirect ones. We relax the standard assumptions of Rubin's classical causal framework by allowing subsidy receipts to interfere across hotel outcomes, i.e., we relax the SUTVA assumption. The framework is applied in a dynamic treatment context in which we evaluate the effect of the sequence of treatments obtained by a hotel over a period of time on its final outcome, also accounting for the effect due to the sequence of treatments given to other hotels. Our econometric framework also allows estimation of both direct average treatment and indirect effects by considering only hotels located in the eligible area.

This empirical application also contributes to the literature on policy evaluation. We evaluate the effect of a place-based subsidisation programme directed to co-finance capital investments of micro and small hotel businesses, which represent the bulk of firms in many destinations. Quantitative analysis is scanty in this respect, and previous studies (e.g., Bernini and Pellegrini, 2013) do not shed light on the effectiveness of public subsidies directed to micro and small firms.

The analysis is carried out on several measures of hotel productivity. Our results point to the positive direct effects of subsidies on hotel performance. We also find empirical evidence of SUTVA violation and indirect subsidy effects. Specifically, our results indicate negative externalities generated by heightened competition among hotels within destinations, as a result of public intervention.

2 A new look at the evolution of productivity of Italian firms: distance to the technological frontier, human capital, and technological progress [1]

2.1 Introduction

Since the mid-1990s, in a context of increased competitivity of new industrialising countries with cheaper labour available in their internal labour market (e.g., China) and after the introduction of the euro, which eliminated competitive devaluation leverage, Italy has sunk into long-lasting economic stagnation.

Empirical analyses have given various explanations for the poor productivity dynamics of the Italian productive system: the overwhelming predominance of small and medium-sized firms (Zanetti and Alzona, 2004; Onida, 2004; Foresti et al., 2008), export composition (Boffa et al., 2009), inadequate endowment of public infrastructures (La Ferrara and Marcellino, 2000) and of public capital (Marrocu and Paci, 2010), and little innovation and technical progress (Daveri and Jona-Lasino, 2005; Hall et al., 2008). Faini and Sapir (2005) argued that the insufficient innovative capacity of Italian firms and their inability to introduce new technologies, essential for increasing productivity, were due to insufficient numbers of educated and qualified workers. The lack of skilled workers not only prevented the adoption and effective use of new technologies, but also adaptation to new organisational models (Bugamelli and Pagano, 2004; Fabiani et al., 2005).

However, recent studies have emphasised the wide heterogeneity of firms' behaviour under flat aggregate productivity dynamics. Bugamelli et al. (2010), using

[1] This chapter draws on a joint research project with Roberto Gabriele, Sandro Trento and Enrico Zaninotto on the Italian productivity slowdown at DEM-University of Trento. The chapter extends some results of the research already published in Tundis et al. (2012).

labour productivity as an indicator of firm restructuring, argued that increased competitive pressure, mainly due to the adoption of the euro, forced Italian firms to make internal changes, even though the effects of this restructuring were unevenly distributed across firms. In addition, the shock due to the arrival of the euro, which may be considered as equivalent to a trade liberalisation shock, did not seem to spur the selection process as one would expect. In fact, Dosi et al. (2012), analysing a large sample of firms in all economic sectors, highlighted the apparent weakness of markets in selecting more efficient incumbent firms and found that the support of the sectoral distribution of firms' labour productivity between 1989 and 2004 was ample and did not shrink over time, giving rise to a kind of "neo-dualism" among firms (Dosi et al., 2012). Recently, the establishment of a two-tier labour market has been put forward as a possible reason for the increase in labour productivity dispersion among Italian manufacturing firms (Boeri and Garibaldi, 2007), although thorough analysis of the existence and evolution of productivity dispersion is still lacking.

From the firm level perspective, the contribution of this chapter is twofold. First, instead of considering labour productivity, we estimated and decomposed firm Total Factor Productivity (TFP) dynamics for a sample of manufacturing firms.[2] We relied on a framework which makes use of non-parametric production frontier methods (i.e., Data Envelopment Analysis), which allows several meaningful decompositions of firm level TFP variations (Färe et al., 1992, 1994; Färe and Grosskopf, 1996). Two distinct components of TFP growth were distinguished. The first is technological progress associated with shifts of the best-practice production frontier of an industry, i.e., changes made by successful innovators in a sector. The second component is technical efficiency, which is related to improvements in the ability with which firms make use of technologies previously introduced to an industry. This component accounts for changes in firms' distance to the technological frontier over time. Both components were then further decomposed into their related subcomponents.

Our measures give further confirmation of the widespread heterogeneity of Italian firms. In particular, we show how the contribution of the two main sources of productivity growth - technological change and efficiency change - varied dramatically

[2] Note that, unlike labour productivity, inter-firm differences in TFP also account for differences in relative input factor intensities.

over the period analysed. In particular, we identify a clear-cut discontinuity after the adoption of the euro, highlighting the increasing gap between firms which contribute to technological advance, and firms whose performance worsens and which have moved away from the technological frontier.

Secondly, the chapter extends analysis of the causes of the increased dispersion of productivity. We examined the hypothesis that firms adapted to external shocks in different ways. In particular, more dynamic firms choose more highly skilled labour in order to achieve a quality- or value-added advantage over competitors; in other words, they take the “high road” (Michie and Sheehan, 2001, 2003). In contrast, less dynamic firms choosing a cost-cutting strategy take the “low road” – for instance, by giving employees short-term contracts and/or part-time work, and accepting less skilled labour as a solution to cope with the new competitive environment. For these firms, the introduction of flexible practices in the labour market is an extra competitive option.

After classifying firms into four groups based on their initial efficiency level (i.e., distance to the fronter) and productivity dynamics over time, we explored the relationship between firms belonging to groups and a set of their characteristics - in particular, the quality and composition of the workforce. Firms belonging to the least dynamic group, i.e., those characterised by greater distance from the frontier and slower productivity growth, use labour of poorer quality and draw from the flexible labour market more extensively than other firms.

The analysis exploited an original database of single-location firms over 11 years, from 1996 to 2006, obtained by integrating detailed and highly reliable data on firm employment from the Italian Institute of Social Security (INPS) with information on balance-sheet data, sector of activity and location. The level of analysis close to the single establishment level allowed us to avoid almost entirely the spurious effect stemming not only from mergers and acquisitions but also intra-group reallocation of the workforce, and also to capture technological and efficiency changes stemming from actual changes in production processes.

The rest of the chapter is organised as follows. Section 2.2 reviews the relevant literature. Section 2.3 presents the productivity estimation strategy. Section 2.4 describes the database, and section 2.5 presents results from the analysis of productivity growth and its components. Section 2.6 isolates some factors characterising firms' performance. Lastly, section 2.7 concludes the chapter, with a summary of its main implications.

2.2 Literature review

Two important issues emerged from the empirical literature on productivity. The first is the slowed productivity which has affected many countries worldwide in the recent past (Cameron, 2003; Oliner et al., 2007, Mas et al., 2008). The comparison between Europe and the United States at macro level reveals a number of factors which may account for the recent productivity decline in several countries: late development of industries with high intellectual capital intensity in Europe (Van Hark et al., 2008), the generalised increase in total factor productivity for industries which use new technologies (i.e., IT) in the U.S. (Jorgenson et al., 2008), and the impact of different institutional settings (Scarpetta et al., 2002).

Secondly, the improvement over sectoral and macro studies obtained by examining a firm, the unit of observation which actually makes decisions, showed the existence of great productivity dispersion among firms (Nelson, 1981; Bartelsman and Doms, 2000; Syverson, 2011). Considerable productivity heterogeneity remains even after taking into account input and output quality (Fox and Smeets, 2011), measurement issues (Bartelsman and Doms, 2000; Foster et al., 2008) and differing measurement methods (Van Biesebroeck, 2007). The observed widespread differences in efficiency across firms and plants do appear to be independent of the level of sectoral disaggregation in question (Griliches and Mairesse, 1997). For instance, Bottazzi et al. (2007) revealed the wide heterogeneity at three-digit disaggregation in the Italian industry. Syverson (2004, 2011) found that, for U.S. manufacturing industries, even at four-digit disaggregation, the 90-10 percentile average labour productivity ratio was 4:1 and, after controlling for other factors, the average TFP ratio was nearly 2:1. Hsieh and Klenow (2009) found even larger dispersion in China and India, with average 90-10 TFP ratios over 5:1.

While the early literature on firm level productivity documented the distribution, evolution and growth of productivity over time (Baily et al., 1992; Bartelsman and Doms, 2000), more recent studies have made advances in our knowledge of what determines firm productivity (Bloom and Van Reenen, 2007; Syverson, 2011, Mohnen and Hall, 2013). However, further investigation of this issue is recommended. First, the existence, magnitude, and way in which productivity dispersion evolves over time is still puzzling: in particular, which factor matters most is still the object of enquiry

(Syverson, 2011). Examination of the reasons for the existence of large productivity disparities among firms within sectors will certainly provide interesting insights to policy-makers aiming at fostering the economic growth process of countries (Economist, 2009).

Various theoretical underpinnings have been advanced to explain the evolution of productivity dispersion. One prominent explanation is related to technology, particularly technological change (Dosi and Nelson, 2010). There are two sources of technological change, the result not only of the adoption of existing technologies, but also of innovation. Thus, the evolution of firms' productivity distribution stems from the interplay of innovation and imitation (König et al., 2012; Iwai, 2000): innovation increases heterogeneity, whereas imitation tends to reduce it. The most recent theoretical papers on this topic have assigned a crucial role to the distance to the frontier as the mediator of these processes. Notably, König et al. (2012) predict that firms which are close to the frontier innovate, driving the movement of the frontier; firms lagging behind choose to imitate, and the probability of successful imitation increases with the distance to the frontier.

Some consequences on the role of human capital emerge from the relationship between distance to the frontier and technological progress. Support for the hypothesis that education plays a role in reducing the distance (Nelson and Phelps, 1966) comes from cross-country empirical works (Benhabib and Spiegel, 1994; Acemoglu et al. 2006; Aghion et al., 2008). In particular, for several OECD countries, Vandenbussche et al. (2006) show that a skilled workforce has a higher growth-enhancing effect closer to the technological frontier. Instead, there is little firm-level empirical research on the role of the quality of human capital at different distances from the technological frontier in explaining the evolution of firm productivity distribution (Batelsman et al., 2013).

Labour market institutions, especially those introducing labour flexibility practices, have also been considered as an explanation for productivity differentials, although empirical evidence varies in this regard. A rigid labour market may have a negative impact on aggregate productivity. The more easily inputs can move towards more productive firms, the faster the market share reallocation mechanism works (Hsieh and Klenow, 2009). In addition, when institutional settings do not allow adjustment costs of labour (hiring and firing costs), then rigidities in the labour market become detrimental for innovation and the adoption of new technologies, leading to lower productivity (Bassanini and Ernst, 2002; Scarpetta and Tressel, 2004).

Other scholars, however, suggest that there is a negative relationship between increased labour flexibility and innovation and productivity at firm level. In order to adopt new technologies successfully and to be able to integrate them within their organisations, firms must invest in developing new skills and/or to upgrade their employess' levels of skill. However, investing in training flexible workers is not always convenient for firms, and temporary and part-time employees are expected to apply less effort, for reasons connected with individual motivations and incentive structures which are different than those of regular workers. Acharya et al. (2010) empirically found that innovation and economic growth are fostered by stringent laws governing dismissal of employees in the United States, especially in the more innovation-intensive sectors. On innovation for British firms, Michie and Sheehan (2001, 2003) found a positive effect of internal flexibility, but a negative effect of external flexibility. Kleinknecht et al. (2006) obtained similar results with reference to the labour productivity growth of Dutch firms. Arvanitis (2005) found no significant effect of external flexibility on labour productivity in a sample of Swiss firms. Basing their results on Spanish data, Dolado and Stucchi (2008) found that higher numbers of temporary workers decrease firms' total factor productivity.

As regards Italy, Boeri and Garibaldi (2007) argue that the decline of labour productivity and its increased dispersion among Italian manufacturing firms over the period 1995–2000 was related to labour reforms which established a labour market with two components, one rigid and one flexible. Lucidi and Kleinknecht (2009) confirmed the negative effect of an increase in the share of fixed-term contracts on labour productivity growth in a sample of Italian manufacturing firms during the period 2001–2003. Lotti and Viviano (2010) also estimated the negative impact of the proportion of temporary employees on the efficiency and profitability of a sample of firms from the Invind survey of the Bank of Italy.

In this chapter, we aim to shed further light on the productivity slowdown which has affected the Italian productive system since the mid-1990s. We first investigate TFP dynamics as stemming from the interplay of technological progress and the movements of firms behind the frontier. Lastly, we examine the relationship between productivity dispersion and firms' choices in investing in human capital.

2.3 Measuring and decomposing Total Factor Productivity

Several models and techniques have been proposed to estimate TFP and its dynamics (Del Gatto et al., 2011; Van Biesebroeck, 2007; Heshmati, 2003). In this chapter, we use a non-parametric approach to the frontier framework as an estimation strategy. Specifically, we employ the DEA technique (Cooper et al., 1978; Banker et al., 1984), since it has some characteristics which make it very appealing for analysis. First, it yields consistent estimates of the production frontier (Kneip et al., 1998, 2008; Simar and Wilson, 2008); second, when firms are likely to employ different technologies, DEA estimates are among the most robust (Van Biesebroeck, 2007). Third, DEA does not make *a priori* assumptions about the shape of the frontier function. Lastly, the DEA framework allows measures of Total Factor Productivity change to be obtained by means of the Malmquist index.

The Malmquist index was first introduced by Caves et el. (1982). Färe et al. (1992) combined Farrell's (1957) measurement of efficiency with that of Caves et al. (1982) to develop a new Malmquist index of productivity change. This index computes firm productivity change over time directly from input and output data and allows meaningful decomposition of productivity dynamics in one technological component – related to the best-practices frontier shift – and another component linked to efficiency improvements – related to firms' distance from the frontier. It allows us to relax the assumption of neutral technology in dividing the technical change component into bias and magnitude index terms (Färe and Grosskopf, 1996).

Within this frontier framework, the shape of the frontier and consequently the estimated productivity change depends on the choice of production set. One possibility is to employ contemporaneous frontiers, i.e., production sets are constructed at each point in time from observations at that time only. In this case, production sets can expand or contract from one year to another, and outward (technological progress) as well as inward (technical regress) shifts of the frontier can occur with respect to the base time period considered. Alternatively, a single intertemporal production set, obtained from the full dataset, or a sequential frontier, obtained from accumulated data until the baseline year, can also be constructed (Tulkens and Vanden Eeckaut, 1995). In both cases, no inward shift of the frontier is allowed. As in the the original Malmquist TFP approach (Färe et al., 1992, 1994) and the majority of Malmquist TFP applications in the literature (Heshmati, 2003), this study employs the contemporaneous frontier approach, allowing for both upward and inward shifts of the frontier. This choice is particularly useful, since it reveals how best-practices firms and firms below the frontier move with respect to each other over time.

2.3.1 The Malmquist index

Let us consider a firm producing a vector of outputs, $\mathbf{y} \in \Re_{+}^{M}$, from a vector of inputs, $\mathbf{x} \in \Re_{+}^{S}$. We assume a convex production possibility set with freely disposable inputs and outputs. The output distance function[3] can then be defined on the technology $T = \{(\mathbf{x},\mathbf{y}) : \mathbf{x} \text{ can produce } \mathbf{y}\}$, as in Shepard (1970)[4]:

$$D(\mathbf{x},\mathbf{y}) = \inf_{\theta}\left\{\theta > 0 : \left(\mathbf{x}, \frac{\mathbf{y}}{\theta}\right) \in T\right\} \qquad \textbf{Eq. 2.1}$$

The distance function defined in Eq. 2.1 is relative to each firm and can be interpreted as the potential increase of output which can be achieved by a firm which uses a given amount of inputs. In particular the scalar $\theta \in (0,1]$ identifies the potential expansion of the output y, so that the production possibility $(x, y/\theta)$ lies on the efficient frontier T. Therefore a firm will be efficient (laying on the frontier) iff $D(\mathbf{x},\mathbf{y}) = 1$.

Since the production possibilities set T is not known, we estimate it by means of the Data Envelopment Analysis estimator. The DEA production set assuming Constant Return to Scale (CRS) (Cooper et al, 1978) is defined as:

$$\hat{T}_{CRS} = \left\{(\mathbf{x},\mathbf{y}) : \sum_{j=1}^{N} \lambda_j y_{jm} \geq y_m,\ m = 1,\ldots,M;\ \sum_{j=1}^{N} \lambda_j x_{js} \geq x_s,\ s = 1,\ldots,S;\ \lambda \in \Re_{+}^{N}\right\} \qquad \textbf{Eq. 2.2}$$

and also assumes a Variable Return to Scale (VRS) by (Banker et al 1984):

[3] An input-oriented distance function can be symmetrically defined. In this chapter we present however only the output-oriented case.
[4] Shepard (1970) discusses assumption regarding Technology set T, that is convexity, that all production requires use of some inputs, and that both inputs and outputs are strong disposable. See also Battese (2005) et al for further details.

$$\hat{T}_{VRS} = \left\{ (\mathbf{x}, \mathbf{y}) : \sum_{j=1}^{N} \lambda_j y_{jm} \geq y_m,\ m = 1,...,M;\ \sum_{j=1}^{N} \lambda_j x_{js} \geq x_s,\ s = 1,...,S;\ \sum_{j=1}^{N} \lambda_j = 1,\ \lambda \in \Re_+^N \right\} \qquad \textbf{Eq. 2.3}$$

where in both cases $\hat{T}$ is an estimate of the true production set T based on the observed data. The consistent estimators of $D(\mathbf{x}, \mathbf{y})$ defined in Eq. 2.1 can then be obtained by substituting the true, but unknown, production set T with estimator $\hat{T}$ (Simar and Wilson, 2008). In practices, estimates of $D(\mathbf{x}, \mathbf{y})$ under the assumption of CRS, are computed by solving a linear program. Specifically, the distance of a firm from the empirical production frontier is estimated by solving the following linear programming model:

$$\frac{1}{\hat{D}_p^{CRS}(\mathbf{x}_k, \mathbf{y}_k)} = \max_{\varphi} \left\{ \begin{array}{ll} \sum_{j=1}^{N} \lambda_j y_{jm}^p \geq \varphi y_{im}^k, & m = 1,...,M, \\ \sum_{j=1}^{N} \lambda_j x_{js}^p \geq x_{is}^k, & s = 1,...,S \end{array} \right\} p, k = t, t + \Delta t \qquad \textbf{M. 2.1}$$

where $\hat{D}_p^{CRS}(\mathbf{x}_k, \mathbf{y}_k)$ is the estimated distance of a firm at time $k = t, t+\Delta t$ from the CRS frontier at time $p = t, t+\Delta t$. Estimates of distance assuming VRS are computed (Banker et al., 1984):

$$\frac{1}{\hat{D}_p^{VRS}(\mathbf{x}_k, \mathbf{y}_k)} = \max_{\varphi} \left\{ \begin{array}{ll} \sum_{j=1}^{N} \lambda_j y_{jm}^p \geq \varphi y_{im}^k, & m = 1,...,M, \\ \sum_{j=1}^{N} \lambda_j x_{js}^p \geq x_{is}^k, & s = 1,...,S \\ \sum_{j=1}^{N} \lambda_j = 1 & \end{array} \right\} p, k = t, t + \Delta t \qquad \textbf{M. 2.2}$$

For each firm, the Malmquist index represents productivity changes between two periods, t and $t+\Delta t$. This index can be derived as the ratio of distances from the CRS production frontier – composed of the best-practice firms in the observed set of firms – in each period. The link between calculated distances and TFP change is:

$$Malmquist_t = \Delta T\hat{F}P_t = \frac{\hat{D}_t^{CRS}\left(\mathbf{x}_{t+\Delta t}, \mathbf{y}_{t+\Delta t}\right)}{\hat{D}_t^{CRS}\left(\mathbf{x}_t, \mathbf{y}_t\right)} \qquad \textbf{Eq. 2.4}$$

This is the ratio between the distance of the firm in period $t+\Delta t$ from the frontier in period t, and the distance in period t from the frontier in period $t+\Delta t$. The Malmquist index can also be defined with respect to the frontier at time $t+\Delta t$ as follows:

$$Malmquist_{t+\Delta t} = \Delta T\hat{F}P_{t+\Delta t} = \frac{\hat{D}_{t+\Delta t}^{CRS}\left(\mathbf{x}_{t+\Delta t}, \mathbf{y}_{t+\Delta t}\right)}{\hat{D}_{t+\Delta t}^{CRS}\left(\mathbf{x}_t, \mathbf{y}_t\right)} \qquad \textbf{Eq. 2.5}$$

Färe et al. (1994) defined a Malmquist index as geometric average between the two indexes defined in Eq. 2.4 and 2.5 as follows:

$$Malm = \left[\frac{\hat{D}_t^{CRS}\left(\mathbf{x}_{t+\Delta t}, \mathbf{y}_{t+\Delta t}\right)}{\hat{D}_t^{CRS}\left(\mathbf{x}_t, \mathbf{y}_t\right)} \; \frac{\hat{D}_{t+\Delta t}^{CRS}\left(\mathbf{x}_{t+\Delta t}, \mathbf{y}_{t+\Delta t}\right)}{\hat{D}_{t+\Delta t}^{CRS}\left(\mathbf{x}_t, \mathbf{y}_t\right)}\right]^{\frac{1}{2}} \qquad \textbf{Eq. 2.6}$$

The index can be decomposed as follows:

$$\begin{aligned} Malm &= \frac{\hat{D}_{t+\Delta t}^{CRS}\left(\mathbf{x}_{t+\Delta t}, \mathbf{y}_{t+\Delta t}\right)}{\hat{D}_t^{CRS}\left(\mathbf{x}_t, \mathbf{y}_t\right)} \times \left[\frac{\hat{D}_t^{CRS}\left(\mathbf{x}_{t+\Delta t}, \mathbf{y}_{t+\Delta t}\right)}{\hat{D}_{t+\Delta t}^{CRS}\left(\mathbf{x}_{t+\Delta t}, \mathbf{y}_{t+\Delta t}\right)} \; \frac{\hat{D}_t^{CRS}\left(\mathbf{x}_t, \mathbf{y}_t\right)}{\hat{D}_{t+\Delta t}^{CRS}\left(\mathbf{x}_t, \mathbf{y}_t\right)}\right]^{\frac{1}{2}} \\ &= EffCh \times TeCh \end{aligned} \qquad \textbf{Eq. 2.7}$$

where productivity change is broken down into two parts. The first part is the ratio of the distances of a firm to the frontier at two different time-points, and shows how much closer (or further away) a firm gets to the best-practice frontier. It is higher (lower) than one if there has been an increase (or decrease) in efficiency. The second part can be considered as a proxy of the shifts of the empirical production frontier (i.e., the growth rate of technological progress) from t to $t+\Delta t$, and reveals the extent to which the best-practice firms are changing their performance (improving or deteriorating).

Efficiency change (*EffCh*) can be further decomposed as follows (Färe et al., 1994):

$$EffCh = \frac{\hat{D}^{VRS}_{t+\Delta t}\left(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t}\right)}{\hat{D}^{VRS}_{t}\left(\mathbf{x}_{t},\mathbf{y}_{t}\right)} \times \left(\frac{\hat{D}^{CRS}_{t+\Delta t}\left(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t}\right)}{\hat{D}^{VRS}_{t+\Delta t}\left(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t}\right)} \frac{\hat{D}^{VRS}_{t}\left(\mathbf{x}_{t},\mathbf{y}_{t}\right)}{\hat{D}^{CRS}_{t}\left(\mathbf{x}_{t},\mathbf{y}_{t}\right)} \right) = PEffCh \times SEffCh \qquad \text{Eq. 2.8}$$

where *PEffCh* and *SEffCh* are measures of pure efficiency change – i.e., efficiency change with respect to the VRS frontier – and change in scale efficiency, respectively. Values higher (or lower) than one indicate an increase (or decrease) in these quantities.

While pure efficiency change and scale efficiency change are related to VRS frontier movements between two different periods, *TeCh* variation still refers only to CRS frontier shifts over time. Wheelock and Wilson (1999) observed that if a generic firm in the input-output space remains fixed between time t and $t+\Delta t$, and the only change which occurs is in the VRS estimate of technology, the *TeCh* component, as measured in previous equations, is equal to one, indicating no change in technology, since the only way in which *TeCh* can change is if the CRS estimate of the technology changes. This being the case, the CRS estimate of the technology is thus statistically inconsistent. Since the VRS estimator is always consistent (Kneip et al., 1998), a further decomposition of Technological change is proposed by introducing VRS estimates:

$$\begin{aligned} TeCh = {} & \left[\frac{\hat{D}^{VRS}_{t}\left(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t}\right)}{\hat{D}^{VRS}_{t+\Delta t}\left(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t}\right)} \frac{\hat{D}^{VRS}_{t}\left(\mathbf{x}_{t},\mathbf{y}_{t}\right)}{\hat{D}^{VRS}_{t+\Delta t}\left(\mathbf{x}_{t},\mathbf{y}_{t}\right)} \right]^{\frac{1}{2}} \times \\ & \times \left[\frac{\hat{D}^{CRS}_{t}\left(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t}\right) / \hat{D}^{VRS}_{t}\left(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t}\right)}{\hat{D}^{CRS}_{t+\Delta t}\left(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t}\right) / \hat{D}^{VRS}_{t+\Delta t}\left(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t}\right)} \frac{\hat{D}^{CRS}_{t}\left(\mathbf{x}_{t},\mathbf{y}_{t}\right) / \hat{D}^{VRS}_{t}\left(\mathbf{x}_{t},\mathbf{y}_{t}\right)}{\hat{D}^{CRS}_{t+\Delta t}\left(\mathbf{x}_{t},\mathbf{y}_{t}\right) / \hat{D}^{VRS}_{t+\Delta t}\left(\mathbf{x}_{t},\mathbf{y}_{t}\right)} \right]^{\frac{1}{2}} \\ = {} & PTeCh \times STeCh \end{aligned} \qquad \text{Eq. 2.9}$$

where *TeCh* is further decomposed into Pure Technical Changes (*PTeCh*) and Scale Technical Changes, i.e. changes in the scale of technology (*STeCh*). The first component is the geometric mean of two ratios which measure the shift in the VRS frontier estimate relative to a firm's position at times t and $t+\Delta t$. When *PTeCh* is greater than one, it indicates an expansion in pure technology, i.e., an upward shift of the VRS estimate of the technology. *STeCh* provides information regarding the shape of that technology: it describes the change in returns to scale of the VRS technology estimate at times t and $t+\Delta t$. When *STeCh* is greater than one, the indication is that the technology is moving farther from CRS and is becoming more and more convex. Conversely, when this index is less than one, the technology is moving towards CRS; an index value of one indicates no changes.

Differing decompositions of technological change are also possible. Technical progress can in fact be independent of or dependent on any changes in the composition of input used and/or output produced by firms. Therefore, the technical change component may be rewritten as follows (Fare and Grosskopf, 1996):

$$
\begin{aligned}
TeCh = {} & \frac{\hat{D}_t^{CRS}(\mathbf{x}_t,\mathbf{y}_t)}{\hat{D}_{t+\Delta t}^{CRS}(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t})} \times \left[\frac{\hat{D}_t^{CRS}(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t})}{\hat{D}_{t+\Delta t}^{CRS}(\mathbf{x}_{t+\Delta t},\mathbf{y}_{t+\Delta t})}\frac{\hat{D}_{t+\Delta t}^{CRS}(\mathbf{x}_{t+\Delta t},\mathbf{y}_t)}{\hat{D}_t^{CRS}(\mathbf{x}_{t+\Delta t},\mathbf{y}_t)}\right]^{\frac{1}{2}} \times \\
& \times \left[\frac{\hat{D}_{t+\Delta t}^{CRS}(\mathbf{x}_t,\mathbf{y}_t)}{\hat{D}_t^{CRS}(\mathbf{x}_t,\mathbf{y}_t)}\frac{\hat{D}_t^{CRS}(\mathbf{x}_{t+\Delta t},\mathbf{y}_t)}{\hat{D}_{t+\Delta t}^{CRS}(\mathbf{x}_{t+\Delta t},\mathbf{y}_t)}\right]^{\frac{1}{2}} \\
= {} & MaTeCh \times \mathrm{Ob}TeCh \times \mathrm{Ib}TeCh
\end{aligned}
\qquad \textbf{Eq. 2.10}
$$

MaTeCh (Magnitude Tchnical Change) is related to Hicks-neutral technical change. If the magnitude effect is greater (lor ower) than one, it means that output of the same composition but greater (or lower) in terms of volume is obtained with the same input mix. *IbTeCh* (Input Biased Technical Change) refers to a non-neutral shift in the best-practices production frontier due to a different input mix, and *ObTeCh* (Output Biased Technical Change) refers to a non-neutral shift in the best-practices production frontier due to different output mix. Values of *IbTeCh* (or *ObTeCh*) greater than one indicate that the biased technical change amplifies TFP growth, and values of *IbTeCh* (or *ObTeCh*) less than one signify that the biased technical change shrinks TFP growth.

2.4 Database and variables description

The primary source of the data used in this study is the Bureau Van Dijk's AIDA database, which provides detailed information on the financials, geographical location, number of employees and local units for a large sample of limited liability Italian firms. A subsample of single-location manufacturing firms which were continuously active during the period 1996-2006 was selected from the original data collection. Since the original employment figures were missing for several firms, data were supplemented with workforce information from the Italian Institute of Social Security (INPS). This additional source yielded the yearly average number of employees for all firms in the sample. The data also allowed us to decompose the workforce into white- and blue-collar workers, as well as between full and part-time contracts for the eleven years covered in this analysis.

Lastly, the empirical analysis exploits an original dataset containing information on 7,712 Italian manufacturing firms (84,832 observations) over the period 1996-2006. The database represents a unique collection of data for Italy and allows us to extend understanding of the dynamics of incumbent firms over a relatively long period of time. In addition, dealing with single-location firms means that we can work at a level of analysis which is as close as possible to the single establishment level. Focusing on single-location firms also means that changes such as mergers, acquisitions and divestitures only marginally affect the group of firms in the sample. The spurious effect stemming from the intra-group reallocation of equipment and personnel is also neutralised. The industry distribution of our dataset generally reflects the distribution of firms described by the ISTAT "*8° Censimento Industria e Servizi*" in 2001 – the mid-point in the observation period (see Table 2.1).

Table 2.1. Number of Firms and Employment for industries. Year, 2001

Industry	*Firms*				*Employees*			
	ISTAT[a]		*Our Database*		*ISTAT*[a]		*Our Database*	
	Number	*%*	*Number*	*%*	*Number*	*%*	*Number*	*%*
Food and beverages	8,328	7.2	564	7.3	220,922	6.8	25,404	6.2
Textiles and clothing	13,929	12.0	911	11.8	352,291	10.8	51,645	12.6
Leather goods	4,869	4.2	365	4.7	113,573	3.5	19,971	4.8
Wood	3,281	2.8	204	2.6	56,284	1.7	9,071	2.2
Paper and printing	9,838	8.5	479	6.2	178,708	5.5	21,419	5.2
Petroleum	352	0.3	22	0.3	24,192	0.7	1,045	0.2
Chemicals	3,797	3.3	309	4.0	197,340	6.0	17,313	4.2
Rubber and plastic mat.	5,993	5.2	492	6.3	175,330	5.4	26,858	6.5
Non-met. mineral prod.	6,399	5.5	433	5.6	175,035	5.4	21,676	5.3
Fabricated metal prod.	20,545	17.7	1,445	18.7	503,712	15.4	77,814	19.0
Machinery and equip.	15,879	13.7	1,137	14.7	498,507	15.3	62,991	15.3
Electronics	11,291	9.7	574	7.4	344,198	10.5	31,104	7.6
Transportation equipment	2,697	2.3	161	2.1	253,778	7.8	10,691	2.6
Other manufacturing	8,716	7.5	616	7.9	174,104	5.3	32,288	7.8
Manufacturing	115,914	100.0	7.712	100.0	3,267,974	100.0	409,290	100.0

NOTE: [a] Values refer to entire population

2.4.1 Input and output variables

Input and output variables were constructed from balance-sheet data, with the exception of data on labour. The raw data were corrected and deflated in order to obtain real values. In this study, we used sectoral deflators constructed from ISTAT data.

Output was measured by revenues from sales and services at the end of the year, net of inventory changes or changes to contract work in progress; labour input was measured as the total number of employees at the end of the year. Two intermediate inputs were considered: (a) costs of raw materials consumed and goods for resale (net of changes in inventories); (b) cost of services; the capital stock estimate in a given year was proxied with a modified perpetual inventory method on the nominal value of tangible fixed assets over the period analysed (See Appendix 2A for further details of estimation procedure).

All monetary measures are expressed in thousands of euros and are deflated by the proper industry level index. The deflator for the turnover variable was constructed by processing the time series of national production. The deflator for intermediate inputs was constructed with a weighted deflator of production, with weights calculated as the average of the column coefficients of the input/output matrix for the year 2001 of a set of Italian regions.

Table 2.2 lists descriptive statistics on the variables of input and output for 2006, the final year of observation in our dataset.

2.4.2 Outliers treatment

Several authors have addressed the problem of outliers in DEA efficiency estimation (Wilson, 1993, 1995; Simar, 2003; Banker and Chang, 2006). In fact, DEA produces efficiency scores by comparing the input/output combinations of each firm with respect to a piecewise linear frontier, obtained as convex combinations of the best-performing firms in the set. This implies that measurement errors for those observations defining the frontier may cause distortions in the measured efficiency for the entire population.

In order to detect outliers, we carried out a preliminary analysis to check the impact of each single observation on the distances of the nearest firm – whose distance depended from that particular observation – using a method based on the concept of leverage, that is, the effect produced on the efficiencies of all the other firms when the observed firm is removed from the dataset (Stosic and Sampaio de Souza, 2005). Observations with a wider impact on the nearest firms were then discarded from the final calculation (see General Appendix A for details).

Table 2.2. Input and output variables. Year 2006

Industry		*Turnover (Th €)*	*Labour (n. emplyees)*	*Services (mgl €)*	*Row Mat. (Th €)*	*Tangible fix. assets (Th €)*
Food and beverages	Avg	15,669.5	44.31	2,652.3	10,263.4	3,490.4
	St.dev.	25,117.2	55.56	4,747.6	18,072.1	5,209.3
Textile and wearing	Avg	9,109.3	50.33	2,941.1	3,931.2	1,629.7
	St.dev.	13,017.2	65.79	4,488.2	6,346.0	3,459.8
Leather	Avg	10,510.2	45.70	2,647.6	5,899.3	1,186.6
	St.dev.	13,650.8	48.80	3,554.8	8,682.2	1,738.5
Wood	Avg	8,185.0	43.38	1,749.4	4,425.8	2,030.9
	St.dev.	9,979.3	40.97	2,824.6	5,586.4	3,055.5
Paper and printing	Avg	8,662.5	43.94	2,155.0	3,979.7	2,153.4
	St.dev.	9,640.1	40.79	2,611.1	5,698.8	3,512.9
Petroleum	Avg	26,414.5	51.24	2,561.3	18,993.9	8,176.1
	St.dev.	42,909.3	70.51	3,856.4	37,197.5	25,167.8
Chemical	Avg	18,540.3	59.50	4,234.7	9,706.4	2,764.4
	St.dev.	38,739.3	75.74	12,159.0	18,641.5	4,774.9
Rubber and plastic mat.	Avg	10,846.8	54.77	2,055.2	5,898.8	2,484.2
	St.dev.	16,665.0	71.06	2,981.7	10,270.9	7,319.7
Non-met. mineral prod.	Avg	10,014.8	49.65	2,429.3	4,704.8	2,459.3
	St.dev.	14,122.2	59.21	4,190.4	6,737.6	3,500.9
Fabricated metal prod.	Avg	13,774.9	54.73	2,292.0	8,215.4	2,330.1
	St.dev.	55,741.7	63.06	4,576.7	50,413.3	4,813.5
Machinery and equipment	Avg	11,097.2	56.81	2,245.3	5,601.1	1,556.4
	St.dev.	16,495.7	66.52	3,246.3	9,926.1	2,514.6
Electronics	Avg	9,987.7	52.98	1,936.2	5,138.7	1,258.7
	St.dev.	16,243.5	52.34	2,102.5	12,652.7	2,210.3
Transportation equipment	Avg	14,649.7	63.88	2,836.3	8,344.9	2,115.5
	St.dev.	28,463.5	70.80	4,474.4	21,173.8	2,719.7
Other manufacturing	Avg	8,868.7	49.52	2,141.6	4,647.5	1,752.0
	St.dev.	11,117.8	49.03	3,332.0	6,582.7	2,960.9

2.5 The dynamics of productivity

In this section, we focus on analysis of the evolution of productivity, as measured by Malmquist indexes and their components over the period 1996-2006. The distances from the estimated industry frontier at two-digit level are estimated for each firm and combined to construct and decompose Malmquist indexes. We calculate the annual growth rate of quantities of interest for each firm and then take weighted averages of annual growth rates for each industry, rather than estimates related to individual firm, accounting for the relative importance of each observation the productivity index of which enters the average (Zelenyuk, 2006).

2.5.1 Main Results

Table 2.3 lists the annual growth rates of productivity among sectors for the entire period 1996-2006. Productivity, with the exception of a few cases such as Machinery and Equipment and Electronics, shows annual growth rates below 1%. In the majority of industries considered, the annual growth rate was less than 0.5% and in some industries it was even negative. The two components of the Malmquist index – efficiency change and technological change – also behaved differently in determining productivity dynamics. There were industries, such as Textiles and clothing, Leather goods, Metal products, and Electronics, in which, on average, technology improved and efficiency declined, whereas there were others, such as Paper and Printing and Chemicals, in which the opposite occurred. Lastly, there were industries in which both components were positive, as in Machinery and Transportation.

Table 2.3. Malmquist index and its decomposition into Efficiency Change (*EffCh*) and Technological change (*TeCh*). Period 1996-2006.

Industry	*1996-2006*		
	Malm	*EffCh*	*TeCh*
Food and beverages	1.069	0.050	1.018
Textiles and clothing	0.353	-0.221	0.574
Leather goods	-0.004	-0.171	0.167
Wood	0.268	0.226	0.043
Paper and printing	0.090	0.534	-0.442
Petroleum	-1.004	-0.685	-0.326
Chemicals	-0.032	0.147	-0.180
Rubber and plastic mat.	0.490	0.194	0.296
Non-met. mineral prod.	0.068	0.041	0.030
Fabricated metal prod.	0.273	-0.033	0.307
Machinery and equipment	1.019	0.143	0.873
Electronics	1.224	-0.120	1.346
Transportation equipment	0.558	0.169	0.387
Other manufacturing	0.196	-0.175	0.372

The whole period was then broken down into three subperiods: 1996-2000, 2000-2003, and 2003-2006. This allowed us to capture three different phases: the period just before the introduction of the euro (i.e., 1999), the turning-point of the economic cycle around 2001, and the period before the beginning of the current crisis. Table 2.4 lists results for each subperiod.

Table 2.4. Malmquist index and its decomposition into Efficiency Change (*EffCh*) and Technological change (*TeCh*). Subperiods: 1996-2000, 2000-2003, 2003-2006

Industry	*1996-2000*			*2000-2003*			*2003-2006*		
	Malm	*EffCh*	*TeCh*	*Malm*	*EffCh*	*TeCh*	*Malm*	*EffCh*	*TeCh*
Food and beverages	-0.849	0.346	-1.189	1.624	0.311	1.315	6.992	-0.511	7.509
Textiles and clothing	-0.355	0.046	-0.400	0.823	-0.235	1.063	1.007	-0.400	1.408
Leather goods	-1.001	-0.106	-0.895	0.860	0.064	0.769	1.295	-0.401	1.676
Wood	-0.068	0.636	-0.701	0.975	-0.641	1.628	0.479	0.596	-0.118
Paper and printing	-1.579	1.228	-2.775	1.908	0.876	1.021	0.765	-0.584	1.369
Petroleum	-4.327	-0.178	-4.155	8.473	-0.184	8.668	-4.522	-1.587	-2.959
Chemicals	-1.223	-0.165	-1.058	1.794	1.202	0.579	-0.164	-0.358	0.194
Rubber and plastic mat.	0.041	0.887	-0.835	1.738	0.597	1.135	0.050	-1.078	1.143
Non-met. mineral prod.	-0.702	0.677	-1.357	0.391	0.496	-0.104	1.144	-0.860	2.033
Fabricated metal prod.	-0.218	0.654	-0.864	1.239	0.396	0.841	0.346	-1.305	1.667
Machinery and equip.	-0.510	0.636	-1.134	0.767	-0.058	0.830	3.544	-0.188	3.740
Electronics	0.500	0.703	-0.200	1.200	0.258	0.948	2.652	-1.622	4.337
Transportation equipment	-1.010	0.197	-1.206	0.523	0.768	-0.237	2.631	-0.569	3.209
Other manufacturing	-0.628	0.201	-0.826	0.055	-0.379	0.443	1.649	-0.349	2.005

Productivity dynamics showed marked differences over time. First, after the negative trend of subperiod 1 in all industries, a widespread increase in productivity followed in subperiods 2 and 3. Second, the sign of the technological (*TeCh*) and efficiency (*EfCh*) components of productivity growth changed radically among subperiods. Figure 2.1 shows in more detail the evolution across subperiods of both components; we concentrate on the first and last ones. During subperiod 1, the fall in productivity levels was driven by a sort of "technological regression" (negative sign of *TeCh*) in all sectors. The downward frontier shift was only partly offset by efficiency gains. However, in subperiod 3, productivity growth in all industries was driven primarily by technological advance – as shown by the positive sign of the *TeCh* component – while average efficiency decreased – the negative sign of the annual growth rate of *EffCh*.

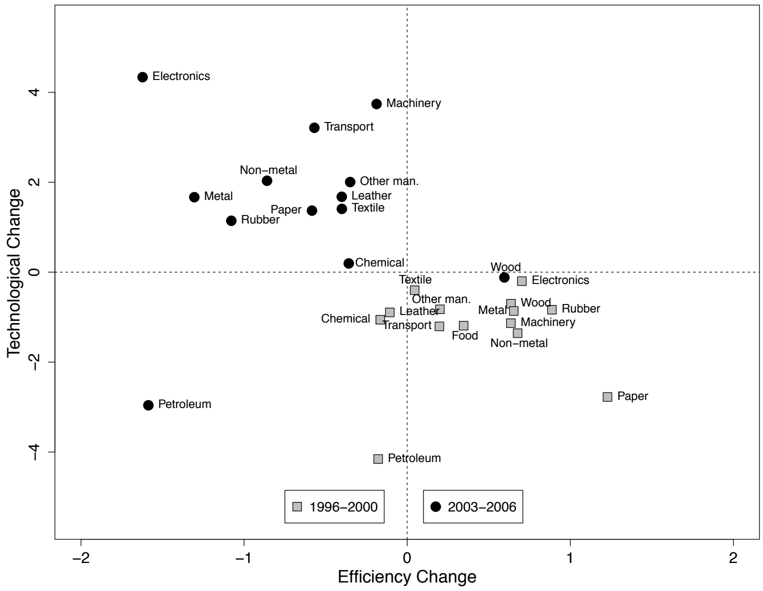


Figure 2.1 Technological Change (*TeCh*) and Efficiency Change (*EffCh*). Subperiods: 1996-2000 and 2003-2006.

This evidence suggests a process of technological advance which started in the early 2000s and mainly involved those firms closest to the frontier, while the majority of firms lagged behind. Consistent with a technological explanation of the increased dispersion of productivity (see Faggio et. al, 2007), the shift of the technological frontier appeared to be more extensive in industries in which new technologies were expected to be more important, such as Electronics and Machinery. The diffusion and improved use of technology already in the market (captured by *EfCh* index) did not in fact counterbalance the impact of technical change on dispersion in many sectors. Figure 2.2 further clarifies this dynamic, showing the evolution of the distribution of estimated efficiencies, i.e., distances to the frontier, for the Electronics industry.[5] At the end of subperiod 1 (left panel), efficiency distribution had shifted to the right, indicating a generalised increase in average efficiency. This changed drastically in subperiod 3 (right panel), during which the leftward shift of the distribution reveals a widespread loss of efficiency among firms, pointing to great heterogeneity in firm behaviour.

[5] To obtain kernel estimates of efficiencies, we used the eff.dens() function based on Silvrman's reflection method and available in the R package "Benchmarking" (Bogetoft and Otto, 2011).

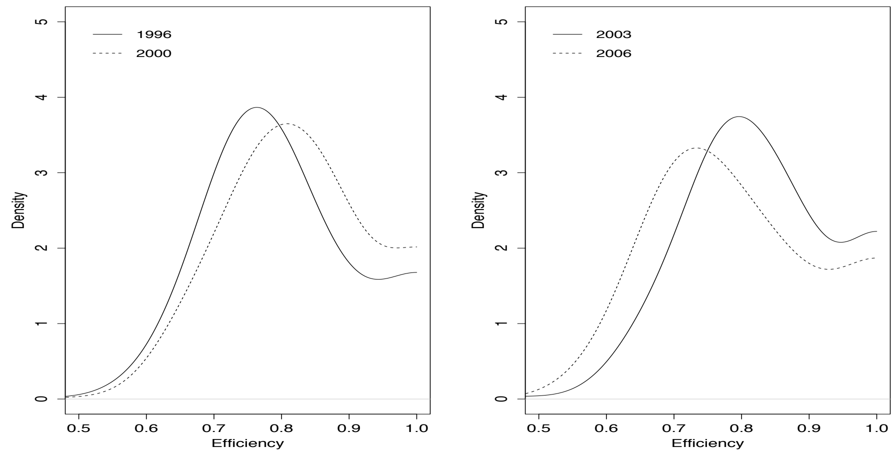


Figure 2.2 Kernel density estimation of efficiency in the Electronics industry.

The estimation method employed here enabled us to extend analysis by: (a) isolating the effect of production scale from that of pure efficiency change in the efficiency component of productivity change; and (b) separating both the effect of production scale and type of technological progress in the technological component of productivity.

Table 2.5 lists the decomposition of the efficiency change for each subperiod. Increases in efficiency in subperiod 1 occurred simultaneously, due to reduction in pure inefficiencies and a recovery of scale. The opposite occurred in subperiod 3, when the loss of efficiency was due to the contemporaneous decrease in pure and scale efficiencies. This provides additional evidence of two different stories: what took place at the beginning of the observed period (before 2000) and what happened after it.

The evolution of firm size further supports this idea (see Table 2.6). The average firm size, measured in terms of number of employees, increased between 1996 and 2000 in all sectors, but thereafter stabilised. The average size expressed in terms of nominal turnover followed the same pattern, although it is less evident.

Table 2.7 shows the decomposition of the technological component (*TeCh*). In subperiod 1 the two components – pure (*PTeCh*) and scale technological change (*STeCh*) – caused the downward shift of the frontier in different ways across industry. In subperiod 3, a general upward shift of the frontier prevailed. At the same time, it tended to modify its shape, moving towards a constant return to scale (negative sign of growth rate of *STeCh*).

Table 2.5. Efficiency Change (*EffCh*) and its decomposition into Pure Efficiency Change (*PEffCh*) and Scale Efficiency Change (*SEffCh*). Subperiods: 1996-2000, 2000-2003, 2003-2006

Industry	*1996-2000*			*2000-2003*			*2003-2006*		
	EffCh	*PEffCh*	*SEffCh*	*EffCh*	*PEffCh*	*SEffCh*	*EffCh*	*PEffCh*	*SEffCh*
Food and beverages	0.346	0.520	-0.170	0.311	0.216	0.100	-0.511	-0.412	-0.096
Textiles and clothing	0.046	-0.215	0.268	-0.235	-0.129	-0.100	-0.400	-0.198	-0.189
Leather goods	-0.106	-0.095	-0.009	0.064	0.122	-0.052	-0.401	-0.486	0.088
Wood	0.636	0.280	0.357	-0.641	-0.314	-0.323	0.596	0.336	0.264
Paper and printing	1.228	0.841	0.390	0.876	0.946	-0.057	-0.584	-0.707	0.132
Petroleum	-0.178	-0.069	-0.108	-0.184	0.202	-0.385	-1.587	-0.208	-1.382
Chemicals	-0.165	-0.202	0.040	1.202	0.218	0.991	-0.358	0.194	-0.549
Rubber and plastic mat.	0.887	0.591	0.303	0.597	0.168	0.432	-1.078	-0.514	-0.562
Non-met. mineral prod.	0.677	0.545	0.133	0.496	-0.021	0.522	-0.860	-0.857	0.000
Fabricated metal prod.	0.654	0.011	0.646	0.396	0.186	0.216	-1.305	-0.451	-0.854
Machinery and equip.	0.636	0.118	0.521	-0.058	0.299	-0.352	-0.188	-1.025	0.865
Electronics	0.703	0.354	0.361	0.258	-0.578	0.850	-1.622	-1.046	-0.580
Transportation equipment	0.197	0.124	0.084	0.768	0.538	0.235	-0.569	-0.150	-0.421
Other manufacturing	0.201	0.071	0.134	-0.379	0.316	-0.686	-0.349	-0.195	-0.149

Table 2.6. Number of employee for different years

Industry		*Year*			
		1996	*2000*	*2003*	*2006*
Food and beverages	Avg	40.03	44.87	46.35	44.31
	St.dev.	45.30	53.40	56.22	55.56
Textiles and clothing	Avg	53.62	57.05	53.91	50.33
	St.dev.	64.86	67.58	64.73	65.79
Leather goods	Avg	52.45	54.74	50.37	45.70
	St.dev.	59.27	61.22	53.97	48.80
Wood	Avg	39.88	45.10	43.57	43.38
	St.dev.	34.10	41.07	39.80	40.97
Paper and printing	Avg	41.16	44.87	44.03	43.94
	St.dev.	39.03	40.35	39.18	40.79
Petroleum	Avg	43.27	44.09	47.14	51.24
	St.dev.	66.53	60.07	60.57	70.51
Chemicals	Avg	49.95	56.52	56.40	59.50
	St.dev.	74.14	80.73	76.81	75.74
Rubber and plastic mat.	Avg	46.12	54.81	54.17	54.77
	St.dev.	50.17	62.59	65.02	71.06
Non-met. mineral prod.	Avg	44.46	49.43	49.79	49.65
	St.dev.	48.68	54.80	57.30	59.21
Fabricated metal prod.	Avg	46.26	53.83	53.42	54.73
	St.dev.	48.68	56.34	58.58	63.06
Machinery and equipment	Avg	49.30	55.37	55.08	56.81
	St.dev.	51.75	56.71	59.94	66.52
Electronics	Avg	46.35	54.10	52.73	52.98
	St.dev.	42.92	51.34	52.17	52.34
Transportation equipment	Avg	60.47	67.21	63.57	63.88
	St.dev.	70.66	74.55	67.01	70.80
Other manufacturing	Avg	45.67	52.67	51.23	49.52
	St.dev.	38.33	44.25	46.28	49.03

Table 2.7. Technological Change (*TeCh*) and its decomposition into Pure Technological Change (*PTeCh*) and Scale Technological Change (*STeCh*). Subperiods: 1996-2000, 2000-2003, 2003-2006

Industry	*1996-2000*			*2000-2003*			*2003-2006*		
	TeCh	*PTeCh*	*STeCh*	*TeCh*	*PTeCh*	*STeCh*	*TeCh*	*PTeCh*	*STeCh*
Food and beverages	-1.189	-1.042	-0.096	1.31	1.865	-0.490	7.509	-	-
Textiles and clothing	-0.400	0.171	-0.492	1.06	0.557	0.516	1.408	1.604	-0.181
Leather goods	-0.895	-0.997	0.144	0.77	-0.746	0.740	1.676	1.642	-0.004
Wood	-0.701	0.108	-0.742	1.63	1.004	0.511	-0.118	0.873	-0.958
Paper and printing	-2.775	-1.755	-0.814	1.02	0.789	0.172	1.369	2.142	-0.727
Petroleum	-4.155	-5.022	1.037	8.67	8.555	-0.031	-2.959	-4.046	1.120
Chemicals	-1.058	-0.134	-0.638	0.58	1.631	-1.018	0.194	-0.350	0.610
Rubber and plastic mat.	-0.835	0.174	-0.924	1.13	1.420	-0.262	1.143	1.202	-0.005
Non-met. mineral prod.	-1.357	-0.735	-0.530	-0.10	0.353	-0.432	2.033	2.716	-0.650
Fabricated metal prod.	-0.864	0.011	-0.850	0.84	1.052	-0.252	1.667	1.152	0.560
Machinery and equip.	-1.134	-0.415	-0.680	0.83	0.552	0.284	3.740	5.095	-1.308
Electronics	-0.200	0.537	-0.681	0.95	2.015	-1.119	4.337	4.465	-0.027
Transportation equipment	-1.206	0.138	-1.096	-0.24	-0.017	-0.214	3.209	3.222	-0.054
Other manufacturing	-0.826	-0.413	-0.357	0.44	-0.161	0.614	2.005	2.018	-0.050

Further insights come from analysis of the nature of technological progress (Table 2.8). The technological regression observed during subperiod 1 was mainly due to a Hicks-neutral shift, whereas in subsequent periods the outward shift of the frontiers was both Hicks-neutral and input-biased.

Table 2.8. Technological Change (*TeCh*) and its decomposition into *MaTeCh* and Input Biased Technological Change (*IbTeCh*). Subperiod: 1996-2000, 2000-2003, 2003-2006

Industry	*1996-2000*			*2000-2003*			*2003-2006*		
	TeCh	*MaTeCh*	*IbTeCh*	*TeCh*	*MaTeCh*	*IbTeCh*	*TeCh*	*MaTeCh*	*IbTeCh*
Food and beverages	-1.189	-1.558	0.406	1.315	0.380	0.958	7.509	-0.594	9.473
Textiles and clothing	-0.400	-0.645	0.270	1.063	0.897	0.183	1.408	1.148	0.266
Leather goods	-0.895	-1.213	0.348	0.769	-0.252	1.045	1.676	1.236	0.780
Wood	-0.701	-1.133	0.461	1.628	1.004	0.641	-0.118	-0.657	0.577
Paper and printing	-2.775	-3.061	0.329	1.021	0.689	0.353	1.369	1.071	0.353
Petroleum	-4.155	-11.724	9.503	8.668	4.349	4.129	-2.959	-7.801	5.914
Chemicals	-1.058	-1.842	0.958	0.579	0.311	0.279	0.194	-0.231	0.449
Rubber and plastic mat.	-0.835	-1.071	0.252	1.135	0.918	0.237	1.143	0.918	0.236
Non-met. mineral prod.	-1.357	-1.790	0.458	-0.104	-0.380	0.283	2.033	1.774	0.266
Fabricated metal prod.	-0.864	-1.315	0.479	0.841	0.589	0.265	1.667	0.290	1.421
Machinery and equip.	-1.134	-1.343	0.218	0.830	0.661	0.171	3.740	3.396	0.347
Electronics	-0.200	-0.505	0.318	0.948	0.729	0.220	4.337	3.459	0.870
Transportation equipment	-1.206	-1.830	0.742	-0.237	-0.850	0.655	3.209	2.414	0.789
Other manufacturing	-0.826	-1.047	0.236	0.443	0.188	0.275	2.005	1.593	0.416

Lastly, in the proposed DEA framework, the estimated distances to the frontier would be biased if the most efficient firms within the population were not observed (Simar and Wilson, 1998). Consequently, the Malmquist indexes and their components are also biased estimators of productivity growth. We followed Simar and Wilson (1999) and estimated also bias-corrected Malmquist indexes and their components by bootstrapping distance measures. The resulting bias-corrected estimates confirm our results. Appendix 2B lists the procedure in more detail and includes bias-corrected annual growth rates of the quantities of interest.

2.5.2 Discussion

It is important to bear in mind the most important changes which took place in the input and output markets during the period under analysis.

The most important change on the input side seems to be the sequence of labour reforms which occurred in Italy in the early 1990s. In particular, during this period, a series of labour flexibility practices were introduced, which enabled firms to use fixed-term contracts, to adjust working hours in response to external shocks, and to increase wage flexibility at firm level. The introduction of the euro in 1999 was probably the greatest external shock which influenced the output side. In a context of increasing globalisation and the entry of new competitors, the introduction of the new currency eliminated exchange rate policies as instruments to support the competitiveness of Italian firms.

The downward shift of the frontier observed at the end of subperiod 1 is puzzling. On one hand, the most efficient firms may have over-invested in productive capacity in the early 1990s, when demand was driven by competitive devaluation. On the other hand, labour market reforms may have fostered a process of restructuring of the input mix which was still ongoing at the beginning of the 2000s. However, the breakdown of the technological change index in magnitude (*MaTeCh*) and input composition (*IbTeCh*) effects suggests that regression from the frontier was mainly driven by the output reduction effect. The simultaneous improvement in efficiency may partly have been due to a sort of side-effect of the downward shift of the frontier: if the frontier regresses, the distance to it of inefficient firms may only be apparently reduced.

However, decomposition of the efficiency change indexes indicates that a true reduction in inefficiency, based on adjustment of the production scale, did occur.

As from the early 2000s, the technological frontier shifted upwards and the average distance of firms from the frontier increased. On one hand, this suggests that firms close to the frontier undertook a process of innovation which led to the upward shift of the frontier, both Hicks-neutral and input-biased, with the movement of the VRS frontier towards the estimated CRS frontier. On the other hand, the increased distance from the frontier of some firms is consistent with technological progress unevenly distributed across firms or, at least, that different outcomes took place in terms of productivity enhancement.

In this regard, several analyses (Rossi, 2006; Brandolini and Bugamelli, 2009; Bugamelli et al., 2010; De Nardis, 2010) describe a profound process of firm restructuring in Italian manufacturing in terms of technological content and quality, spurred by the introduction of the euro. Bugamelli et al. (2010) observed an increasing dispersion of labour productivity from 1999 onwards. Our results, looking at a measure of Total Factor Productivity instead of labour productivity, are also consistent with restructuring which had different outcomes across firms, as one would expect during such episodes. Antonelli et al. (2013), using a sample of Italian manufacturing firms for the period 1996-2005 comparable with our sample, also support this interpretation. They addressed the central role of changes in input and output markets in determining the diverse innovative outcome of firms (measured in terms of productivity changes). Firms innovated to react to external shocks, but their innovations were productivity-enhancing only for firms whose internal characteristics blended better with the new context in which they were operating. Matching our results, the above authors noted an increased percentage of persistent innovators after 2000, with respect to the second half of the 1990s.

From a theoretical point of view, our evidence can be framed in a Schumpeterian perspective. After the introduction of the euro at the end of the 1990s, which acted as a trade liberalisation shock, and after the turning-point of the economic cycle in the early 2000s, competitive pressure increased, profit margins fell (see Bianco et al., 2012), and the incentive for firms already in the market to take costly innovation actions which they might otherwise not have taken, increased, allowing those firms to survive. However, their incentives to make productivity-enhancing investments because of heightened competition may have differed. For instance, an increase in competition may incentivise "good" firms, that is, those close to the frontier, to invest in new technologies and new production processes in order to retain their market, but it may discourage innovation in "bad" firms, i.e., ones which lag far from the frontier, as their expected profits are reduced because their efficiency is too low to allow them to compete with more efficient firms (Aghion et al., 2005; Iacovone, 2012). Empirical evidence from various countries (Sabirianova et al., 2005, Konings and Vandenbussche, 2007; Iacovone, 2012) confirms the non-linearity and heterogeneity of the relationship between competition and innovation, as well as of the central role of initial efficiency level as a moderator of the impact of competition on firm productivity growth. Our results are indeed similar.

In sum, what emerges in the first part of our analysis suggests the existence of various "types" of firm. In the next section, we explore the hypothesis that, since labour market reforms made flexible labour accessible at lower prices, some firms could have pursued a process of adaptation to the new conditions in the input market by drawing on the less protected part of the labour market. In particular, we explore the hypothesis that (some) firms reduced the quality of their human capital. Wage flexibility and a less rigid labour market may have been an extra competitive option for non-innovating firms (Kleinknecht, 1998). Instead of innovating, weak "bad" firms could easily pursue a cost-cutting strategy – the "low road" – by, for instance, giving employees short-term contracts and/or offering them part-time work, and accepting less skilled labour, with negative effects any on innovation effort as a solution to cope with the more competitive environment.

2.6 The role of human capital to explain productivity differentials

This section explores the factors behind the evidence about productivity dynamics presented in the first part of this chapter. In particular, we proceed to a second stage of analysis, supporting the hypothesis that the increased dispersion of productivity observed across years was due to the differing strategies adopted by firms to cope with changes in the competitive environment. We focus in particular on factors related to firm choices about the quality of human capital. The evidence of the previous section is consistent with different strategic behaviour. On one hand, we have a group of dynamic firms which, after the shock of the new currency, followed a path of technological innovation leading to a shift in the technological frontier; on the other hand, we have a large group of firms which, taking advantage of the new flexibility of the labour market, hired less protected workers and reduced investment in human capital.

In exploring the relationship between strategic choices and productivity dispersion, we believe it is important to take into account both efficiency levels, i.e., distance to the frontier, and productivity dynamics[6]. The mediating role of distance to the frontier empirically emerged as important in explaining the effectiveness of firm strategies (Coad, 2011). Thus, we first ranked firms with respect to their distance to the frontier and observed productivity growth. Then we grouped them, for each of the three periods, with respect to the industry average value of the two variables as firms with high or low initial efficiency levels at the beginning of each period, and firms with high or low productivity dynamics observed in the same period. Figure 3.3 shows the resulting classifications.

Four distinct "types" of firms were identified: laggards (1) are firms with low initial efficiency and below average productivity growth; climbers (2) are ones with low initial efficiency, which move rapidly towards the frontier and sometimes induce its shift. Productivity growth for these firms may be particularly fast, as they can act on two factors: efficiency gains related to imitative processes, and independent technological advances; static leaders (3) are firms close to the frontier but with low productivity growth, which therefore tend, over time, to move away from the frontier; dynamic leaders (4) are firms closer to the technological frontier at the onset of the period which show above-average productivity growth. These firms are likely to improve their productivity, mainly through innovative strategies rather than improvements in efficiency.

[6] Our main interest is in how best-practices firms and firms below the frontier move with respect to each other over time. Consequently, in the second part of the chapter, DEA scores are treated as descriptive measures of the relative distance of firms from the observed frontier (as in McDonald, 2009). This allows us to rank firms and then cluster firms with respect to the measures obtained in the first part of the chapter.

Efficiency level $_t$	*Productivity change* $_{t+\Delta t}$: *High*	*Low*
High	**Dynamic leader (4)** *N. obs.:* *Period1 = 1247* *Period2 = 1230* *Period3 = 1289*	**Static Leader (3)** *N. obs.:* *Period1 = 2193* *Period2 = 2303* *Period3 = 2275*
Low	**Climbers (2)** *N. obs.:* *Period1 = 2468* *Period2 = 2242* *Period3 = 2090*	**Laggards (1)** *N. obs:* *Period1 = 1439* *Period2 = 1572* *Period3 = 1693*

Figure 2.3 The four types of firms (see definition in text).

A multinomial logit regression model was estimated to isolate some significant relationships between a set of explanatory variables and types of firms:

$$P\left(y=j \mid \mathbf{x}\right)=\exp\left(\mathbf{x}\beta_j\right) \Big/ \left[1+\sum_{k=2}^{4}\exp\left(\mathbf{x}\beta_k\right)\right] \qquad \textbf{M. 2.3}$$

where $P\left(y=j \mid \mathbf{x}\right)$ represents the probability of belonging to group j = 2, 3, 4 indicationg firm types, $\mathbf{x}$ represents explanatory variables and controls, and β_j are the parameters to be estimated. Obviously, for the reference group (1) we have:

$$P\left(y=1 \mid \mathbf{x}\right)=1 \Big/ \left[1+\sum_{k=2}^{4}\exp\left(\mathbf{x}\beta_k\right)\right] \qquad \textbf{M. 2.4}$$

The hypothesis of the existence of differing strategic behaviour as a result of the composition of the labour force was studied by means of a set of explanatory variables which proxies the quality of human capital employed by firms. In particular, we assume that, on average, the higher quality of human capital costs more, and we therefore use the unit cost of labour (*labour_cost*) as a proxy of the quality of human capital available to the firm[7]. However, a different unit cost of labour between firms may represent either

[7] Labour cost has already been used as an indicator of the level of human capital for Italian manufacturing firms. See, for instance, Antonelli et al. (2013).

a different quality of labour employed or, in a segmented labour market, labour of the same quality but at a lower price.[8] However, the effect on efficiency is expected to be different in the two cases. In the former case, between-firm variations of cost of labour due to the (not observed) use of labour of a different quality results in production inefficiency; in the latter case, a difference in cost of labour will only imply allocative inefficiency if firms do not adjust the composition of production factors (i.e., if they do not employ only less costly labour). The evidence of a relationship between the unit cost of labour and productive efficiency should therefore support the hypothesis that a less rigid labour market leads to differentiation not only in terms of the price of labour but also of firms' choices about its quality.

To account for different firm choices as regards the quality of the workforce against simple adjustments due to changes in labour costs, we also consider the ratios of white-collar to blue-collar workers (*skill_ratio*) and of part-time employees to total employees (*part-time*). The *skill_ratio* is used as a proxy of the the share of skilled workers and the role which upstream and downstream activities have in business strategies (Bugamelli et al., 2010); the share of part-time employment on total employment (*part-time*), is a proxy of the use of flexible labour (Arvanitis, 2005), which has a impact on the quality of labour under the assumption that the contribution of full-time employees is of higher quality than that of part-time employees, for reasons related to individual motivations, incentive structure, level and rate of learning (Dolado and Stucchi, 2008). We also consider the following control variables:

- Firm size in terms of number of employees (*size*). In this regard, in a study of American firms, Dhawan (2001) shows that small businesses are significantly more productive than larger ones, suggesting a negative relationship between productivity growth and firm size. Recently, however, Harris and Moffat (2011) showed that manufacturing firms in the UK are operating under increasing returns to scale and that firm size is positively related to the dynamics of total factor productivity.
- The age (*age*) of the firm, which may have a negative or positive effect on productivity growth, either due to the effect of technological obsolescence, or

[8] Let us presume that employees are divided into two groups: regular and flexible employees. Two scenarios are possible. In the first, firms hire employees of the same quality but at different cost: regular employees cost more than irregular ones. In the second scenario, firms choose only employees in one group but pay them differently, depending on their skills or quality.

that learning-by-doing prevails (Argote et al., 2003; Cohen and Levinthal, 1990; Harris and Moffat, 2011).

- Cash flow (*cash_flow*). The literature shows that more stringent financial constraints have a negative effect on firm performance in terms of growth and profitability (Fagiolo and Luzzi, 2006) and productivity (Bottazzi et al., 2008; Bottazzi et al., 2011).
- Three sets of dummy variables account for time, sector of activity, and location in terms of geographic area, respectively. These variables control for the various external conditions in which firms operate.

2.6.1 Main results

Table 2.9 lists average values and standard deviations of the explanatory variables. Laggards have on average a higher number of employees (54.5), use more part-time workers (0.043) and are older (22.5) than firms in the other groups. Dynamic leaders pay more for labour (23.8), have a higher cash flow (564.3), use more skilled labour (0.88), and are younger compared with the other groups. Lastly, static leaders are similar to dynamic leaders in terms of labour costs, but use fewer part-time workers. However, they have higher cash flows and lower skill ratios.

The correlation matrix (Table 2.10) shows that the number of employees and cash flow are positively correlated (0.597). Correlations are very low for all the other pairs of explanatory variables.

Table 2.9. Descriptive statistics

Variable	*Laggards*		*Static leaders*		*Climbers*		*Dyn. leaders*	
	Avg	*Std*	*Avg*	*Std*	*Avg*	*Std*	*Avg*	*Std*
Labour_cost (Th. €)	20.7	5.2	23.8	7.4	20.0	5.6	23.8	7.5
Skill_ratio (ratio)	0.46	1.42	0.66	2.53	0.47	1.28	0.88	3.51
Partime (ratio)	0.043	0.060	0.037	0.053	0.041	0.058	0.039	0.056
Cash_flow (Th. €)	393.0	723.0	649.8	1246.6	327.7	576.6	564.3	1151.8
Size (n. employees)	54.5	52.9	47.5	52.8	53.0	49.6	44.0	46.6
Age (years)	22.5	12.4	21.7	13.2	21.1	12.4	20.9	12.7

Table 2.10. Correlation matrix

Variable	*Labour cost*	*Skill ratio*	*Partime*	*Cash flow*	*Size*	*Age*
Labour cost	1					
Skill ratio	0.167*	1				
Partime	-0.141*	0.034*	1			
Cash flow	0.225*	0.078*	-0.075*	1		
Size	0.147*	-0.009	-0.065*	0.597*	1	
Age	0.256*	0.007	0.038*	0.092*	0.158	1

* indicates significativity at 5%

Table 2.11 lists the estimated multinomial model with different sets of explanatory variables. In all specifications of the model, we consider the entire set of controls on: financial constraints, size and age of the firm, and the dummies for period, sector and geographical location. The estimated coefficients represent the log-odds ratios, i.e., the logarithm of the ratio of the probability of being in group j ($j = 2, 3, 4$) to the probability of being in the baseline group ($j = 1$, i.e., laggards)[9].

Our measure of the quality of human capital (*labour_cost*) and the probability of belonging to the group of leaders, either static or dynamic, compared with the baseline category (laggards) are positively related. A higher value of *skill_ratio* is associated with a greater probability of being a leader or a climber with respect to the baseline group, whereas increasing the number of part-time employees reduces the probability of belonging to any of the groups other than the laggards. Looking at the control variables, we see that, compared with the baseline group (laggards) *cash_flow* increases the probability of belonging to a leader group and reduces the likelihood of being a climber (the effect, although statistically significant, is very low) and that probability of being a leader decreases with the age of the firm.

[9] The multinomial logit model is based on the assumption of Independence of Irrelevant Alternatives (IIA), meaning that the odds ratio between any two choices is not affected by any other alternative choice. Rejection of the IIA assumption leads to biased predictions of probabilities by the model. We tested the IIA assumption of our model specifications with the Small-Hsiao test.

Table 2.11. Multinomial logit estimates (log-odds ratios). Reference group: *Laggards* (1)

	Model 1			*Model 2*			*Model 3*		
Variable	*Climbers (2)*	*Static leaders (3)*	*Dynamic leaders (4)*	*Climbers (2)*	*Static leaders (3)*	*Dynamic leaders (4)*	*Climbers (2)*	*Static leaders (3)*	*Dynamic leaders (4)*
labour_cost	- 0.021***	0.118***	0.122***	- 0.024***	0.117***	0.118***	0.003	0.127***	0.138***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)	(0.007)
skill_ratio	-	-	-	0.032*	0.036*	0.060***	0.034*	0.036*	0.061***
				(0.019)	(0.018)	(0.018)	(0.019)	(0.019)	(0.018)
partime	-	-	-	- 0.655*	- 0.757**	- 0.705	- 0.718**	- 0.754*	- 0.726*
				(0.353)	(0.385)	(0.436)	(0.353)	(0.385)	(0.437)
*p_2 * labour_cost*	-	-	-	-	-	-	- 0.038***	- 0.017*	- 0.039***
							(0.009)	(0.009)	(0.010)
*p_3 * labour_cost*	-	-	-	-	-	-	- 0.042***	- 0.001	- 0.022**
							(0.009)	(0.009)	(0.010)
Controls									
cash flow	- 0.0003***	0.0008***	0.0008***	- 0.0003***	0.0008***	0.0008***	- 0.0003***	0.0008***	0.0008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(age)	- 0.143***	- 0.375***	-0.444***	- 0.130***	- 0.369***	- 0.431***	- 0.146***	- 0.374***	- 0.440***
	(0.036)	(0.037)	(0.041)	(0.036)	(0.037)	(0.042)	(0.036)	(0.037)	(0.042)
ln(size)	0.133***	- 0.968***	-1.033***	0.137***	- 0.961***	- 1.020***	0.135***	- 0.963***	- 1.023***
	(0.032)	(0.035)	(0.039)	(0.033)	(0.036)	(0.040)	(0.033)	(0.036)	(0.040)
Time dummies		Yes			Yes			Yes	
Sector dummies		Yes			Yes			Yes	
Location dummies		Yes			Yes			Yes	
Constant	0.877***	2.130***	1.686***	0.900***	2.132***	1.703***	0.421**	1.969***	1.310***
	(0.161)	(0.165)	(0.186)	(0.165)	(0,170)	(0.192)	(0.188)	(0.197)	(0.221)
Statistics									
Obs		21.258			21.030			21030	
Log-likelihood		- 26569.4			- 26294.7			- 26274,2	
McFadden's adj R2		0.076			0.075			0.075	
Nagelkerke R2		0.207			0.205			0.207	
LR χ2 (degr. of fred.)		4562.5 (66)			4479.1 (72)			4519.9 (78)	

To extend our analysis further, we estimated the marginal effect of a variable on the probability of belonging to each group.

Table 2.12. Marginal effects

Variable	*Model 3*			
	Laggards (1)	*Climbers* (2)	*Static leaders* (3)	*Dynamic leaders* (4)
labour_cost	- 0.0141***	- 0.0181***	0.0195***	0.0128***
	(0.0010)	(0.0011)	(0.0010)	(0.0007)
skill_ratio	- 0.0070**	0.0006	0.0014	0.0050***
	(0.0030)	(0.0024)	(0.0021)	(0.0012)
partime	0.1260**	-0.0432	- 0.0566	- 0.0265
	(0.0542)	(0.0617)	(0.0659)	(0.0515)
*p_2 * labour_cost*	0.0051***	- 0.0045***	0.0020	- 0.0027***
	(0.0013)	(0.0014)	(0.0013)	(0.0010)
*p_3 * labour_cost*	0.0043***	- 0.0068***	0.0030**	-0.0005
	(0.0013)	(0.0015)	(0.0014)	(0.0010)
Controls				
cash_flow	- 7.26e-05***	- 0.0002***	0.0002***	8.79e-05***
	(6.38e-06)	(8.02e-06)	(6.18e-06)	(4.06e-06)
ln(age)	0.0520***	0.0264***	- 0.0431***	- 0.0352***
	(0.0055)	(0.0058)	(0.0059)	(0.0046)
ln(size)	0.0961***	0.169***	- 0.164***	- 0.101***
	(0.0049)	(0.0056)	(0.0057)	(0.0043)

Note: controls on time, sector and location are considered

Table 2.12 lists the estimated marginal effects (Model 3). An increase in the quality of human capital (*labour_cost*) increases the probability of belonging to the group of firms close to the frontier (both static and dynamic leaders) and decreases that of being laggards or climbers. The estimated coefficient of *labour_cost*, although remaining negative in all periods, also shows a different evolution over time: there is a downward trend of its negative impact on the probability of belonging to the laggards – as indicated by the positive coefficient of the interaction between the quality of human capital and time, *p * labour_cost,* in the second (0,0051) and third (0.0043) periods – while an increase of (negative) magnitude of the impact on the probability of belonging to the climbers is observed – as shown by the negative coefficients of *p * labour_cost* in the second (-0.0045) and third (-0.0068) periods.

2.6.2 Discussion

The second part of this chapter allows us to characterise the four groups of firms: laggards, climbers, and static and dynamic leaders. Laggards employ a cost-cutting strategy based on the use of labour of lower quality and take a cost advantage from the flexible labour market. Leader firms are younger, smaller, and use more skilled labour. The climbers use a mixture of strategies to reach the frontier.

The sign of *skill_ratio* is in the expected direction. Variations in this ratio have an effect especially on the extreme groups: an increase in the ratio is positively associated with the increased probability of being dynamic leaders and reduces the probability of belonging to the group of laggards. This result supports the hypothesis that investment in human capital is more valuable for firms close to the productivity frontier. A higher share of part-time contracts increases the probability of belonging to the group of laggards. Firms in this group use flexible labour more than other firms. This evidence is consistent with previous studies: Lucidi and Kleinknecht (2009) found that Italian manufacturing firms with a high share of flexible workers and lower labour costs had significantly lower rates of labour productivity growth from 2001 to 2003.

Despite their propensity to lower the quality of labour over time, climbers tend to catch up with the frontier over time. However, reduction of their distance to the frontier may be associated with the effect of successful servitisation strategies (Baines et al., 2009), with the expansion of upstream (e.g., product design) and downstream (e.g., marketing and sales) activities. This is explained by the fact that these firms have a higher and less dispersed ratio of white- to blue-collar workers with respect to laggards.

The negative effect of firm size contrasts with a substantial proportion of the literature, which shows a positive relationship between size and productivity. However, firms may have undergone downsizing. And, as we saw in the first period, increased efficiency was also due to scale effects. The results of the effect of age and firm size on productivity dynamics are in fact consistent with those identified by Hall et al. (2009). Analysing a panel of SME Italian manufacturing firms in the period 1995-2003, these authors found that larger and older firms were less productive. A negative relationship between size and efficiency was also found by Diaz and Sanchez (2008) in the case of Spanish firms and by Dhawan (2001) in the United States.

2.7 Conclusions

Earlier studies on the Italian economic slowdown pointed to a generalised failure of the entire productive system to meet the challenges posed by increased globalisation of markets. However, the analysis presented here indicates that the high heterogeneity of firm behaviour lay behind this generalized economic stagnation.

The evidence presented here is consistent with that obtained in other studies carried out with different methods (Antonelli et al., 2013; Bugamelli et al., 2010; Dosi et al., 2012). The approach we followed more precisely isolated the component of productivity growth due to technological change. Our results clearly point to growing dualism among firms. Some firms showed sustained productivity growth, while others clearly failed to keep pace with the group of innovators. In the latter part of the chapter, we question whether this dynamic is related to different patterns of strategic adaptation.

The evidence reinforces the hypothesis that firms followed different paths in adapting to external shocks and that the different use of labour played a decisive role in this process. The labour market reforms implemented in Italy in the 1990s definitely and dramatically reduced labour costs, and also the quality of newly hired workers. We hypothesised that firms took advantage of the emergence of a dualistic labour market. The availability of flexible labour, less expensive but also less skilled, was the easiest solution to competition for some firms, whereas more efficient and dynamic ones competed in innovation. Nevertheless, it is difficult to assess the long-term effectiveness of these different modes of adaptation, although the initial evidence we have encourages more careful analysis of this hypothesis.

The analysis is based on a sample of continuing firms and is silent about the actual effect of entry and exit on technological progress. Population ecology theories suggest that innovation, in the form of organizational change, occurs at the population level essentially through organizational births and deaths (Hannan and Freeman, 1989). The hypothesis of newly established firms being more science-based and technologically advanced is consistent with the entrepreneurial process of 'creative destruction' (Schumpeter, 1934). However, in an intermediate-technology context such as Italian manufacturing, young innovative firms may not be enough creative and autonomous to shape their innovative processes. Hence, they need to acquire external knowledge in order to foster their own innovation activity (Pellegrino et al, 2011). In our context, new entrants do not necessarily cause a shift of the technological frontier, but they are more likely to acquire technologies already in the market, and the survivors occasionally produce changes of the frontier. This pattern would be consistent with our findings and with the strand of research which suggests within-firm changes in existing firms as the principal driver of aggregate productivity dynamics (see, e.g. Bottazzi et al., 2010). It is nevertheless necessary to integrate findings discussed in this chapter with empirical evidence on the impact of entry and exit for better understanding of the origins of the long stagnation of productivity in Italy.

A final remark is necessary. Our results can only give some insights into the strategic nature of the observed heterogeneity of productivity. Although the explanatory variables used were measured at the beginning of each period, concerns about endogeneity (cash flow, in the first place) still remain. The evidence put forward should also only be considered in a descriptive sense, although it does suggest that the strategic nature of the observed heterogeneity has a foundation and that different groups of firms actually pursue different strategies to adapt to new market conditions.

2.8 Appendix

2.8.1 2A: Capital stock estimation procedure

To obtain estimates of capital stock, the procedure used historical values of tangible assets and adapted the perpetual inventory method. Specifically, the procedure assumes that assets are purchased and then replaced over a certain period of time depending on their estimated average duration.

The first step consisted of estimating capital for the base year – the firs year. It is was assumed that first-year assets were bought gradually in the past and then replaced in subsequent years. For the base year, the historical value of tangible assets was divided for the estimated average duration and each portion deflated with the deflator for the period in question. The estimated capital stock for the first year (*base*) was as follow:

$$\hat{k}_{base} = \frac{k_{base}}{\bar{d}} \times \frac{1}{defl_{base}} + \frac{k_{base}}{\bar{d}} \times \frac{1}{defl_{base-1}} + \cdots + \frac{k_{base}}{\bar{d}} \times \frac{1}{defl_{base-\bar{d}}} = \left(\frac{k_{base}}{\bar{d}} \times \sum_{i=base-\bar{d}}^{base} \frac{1}{defl_i} \right)$$

where k_{base} is the historical value of tangible assets for the *base* year, $\bar{d}$ is the average asset duration calcuated at two-digit level and $defl_i$ is the deflator for year i. Deflators were obtained by processing ISTAT data. In particular, due to the unavailability of the investments series at two-digit level, the deflator was common to all firms and was built as the ratio of the monetary value of total investments at current prices, in a given year, over the corresponding value in the chained series; the base year was 2000.

For subsequent years, capital stock was divided into two parts: the estimated quantity of capital which survive dat time t and the estimated new investment at time t. Thus for year t the adjusted value of tangible assets k_t is as follows:

$$k_t = \left(k_{t-1} - \frac{k_{t-1}}{d_{t-1}} \right) + \left[k_t - \left(k_{t-1} - \frac{k_{t-1}}{d_{t-1}} \right) \right]$$

where k_{t-1} is the historical value of tangible assets at time t-1 and d_{t-1} is the average duration caculated for year t-1. Specifically, the first component on the right-hand side of the above equation represents the estimated volume of tangible assets still surviving at time t, and the second component is the estimated new investment at time t. Therefore, the estimated stock of capital $\hat{k}_t$ at time t was obtained as follows:

$$\hat{k}_t = \left(\frac{\left(k_{t-1} - \frac{k_{t-1}}{d_{t-1}} \right)}{(\bar{d} - 1)} \times \sum_{i=t-\bar{d}}^{t-1} \frac{1}{defl_i} \right) + \left(\frac{k_t - \left(k_{t-1} - \frac{k_{t-1}}{d_{t-1}} \right)}{defl_t} \right)$$

The procedure was implemented with the Stata software.

2.8.2 2B: Bootstapping Malmquist index

Simar and Wilson (1998, 2000) defined a bootstrap simulation method, which can construct confidence intervals and bias-corrected DEA efficiency scores.

The idea underlying the bootstrap method of Simar and Wilson (1998) is to approximate the sampling distributions of the DEA indexes by mimicking the data-generating process (DGP). The authors used a univariate kernel estimator of the density of the original distance function estimates, and constructed pseudo-data from this estimated density. Re-solving the DEA model for each observation with the new data and repeating this process many times lead to a good approximation of the true distribution.

Simar and Wilson (1999) extended the bootstrapping distance estimator presented in Simar and Wilson (1998) to the case of Malmquist indexes. They proposed a consistent method, using a bivariate kernel density estimate via the covariance matrix of data from adjacent years and adaptation of the reflection method of Silverman (1986) to gain consistency. The procedure may be summarized as follows:

[1] Calculate the Malmquist index $\hat{Malm}$ for each firm in a given period t, $t+\Delta t$;

[2] Construct the pseudo-data set $\left\{\left(\mathbf{x}_{it}^{*},\mathbf{y}_{it}^{*}\right), i=1,...,N; t=t,t+\Delta t\right\}$ to create the reference bootstrap technology using the bivariate kernel density estimation and adapting the reflection method of Silverman (1986);

[3] Calculate the bootstrap estimate of the Malmquist index $\hat{Malm}^{*}$ for each firm by applying the original estimator to the pseudo-sample attained in step 2;

[4] Repeat steps 2 and 3 for a large number of times B, thus obtaining B sets of estimates for each firm.

With the calculated bootstrap value, a bias-corrected estimate of Malmquist index may be computed as:

$$Malm^{bc} = Malm - \text{bias}\left[\hat{Malm}\right] = 2\hat{Malm} - \frac{1}{B}\sum_{b=1}^{B}\hat{Malm}_{b}^{*}$$

in which:

$$bias\left[\hat{Malm}\right] = \frac{1}{B}\sum_{b=1}^{B}\hat{Malm}_{b}^{*} - \hat{Malm}$$

The bias-corrected estimator may have a higher mean-square error than the original one. Simar and Wilson (1999) suggested that the bias-corrected estimator should be considered when the sample variance of bootstrap values $\left\{\hat{M}alm_b^*\right\}_{b=1,\dots,B}$ is less than one-third of the squared bootstrap bias estimate of the original estimator.

The procedure was implemented with the "FEAR" R package (Wilson, 2008).

Table 2.3-b. Bias-corrected Malmquist index and its decomposition into Efficiency Change (*EffCh*) and Technological change (*TeCh*). Period 1996-2006.

Industry	*1996-2006*		
	Malm	*EffCh*	*TeCh*
Food and beverages	1.037	0.066	0.960
Textiles and clothing	0.356	-0.453	0.779
Leather goods	0.019	-0.304	0.312
Wood	0.250	0.297	-0.059
Paper and printing	0.053	0.613	-0.579
Petroleum	-1.012	-1.039	-0.035
Chemicals	-0.123	0.136	-0.274
Rubber and plastic mat.	0.452	0.194	0.249
Non-met. mineral prod.	0.059	-0.005	0.051
Fabricated metal prod.	0.226	-0.052	0.262
Machinery and equip.	1.011	0.153	0.846
Electronics	1.153	-0.164	1.304
Transportation equipment	0.553	0.221	0.303
Other manufacturing	0.190	-0.216	0.397

Table 2.4-b. Bias-corrected Malmquist index and its decomposition into Efficiency Change (EffCh) and Technological change (TeCh). Subperiod: 1996-2000, 2000-2003, 2003-2006.

Industry	*1996-2000*			*2000-2003*			*2003-2006*		
	Malm	*EffCh*	*TeCh*	*Malm*	*EffCh*	*TeCh*	*Malm*	*EffCh*	*TeCh*
Food and beverages	-0.871	0.362	-1.251	1.603	0.509	1.063	6.899	-0.725	7.646
Textiles and clothing	-0.341	0.071	-0.431	0.883	-0.305	1.171	0.870	-1.147	1.947
Leather goods	-0.914	-0.217	-0.715	0.811	0.091	0.693	1.234	-0.762	1.960
Wood	-0.066	0.872	-0.962	0.980	-0.809	1.786	0.452	0.660	-0.230
Paper and printing	-1.578	1.578	-3.166	1.893	0.904	0.950	0.681	-0.865	1.539
Petroleum	-4.299	-0.859	-3.567	8.494	0.218	8.178	-4.586	-2.337	-2.352
Chemicals	-1.378	-0.231	-1.167	1.771	1.354	0.361	-0.239	-0.459	0.188
Rubber and plastic mat.	0.013	0.974	-0.966	1.729	0.654	1.049	-0.052	-1.257	1.207
Non-met. mineral prod.	-0.699	0.792	-1.495	0.369	0.663	-0.321	1.055	-1.387	2.442
Fabricated metal prod.	-0.236	0.771	-1.029	1.228	0.420	0.779	0.181	-1.643	1.801
Machinery and equip.	-0.507	0.648	-1.161	0.739	-0.098	0.822	3.472	-0.198	3.655
Electronics	0.508	0.826	-0.342	1.087	0.360	0.693	2.485	-2.109	4.643
Transportation equipment	-1.031	0.174	-1.275	0.459	0.794	-0.421	2.632	-0.434	3.001
Other manufacturing	-0.569	0.316	-0.900	0.045	-0.542	0.573	1.573	-0.487	2.041

Table 2.5-b. Bias-corrected Efficiency Change (EffCh) and its decomposition into Pure Efficiency Change (PEffCh) and Scale Efficiency Change (SEffCh). Subperiods: 1996-2000, 2000-2003, 2003-2006.

Industry	*1996-2000*			*2000-2003*			*2003-2006*		
	EffCh	*PEffCh*	*SEffCh*	*EffCh*	*PEffCh*	*SEffCh*	*EffCh*	*PEffCh*	*SEffCh*
Food and beverages	0.362	0.630	-0.304	0.509	0.312	0.160	-0.725	-0.708	-0.049
Textiles and clothing	0.071	-0.141	0.150	-0.305	-0.382	0.000	-1.147	-1.499	0.125
Leather goods	-0.217	-0.185	-0.095	0.091	0.047	-0.021	-0.762	-0.832	0.001
Wood	0.872	0.497	0.336	-0.809	-0.551	-0.292	0.660	0.483	0.136
Paper and printing	1.578	1.161	0.288	0.904	1.193	-0.390	-0.865	-1.009	0.064
Petroleum	-0.859	-0.886	-0.002	0.218	0.615	-0.408	-2.337	-1.008	-1.363
Chemicals	-0.231	-0.422	0.110	1.354	0.570	0.683	-0.459	0.112	-0.627
Rubber and plastic mat.	0.974	0.804	0.110	0.654	0.149	0.451	-1.257	-0.841	-0.477
Non-met. mineral prod.	0.792	0.852	-0.142	0.663	-0.255	0.820	-1.387	-1.263	-0.217
Fabricated metal prod.	0.771	0.063	0.656	0.420	0.122	0.247	-1.643	-0.694	-1.027
Machinery and equip.	0.648	0.048	0.531	-0.098	0.205	-0.376	-0.198	-1.011	0.744
Electronics	0.826	0.547	0.186	0.360	-0.807	1.103	-2.109	-1.398	-0.812
Transportation equipment	0.174	0.481	-0.467	0.794	0.527	0.140	-0.434	0.167	-0.704
Other manufacturing	0.316	0.163	0.113	-0.542	0.308	-0.878	-0.487	-0.318	-0.213

Table 2.7-b. Bias-corrected Technological Change (*TeCh*) and its decomposition into Pure Technological Change (*PTeCh*) and Scale Technological Change (*STeCh*). Subperiod: 1996-2000, 2000-2003, 2003-2006

Industry	*1996-2000*			*2000-2003*			*2003-2006*		
	TeCh	*PTeCh*	*STeCh*	*TeCh*	*PTeCh*	*STeCh*	*TeCh*	*PTeCh*	*STeCh*
Food and beverages	-1.251	-1.257	0.035	1.063	1.784	-0.669	7.646	0.186	0.202
Textiles and clothing	-0.431	0.011	-0.398	1.171	0.831	0.302	1.947	2.357	-0.502
Leather goods	-0.715	-0.923	0.217	0.693	-0.747	0.639	1.960	1.876	0.008
Wood	-0.962	-0.189	-0.709	1.786	1.156	0.492	-0.230	0.594	-0.815
Paper and printing	-3.166	-2.293	-0.695	0.950	0.461	0.400	1.539	2.143	-0.608
Petroleum	-3.567	-4.409	0.952	8.178	8.046	-0.007	-2.352	-3.427	1.071
Chemicals	-1.167	-0.052	-0.890	0.361	1.153	-0.837	0.188	-0.489	0.700
Rubber and plastic mat.	-0.966	-0.201	-0.730	1.049	1.347	-0.308	1.207	1.312	-0.091
Non-met. mineral prod.	-1.495	-1.138	-0.300	-0.321	0.428	-0.777	2.442	2.932	-0.513
Fabricated metal prod.	-1.029	-0.229	-0.810	0.779	1.040	-0.334	1.801	1.064	0.739
Machinery and equip.	-1.161	-0.503	-0.650	0.822	0.534	0.249	3.655	4.823	-1.182
Electronics	-0.342	0.101	-0.437	0.693	2.032	-1.421	4.643	4.477	0.216
Transportation equipment	-1.275	-0.416	-0.733	-0.421	-0.245	-0.255	3.001	2.878	0.008
Other manufacturing	-0.900	-0.605	-0.258	0.573	-0.207	0.771	2.041	1.955	0.022

Table 2.8-b. Technological Change (TeCh) and its decomposition into MaTeCh and Input Biased Technological Change (IbTeCh). Subperiod: 1996-2000, 2000-2003, 2003-2006.

Industry	*1996-2000*			*2000-2003*			*2003-2006*		
	TeCh	*MaTeCh*	*IbTeCh*	*TeCh*	*MaTeCh*	*IbTeCh*	*TeCh*	*MaTeCh*	*IbTeCh*
Food and beverages	*-1.251*	*-1.603*	*0.380*	*1.063*	*0.129*	*0.956*	*7.646*	*-0.456*	*9.457*
Textiles and clothing	-0.431	-0.644	0.230	1.171	1.046	0.132	1.947	1.663	0.278
Leather goods	-0.715	-0.982	0.284	0.693	-0.318	1.033	1.960	1.526	0.767
Wood	-0.962	-1.322	0.381	1.786	1.170	0.625	-0.230	-0.759	0.564
Paper and printing	-3.166	-3.349	0.212	0.950	0.611	0.351	1.539	1.223	0.358
Petroleum	-3.567	-11.201	9.495	8.178	3.786	4.205	-2.352	-7.177	5.851
Chemicals	-1.167	-1.957	0.954	0.361	0.138	0.221	0.188	-0.199	0.404
Rubber and plastic mat.	-0.966	-1.163	0.207	1.049	0.831	0.232	1.207	0.989	0.222
Non-met. mineral prod.	-1.495	-1.940	0.458	-0.321	-0.630	0.307	2.442	2.146	0.295
Fabricated metal prod.	-1.029	-1.468	0.462	0.779	0.523	0.264	1.801	0.403	1.447
Machinery and equip.	-1.161	-1.375	0.213	0.822	0.657	0.161	3.655	3.306	0.347
Electronics	-0.342	-0.606	0.266	0.693	0.480	0.204	4.643	3.751	0.872
Transportation equipment	-1.275	-1.817	0.647	-0.421	-0.987	0.599	3.001	2.224	0.752
Other manufacturing	-0.900	-1.109	0.216	0.573	0.332	0.255	2.041	1.630	0.411

3 Uncovering the influence of managerial and location factors on efficiency of personal service firms: the case of hotels[10]

3.1 Introduction

The observation of wide differences in productivity across sectors and countries, especially in services (Inklaar et al., 2008), has spurred a debate on what lies behind this phenomenon. Although there is still little empirical evidence regarding firm-level productivity in the services, pioneering studies have found that the dispersion of firm productivity is even greater in services than in the manufacturing industry (Oulton, 1998; Faggio et al., 2007).

In the services sectors, two - not necessarily exclusive - explanations are proposed and compared. In the first, dispersion of efficiency is common in a sector in which the use of resources depends greatly on demand. If fixed factors enter the production function and demand depends on firm location, production efficiency simply reflects the intensity of that demand: better located firms will attract more customers and consequently use resources better than firms located in less fortunate environments. By contrast, other scholars maintain that this explanation does not fully explain the observed heterogeneity and assign roles to internal factors, such as management (Bloom et al., 2012), the use of information and communication technologies (ICTs) and the quality of human capital. In this second case, efficiency dispersion is also observed among firms with similar locations and sharing the same demand.

Distinguishing the various sources of efficiency differences is particularly interesting for research in tourism management, and in the hotel industry in particular. In this context productive efficiency is a key dimension of organizational performance

[10] This chapter is part of a joint research project with Marco Corsino (University of Bologna) and Enrico Zaninotto (University of Trento) on efficiency in the hotel industry.

(Barros, 2005a), playing a crucial role in determining the profitability and survival of hotels (Chen, 2007). Efficiency scores are also used to estimate the relative position of hotels with respect to competitors and to design programs for performance improvement (Hwang and Chang, 2003; Morey and Dittman, 2003). However, lack of knowledge of the relevant sources of efficiency differences may hamper improvements in performance and make benchmarking ineffective. In spite of this, with few exceptions (e.g. Assaf and Knežević, 2011), existing studies in the literature on hotel efficiency are mainly concerned with measuring efficiency, without a thorough analysis of the factors which explain the heterogeneity in efficiency levels across hotels.

Efficiency is essentially a residual; it refers to the comparison between observed and 'optimal' outputs and inputs. As Lovell (1993) stated, "the identification of the factors that explain differences in efficiency is essential for improving the results of firms although, unfortunately, economic theory does not supply a theoretical model of the determinants of efficiency". This chapter aims at contributing to the literature by empirically exploring, respectively, the influence of location and selected entrepreneurial factors on hotel efficiency, in a two-step approach. After a measure of productive efficiency had been obtained by Data Envelopment Analysis (DEA), an evaluation of the heterogeneity due to the location in various destinations was first obtained. For this, a metafrontier approach was used since, in a DEA framework and for destinations characterized by clear-cut demand patterns, it helps to distinguish the efficiency component due to destination from a residual component attributed to firm management features. With this method, it was found that much of the variance of productive efficiency cannot be explained by destination, and the residuals, presumably due to entrepreneurial factors, are still very large. Second, the role of entrepreneurial factors was directly estimated by regressing efficiency scores, measured with respect to the local (i.e. destination) frontier, on a number of covariates which represent some entrepreneurial features and management choices. This two-stage approach to productive efficiency analysis in the hotel sector allowed us to isolate some firm characteristics affecting efficiency: for instance, family involvement in hotel operations and investment behavior in technological improvements can definitely influence productive efficiency even after controlling for intra-destination demand factors.

Our analysis was carried out in a region in the Alps, the Trentino province in north-east Italy, on a very large sample of the hotels in the region. On one hand, this relatively small geographical area contains several highly homogeneous locations, allowing us to compare locations which face very different patterns of demand. On the other hand, the rather uniform character of the large majority of hotels (small, single-outlet, family-run) gives particular value to our analysis and reduces control problems of firm-specific features.

The evidence of several external and internal factors affecting productive efficiency has important consequences, particularly from the viewpoint of public policies in the sector. The large weight given in the past to the role of demand on using of production factors indicated an approach to destination management focusing on promotion of tourist resorts. The evidence we present, giving weight to internal determinants of efficiency, shows that there is room for improvements in existing hotel performance which are independent of demand management.

The chapter is structured as follows. Section 3.2 we review the literature on hotel efficiency. Section 3.3 illustrates our estimation method and Section 3.4 presents the empirical context and the dataset. Section 3.5 discusses the results. In the concluding section, we draw some consequences of our analysis in terms of management implications and public policies toward tourism.

3.2 Literature Review

In the services context, and for personal service industries in particular, simultaneity of production and consumption is a distinctive characteristic. As a result, both the demand density of the particular area in which firms are located and the demand fluctuation over time greatly affects firm productivity (Morikawa, 2011, 2012). However, recent contributions in the field of economics (Bartelsman and Doms, 2000; Chun et al., 2011) however, have demonstrated persistent differences in productivity and efficiency levels which recommend that careful study should be applied to the relative importance of factors such as ICT adoption, human capital, and managerial practices (Bloom and Van Reenen, 2007; Bloom et al., 2012), as opposed to sources of performance heterogeneity which are external to the firm (Syverson, 2011).

This problem of what determine efficiency is particularly interesting in research on the hotel industry. Higher levels of efficiency are indeed positively related to hotel profitability and the likelihood of surviving when competitive pressure increases (Hwang and Chang, 2003; Chen, 2007).

The primary concern of the literature on efficiency and productivity in the hotel industry refers to measurement of productive efficiency. Research measures the managerial efficiency of hotels by assessing their distance from a production frontier which represents the best observed input/output combination. Contributions draw on various methodologies, such as Data Envelopment Analysis (Hwang and Chang, 2003; Sigala et al., 2004; Barros, 2005a,b; Barros and Dieke, 2008; Barros et al., 2009; Assaf and Knežević, 2010; Shang et al., 2010; Wu et al., 2011), and Stochastic Frontiers methods (Anderson et al., 1999; Barros, 2004; Pérez-Rodríguez and Acosta-González, 2007).

Less attention has been paid to the factors explaining the great heterogeneity in the levels of productive efficiency across hotels. Drawing on the existing literature, we identify two groups of factors claimed to account for these differences.

One group focuses on location effects: for example, contrasting city vs rural (Barros, 2005b) or seaside areas (Bernini and Guizzardi, 2010), as well as differences in infrastructural endowment (Barros, 2005b). Agglomeration effects may also convey positive externalities (Barros, 2005b) and destination management may influence hotel performance (Molina-Azorin et al., 2010). Also, demand for hotel services is generally derived from attractions – for instance, ski trials – or activities located in specific areas. Consequently, on the one hand, location determines proximity to points of tourist interest influencing demand uncertainty, excess capacity costs, and eventually affects hotel efficiency. On the other hand, hotel efficiency is to large extent influenced by competitors located within the same destination. Baum and Mezias (1992) demonstrate significant impacts of localized competition on failure rates of hotels. Economic literature linking market size and firm selection (e.g., Syverson, 2004) shown how in a denser market are less efficient firms that are less likely to survive.

A second group of factors comprises ones related to the internal characteristics of hotels. In particular, it has been shown that factors such as ownership (Barros, 2004; Barros and Dieke, 2008; Assaf et al., 2010), strategy, quotation on the stock market and M&A (Barros et al, 2011), firm size and classification (Assaf et al., 2010), star rating (Assaf and Knežević, 2010) and organizational form (Botti et al., 2009) all affect hotel efficiency. Very few papers look at management practices and characteristics. Assaf and Knežević (2011) report the negative influence of management tenure on the efficiency of 23 large hotels in Slovenia. Daskalopoulou and Petrou (2009) report the positive influence of age, training and previous experience in the tourist sector but the negative influence of experience in management on the efficiency of 95 tourist businesses in a single Greek city.

As the above analyses are based on small samples of hotels or are concentrated on a restricted number of managerial practices and entrepreneurial characteristics, the results can hardly be generalized to the industry as a whole. Indeed, to our knowledge, there is no empirical evidence of the relationship between family involvement and hotel performance. This fact is quite curious, in view of the family business nature of many tourism businesses.

To address this shortcoming, an empirical exploration based on a large, representative sample of hotels located in an Italian Alpine region (Trentino) was carried out. Drawing on a large sample allows us to address issues of potential selection bias and considerably improve the internal validity of the analysis (Denrell and Kovacs, 2008).

Efficiency was measured by DEA; with a metafrontier approach, the part of inefficiency which can be properly attributed to internal factors was isolated. The explanatory power of a large set of management and entrepreneurial variables was then tested in a regression analysis based on model of Simar and Wilson (2007) model. In particular, we focused on the quality of managerial practices, such as the introduction of quality programs, the family business character of the firm, adoption of information technology, decisions to carry out substantial physical improvements to the hotel building and its facilities, and quality of entrepreneurial human capital.

3.3 Econometric framework

The estimation procedure starts by measuring the productive efficiency of each hotel, defined as its distance from the production frontier, i.e., the boundary of the production possibility set. In formal terms, two vectors of inputs $x \in \Re_{+}^{Q}$ and outputs $y \in \Re_{+}^{M}$ represent each hotel, and production possibility set T is defined as the set of all feasible input/output combinations:

$$T = \{(x, y): x \in \Re_+^Q, y \in \Re_+^M, x \text{ can produce } y\}. \qquad \textbf{Eq. 3.1}$$

An output-oriented distance function is defined with respect to the production possibility set *T* as:

$$D(x, y) = \inf_\theta \left\{ \theta > 0 : \left(x, \frac{y}{\theta} \right) \in T \right\} \qquad \textbf{Eq. 3.2}$$

This distance function is relative to each firm and may be interpreted as the potential increase of output which can be achieved by that firm using a given quantity of inputs. In particular, scalar $\theta \in (0,1]$ identifies the potential expansion of output *y*, so that production possibility $(x, y/\theta)$ lies on the production frontier. Therefore, a firm may be said to be efficient if and only $D(x, y) = 1$.

Once data on inputs and outputs for random samples of hotels are available, we can estimate efficiency by either a parametric or a non-parametric approach. However, as pointed out by Simar and Wilson (2008): "the parametric specification must be a reasonable approximation of the underlying true model". Non-parametric estimators avoid the risk of misspecification and allow the treatment of multi-output units, but are more sensitive to outliers and have a rate of convergence which is slower than that of parametric estimators. In this chapter we use the DEA estimator.

The DEA technology set assuming CRS and free disposability of input and output is estimated as:

$$\hat{T}_{CRS} = \left\{ (x, y): \sum_{j=1}^{N} \lambda_j y_{mj} \geq y_m, m = 1, \ldots, M; \sum_{j=1}^{N} \lambda_j x_{qj} \leq x_q, q = 1, \ldots, Q; \lambda_j \in \Re_+^N \right\} \qquad \textbf{Eq. 3.3}$$

Consistent estimators of $D(x, y)$ can then be obtained by substituting true, but unknown, production set *T* with estimator $\hat{T}$ (Simar and Wilson, 2008). Estimates of $D(x, y)$, assuming CRS and output orientation, are computed by solving the linear program (Charnes et al., 1978):

$$\left[\hat{D}(x,y)\right]^{-1} = \frac{1}{\hat{\theta}_o} = \max \varphi$$

$$\begin{aligned} st \sum_{j=1}^{N} \lambda_j y_{mj} &\geq \varphi y_{mo} \quad m = 1,\ldots,M \\ \sum_{j=1}^{N} \lambda_j x_{qj} &\leq x_{qo} \qquad q = 1,\ldots,Q \\ \lambda_j &\geq 0 \end{aligned} \qquad \textbf{M.3.1}$$

We used the DEA output-oriented model under Constant Return to Scale (CRS). CRS has already been found in the hotel industry (Brown and Dev, 2000) and is a reliable assumption when analyses of small firms are carried out. By measuring the efficiency of firms with respect to the same level of scale, we can obtain higher discrimination power (see, e.g. Curi et al., 2012).

Estimating efficiency for each hotel is the first step of our analysis. The second step aims at exploring the different source of heterogeneity in observed hotel efficiency.

So far, we have made the (implicit) assumption that hotels located in the region shared the same common production frontier. However, in some conditions firms may face different production opportunities, attributed to the physical, social and economic environments in which production takes place (O'Donnel et al., 2008). This means that part of the observed performance heterogeneity may be due to the fact that firms belong to different technology sets (groups). This problem takes on particular relevance when the focus of analysis is the hotel industry, in which the destination in which hotels are located plays an important role.

As a general point, local differences in the level of external inputs available to firms indicate that production frontiers should be location-specific (Tveteras and Battese, 2006). In the hotel industry customers (tourists) first chooses their preferred destination and then hotels inside that destination (Molina-Azorin et al., 2010). This implies different demand conditions across destinations which cannot be controlled by the single hotel. In view of the simultaneous occurrence of production and consumption which characterizes the hotel industry, demand factors are likely to influence the technology set and therefore the production frontier of destinations.

The metafrontier approach (O'Donnel et al., 2008) provides a suitable method to capture influences associated with the destination effect successfully. In detail, by taking into account the existence of destination-specific frontiers, we consider the estimated regional frontier as a *metafrontier*, defined as:

$$T = Convex\,hull\left\{T^1 \cup T^2, \ldots, \cup T^K\right\} \qquad \textbf{Eq. 3.4}$$

where T^{dest} is the group-specific production possibility set – in our case, the production possibility sets of destination $dest = 1, \ldots, K$. Therefore, for each hotel, we also obtain the distance from its destination frontier $D^{dest}(x,y)$, constructed by estimating DEA model M. 3.1 and using as reference the group of hotels operating in its destination. The following relationship can then be established between the distance from the regional frontier and the destination frontier itself:

$$M\hat{T}R = \frac{\hat{D}(x,y)}{\hat{D}^{dest}(x,y)} \qquad \textbf{Eq. 3.5}$$

$M\hat{T}R$ $\left(0 < M\hat{T}R \leq 1\right)$ is called the *metatechnology ratio,* and gives an estimate of the influence of destination on the production frontier. It may be interpreted as the relative disadvantage (or advantage) of running the business in a particular destination within the region.

The use we made of the metafrontier approach may be seen as equivalent to the conditional frontier approach (Daraio and Simar, 2005, 2007; Badin et al., 2012) in which the efficiency score of each production unit analysed is evaluated with respect to a frontier constructed by conditioning on uncontrollable external factor[11]. Here, we defined an indicator variable which accounts for the different destination belonging: conditioning on this variable, separate frontiers are then estimated for each destination. Accordingly, we estimate efficiency with respect to the metafrontier (unconditional efficiency) and with respect to destination frontiers.

The efficiency measure obtained by conditioning the frontier on the hotel destination can be attributed to hotel-specific factors[12]. We use the conditional

[11] We share this interpretation with other authors such as Fallah-Fini et al. (2012)
[12] Here we assume that external conditions are homogeneous for hotels within each destination.

efficiency later, in a second stage, in which we regress this quantity on a set of explanatory variables related to several hotel factors[13].

3.3.1 Regressing efficiency scores on firm factors

In order to allow valid inferences on the relationship between the set of covariates and efficiency scores in the chosen DEA approach, the two-stage semi-parametric methods of Simar and Wilson (2007) were applied. This statistical model assumes Farrell's (1957) output efficiency measure $\hat{\delta}_i \in [1,+\infty)$, $i = 1,\ldots,N$, to be a function of a set of covariates.[14]

We expressed efficiency scores according to Farrell (1957), i.e., the reciprocal of the distance function used in the first step: $\hat{\delta}^{dest} = \left[\hat{D}^{dest}(x,y)\right]^{-1}$. It follows that, the closer the score to one, the more efficient the firm. Consequently, a negative sign of the estimated parameters reveals an increase in hotel efficiency, and a positive sign indicates a decrease.

As in Simar and Wilson (2007), we chose a linear function specification:

$$\hat{\delta}_i^{dest} = Z_i\beta + \varepsilon_i \geq 1 \quad \forall i = 1,\ldots,N \qquad \textbf{M. 3.2}$$

where, Z_i is the vector of covariates, β the vector of parameters to be estimated, and ε_i is an independently distributed random variable representing the part of inefficiency not explained by Z_i. Error term ε_i in M.3.2 was assumed to be distributed $N(0,\sigma_\varepsilon^2)$ with left-truncation at $1 - Z_i\beta$. As recommended by Simar and Wilson (2007), a truncated normal regression was performed. As DEA is a consistent estimator, we obtained consistent estimates of the regression parameters by maximum likelihood estimation,

[13] In Badin et al. (2012) conditional efficiency is regressed nonparametricaly on the environmental (external) factors. In this chapter we used a parametric linear specification of the second stage model. Although this choice adds more structure to the model, it does allow us to easily manage and distinguish the separate effect on efficiency of continuous, categorical and dummy independent variables. More flexible regression models may be considered in future research.

[14] The model in Simar and Wilson (2007) requires some regularity conditions, including the separability assumption, which allows environmental variables to affect the efficiency scores but not the frontier. In our second stage we still have the problem of separability, which may be relaxed in future work.

and were therefore able to make inferences about regression parameters by carrying out parametric bootstrapping of the regression model.

The estimation procedure involves the following steps (Algorithm #1 in Simar and Wilson, 2007)[15]:

[1] Estimate the following truncated regression by maximum likelihood: $\delta_i = Z_i\beta + \varepsilon_i \quad i = 1,...,n$ where δ_i, $i=1,\ldots,n$ is the Ferrell efficiency score computed as reciprocal of the Shepard distance obtained in the first stage with respect to the local frontier, Z_i is a vector of covariates and β is a vector of parameters to be estimated using the $m < n$ observations where $\delta_i > 1$ and obtain an estimate $\hat{\beta}$ of β and $\hat{\sigma}_\varepsilon$ of σ_ε.

[2] Loop over the next three steps ([2.1] - [2.3]) L times to obtain a set of bootstrap estimates $A = \left\{\left(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*\right)\right\}_{b=1}^{L}$ as follows.

[2.1] For each $j = 1,...,m$ draw ε_j from the $N\left(0, \hat{\sigma}_j^2\right)$ distribution with left-truncation at $\left(1 - Z_j\hat{\beta}\right)$.

[2.2] Compute: $\delta_j^* = Z_j\hat{\beta} + \varepsilon_j, \quad \forall j = 1,...,m$

[2.3] Use the maximum likelihood method to estimate the truncated regression of δ_j^* on Z_j, yielding estimates $\left(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*\right)$.

[3] Use the L bootstrap values in A and the original estimates $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ to construct percentile bootstrap confidence intervals for each element of β and using the k-th element of each bootstrap value $\hat{\beta}^*$ to find values a_α^* and b_α^* such that : $\Pr\left[-b_\alpha^* \le \left(\hat{\beta}^* - \hat{\beta}\right) \le -a_\alpha^*\right] \approx 1 - \alpha$

[4] calculate the estimated confidence interval: $\left[\hat{\beta}_k + a_\alpha^* \ , \ \hat{\beta}_k + b_\alpha^*\right]$.

[15] The procedure was been implemented with the R statistical package.

3.4 Empirical context and database

This study is based on a large dataset covering nearly all the hotels operating in a small region (the province of Trento, or Trentino), the features of which are known in great detail. It was thus possible to identify resorts with similar patterns of demand inside the region.

Trentino is an Alpine province with nearly 500,000 inhabitants. Thanks to the variety of attractions – Lake Garda and its surroundings, the Dolomites, and many historic towns and cities, about 2,300,000 tourists visited the region in 2006, spending more than 11,000,000 nights in it. The contribution of the hotel and restaurant industry to the local value added ranged between 6.7% and 6.9% in the period 2004-2006.

The region contains as many as 14 distinct tourist districts, each with quite different environmental conditions. Figure 3.1 shows the distribution of monthly average tourist numbers during the year in selected destinations: those in the most popular Alpine resorts are characterized by full winter and summer seasons, and have a two-peak tourist season (e.g., Valle di Fassa and Brenta-Paganella); other districts only have a summer peak (e.g., Garda); ancient towns enjoy a fairly constant arrival of tourists throughout the year (e.g., Trento).

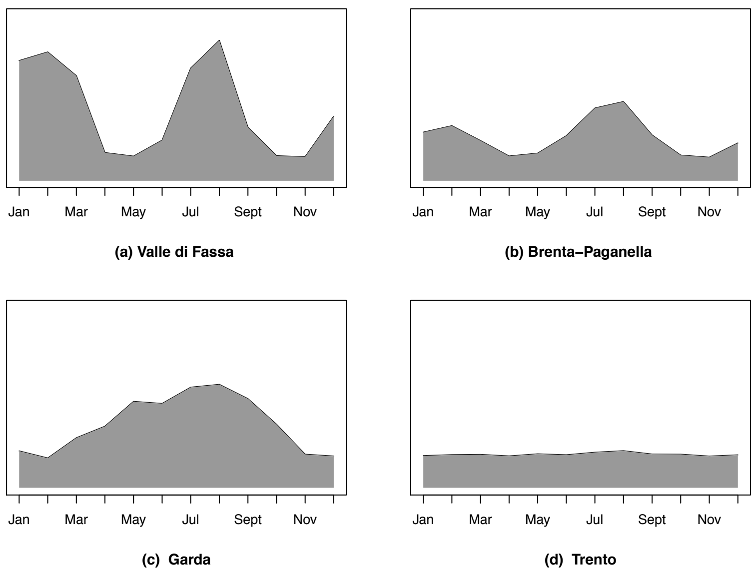


Figure 3.1. Average number of presences (nights spent) over the year in selected destinations

Each district has a public agency (coordinated by a central office) defining promotion policies in the area. In 2006, 1600 hotels were registered, for a total number of more than 47,000 rooms. Although the hotels are unevenly distributed among the tourist districts, despite the wide heterogeneity of demand, they are highly homogeneous: most of them, without regard to the district in which they operate, are small family firms, a common feature of the tourist industry in Alpine regions, in Italy, Austria and Switzerland. In 2006, the hotels had an average of 30 rooms each, with 6.2 employees; only 15% were owned by limited liability companies. Two-thirds of them were three-star hotels.

3.4.1 Data

The database is a unique and original collection of data allowing thorough exploration of productivity differentials in the hotel industry. The final database (DBhotelTN database) consisted of establishment-level data for a representative sample of hotels located in the Trentino province, constructed in collaboration with the Statistics Office of the local government. Some of the strengths of these data are worth mentioning. First, their fine-grained spatial disaggregation can capture location effects at very detailed level. Second, the sample is representative of the entire population of hotels even at destination level. Third, analysis can be made of small privately owned hotels which are not generally considered, due to lack of data.

The construction of the database involved several stages: Administrative archives were examined in order to identify all legal entities located in the province of Trentino in 2006, the primary activity of which accrues to the 3-digit sector 55.1 - hotels and similar accommodation - as defined in the NACE Rev.2 classification of economic activities. Consultation of these archives led us to identify 1382 subjects fulfilling this criterion in 2006. The numbers of active units in the previous four years were respectively 1372 in 2005, 1395 in 2004, 1367 in 2003, and 1407 in 2002. The archives allowed us to retrieve information on legal form (i.e., sole proprietorships, partnerships and limited liability companies) and on the revenue figures of each hotel considered here.

The previously identified units were matched with those profiled in the Informative Tourism System at the Statistics Office of the province of Trentino. This second source comprises information on structural characteristics, tourism flows and workforce for the population of hotels operating in the entire territory. We matched 1142 legal entities from the first source with 1188 hotels profiled in the second source for year 2006: this implies that 46 legal entities were linked to more than one hotel. For the previous four years, the matching procedure gave the following results: 1094 legal entities associated with 1143 hotels in 2005, 1062 legal entities and 1108 hotels in 2004, 1017 legal entities and 1062 hotels 2003, and 981 legal entities and 1023 hotels in 2002.

We integrated the data with the geographical coordinates of each hotel obtained from the ASIA database, the statistical enterprise archive managed by ISTAT (Italian Institute of Statistics). The ASIA database is the most comprehensive and reliable collection of information on the location and sector of economic activity for the population of firms operating in Italy.

Lastly, we matched the hotels constituting Sample A with data from the survey "Indagine sull'imprenditoria alberghiera in Trentino" (survey of hotel management in Trentino), covering the population of entrepreneurs running hotels in the province, carried out by the local Statistics Office in 2004. The survey detailed hotel-level data on management characteristics (personal data of owners/managers, i.e. age, education and training), human resources, scope and financing arrangements for structural improvement of hotels, and adoption of management practices. Merging the data in Sample A with the above survey data yielded detailed descriptions of several management and entrepreneurial factors for 753 hotels (Sample B).

3.4.2 Input and output variables

We define input and output variables following the literature on productivity and efficiency analysis in services (Morikawa, 2011) and in the hotel sector in particular (Anderson et al., 1999; Brown and Dev, 2000; Barros, 2005a; Daskalopoulou and Petrou, 2009; Assaf et al., 2010; Barros et al., 2011). Three input variables were selected: labor, fixed capital, and intermediate input. Labor input was measured by aggregating the annual average of two categories of workers: family workers and paid employees, including part-time workers. The number of available rooms was used as a proxy for fixed capital. Intermediate inputs were measured as the total cost of raw materials and services.

Various measures of output may be used. In manufacturing, in which the output constant quality assumption is more reliable, physical measures are the preferred way of measuring output. In services, instead, financial measures are more suitable to incorporate the quality variations caused by the heterogeneity of services and the effects on perceived quality by customers participation (Grönroos and Ojasalo, 2004). Thus, as aggregate output we chose the monetary value of revenue (Brown and Dev, 2000; Daskalopoulou and Petrou, 2009). We also deflated hotel revenues by a sectoral price index in order to mitigate the distorting effect of inflation on prices and consequently on revenues. However, prices may reflect idiosyncratic demand shifts or market power variations rather than quality. In order to avoid this problem we also considered as second output a physical output, i.e. the number of nights guests spent in the hotels. In the end, the production model consists of three input and two output.

Table 3.1 provides descriptive statistics of the input and output variables for hotels in Sample A for the year 2004, the mid point in the observation period.

Table 3.1. Descriptive statistics for input and output variables (*year 2004; n=1068*).

Variable	*Description*	*Mean*	*St dev*	*Min*	*Max*
employees	average number of employees (input)	6.5	5.5	0.3	50.8
rooms	number of rooms (input)	31.3	17.8	5.0	154.0
intermed_inputs	costs of row mat. and services (input) *(€)*	157680.0	178136.9	2618.0	2773761.0
nights_spent	nights guests spent in the hotel (output)	7476.4	6701.8	91.0	83585.0
revenue	hotel revenue (output) *(€)*	364461.1	384273.4	7083.0	4738303.0

3.4.3 Firm-level determinants of efficiency

The main aim of this chapter was to distinguish the effect of external from that of internal to the hotel factors on efficiency. Several firm-level sources of performance heterogeneity were taken into account. In particular, three sets of variables to explain differences in hotel residual efficiency were used.

The first set includes proxies of the investing behavior, quality of management practices, and hotel organization. Investing in hotel improvements may affect not only the production function but also efficiency measured with respect to it, as a consequence of better technology embedded in new capital (Blake et al., 2006) or higher effort exerted by hoteliers to recover the investments. As a proxy of the propensity to invest in physical capital, we defined a variable which took value 1 if the hotelier answered positively to the question of whether the hotel had been extended or improved during the ten years before the survey (i.e., until 2003) and 0 otherwise. Hotels whose owners introduced information technologies tended to perform better (Law et al., 2009). The variable *ict_adopt* was then added, with value 1 if the hotel used a computer and 0 if not, as a proxy of the adoption of ICT.

The introduction of quality programs (e.g., ISO 9000) can improve both management practices and production processes, and these improvements may translate into efficiency gains (Corbett et al., 2005; Tzelepis et al., 2005). We used the variable *quality,* with a value of 1 if the hotel adopted a quality process certification, and 0 otherwise.

Both agency theory and the resource-based view of the firms indicated that certain family factors can lead to benefits, while others impose costs and are liabilities to firm performance (Dyer, 2006). We thus defined two variables to distinguish two dimensions of family participation in hotel operations. The first is a measure of the intensity of family involvement, that is, the number of family members employed in the hotel *(fam_num)*. On one hand, family ties are expected to align goals and eventually increase efficiency (Herrero, 2011); on the other, they may favor redundancies and slackness on the part of family employees. The second variable *family_involv* was assigned value 1 if three key activities – accounting and administration, customer relations, and marketing – were simultaneously run by family members, and 0 if not. This variable captures a more qualitative aspect of the employment of family members, as such members may be more motivated, but perhaps less well trained, than professional employees.

Hotel's performance may be related to the education, experience, and skills of the entrepreneurs, as well as to their personal entrepreneurial characteristics (Lerner and Haber, 2001; Daskalopoulou and Petrou, 2009). A second set of variables covers some entrepreneurs' demographic characteristics: age, experience as hoteliers, and education. For this set, we defined three categorical (3-level) variables, *entr_age*, *entr_wexp* and *entr_edu*, related respectively to entrepreneurs' age, experience as hoteliers, and education level.

Lastly, we defined two variables related to structural choices: a categorical variable *legal*, with value 1 in the case of sole proprietorship, value 2 if a partnership, and value 3 if a limited liability company, and a dummy variable *category,* with value 1 if the hotel belonged to three-star, four-star, or higher categories, and 0 if it was one-star or two-star.

Table 3.2 lists explanatory variables, categories defined for each variable, and descriptive statistics for hotels in Sample B.

Table 3.2. Descriptive statistics for variables explaining productive efficiency (*n = 753*).

Variable	*Description*	*Mean*	*St dev*	*Min*	*Max*
Managerial factors					
invest	propensity to invest (*dummy*)	0.563	0.496	0	1
quality	quality process certification (*dummy*)	0.074	0.261	0	1
fam_num	number of family members	2.395	1.369	0	8
fam_involv	involvement of family members in key activities	0.540	0.499	0	1
ict_adopt	current use of computers (*dummy*)	0.910	0.285	0	1
Entrepreneur's experience as hotelier (*categorical*)					
entr_wexp1	<10 years	0.150	0.357	0	1
entr_wexp2	10-35 years	0.468	0.499	0	1
entr_wexp3	>35 years	0.382	0.486	0	1
Entrepreneur's education (*categorical*)					
entr_edu1	middle school	0.255	0.436	0	1
entr_edu2	secondary school	0.675	0.468	0	1
entr_edu3	university	0.069	0.254	0	1
Entrepreneur's age (*categorical*)					
entr_age1	18-33 years old	0.131	0.337	0	1
entr_age2	34-65 years old	0.797	0.403	0	1
entr_age3	>65 years old	0.072	0.259	0	1
Legal form (*categorical*)					
legal1	sole proprietorship	0.177	0.381	0	1
legal2	partnership	0.709	0.454	0	1
legal3	limited liability company	0.114	0.318	0	1
category	category (*dummy*)	0.692	0.462	0	1

3.5 Results and discussion

As suggested in the literature, we first screened outliers (Simar, 2003; Banker and Chang, 2006). To this aim we apply the approach of Sampaio de Souza and Stosic (2005), based on the effect produced on the estimated efficiencies of all the other observations when each observed firm is removed from the dataset. The outliers are expected to display very large effects (see Appendix A, for further details).

After detecting outliers, efficiency was obtained by applying DEA model M.3.1 to the pooled dataset of hotels in the whole region, i.e. with respect to the common regional frontier (*D*). We then estimated efficiency with respect to destination frontier (D^{dest}) and calculated the ratio between destination frontier and common regional frontier, i.e., the metatechnology ratio (*MTR*). The relative quantities were calculated for each year in the period 2002-2006 for the hotels in Sample A; all quantities were calculated for each hotel and then aggregated at the level of tourist destination. Table 3.3 lists the estimated averages and standard deviations of the quantity defined above for each destination. The data reveal large differences in the average performance of hotels belonging to different destinations. In particular, there is a considerable difference in terms of global performance (*D*) between the average efficiency of the best performing destination (Lake Garda area, 76.8%) and the worst (Piné-Cembra area, 54.4%). Also identified is a group of the best-performing destinations, for which the average efficiency ranges from 76.8% at Garda Trentino to 67.6% for the Madonna di Campiglio area.

Table 3.3. Estimated efficiencies and metatechnology ratio by destination.

Destination	*Year*	*D*		*MTR*		D^{dest}	
		Mean	*St dev*	*Mean*	*St dev*	*Mean*	*St dev*
Trento	2004	0.728	0.179	0.841	0.075	0.859	0.169
	All years	0.716	0.177	0.837	0.084	0.852	0.168
Brenta-Paganella	2004	0.678	0.140	0.861	0.059	0.786	0.142
	All years	0.694	0.142	0.859	0.058	0.806	0.144
Pinè-Cembra	2004	0.511	0.091	0.582	0.054	0.880	0.142
	All years	0.544	0.114	0.626	0.071	0.872	0.140
Valle di Fiemme	2004	0.639	0.141	0.792	0.093	0.804	0.138
	All years	0.652	0.137	0.795	0.090	0.818	0.135
Valle di Fassa	2004	0.705	0.128	0.949	0.047	0.744	0.134
	All years	0.711	0.136	0.940	0.058	0.757	0.137
San Martino di Castrozza	2004	0.606	0.157	0.756	0.080	0.794	0.168
	All years	0.622	0.152	0.767	0.090	0.808	0.160
Valsugana-Tesino	2004	0.602	0.164	0.755	0.075	0.794	0.175
	All years	0.609	0.165	0.769	0.075	0.789	0.183
Folgaria	2004	0.568	0.144	0.736	0.076	0.773	0.174
	All years	0.568	0.140	0.713	0.079	0.796	0.160
Rovereto	2004	0.570	0.176	0.741	0.117	0.770	0.186
	All years	0.634	0.204	0.804	0.126	0.785	0.192
Garda	2004	0.742	0.155	0.944	0.036	0.784	0.153
	All years	0.768	0.159	0.951	0.048	0.806	0.158
Comano-Brenta	2004	0.544	0.133	0.689	0.058	0.792	0.186
	All years	0.570	0.148	0.737	0.076	0.775	0.181
Madonna di Campiglio	2004	0.659	0.155	0.889	0.096	0.746	0.172
	All years	0.676	0.160	0.873	0.083	0.775	0.168
Valle di Sole	2004	0.684	0.131	0.855	0.060	0.799	0.135
	All years	0.692	0.139	0.867	0.061	0.797	0.145
Valle di Non	2004	0.544	0.171	0.706	0.111	0.779	0.231
	All years	0.565	0.179	0.745	0.091	0.762	0.224
Places outside tourism destinations	2004	0.538	0.126	-	-	-	-
	All years	0.544	0.145	-	-	-	-

NOTE: All Years: values calculated as average over period 2002-2006.

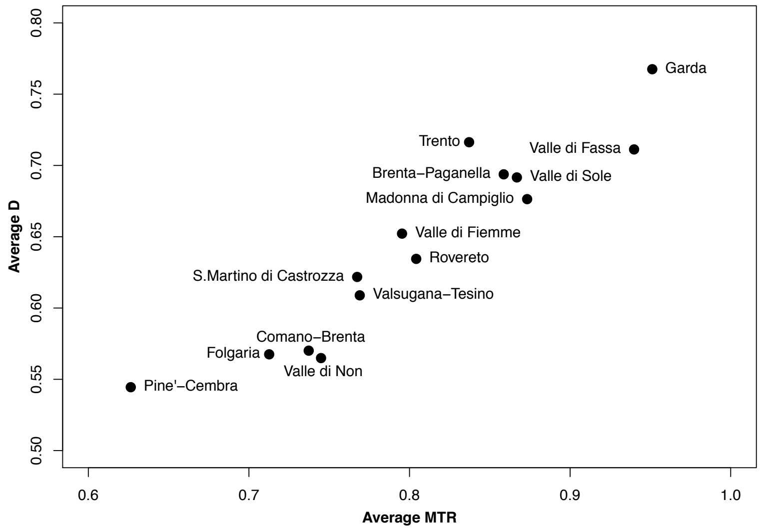


Figure 3.2. Relationship between global efficiency (D) and metatechnology ratio (MTR).

The destinations with higher *MTR* are Garda Trentino (95.1%), Valle di Fassa (94.0)% and Madonna di Campiglio (87.3%). Therefore, the best-performing hotels in these destinations largely define the regional frontier (metafrontier).

Figure 3.2 shows a positive linear relationship (ϱ=0.540, statistically significant at 5%) between production efficiency calculated as the distance from regional frontier (*D*) and *MTR*. The average level of efficiency with respect to the global frontier of the province of Trento is higher in those areas where the destination frontier is closer to the regional frontier. Thus, we can argue that the contextual factors which characterize each area drive the destination frontier as close as possible to the regional frontier and raise the average performance of hotels, measured in terms of overall efficiency. The upper right-hand part of the figure shows the areas with the best results: these are the most prestigious destinations in the province and have a greater flow of tourists over longer seasons.

In contrast, Figure 3.3 shows that there is no association between *MTR* and average efficiency calculated with respect to destination frontier D^{dest} (ϱ=-0.015). This indicates that favorable local conditions do not affect the efficiency of hotels lagging behind the best performers in the same location. The hotels in each destination produce about 80% of the output of the best-performing units in the same area; the two exceptions are those of Pine-Cembra (87.2%) and Trento (85.2%).

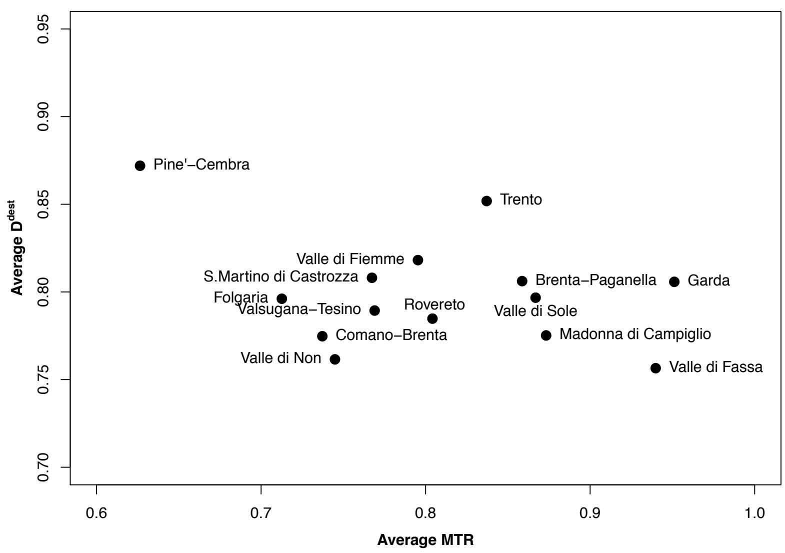


Figure 3.3. Relationship between local efficiency (D^{dest}) and metatechnology ratio (MTR).

To summarize, although the results are consistent with the hypothesis that environmental conditions impose restrictions on the production frontier, in all destinations, including those with better environmental conditions, a significant proportion of inefficiency is not due to location. In the rest of this section, we assess whether and how factors related to hotel management can account for the unexplained variation.

3.5.1 Influence of managerial factors

We now turn to the internal factors explaining the residual component of the efficiency of hotels with respect to the best-performing ones operating in the same external conditions. Cross-sectional analysis was carried out by regressing the destination efficiency scores previously calculated on a set of hotel-level variables. We used the data for the hotels in Sample B - for which detailed information on entrepreneurial characteristics and management practices at the end of 2003 were available - and the calculated efficiency scores for 2004. Consequently, in our regression analysis the estimated efficiency (dependent variable) and the independent variables were not observed simultaneously; this procedure, albeit not completely, does avoid endogeneity problems, particularly with respect to investment choices.

Table 3.4 lists the results obtained by regressing the efficiency scores on the set of covariates previously identified.

Table 3.4. Estimated coefficients and confidence intervals. (*Mod. 1*)

		Bounds of bootstrap estimated Confidence Intervals[b]					
	Est. Coeff.[a]	*(90%)* Lower	*(90%)* Upper	*(95%)* Lower	*(95%)* Upper	*(99%)* Lower	*(99%)* Upper
Constant	1.480 ***	1.289	1.671	1.256	1.712	1.192	1.796
legal1	0.103	-0.013	0.221	-0.037	0.247	-0.078	0.291
legal3	-0.248*	-0.452	-0.023	-0.489	0.033	-0.550	0.153
category	-0.257***	-0.372	-0.149	-0.394	-0.127	-0.435	-0.065
entr_wexp1	0.032	-0.102	0.184	-0.129	0.213	-0.182	0.271
entr_wexp3	0.022	-0.090	0.129	-0.107	0.150	-0.152	0.195
entr_edu1	-0.015	-0.125	0.098	-0.151	0.123	-0.201	0.160
entr_edu3	0.151	-0.031	0.350	-0.068	0.389	-0.129	0.481
entr_age1	0.103	-0.057	0.269	-0.088	0.305	-0.136	0.371
entr_age3	0.101	-0.066	0.284	-0.093	0.330	-0.164	0.414
invest	-0.270***	-0.376	-0.169	-0.395	-0.144	-0.440	-0.089
fam_num	0.084***	0.047	0.123	0.040	0.130	0.022	0.145
fam_involv	-0.166***	-0.262	-0.065	-0.286	-0.046	-0.319	-0.007
quality	-0.147	-0.332	0.073	-0.362	0.119	-0.424	0.243
ict_adopt	-0.261***	-0.405	-0.119	-0.433	-0.086	-0.484	-0.026
$\hat{\sigma}_\varepsilon$	0.439	0.397	0.498	0.385	0.506	0.366	0.518

[*], [**], and [***] : statistical significance at 10%, 5%, and 1%, respectively; [a] Efficiency scores expressed according to Farrell (1957), i.e., parameters with negative sign indicate sources of efficiency; [b] Number of bootstrap iterations: 3000.

Let us first comment on the firm variables which represent structural choices: hotel class and legal form. Limited liability companies and partnerships are subject to requirements which increase administrative, structural and organizational fixed costs, e.g., formal accounting practices, which can be afforded if demand and costs are carefully managed. The same is true of hotel class: higher classes require better standards in terms of room equipment and services. The results of our analysis indicate that higher-class as well as limited liability hotels (significance level 10%) achieve higher efficiency.

A second group of factors is related to the effect of entrepreneurs' human capital on efficiency. We used the largest category as a reference for each variable.[16] Note that, despite the expected signs, we found little evidence of the influence of individual managers' characteristics, such as experience, education or age, on productive performance. Lastly, the analysis revealed that several factors had a statistically significant effect on efficiency scores. First, a higher propensity to invest in technological improvements, measured by *invest*, had a positive bearing on the productive efficiency levels of hotels. This result confirms the positive relationship between efficiency and investing attitude in renewing physical capital by providing new equipment and infrastructures (Blake et al., 2006). Investment is usually considered to improve productivity, due to the innovations involved in it. Investment also commits managers and entrepreneurs to better use of capital, or investors self-select on the basis of their managerial skills.

Second, the coefficient of the variable *fam_num* has a positive sign, implying that a higher numbers of family members are associated with lower efficiency. In our context, the firms are mainly small hotels, i.e. it is probable that family members cannot easily be made redundant, even when their performance is poor. In addition, it is not easy for small family firms to attract and finance qualified employees from the labor market.

Family members may be entrusted with auxiliary services, ranging from cooking to routine maintenance, but also with important functions. In this regard, the coefficient of *fam_involv* shows a negative sign, pointing to a positive relationship between family members filling crucial roles, such as accounting, customer relations and marketing, and hotel efficiency. In other words, hotels which can develop the skills necessary to run key activities within the family boundary have a competitive advantage and suffer less from agency problems.

[16] When a qualitative variable with more than two categories is included in the regression equation, additional constraints on the parameters are required. A common strategy in this case consists of omitting one of the dummy variables related to each category. The decision as to which category to omit is often arbitrary. In our case for each variable we omitted the largest group. The omitted category was then the category to which all the other categories were be compared: the coefficient on each dummy variable related to a particular category shows the effect on efficiency of being in this category rather than on the omitted.

As regards the effect of the adoption of ICT, Table 3.2 clearly shows that the proportion of firms which do not use computers (our proxy of the adoption of ICT) is limited: this is indeed a particularly conservative indicator of the attitude toward information technologies, and results confirm that it is associated with low productive performance. Lastly, the introduction of quality control has no statistically significant effect.

Our results need a final comment. In the two-stage approach of Simar and Wilson (2007) we often reject the hypothesis that the coefficient of a dummy variable (modeled to represent differences in levels between groups) is significantly different from zero, because of the low power of the test of the significance of coefficients for this type of variable in the stage 2 regression (Zelenyuk, 2009). Consequently, on one hand, although caution is recommended in inferring no differences in efficiency between groups when the estimated coefficients of dummy variables are not statistically significant, on the other, the difference in efficiency levels between groups is likely to be quite large in reality, when the estimated coefficients are found to be statistically significant. This fact reinforces our findings related to investment behavior, family management, and structural choices

3.6 Robustness check

In the first part of the analysis we disentangled the effect of destination factors on the production frontier and obtained efficiency estimates that account for different destination frontiers. We then explained efficiency scores as function of hotel-level factors.

However, demand variability can affect efficiency also within destinations, where best located hotels are likely to enjoy better demand conditions during the year, than peripheral ones. Specifically, hotel can enjoy externalities due to factors exogenous to the economic actors related to the capacity of a particular location to attract visitors and consumers. Attraction factors may include natural features of the environment (e.g., scenic landscapes), man-made features (e.g., historic and artistic attractions), or even more practical ones (such as high level of tourism facilities). Touristic flows can be thought to be spatially distributed depending on the distribution of these touristic attractions within destinations and it is reasonable to consider that proximity to physical and natural attraction points gives to each hotel a different degree of attractiveness and eventually impacts on efficiency.

We use a market-potential function (Harris, 1954; Mion, 2004; Graham, 2009) to construct an index of proximity such that the impact of tourism attraction points on hotel performance decreases with their distance from the hotel. Given the specificity of alpine tourism, we consider ski areas, touristic lakes and places with scenic views as the most important touristic attractions. Formally, our measure of hotel market proximity is defined as the sum of the reciprocal of the distance from the selected attraction points as follow:

$$MP\_h_i = \sum_{j=1}^{T} \left[d_{ij} \right]^{-1} \qquad \forall i = 1,\ldots,N \qquad \textbf{Eq. 3.6}$$

where MP_h_i is the market proximity of an hotel in location i and d_{ij} is the (euclidean) distance between the hotel i and the attraction point j, $j = 1 ,\ldots, T$.[17] The above function assigns then to each hotel an index that measures the intensity of possible contact with tourists: the higher is the market proximity of the location in which a hotel is located the more attractive for tourist the hotel is.

To account for externalities that arise from concentration of attraction points at different (small) spatial scales, we constraint our measures of proximity on several distance thresholds. From the point where the focal hotel is located we calculated the proximity to attraction points at distance bands corresponding to radius of 0.5, 1, 2.5 and 5 kilometers respectively. Therefore we introduce the *MP_h* index in the regression analysis as additional fine-grained control of the effect of demand factors on hotel efficiency.[18]

Moreover, other unobserved destination conditions (e.g., different degree of effectiveness of destination management policy) can impact also on how far hotels are from the destination frontiers, i.e. efficiency, other than on the shape of the frontier. We control for this possibility by further adding the set of destination dummies in the

[17] We retrieved information on latitude and longitude of attraction points from the Geographical Information System (GIS) of the Trentino province.

[18] Proximity could be better measured by transport time instead of distance from the attraction points. However, given the small spatial scale of our empirical setting, we think that distance can be a suitable measure of proximity.

second stage regression. Finally, by assuming constant return to scale technology, part of estimated inefficiency may be due to departure from the optimal production scale. Therefore, we introduce in the regression analysis a proxy of firm size (see Curi et al., 2012). In accordance with the literature on hotels (De Jorge and Suárez, 2013), we use as proxy of hotel's size the number of available beds.

Table 3.5 reports the results obtained by adding the above controls to the second stage regression. As expected, demand factors are positively related to hotel efficiency even at very small spatial scales. Notwithstanding, the effect of the propensity to invest, the effect of category as well as the relationship between family involvement and hotel efficiency are confirmed. While the sign of the coefficients related to the legal form are still in the expected direction, they are no longer statistically significant.

3.7 Management implications and conclusions

The above analysis: a) separates the effects of location of efficiency from that under the control of hotels; b) assesses in depth how managerial factors affect efficiency. The study shows that the regional best practice frontier is determined by hotels which operate in the most prestigious tourist areas, i.e., those which have better destination characteristics. Hotels with better organization and management in these areas can offer services of the highest quality which result in higher performance, and can better exploit fixed costs, due to higher demand over longer seasons. However, a relatively less expected result was that differences between destinations only explains a small proportion of the variability in hotel efficiency. In particular, the average inefficiency of hotels is high everywhere and is not dissimilar between destinations. Destination, in other words, affects the performance of the more efficient hotels, whereas most hotels do not seem to be able adequately to detect and exploit the opportunities which various contexts make available to them.

If we assume that, after separating the destination effect from efficiency, the residual component of efficiency mainly reflects factors under the control of hotels, this means that there is room for improvement, regardless of the "comparative advantage" which some hotels have in terms of destination endowment. We isolated three sets of internal factors which may affect managerial efficiency. The first set is related to managerial behavior and practices, the second to the personal characteristics of the entrepreneur who runs the hotel, and the third covers structural management choices such as category and legal form. Results show that management practices and structural

Table 3.5. Robustness check: estimated coefficients.

	Mod. 2	*Mod. 3*	*Mod. 4*	*Mod. 5*
Constant	1.940 ***	1.949 ***	1.953 ***	1.962 ***
	[1.671, 2.214]	[1.677, 2.239]	[1.680, 2.242]	[1.701, 2.249]
legal1	0.082	0.080	0.079	0.076
	[-0.043, 0.218]	[-0.040, 0.207]	[-0.045, 0.207]	[-0.045, 0.206]
legal3	-0.181	-0.180	-0.180	-0.180
	[-0.387, 0.039]	[-0.394, 0.039]	[-0.408, 0.042]	[-0.388, 0.046]
category	-0.158 ***	-0.152 **	-0.150 **	-0.148 **
	[-0.300, -0.034]	[-0.296, -0.031]	[-0.291, -0.028]	[-0.275, -0.023]
entr_wexp1	0.001	-0.002	0.003	0.004
	[-0.151, 0.152]	[-0.147, 0.147]	[-0.145, 0.154]	[-0.152, 0.154]
entr_wexp3	0.010	0.008	0.007	0.008
	[-0.107, 0.121]	[-0.110, 0.124]	[-0.105, 0.125]	[-0.105, 0.118]
entr_edu1	-0.034	-0.035	-0.031	-0.031
	[-0.151, 0.079]	[-0.152, 0.082]	[-0.145, 0.087]	[-0.150, 0.086]
entr_edu3	0.141	0.148	0.152	0.150
	[-0.044, 0.349]	[-0.036, 0.366]	[-0.029, 0.363]	[-0.032, 0.353]
entr_age1	0.103	0.102	0.101	0.100
	[-0.057, 0.279]	[-0.047, 0.279]	[-0.051, 0.273]	[-0.057, 0.268]
entr_age3	0.109	0.110	0.104	0.099
	[-0.066, 0.305]	[-0.071, 0.308]	[-0.076, 0.304]	[-0.074, 0.288]
invest	-0.267 ***	-0.269 ***	-0.268 ***	-0.268 ***
	[-0.382, -0.173]	[-0.383, -0.171]	[-0.385, -0.177]	[-0.383, -0.175]
fam_num	0.081 ***	0.081 ***	0.079 ***	0.077 ***
	[-0.044, 0.125]	[-0.041, 0.125]	[0.043, 0.122]	[0.041, 0.122]
fam_involv	-0.174 ***	-0.175 ***	-0.175 ***	-0.172 ***
	[-0.283, -0.078]	[-0.285, -0.079]	[-0.284, -0.073]	[-0.281, -0.073]
quality	-0.100	-0.099	-0.094	-0.094
	[-0.278, 0.109]	[-0.285, 0.114]	[-0.285, 0.109]	[-0.276, 0.102]
ict_adopt	-0.153 ***	-0.151 **	-0.150 **	-0.146 **
	[-0.312, -0.001]	[-0.316, -0.003]	[-0.314, -0.003]	[-0.308, -0.004]
size	-0.002	-0.002	-0.002	-0.002
	[-0.004, 0.001]	[-0.004, 0.001]	[-0.004, 0.001]	[-0.004, 0.001]
MP_h_0.5km	-0.157 ***	-	-	-
	[-0.254, -0.057]			
MP_h_1km	-	-0.160 ***	-	-
		[-0.254, -0.057]		
MP_h_2.5km	-	-	-0.142 ***	-
			[-0.226, -0.057]	
MP_h_5km	-	-	-	-0.144 ***
				[-0.222, -0.068]
Dummies destination	Yes	Yes	Yes	Yes
$\hat{\sigma}$	0.399	0.397	0.397	0.395
	[0.371, 0.464]	[0.369, 0.462]	[0.368, 0.462]	[0.370, 0.460]

Note: Bounds of bootstrap estimated confidence intervals at 95% level in parenthesis; Number of bootstrap iterations: 3000 choices are the main internal drivers of productive efficiency; the influence which entrepreneurs may have on the productive efficiency of hotels is less clear. Results are confirmed even after controlling for demand influence at fine-grained spatial scale.

Some management implications follow. First, the weight given to destination management, as a way of improving tourist resort welfare, is only partly justified. Promotion of demand should be accompanied by actions aimed at improving hotel management and at inducing better use of resources. This is particularly important when demand grows, especially in areas sensitive to environment sustainability like Alpine resorts: more efficient established hotels, instead of new ones, may successfully cope with the increasing number of tourists. Second, particular attention must be paid to family businesses. Highly motivated, well-trained family members are of value for hotel efficiency. Conversely, family ownership may induce overstaffing and slack periods which depress hotel productivity. Training plans and the adoption of a professional attitude in family-run hotels can transform a cause of inefficiency into a competitive asset.

Our results do offer some insights for managers and public policy-makers in designing programs for performance improvement. In the past, much attention has been given to destination management as a tool for improving the tourist sector. Without denying the importance of destination management, our study supports the view that there is room for improvement within each destination. Significant improvements in efficiency can be obtained by focusing on the internal operations of hotels, considering the most important factors which improve efficiency: primarily, the quality of human capital, demand and cost management, and updating of organizational practices.

4 Evaluating the effect of public subsidies on firm performance: Empirical and methodological issues in the case of hotel businesses[19]

4.1 Introduction

Although the provision of public money to firms through subsidies is seen as a viable policy instrument to rectify market failures, reduce unemployment and boost economic growth, its efficacy is debated (Buigues and Sekkat, 2011). Public intervention is expected to be beneficial for firms directly supported, but it may generate both positive and negative externalities, which extend the effect of the policy to non-supported firms. However, the econometrics on which quantitative evaluations are generally based – Rubin's (1974) causal model – is centred on the assumption that the potential outcomes of a unit are fixed and do not depend on the treatment status of other units - the Stable Unit Treatment Value Assumption (SUTVA, Rubin, 1986). Under SUTVA, interactions among firms are ruled out, making it difficult to identify the indirect effects due to the externalities that public policies are likely to generate. This fact has implications for the quality of the estimated effects and prevents knowledge of the true effectiveness of a policy.

This chapter contributes to the empirical literature on industrial policy evaluation by estimating both direct and indirect effects of a place-based subsidisation policy directed to co-finance capital investments on the performance of micro and small hotel businesses, which form an important part of tourist services in Italy. We exploit a detailed and unique dataset on a large, representative sample of eligible hotels operating in the Trentino province (north-east Italy) over the period 2002-2006, obtained by

[19] This chapter has been developed in the research project DEM/FBK-IRVAPP: "Analisi della produttività nel settore alberghiero: fattori manageriali e ruolo delle politiche pubbliche" financed by the Caritro Foundation and under the supervision of Enrico Zaninotto (University of Trento) and Roberto Gabriele (University of Trento).

integration of several data sources. The empirical domain of analysis has two important advantages: the local dimension of the context of analysis and the focus on a single narrowly defined sector reduce the *ex ante* heterogeneity of the firms analysed, and the firms in the region cannot receive grants from other institutions other than the Trentino province. This is because, in 2002, provincial law 6/99 was the only tool of intervention in the economic activities of the local government and therefore the only source of subsidies available to firms in the region.

Several steps were followed in the construction of the econometric model and estimation, starting with the standard model and addressing and overcoming empirical and methodological issues in each step. Under standard assumptions[20], we first estimated the direct average treatment effect on treated hotels in a single treatment, i.e., hotels which applied for and actually received only one grant during the period 2002-2006 were considered as treated. We therefore extended the matching estimator of Abadie and Imbens (2002) and Imbens (2004) in a panel data setting by implementing a Conditional Difference-in-Difference matching estimator

In the second step, we extended the framework to the case of time-varying treatments, i.e., we examined the hotels' history of treatments over the period of analysis. Under the Sequential Conditional Independence Assumption (SCIA, Robins, 2000), which extends the standard model to a dynamic treatment setting, we estimated the direct average treatment effect on the final outcome when the treatment assignment at a given time depended on the history of previous treatments and on time-varying confounders. Drawing on previous literature (Hogan and Lancaster, 2004; Azoulay et al., 2009), we used a Marginal Structural Model and, in order to improve the estimation with selection within this approach, estimated the causal effect of subsidies by the Inverse Probability of Treatment Weighting (IPTW) estimator.

In the third step, we departed further from the standard model by allowing subsidisation to interfere across hotels. In particular, the outcomes of a potential hotel were allowed to change when the treatment status of its neighbours changed. This represents a critical departure from the traditional causal inference framework in which, in the SUTVA assumption, potential outcomes in treatment or control conditions are fixed and do not depend on the overall set of treatment assignments..

[20] The second important assumption is the Conditional Independence Assumption (CIA) to control for confounding factors which drive both assignment to treatment and potential outcomes. We discuss assumptions of standard models later in the chapter.

Relaxing the SUTVA assumption was necessary in order to isolate the indirect effects of a policy, i.e., spillovers or, more generally, externalities. One possibility of relaxing SUTVA and estimating this indirect effect is by design, e.g. selecting proper control units located outside the target area of the policy intervention. In this chapter, however, building on contributions in the emerging strand of research that relaxes SUTVA in analysis (Hong and Raudenbush, 2006; Hudgens and Halloran, 2008; Ferracci et al., 2013), we defined a framework which improves not only the identification and estimation of the direct average treatment effect but also estimation of the indirect effect of a policy, considering only eligible firms, i.e., ones located in the target area. More specifically, as relevant interactions in the hotel industry are expected to be local, that is, among hotels within relatively compact, well-defined geographic areas or destinations (Baum and Mezias, 1992), we considered hotels embedded in their own tourist destinations within the region and defined hotel outcomes as a function of hotel treatment and of that of other hotels in the same destination. We were thus able to extend our econometric framework to explain the hotel's history of treatment and that of other hotels in the same destination.

We considered several single-factor measures of the productive performance of hotels. In the last part of the chapter, we also examined the case in which the outcome is technical efficiency, estimated within the non-parametric frontier framework by DEA models, which also measure total factor productivity since they consider multiple inputs and outputs. In order to estimate the effect of subsidies on efficiency, we added to the two-stage semi-parametric model of Simar and Wilson (2007) a pre-processing step to reduce problems of selection bias (Ho et al., 2007a).

Our results highlight the direct positive effects of subsidies on hotel performance. We also found empirical evidence of SUTVA violation and indirect subsidy effects. Specifically, our results indicate heightened competition among hotels within destinations as a result of policy intervention.

The remainder of the chapter is organised as follows. The next section reviews the relative literature. Section 4.3 defines the conceptual framework guiding empirical exploration, and section 4.4 describes the context in which the analysis was carried out. Section 4.5 details the data and variables used. Section 4.6 presents the econometric framework, within which the direct average treatment effect on treated hotels (section 4.7) in the single treatment was estimated. Section 4.8 extends the analysis to longitudinal histories of treatment, and section 4.9 further extends the framework to allow violation of SUTVA. Section 4.10 adapts the standard framework when the outcome is hotel efficiency, measured within the non-parametric frontier framework. Section 4.11 concludes.

4.2 Literature review

The traditional argument for subsidising particular kinds of investment is the possibility of divergences between private and social returns due to externalities. This indicates the possibility of under-investment in the market. This argument is straightforward as regards investments in Research and Development (R&D), because firms making the investments do not appropriate all the gains originating from their innovative effort (Nelson, 1959; Arrow, 1962). DeLong and Summers (1991) argued that investments in equipment, as opposed to other kinds of fixed capital, may also generate externalities and that private returns from this kind of investment would be below social returns. Subsidies are also seen as viable instruments to reduce unemployment and, in general, to spur economic growth in depressed areas (Bernini and Pellegrini, 2011).

Although public subsidies are widespread among several sectors of economic activity, empirical evidence of their effectiveness is mixed (Buigues and Sekkat, 2011). As regards investments in physical capital, productivity growth is one of the most direct outcomes observed. Bergstrom (2000) examined the effect of capital subsidies on the growth of total factor productivity of a sample of manufacturing firms in Sweden. He found a positive correlation between subsidisation and growth of value added in the first year after the subsidies were granted, but the provision of capital subsidies later appeared to be negatively correlated to total factor productivity growth. Harris and Trainor (2005) presented evidence that capital grants were more likely to have a positive impact on total factor productivity compared with other forms of grant aid in Northern Ireland. In Greece, Skuras et al. (2006) showed that capital subsidies improved total factor productivity through technical change, not through scale efficiency. Tzelepis and Skuras (2004) found that capital subsidisation affects firm growth but fails to improve other measures of performance, such as efficiency. Bernini and Pellegrini (2011) showed that, although subsidies spurred output, employment and fixed assets growth of subsidised Italian manufacturing firms, the productivity growth of subsidised firms was less than that of non-subsidised ones.

A common trait of previous research dealing with evaluation of industrial policy is its focus on manufacturing. In the field of services, tourism is one of the sectors most frequently targeted by subsidy programmes. Subsidies to tourism were mentioned by 62 of the 97 members of the World Trade Association between 1995 and 2004 (WTO, 2006). Although subsidies for the development of tourism-related infrastructure play a significant role in developing countries, in developed countries support to the tourist industry usually takes the form of marketing support or support to small firms (WTO, 2006). Scholars have analysed the effects of subsidies to tourist firms, mainly either theoretically (Schubert and Brida, 2008) or by conducting qualitative analyses (Logar, 2010). Quantitative analysis is lacking.

To our knowledge, Bernini and Pellegrini (2013) are the only scholars who have carried out a rigorous quantitative evaluation of the effectiveness of public subsidies to private firms in the tourist sector. Their analysis was carried out on a sample of Italian tourist corporations which had applied for financial support provided by Italian law 488/1992. A Difference-in-Difference matching estimator was employed; subsidised and control firms were matched on propensity scores, i.e., the probability of receiving subsidies, given a set of observable firm characteristics. Among other measures of performance, the analysis concentrated on labour productivity and found a negative effect of capital subsidisation. It must be noted, however, that this analysis was restricted to tourism corporations with established balance sheets (available in AIDA, a commercial database on Italian limited liability firms, maintained by Bureau van Dijk). As the authors stressed, their results could not be extended to very small firms, which represent the bulk of the accommodation industry in many Italian destinations.

On the estimation side, Rubin's Causal Model (1974) is now the standard framework for quantitative evaluation studies in the literature on both statistics and econometrics (Imbens and Wooldridge, 2009). Rubin's causal inference model, based on the concepts of potential outcomes and assignment to a treatment mechanism, focuses on two fundamental assumptions: the Conditional Independence Assumption (CIA) to control for confounding factors which drive both assignment to treatment and potential outcomes, and the Stable Unit Treatment Value Assumption (SUTVA), which rules out any influence of a unit's treatment status on another individual's potential outcomes (Rubin, 1986).

The need to account for interactions between units, i.e., relaxing the SUTVA assumption, is increasingly viewed as a serious problem in economics applications. Authors dealing with spillovers generally consider as their unit of analysis aggregated areas, such as census areas (Hanson and Rohlin, 2013) or local labour systems (De Castris and Pellegrini, 2012). Cerqua and Pellegrini (2013) made one of the first attempts to address the issue of SUTVA and spillover estimation when the firm is the unit of analysis. These authors discuss a taxonomy of strategies to estimate spillover, centered on assumptions regarding the scope of the spillover and the selection of proper control firms in non-eligible areas (i.e., areas not targeted by the policy), in which spillovers are not likely to be present.

Instead, in a different emerging strand of literature, mostly in the fields of epidemiology and social science, the standard SUTVA is relaxed by incorporating agents' interactions directly in the models. Papers in this literature have modelled unit outcomes as depending not only on individually received treatments, but also on treatments received by other units, in a two-stage randomisation approach in which interference occurs within pre-specified groups and interference between groups is ruled out (Hong and Raudenbush, 2006; Rosenbaum, 2007). Hudgens and Halloran (2008) developed general modelling under randomisation when interference is present. Starting from a two-stage randomisation setting, these authors provided a precise characterisation of causal effects with interference in randomised trials. Tchetgen-Tchetgen and VanderWeele (2010) presented an inferential approach for observational studies, based on a generalisation of the Inverse Probability Weighting (IPW) estimator when interference is present.

In this chapter, we assess the effect of public capital subsidisation on the competitiveness of micro and small firms in the hotel sector in a place-based subsidisation programme. The ex ante homogeneity of units, obtained by focusing on a narrowly defined industry, and the local dimension of the context in which subsidisation was carried out, considerably improved the comparability of the units analysed. We exploited the advantages of our empirical setting by considering only hotels operating in the Trentino province (north-east Italy) and questioning the plausibility of SUTVA, in the emerging strand of research which attempts to relax this assumption in analyses (Hong and Raudenbush, 2006; Hudgens and Halloran, 2008; Tchetgen-Tchetgen and VanderWeele, 2010).

4.3 The effect of capital subsidisation on hotel performance: rationales and empirical implications

In our context, public intervention is aimed at promoting the economic growth and competitiveness of the region (i.e., Trentino province). With respect to tourism, the intervention consists of co-financing capital investments to foster firms' renewal and quality upgrading processes. The particular characteristics of the tourist sector may help to clarify how the effect on hotel performance can be best understood.

Tourist firms cannot be considered separately from the destinations in which they operate. Destination characteristics define the external environment in which hotel businesses operate and, consequently, drive their competitiveness in world markets. The tourist product is thus highly characterised by the destination environment (natural, technological, social), which in turn affects the quality of tourist destinations (Murphy et al., 2000).

However, while destinations are considered as the actors which compete in attracting tourists, the resources and competences used to produce the goods and services composing the final destination product (e.g., accommodation, transport, food, etc.) are related to other firms operating in each destination[21]. The fact that the final product is at the level of destination and resources and competences are at the level of individual firms makes it necessary for individual firms to participate in the co-production of the destination product (Haugland et al., 2011). This product may thus be conceived as a collection of elementary services and goods demanded by tourists and supplied by various private firms, each producing part of the final product (Alvarez-Albelo and Hernandez-Martin 2012; Andergassen et al., 2013; Candela et al., 2008). Accordingly, the success of a destination and that of individual firms are closely connected and rely on the coordinated resources, products and services of individual firms (Beritelli et al., 2007; Haugland et al., 2011).

In an extension to the above argument, upgrading the overall quality of a destination and thus increasing its competitiveness in the market, also relies on the

[21] Here, the destination refers to a system of fragmented services delivered by many firms (mostly micro and small firms) as opposed to centrally managed destinations owned by one or a few subjects (Beritelli et al., 2007; Franch et al., 2010). The former include the traditional European tourist regions with a community character. Governance in these destinations is based on a process of public choice and the role of public authorities is substantial.

collective private investing effort of all firms operating within a specific destination. In fact, improved capital endowment is a good indicator of higher quality of services delivered (Israely, 2002), and the room features and availability of a hotel's amenities and facilities play an important role in tourists' purchasing decisions (Kashyap and Bojanic, 2000; Choi and Chu, 1999). Renewed physical capital may even enhance a hotel's competitiveness by achieving lower costs and higher-quality output, i.e., higher productivity (Orfila-Sintes and Mattsson, 2009). However, coordination among firms does not always happen naturally, due to market failures resulting from significant externalities, and government intervention can be supported.

The incentive for private firms to invest may be low because investment profitability also depends on the actions of other firms (Rodriguez-Clare, 2005). In particular, the quality of a certain hotel affects that of its neighbours (Calveras and Vera-Hernández, 2005). Market failure generated by quality improvement is likely to arise because the benefit to a hotel generated by investing in quality is non-excludable. Let us imagine that, in a certain neighbourhood, one hotel improves its quality, for instance, by restructuring its building and adding new facilities to its accommodation, and pays for these improvements. This action by one hotel also improves the value of the neighbourhood: it may positively affect the quality of tourists' experience, their length of stay and likelihood of return, and may eventually be beneficial for all providers of services and goods – including other hotels – in the neighbourhood, and for the overall image of the destination. Neighbours can add positive externalities to their production process and enjoy these benefits even though they do not pay for them. The presence of externalities creates a discrepancy between the private and public rate of return of investments, and individual hotels therefore tend to under-invest in projects aimed at upgrading their quality. Destination quality upgrades are then conceived as a public good (Calveras and Vera-Hernández, 2005), and government should incentivise hotels to upgrade their physical endowments.

On one hand, to the extent that public intervention can rectify market failures, a positive effect on hotel performance is expected. Investment in physical capital plays an important role in augmenting the productivity and competitiveness of tourist firms (Blake at al., 2006). The reduced cost of capital then makes subsidised hotels more competitive by increasing the demand for their services. As agglomeration externalities in the hotel industry are likely to be mostly demand-side agglomeration (McCann and

Folta, 2009), being close to subsidised hotels will be beneficial also for non-subsidised ones, which can gain from enhanced demand.

On the other hand, subsidisation can enable hotels to capture otherwise neglected opportunities. In this case, subsidisation increases competition among hotels: if destinations compete in attracting tourists (Buhalis, 2000; Murphy et al., 2000), once those tourists have selected a destination, hotels within it will compete to become the tourists' first choice (Molina-Azorin et al., 2010; Zirulia, 2009). Therefore, if two hotels in the same destination are direct competitors but only one of them receives public aid, this will negatively affect the unsubsidised hotel's future competitiveness. This argument even gains strength when applied to micro and small family-owned firms. Small firms often have limited resources which may restrict their ability of access to information, particularly as regards new technologies and opportunities in the market. In addition, small firms find it difficult to obtain capital or credit (Carreira and Silva, 2010) and internal resources become the real way of financing their investments (Carpenter and Petersen 2002).

In the end, the bias in the estimated effect potentially introduced by considering the outcome of hotels to be independent of the support given to other hotels may act in both ways: the overall effect of the policy will be under-estimated (i.e., indirect effects will be positive) if positive spillovers stem from subsidies in supported hotels, but it will be over-estimated (i.e., the indirect effect will be negative) if unsubsidised firms are damaged as they lose relative competitiveness with subsidised hotels.

Mapping the expected effects of public subsidies with observed variables, which properly measure firm outcome, is not always straightforward. Competitiveness is ultimately related to the perceived quality of services and goods, and to how resources and competences are combined to produce them. At firm level, as far as subsidies to physical capital investment are concerned, productivity growth is one of the most direct outcomes studied (Bergstrom, 2000; Harris and Trainor, 2005; Skuras et al., 2006; Tzelepis and Skuras, 2004; Bernini and Pellegrini 2011). In tourism, the effective and efficient use of available resources is a major concern in establishing, raising and sustaining the competitiveness of tourist firms and destinations (Tsai et al., 2009), so that hotel productivity is the preferred measure of hotel competitiveness.

A desirable complementary aim of a public policy should be that of achieving sustainable growth (Schwab, 2012). As argued by scholars in this field (Ritchie and Crouch, 2000), the competitiveness of tourist destinations is in fact illusory without sustainability. Smoothing demand variability over time (i.e., reducing seasonality), especially when tourist demand increases, is one of the main challenges in achieving the policy objective of overall sustainability in this sector (see, for instance, the "Agenda for a sustainable and competitive European tourism", Commission of the European Communities, 2007).

As the hotel industry faces high fixed costs, which make the occupancy break-even level quite high, demand fluctuation becomes very problematic for hotel management. Hotels can partly benefit from destination management policies aimed at promoting the destination by adding new services or attractions during off-peak seasons (Baum and Hagen, 1999). Despite this, hotels which invest in renewing their buildings still face challenges of increased capital intensity. Therefore, receiving subsidies is linked to reduced demand variability, to the extent that the investment increases the attractiveness of the hotel during off-peak months, allowing better use of installed capacity.

4.4 The context of analysis

The Trentino is an Alpine province in north-east Italy, with nearly 500,000 inhabitants. Thanks to the variety of attractions – Lake Garda and its surroundings, the Dolomites, and many historic towns and cities – about 2,300,000 tourists visited the region in 2006, spending more than 11,000,000 nights there. The contribution of the hotel and restaurant industry to the local value added ranged between 6.7% and 6.9% in the period 2004-2006.

The Trentino spans more than 14 tourist districts with quite different environmental conditions: a number of districts enjoy a mild climate most of the year and a long peak season (Lake Garda); the districts in the best Alpine resorts are characterised by full winter and summer seasons, and have a two-peak tourist season; other districts only have a short summer peak season. Lastly, ancient towns enjoy a fairly constant arrival of tourists throughout the year.

Differences among tourist districts are not only due to their endowment in natural resources, because they are community-type destinations (Beritelli et al., 2007; Franch et al., 2010), i.e., areas with a variety of autonomous tourist operators, in which destination marketing is managed by several local agencies *(Aziende di Promozione Turistica*). In these areas, destination management – in which hotels are predominant - plays a fundamental role in coordinating tourist operators to achieve an overall image and increase destination package tours.

In 2006, 1600 hotels were registered, for a total number of more than 47,000 rooms. The hotels are unevenly distributed in the tourist districts. There are very many in Valle di Fassa (18.31% of the total in 2006), near Lake Garda (9.75%) and in the high mountain resorts. As regards class, measured as one to five stars, the majority of which (more than 60%) are three-star hotels. The Trentino hotel industry is characterised by the widespread presence of small family firms. In 2006, its hotels had an average of 30 rooms with 6.2 employees; only 15% were owned by limited liability companies.

A distinguishing feature of this institutional setting is that firms operating in the province of Trento can apply only for subsidies awarded by the local government. In this setting, Provincial Law 6/99 (hereafter, PL6) provides guidelines on the economic incentives to firms operating in the province. It comprises a large set of incentive schemes which are meant to foster fixed investments, research and development expenditure, firm restructuring, the adoption of production processes to safeguard the environment, and re-location of firms within the province.

All firms operating in the province of Trento can apply for PL6 grants by submitting a project to the local authority. Although there is no deadline for submission during the calendar year, since a first-in-first-out criterion is used to assign financial resources, some firms may be refused once the budget is exhausted. There are two types of evaluation mechanism, basically determined by the magnitude of the investment: selective and automatic. Through the selective mechanism, once a hotel applies for a grant, its application is examined for its economic viability and financial sustainability. Only if the project receives a positive assessment can it be co-financed by the local government. Instead, automatic subsidies are granted only after examination of applications.

4.5 Data and description of variables

4.5.1 Data

We relied on several sources to construct the database. Administrative archives, held by the local government, are the primary source of information on hotels receiving grants. In particular, primary data on firms' applications for public subsidies come from the APIAE (*Agenzia provinciale per l'incentivazione attività economiche*), the administrative body that manages the subsidisation programme on behalf of the local government. The APIAE archives (DBApiae database) allowed us to recover all the applications (2774) filed from 1999 to 2011 concerning tourism-related industries: accommodation (hotels, camp-sites, etc.), restaurants, travel agencies and other recreational activities. For each application it was possible to retrieve information on: name of the applicant (ragione sociale), tax code, address of the applicant (sede lagale), description of economic activity, date of submission and of assessment/approval of application, type of subsidization procedure (selective or automatic), final outcome of the application assessment (obtained, rejected, other outcomes). We consider subsidies granted through both selective and automatic procedure.

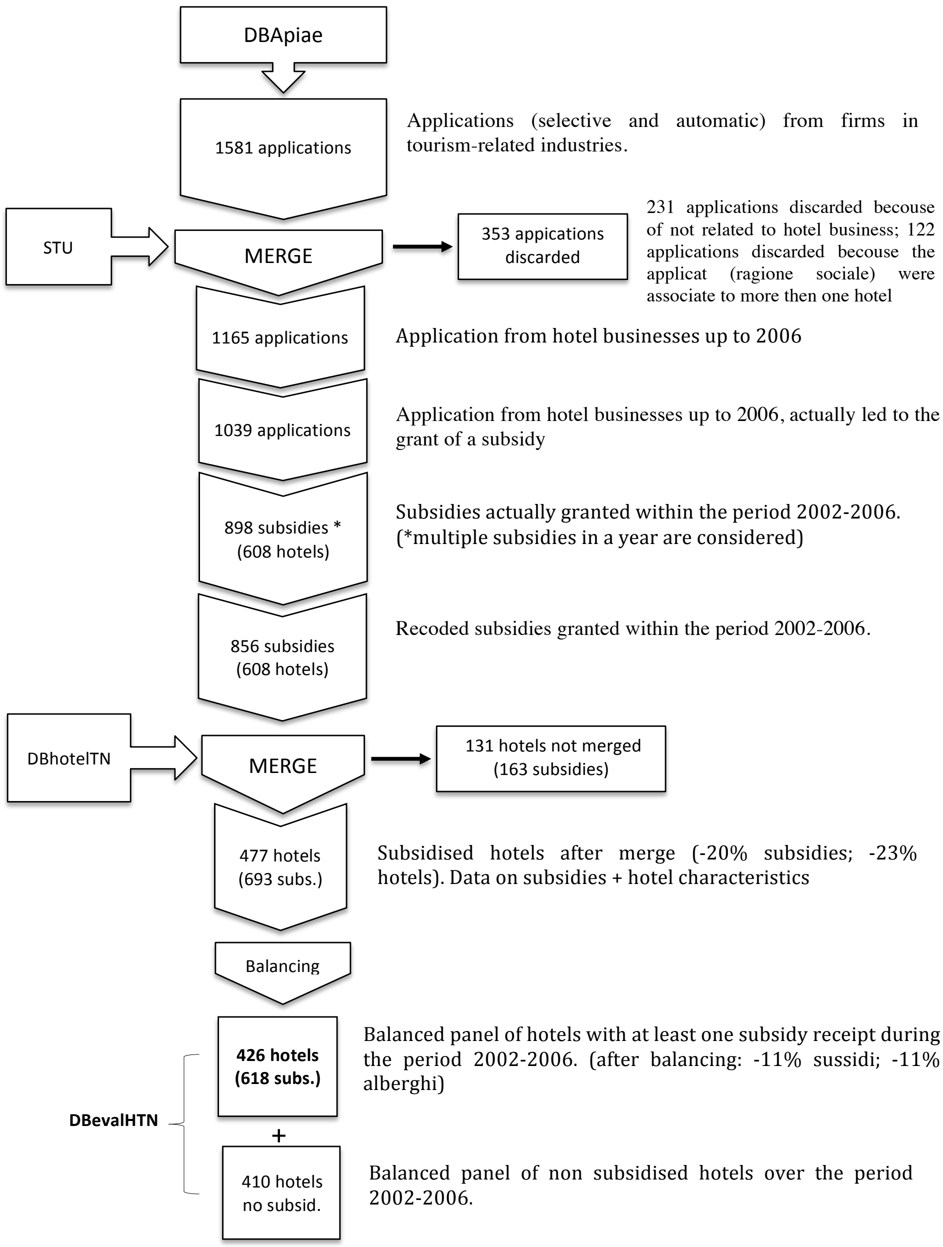
Data collected through subsidy applications are not sufficient for conducting an impact evaluation, mainly because they do not comprise information on firm characteristics and their financial performance. In our context, only about 15% of hotels are limited liability firms. In fact, only limited liability firms are obliged to make publicly available their annual balance sheet, the main source of information at firm level. Therefore, in order to obtain information on hotels in the province we could not rely on publicly available databases.

We overcome this limitations using the DBhotelTN database, an extensive repertoire built in partnership with the Statistical Office of the Trentino province and already used in previous analysis of the hotel sector in the Trentino province[22]. The database contains information on hotel characteristics (e.g., revenue and cost figures, legal form, structural characteristics, location, etc.) for a representative sample of the population of hotels operating in the province. Because of constraints on the time span over which hotel-level data are available in the DBhotelTN database, we focus our

[22] For further details on the DBhotelTN database, see data description in Chapter 3.

analyses on the period from 2002 to 2006. The final database (BDevalHTN) contains data for 426 subsidised and 410 non subsidised hotels over the period 2002-2006.

Figure 4.1. Construction of the final database (BDevalHTN)



The construction of the database unfolded in several steps (see also Figure 4.1):

1. We select all applications for subsidies submitted by firms in tourism-related industries in the Trentino province from 1999 to 2006. We identify 1518 applications.
2. Data on these 1518 applications were merged with the hotels registered in the STU[23]. Records were merged with the tax code, and further checked against the name (the "ragione sociale") and address of the hotel in question. This merging process allowed us to identify the applications related to a hotel business and made possible the subsequent merge with data contained in the DBhotelTN database. The merge was possible for 1165 applications (Table 4.1), while 353 applications were discarded[24].

Table 4.1. Selected applications: type of assessment procedure and final outcome

	granted	rejected	revoked	refused	other	n.a.	TOT
Automatic	745	75	13	0	2	13	848
	72%	*95%*	*68%*	*0%*	*33%*	*93%*	*73%*
	88%	*9%*	*2%*	*0%*	*0%*	*2%*	*100%*
Selective	294	4	6	8	4	1	317
	28%	*5%*	*32%*	*100%*	*67%*	*7%*	*27%*
	93%	*1%*	*2%*	*3%*	*1%*	*0%*	*100%*
TOT	1039	79	19	8	6	14	1165
	100%	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
	89%	*7%*	*2%*	*1%*	*1%*	*1%*	*100%*

3. We focus only on applications which actually led to the grant of a subsidy: 1039 applications submitted by hotels up to the 2006.
4. To evaluate the effect of a subsidy information before and after the treatment (the receipt of a subsidy) is needed. According to the LP6, investments linked to applications following the automatic procedure must be completed one year after the grant of the subsidy. Instead, investment associated with a selective procedure must be completed in the three years after the announcement of allowance of a grant. Unfortunately, our data did not contain exact information on the year of the beginning of the investment. Therefore, we made the

[23] The STU (Sistema Informativo del Turismo – Provincia autonoma di Trento) is the official register of hotel businesses in the Trentino Province managed by the Statistical Office of the local government. The register contains information for the entire population of hotel in the province.

[24] Among the discarded applications, we identify some applications (122) where the applicant (ragione sociale) was associate to more then one hotel, making not possible the one-to-one matching. We identify 78 hotels potentially subsidised, which were escuded.

following assumptions: for selective subsidies the year of subsidisation corresponds to the year in which the hotel receives a notification of allowance from the local government; for automatic subsidies the year of subsidisation is the one in which the application is filed. Following the above assignment rule, we identified 898 subsidies granted to hotel businesses in the period from 2002 to 2006 (see Table 4.2).

Table 4.2. Number of grants directed to hotel businesses during the period 2002-2006.

Year	*Number of subsidies*	*Hotel size*			*Average*	*Std. Dev.*
		micro	*small*	*other*		
2002	332	269	63	0	42368.89	102576.3
2003	119	92	27	0	110181.6	228353.7
2004	137	102	35	0	109191.4	190736.2
2005	128	107	21	0	122794.5	211376.6
2006	182	136	44	1	218077.2	354520.1
Total	898	706	190	1	108698.6	228191.1

5. It can be the case that a hotel received more then one subsidy in a year. We consider a firm as treated if it received at least one subsidy in a given year. Accordingly, we recoded subsidies per year, ending up with 856 subsidisations (608 hotels) over the period 2002-2006.
6. After having identified the subsidised hotels, we merged the data with the DBhotelTN database. The merge (made on the STU internal code) was possible for 693 (about 80%) of subsidization events associated to 477 (78%) hotels. We selected only those hotels observed in each year within the period 2002-2006, hence a balanced panel structure (426 hotels; 618 subsidies). Although this choice can lead to the exclusion of some subsidised hotels, it allows to observe the temporal order of events and to control for time-invariant unobserved individual differences.

At the end of the whole process of merging and balancing, we obtained a balanced panel of 426 hotels that received at least one subsidy during the period 2002-2006. Table 4.3 shows the distribution of subsidies grants to hotels observed in the period for each tourist destination in the region. There is a discontinuity on the number of subsidy, especially after 2002, probably due to the fact that in 2001-2002 there was the first large wave of applications after the necessary period for the policy to become definitely operative.

Table 4.3. Distribution of subsidies across touristic destination and year

TD	*Tourism destination*	2002	2003	2004	2005	2006	TOT.
1	Trento	9	3	1	2	6	21
2	Brenta-Paganella	16	13	14	7	12	62
3	Pinè-Cembra	6	0	3	0	4	13
4	Valle di Fiemme	16	6	6	7	8	43
5	Valle di Fassa	56	20	23	22	31	152
6	San Martino di Castrozza	11	5	4	5	9	34
7	Valsugana-Tesino	22	7	5	7	3	44
8	Folgaria	9	0	2	2	4	17
9	Rovereto	5	3	2	0	0	10
10	Garda	18	6	11	8	11	54
11	Comano-Brenta	6	2	1	5	2	16
12	Madonna di Campiglio	16	8	6	4	6	40
13	Valle di Sole	27	12	9	11	10	69
14	Valle di Non	5	1	5	5	1	17
o.d.	Places outside tourism destinations	10	4	5	4	3	26
TOT.		232	90	97	89	110	618

As final step, we add to the panel of subsidised hotels a panel of 410 hotels that did not received any subsidy (did not apply for subsidy) up to the 2006 contained in the DBhotelTN database. For all of these non-subsidised hotels we have the same type of information as for the subsidized ones. Therefore, we obtained a panel of 836 hotels (DBevalHTN database) for which we have data on the subsidisation status (subsidised vs non-subsidised), hotel characteristics, and outcomes of interest in each year within the period 2002-2006.

After the merging process we checked for possible selection due to the discarding of those hotels which lacked data for our evaluation purposes. We compared our sample with the whole population of hotel in terms of average size and spatial distribution. The data (see Appendix 4A) show that our final sample is representative of the hotel industry in the region.

4.5.2 Outcome variables

We defined several outcome variables and, in particular, used the following single-factor measures of productive performance:

- Labour productivity, measured as the ratio of total deflated revenue to total employment (*lab_prod*). A second proxy of labour productivity was obtained as the ratio of value added to total employment (*lab_prod_2*).

- Occupancy rate (*occ_rate*), defined as the ratio of total guest nights spent in a year to the number of beds available, multiplied by the number of days the hotel was operative. The occupancy rate is an index of the hotel's level of activity. This measure has the advantage of being widely used among hotels. It is also regarded as a performance indicator in the hotel industry (Orfila-Sintes and Mattsson, 2009; Sainaghi, 2010) and performance heterogeneity among hotels stems from the different ability of hotels to transform a given capacity into sold nights and services (Yu and Lee, 2009).
- The revenue per available room (*revpar*), obtained as the ratio of the (deflated) yearly revenue to the number of rooms, multiplied by the number of days the hotel was operative; it is considered as a proxy of capital productivity and is widely used as measure of performance in the hotel industry.
- A measure of variability of the level of activity over time (*occ_var*), defined as the coefficient of variation of the number of monthly arrivals over the year. An increase in this variable (i.e., increased demand variability) may be highly detrimental to productivity in services (Morikawa, 2012).

We also used efficiency scores as an outcome variable, which has the further advantage of explicitly considering multiple inputs and outputs.

We obtained an estimation of hotel efficiency (*efficiency*) by non-parametric CCR DEA. Input and output variables were defined according to the literature on hotel efficiency (Anderson, 1999; Brown and Dev, 2000; Barros, 2005a,b; Assaf et al., 2010; Barros et al., 2011). Three input variables were selected: labour, fixed capital, and intermediate input. Labour input was measured by aggregating the annual average of two categories of workers: family workers and paid employees, including part-time workers. The number of available rooms was used as a proxy for fixed capital. Intermediate inputs were measured as the total cost of raw materials and services. Different measures of output can be used. In manufacturing, where the output constant quality assumption is more reliable, physical measures are the preferred way of measuring output. Instead, in services, financial measures seem to be a more suitable way of incorporating quality variations caused by services heterogeneity and the effects on perceived quality by customer participation (Grönroos and Ojasalo, 2004). We used the deflated hotel revenue as output. However, prices may reflect idiosyncratic demand shifts or market power variations rather than quality. In order to mitigate this problem, we also considered as a second output a physical output, i.e., the number of guest nights.

4.5.3 Covariates

We consider as covariates a set of factors which are likely to influence both the propensity of hotels to apply for public grants and hotel performance:

- The legal form, which indicates the attitude of the firm towards risk and also the chance of entering public subsidisation programmes (Almus and Czarnitzki, 2003). By using a limited liability legal form, for instance, owners can minimise their risk up to a certain amount and thus have higher incentives to pursue more risky projects. In addition, legal forms may signal the varying quality of firms. Hence, we used a categorical variable *legal_form* , which classifies hotels into sole proprietorship, partnership, and limited liability forms.
- Both different levels of subsidies and different performance may depend on firm size. Firm size is also a useful predictor of financial constraints (Hadlock and Pierce, 2010), and the capacity of receiving external finance (e.g., bank loans) is correlated with firm size. In accordance with the literature on hotels (De Jorge and Suárez, 2013), we used hotel size (*size*) as a proxy for the number of available beds.
- Hotel category indicates the level and complexity of services provided. Higher categories comprise more services, equipment complexities and organisational aspects. In our context, hotel category is informative about the "type" of hotelier. In fact there is a sharp polarization of the distribution of "active" and "passive" entrepreneurs across hotel categories: only 7% to 12% of active entrepreneurs belong to 1 and 2 star categories, while only 8% to 12 % of passive entrepreneurs belong to 3 and 4 stars categories (see PAT – Servizio Statistica, 2006). Category cross-comparison can thus explain an important part of the unobserved differences in entrepreneurial behaviour and hotel performance. We defined a variable (*category*) with two values: high for three- and four-star hotels, and low for one- and two-star ones.

- Hotels which are attractive to international tourists are expected to be more efficient (Assaf and Cvelbar, 2011). The international trade literature also supports this claim, arguing that firms which can sell their products to foreign customers are more productive than domestically oriented ones. Hotels operating in foreign markets are also able to generate new knowledge from international tourists and may be more interested in restructuring and improving their equipment and facilities than hotels mainly operating in the domestic market. A high percentage of international sales may also be considered as an indirect measure of quality of management and employment: hosting foreign customers requires higher skills and competences (e.g., knowledge of foreign languages). We defined a measure of internationalisation (*int*) for each hotel as the ratio of the number of nights spent by foreign guests to the total number of nights over the year.
- Location defines the environment in which firms operate and thus influences firms' behaviour and performance. The link between location and firm efficiency is marked in services, and personal services in particular where, due to simultaneity of production and consumption, demand factors are important (Morikawa, 2011). Therefore, in our analysis we controlled for cross-sectional heterogeneity among destinations by introducing a set of dummy variables (*dest*).
- We also account for fine-grained effects of unevenly distributed spatial demand densities. Here, it is reasonable to consider that proximity to physical and natural amenities makes hotels differently attractive to tourists. We used a measure of "proximity" (*prox*), so that the impact of attraction points decreases with distance from the hotel, like the market-potential function (Harris, 1954). As attraction points we considered ski areas, touristic lakes and well-known beauty spots. Formally, our measure of market potential was defined as the decreasing function of the distance from the selected attraction points, as follows:

$$prox_i = \sum_{j=1,\dots,n} \left[d_{ij}\right]^{-1} \qquad \textbf{Eq. 4.1}$$

where d_{ij} is the (Euclidean) distance between hotel i and attraction point j, $j = 1,\dots,n$.

- Co-location may affect hotel performance as well as hotel managers' choice to apply for subsidies. Firms may benefit from positive externalities accruing from agglomeration economies. Several studies have addressed the role of agglomeration in the hotel industry (Baum and Mezias, 1992; Baum and Haveman, 1997; Ingram and Baum, 1997; Chung and Kalnins, 2001; Kalnins and Chung 2004). Co-location may provide opportunities for frequent interactions, exchanges of information among hotel managers and reduced monitoring costs (Gan and Hernandez, 2011). As a consequence, co-location may increase the chances that hotel behaviour, with respect to subsidy opportunities, may be influenced by other existing hotels which are planning to apply for subsidies. We controlled for the co-location effect by using an index (*co_loc*), which is a decreasing function of the distance of a hotel from all other hotels (as in the case of the *prox* variable):

$$co-loc_i = \sum_{j=1,\ldots,m} \left[q_{ij}\right]^{-1} \qquad \textbf{Eq. 4.2}$$

where q_{ij} is the (Euclidean) distance between hotel i and hotel j, $j = 1,\ldots,m$.

- Hotels may have different investing propensity as well as profitability. Firms with smaller capital intensity are expected to have smaller ‘operating leverage’, and therefore smaller volatility of earnings, given the same demand fluctuations (Lev, 1983; Baginski et al, 1999). We used as a proxy of capital intensity (*cap*), the ratio of amortisation of tangible capital to revenue (Baginski et al, 1999; Cheng, 2005; Asthana and Zhang, 2006).

4.6 The Rubin’s causal inference framework: definition and standard assumptions

The reference econometric method is the Rubin’s causal model (Rubin, 1974). Based on the concept of the counterfactual, two structures form the basis for this model: the theory of potential outcomes and the concept of a treatment assignment mechanism.

Let $z \in \{0,1\}$ indicates receipt of treatment: z = 1 if received and z = 0 if not. Accordingly, each unit i has two potential outcomes, $Y_i(1)$ under receipt of treatment, and $Y_i(0)$ under non-receipt. Given the two potential outcomes, the within-individual causal effect of treatment is obtained by contrasting the two outcomes: $\delta_i = Y_i(1) - Y_i(0)$.

The difficulty with inferring a within-individual causal effect from observed data is that only one of the potential outcomes can be observed (the "fundamental problem of causal inference" (Holland, 1986)). In particular, for binary treatment, the observed data on individual i consists of (Z, Y), where $Z \in \{0,1\}$ is the observed treatment status and:

$$Y_i = Z \cdot Y_i(1) + (1 - Z) \cdot Y_i(0) \qquad \textbf{Eq. 4.3}$$

is the observed response. Two causal effects are of main interest: the Average Treatment Effect (ATE) for the overall sample:

$$\text{ATE} = E(Y_i(1) - Y_i(0)) = E(Y_i(1)) - E(Y_i(0)) \qquad \textbf{Eq. 4.4}$$

and the Average Treatment effect for the Treated (ATT):

$$\text{ATT} = E(Y_i(1) - Y_i(0) \mid z_i = 1) = E(Y_i(1) \mid z_i = 1) - E(Y_i(0) \mid z_i = 1) \qquad \textbf{Eq. 4.5}$$

Since only one of the two potential outcomes can actually be observed, we can only obtain the expected treatment outcomes for treated,

$$E(Y_i \mid Z_i = 1) = E(Y_i(1) \mid Z_i = 1) \qquad \textbf{Eq. 4.6}$$

and the expected control outcomes for the non-treated,

$$E(Y_i \mid Z_i = 0) = E(Y_i(0) \mid Z_i = 0) \qquad \textbf{Eq. 4.7}$$

In general, the conditional expectations in Eqs. 4.6 and eq. 4.7 differ from unconditional averages, due to differential selection of units in the treatment and control conditions, leading to biased estimates from observed outcomes.

One way of establishing an ignorable selection mechanism is to randomize units into treatment and control conditions. Randomisation ensures that potential outcomes are independent of treatment assignment *Z*. Because of this independence, the conditional expectation of the outcome of treated is equivalent to the unconditional expectation of the potential treatment outcome:

$$E(Y_i \mid Z_i = 1) = E(Y_i(1) \mid Z_i = 1) = E(Y_i(1)) \qquad \textbf{Eq. 4.8}$$

for treated, and:

$$E(Y_i \mid Z_i = 0) = E(Y_i(0) \mid Z_i = 0) = E(Y_i(0)) \qquad \textbf{Eq. 4.9}$$

for control. Therefore, the difference in observed group means is an unbiased estimator for both ATE and ATT in a randomized experiment.

However, in practice, randomisation is often not possible. In *ex post* evaluations in particular, selection in treatment mechanism is not under the control of the analyst and selection bias problems arise. In our context, some hotels were more likely to apply for public subsidies than others, given certain *ex ante* characteristics. Thus, potential outcomes cannot be considered as independent of treatment status. In the standard Rubin's model the identification and estimation of treatment effect are possible under the following assumptions:

Assumption 1: Stable Unit Treatment Value Assumption (SUTVA)

a. Potential outcomes are fixed and one-dimensional, i.e., the potential outcomes of one unit should be unaffected by the particular assignment of treatments to the other units (no interference).
b. Each treated unit receives the same type of treatment from the policy.

Assumption 2: Conditional independence (CIA) (or selection on observables)

$Y(Z) \amalg Z \mid X$, i.e. Z is independent of $Y(Z)$, $Z = 0,1$ conditional on X = x;

Assumption 3: Overlap

$c < \Pr(Z = 1 \mid X = x) < 1 - c$, for some $c > 0$.

4.7 Average Treatment Effect on Treated in presence of single treatment

Under the assumptions of the standard model (assumptions 1-3), we first estimated the direct average treatment effect on treated (ATT) in presence of single treatment, i.e. for those hotels which received only one subsidy. In this setting we avoid the distorting effect stemming from the receipt of multiple treatments over time; we used a Conditional Difference-in-Difference matching estimator.

4.7.1 Multivariate matching estimator

Several matching estimators have been proposed and can be distinguished according to the method used to match observation from the two groups of treated and controls (Stuart, 2010). We used the nearest neighbor matching estimator introduced by Abadie and Imbens (2002) and Imbens (2004). This estimator summarizes information from multiple variables in a single index according to the vector norm $\mathbf{x}v = \left(\mathbf{x}'V\mathbf{x}\right)^{1/2}$, where V is the positive definite variance matrix[25] used to weight variables trough normalisation by standard deviation. The distance between two observations is defined as $\|\mathbf{w} - \mathbf{z}\|v$, where **w** and **x** are the vectors of observable characteristics for the two observations. The estimator of the ATT is given as:

$$\delta^{ATT} = \frac{1}{N_1} \sum_{i:Z=1}^{N_1} \left[Y_i(1) - \hat{Y}_i(0) \right] \qquad \textbf{Eq. 4.10}$$

where N_1 is the number of observation in the treated group and the subscript i represent individual observations. While $Y_i(1)$ is the observed outcome variable for the i-th treated individual, but $Y_i(0)$ is not observed and is estimated. If M is the predetermined number of matches and $J_M(i)$ = {j : unit j belongs to the group of the M nearest neighbors to unit i} the index set of matches for each unit i = 1, …,N which indicates the M nearest matches for unit i. The imputed potential outcome is defined as follows:

[25] In this chapter V is defined as the diagonal matrix constructed of the inverse of the variances of each element of the covariate vector.

$$\hat{Y}_i(0) = \frac{1}{\# J_M(i)} \sum_{m \in J_M(i)} Y_m(0) \qquad \textbf{Eq. 4.11}$$

The imputed potential outcome for the i-th treated individual, $\hat{Y}_i(0)$ if $Z=1$, is then the average of the outcome variables for all matched observations in the control group.

The matching estimator employed allows for matching over a multi-dimensional set of covariates. Abadie and Imbens (2002) show that when exact matching is not reached the estimator can be biased because of difference in covariates between matched units and their matched controls. In order to address this problem, they develop a bias corrected matching estimator adjusting the difference within the matches for the difference in covariate values through a regression imputation strategy. With the bias correction, the matching estimator can be shown to be consistent (Abadie and Imbens, 2002).

4.7.1.1 Extension to panel data: The Conditional Difference-in-Difference estimator

We extended the cross-sectional matching estimator to a longitudinal setting and implemented a Conditional Difference-in-Differences matching estimator (CDiD). Once matched treated and control observations, we adopt a CDiD matching estimator as follows (Smith and Todd, 2005):

$$\hat{\delta}^{CDiD} = \frac{1}{N_1} \sum_{i \in I_i \cap S_p} \left\{ \left[Y_{t_1 i}(1) - Y_{t_0 i}(0) \right] - \sum_{j \in I_0 \cap S_p} W_{ij} \left[Y_{t_1 j}(0) - Y_{t_0 j}(0) \right] \right\} \qquad \textbf{Eq. 4.12}$$

where N_1 is the number of treated firms; Y_{t0i}, Y_{t1i}, are the values of the outcome variable on respectively before and after the treatment for firm i in the treated group (I_1); Y_{t0j}, Y_{t1j}, are the values of the objective variable on respectively before and after the treatment for firm j in the control group (I_0); W_{ij} represents the weights and depends on the particular cross-sectional matching estimator employed. In our case the implemented CDiD is as follows:

$$\hat{\delta}^{CDiD} = \frac{1}{N_1} \sum_{i:Z_i=1} \left\{ \left[Y_{t_1 i}(1) - Y_{t_0 i}(0) \right] - \frac{1}{\# J_M(i)} \sum_{m \in J_M(i)} \left[Y_{t_1 m}(0) - Y_{t_0 m}(0) \right] \right\}$$

The CDiD estimator allowed us to control also for temporally invariant differences in outcomes between treated and non-treated firms (Smith and Todd, 2005). The control group used in the CDiD is the sample of M non-subsidized hotels which are matched to the treated hotel i in the period (t_0) before receiving the treatment. The differences in performance before (t_0) and after the treatment (t_1) of the two groups are then compared.

4.7.2 Empirical setting

The treatment consists of the receipt of a subsidy in a year. In this section, we focus on those hotels that received only one subsidy during the period 2002-2006, ruling out potential problems due to the overlapping of more than one subsidy received by hotels over time.

An appropriate sample of controls is necessary. Given the definition of treatment used, a condition to be eligible as control is that of not having received any subsidy during the period under analysis. The non-subsidised hotels contained in the DBevalHTN database are then suitable to be used as controls. However, the general condition for identifying the causal effect in the Conditional DiD strategy employed is that treated and controls units should be similar except for the treatment status[26]. If hotels are not subsidised only because of their low propensity to invest, this might introduce a dangerous bias in the analysis. To reduce this concern, we made a preliminary screening of non-subsidised hotels and discarded those with negative changes of amortization cost on tangible assets over the entire period under analysis.[27] After the screening, we were left with 372 non-subsidised hotels.

[26] In the absence of the treatment, variations from pre to post treatment levels of the outcomes among treated and non-treated should be, on average, identical. Formally, this implies that pre-post variations of the outcomes are independent from the treatment, after conditioning for hotel characteristics X.

[27] Amortization of tangible capital is the accounting process of allocating the acquisition costs of tangible assets in a systematic manner to the periods expected to benefit from the use of the asset. For instance, let suppose that a firm invests in a period t, the acquisition cost of the new asset is then split into k shares (usually equal shares) that are recorded in each annual balance sheet over the period from time t to time $t+k$, where k is the useful life of the asset. Therefore, a positive variation in the amount of annual

Under the assumption that hotels in the treatment and control sample show as similar as possible willingness to invest, the selection problem should be addressed. For instance, for larger, more profitable and capital intensive, less risk-averse hotels the outcome can be different from those non-subsidised even in the absence of the incentive. Additionally, location and managerial ability may influence hotel outcome and the probability of being subsidised. The procedure we employ is thus intended to reduce this bias. Specifically, we control for factors which are likely to influence both the propensity of hotels to apply for public grants and hotel performance: the legal form, which indicates the attitude of the firm towards risk; the hotel size which is a useful predictor of financial constraints and the capacity of receiving external finance; the degree of internationalisation as indirect measure of quality of management and employment; an index of capital intensity to account for different past investing decision as well as profitability; and the hotel category which indicates the level and complexity of services provided and explains an important part of unobserved differences in entrepreneurial behaviour and hotel performance. Moreover, we control for location factors, namely the destination, the proximity to attraction points as well as to other competitors, which define the environment in which firms operate and thus influences firms' behaviour to apply for subsidies and performance.

We identify the pre-treatment period as the year before the granting of the subsidy. Differences in outcome between the treated and controls are evaluated in two post-treatment periods: one and two years after the receipt of the subsidy.

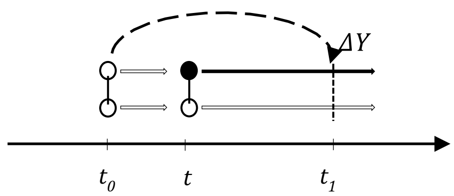


Figure 4.2. CDiD matching approach. Hotels are matched at time t_0 (before treatment) and variations in the outcome of treated hotels are compared with that of comparable controls (the counterfactual) at time t_1 after treatment.

amortization costs recorded at time t with respect to time t-1 would imply that an investment has been done at time t.

We pooled the data across years, i.e. we consider the group of treated firms regardless of the calendar year in which they receive the subsidy. However, an important feature of the chosen matching estimator is that it allows an exact match with respect to a set of covariates. Thus, we stratified control and treated hotels along the relative dimensions. In particular, we imposed exact matching on the category, destination, and also on year. Therefore, treated hotels were matched with control hotels which operate in the same destination, in the same category and with reference to the same year. For the other variables, the bias due to possible not exact match is corrected using the procedure suggested in Abadie and Imbens (2002).[28]

Table 4.4 compares the variables of interest for treated and control hotels.

Table 4.4. Characteristics and outcomes for treated and control hotels (1 year before treatment)

Variable	*Treated*			*Non-treated*			*diff*	*p-value*
	N	*Mean*	*Std. Dev.*	*N*	*Mean*	*Std. Dev.*		
Outcomes								
occ_rate	154	0.329	0.129	1488	0.296	0.134	0.032	0.003
occ_var	154	0.932	0.351	1488	0.942	0.359	-0.009	0.742
revpar	154	23.018	12.638	1488	20.740	14.245	2.277	0.037
lab_prod	154	41078.2	13703.7	1488	41019.0	21699.5	59.192	0.962
lab_prod_2	154	18138.2	12357.1	1488	18479.5	12786.9	-341.26	0.745
Cov. (continuous)								
ext	154	0.249	0.246	1488	0.273	0.260	-0.024	0.242
cap	154	0.174	0.105	1488	0.142	0.124	0.031	0.000
size	154	62.76	37.17	1488	56.56	37.31	6.201	0.030
co-loc	154	542.05	3880.8	1488	1745.6	11631.8	-1203.6	0.005
prox	154	0.0126	0.0078	1488	0.0127	0.0078	-0.0014	0.800
Cov. (discrete*)								
cat	154	0.721		1488	0.623		0.097	0.017
legal_form1	154	0.143		1488	0.250		-0.107	0.003
legal_form2	154	0.753		1488	0.641		0.111	0.006
legal_form3	154	0.104		1488	0.108		-0.004	0.870

NOTE: data are pooled across years; * only mean value are reported.

4.7.3 Results

Table 4.5 lists the estimates of the average treatment effect on treated (ATT) obtained with the conditional difference-in-difference estimator (CDiD). The results indicate that receiving subsidies had a positive and statistically significant effect on all

[28] The analysis was implemented via the *nnmatch* module in Stata (Abadie et al., 2004).

outcomes considered, and that the influence of subsidies increased over time. The occupancy rate (*occ_rate*) of subsidised hotels increased by about 2% after one year and by about 3.5% after two years. The effect on the revenue per available rooms (*revpar*) was also positive and increases over time. The variability in demand over time (*occ_var*) fell for subsidised firms after one year and the fall was even more evident after two years. Labour productivity (*lab_prod*), measured as gross output to employees, was also positively affected by subsidies: the effect is of more then four thousand euro after one year and more than five thousand after two years. When measured as value added to employees, differences in labour productivity growth (*lab_prod_2*) between treated and control hotels followed similar trend.

Table 4.5. Estimates of the Average Treatment Effect on Treated

	Outcomes after one year				*Outcomes after two years*			
	δ^{CDiD}	*Std. Err.*	*z-stat*	*p-value*	δ^{CDiD}	*Std. Err.*	*z-stat*	*p-value*
occ_rate	0.019	0.008	2.59	0.010	0.036	0.012	2.99	0.003
occ_var	-0.092	0.027	-3.38	0.001	-0.108	0.037	-2.89	0.004
revpar	2.624	0.641	4.09	0.000	4.223	1.022	4.13	0.000
lab_prod	4033.3	1696.3	2.38	0.017	5393.9	2062.8	2.61	0.009
lab_prod_2	3563.1	1161.2	3.07	0.002	3770.7	1491.2	2.53	0.011

NOTE: Estimate are given as the difference in levels between Treated and Control hotels; Exact match on hotel category, destination and year; percent of exact matches: 100;

The CDiD estimator controls for time-constant unobserved factors. In view of the short time-period analysed, we reasonably assumed that unobserved factors which are potentially time-varying are also temporally invariant; therefore, in this case, CDiD successfully controls for all unobserved potential sources of bias.

It is possible to derive testable implications of the assumed identifying restriction[29]. In particular, by conditioning on the observable hotel characteristics the changes in the outcomes referring to before treatment periods should be the same among treated and non-treated hotels. If not rejected, this fact provides evidence in favor of the internal validity of the estimated causal parameter. Table 4.6 shows the results of the over-identification test. We consider variations in the outcomes between two and one year before the treatment. The results of the test show not statistically significant difference for subsidized and non-subsidized hotels.

[29] The CDiD identifying restriction is not directly testable since it involves counterfactuals.

Table 4.6. Over-identification test.

outcome	δ^{CDiD}	*Std. Err.*	*z-stat*	*p-value*
occ_rate	-0.001	0.007	-0.14	0.890
occ_var	0.026	0.018	1.44	0.151
revpar	-0.312	0.469	-0.66	0.506
lab_prod	701.4	1161.7	0.60	0.436
lab_prod_2	-1345.4	1035.2	-1.30	0.194

NOTE: Estimate are given as the difference in levels between Treated and Control hotels; Exact match on hotel category, destination and year; percent of exact matches: 99.

4.8 Average Treatment Effect in longitudinal multiple treatments: Extending the CIA

In this section we extended the standard framework to a dynamic treatment setting, i.e. treatment is no longer a single treatment, but is the longitudinal history of treatments up to a certain time *t*. To this aim, we first defined the potential outcomes in terms of a linear model and introduced the Inverse Probability of Treatment Weighting (IPTW) estimator. Finally, we extended the model to handle longitudinal multiple treatments.

4.8.1 Inverse Probability of Treatment Weighting estimator (IPTW)

It possible to define the potential outcomes in terms of a linear model (Hogan and Lancaster, 2004):

$$E[Y(z)] = \alpha^* + \delta^* z \qquad \textbf{M. 4.1}$$

where δ^* is the average treatment effect (i.e., z changes from 0 to 1). The empirical counterpart of model M.4.1 can be specified as a regression model, so that:

$$E(Y \mid Z) = \alpha + \delta Z \qquad \textbf{M. 4.2}$$

Because of nonrandom selection to receipt of treatment, regression parameter δ generally not equal to the causal parameter δ^*: estimation of δ under the empirical model M. 4.2 will yield inconsistent estimates of causal parameter δ^*. In order to improve estimation in presence of selection, the Inverse Probability of Treatment Weighting (IPTW) estimator can be used. As for matching techniques the IPTW estimator relies on the CIA assumption. The idea of IPTW is that units which are underrepresented in the treated or control group are up-weighted and units which are over-represented in one of the groups are down-weighted.

When the estimate of interest is the average treatment effect, the inverse probability of treatment weight for the treated units is given by $w_i = 1/\hat{p}_i$, and for the control units is $w_i = 1/(1-\hat{p}_i)$, where $\hat{p}_i = \Pr(Z_i = 1 \mid X_i)$ is the estimated propensity score for hotel i. For both group together we may write the weights as a function of treatment status and the propensity score:

$$w_i = \frac{Z_i}{\hat{p}_i} + \frac{(1-Z_i)}{(1-\hat{p}_i)} \qquad \textbf{Eq. 4.13}$$

The average treatment effect can be estimated by estimating model M.4.2 by weighted least square with weights w_i. If all the relevant confounders are observed and included in X, weighting by w_i effectively creates a pseudo population in which X no longer predicts selection into subsidizing and the causal association between subsidy and outcome is the same as in the original population[30].

In the next section we extended model M. 4.2 to longitudinal multiple treatments.

4.8.2 IPTW estimation in presence of longitudinal multiple treatments

Let us again consider treatment (i.e. the receipt of subsidies) as binary variable. The set of potential treatments for unit i is now defined in terms of treatment histories

[30] The model described in this section is a Marginal Structural Model (MSM). MSM is a regression model for the relationship between the outcome and the treatment assignments: the confounders are not included in the model, but by weighting each observation with the inverse of the probability of the observed treatments, the distorting effect of confounders is neutralized. Two models must be specified: an outcome model and a model for estimating the weights. However, as suggested in Hogan and Lancaster (2004), variables (X) used as confounders in the treatment model and variables used as control in the outcome model may overlap.

$\bar{z}_{it} = \{z_{i0}, z_{i1}, \ldots, z_{it}\}$ where $\bar{z}_{it} \in \mathrm{H}_t$ represents the treatment histories of hotel i up to time t and H_t is the set of all possible t-sequences of 0s and 1s. Clearly, there are 2^T possible counterfactuals, only one of which is observed for each hotel. The average treatment effect of subsidy history $\bar{z}_{it}$ on outcome y of hotel i is thus defined as $E[y(\bar{z}_{it})] - E[y(0)]$, the average difference between outcomes when i follows the treatment history $\bar{z}_{it}$ and outcomes when never receiving subsidies.

Let us assume that, at each point in time $t = 1, \ldots, T$, for each hotel i we observe (Y, Z, X) where Y, Z and X represent the outcome, treatment status and a vector of hotel characteristics, respectively. In order to reduce the complexity of the problem, we can model the mean of the outcome variable as conditional on control covariates X and treatment history $\bar{Z}$ as (Hogan and Lancaster, 2004):

$$E\left[Y(\bar{z}_{it}) \mid \bar{Z}_{it}, X_{it}\right] = \beta_0 + \beta_1^{'} X_{it} + \delta g(\bar{Z}_{it}) \qquad \textbf{M. 4.3}$$

where $g(\cdot)$ is a known function of treatment history.

To estimate the causal effect consistently, we use an extension of the IPTW estimator. Its reliability depends on the validity of the Sequential Conditional Independence Assumption (SCIA), which provides a formal way of extending the assumption of selection on observables to the case of dynamic treatment (Robins et al., 2000; Hogan and Lancaster, 2004):

Assumption 4: Sequential Conditional Independence (SCIA)

$$Y(z_{it}) \amalg Z_{it} \mid \bar{Z}_{it-1}, \bar{X}_{it-1}^{TVC}, \bar{X}_{it}$$

where $\bar{X}_{it}$ is the history of hotel-level variables and $\bar{X}_{it}^{TVC}$ the history of time-varying confounder that is defined in the IPTW literature (see Azoulay et al., 2009) as a time-varying variable that (i) is correlated with future values of the dependent variable in question, (ii) predicts selection into treatment, and (iii) is itself predicted by past treatment history. Under SCIA the average treatment effect δ is identified and can be recovered by estimating:

$$y_{it} = \beta_0 + \beta_1^{'} X_{it} + \delta g\left(\bar{Z}_{it}\right) + \varepsilon_{it} \qquad \textbf{M. 4.4}$$

by weighted least squares, where the weights correspond to the inverse probability of following the actual treatment history of subsidies up to time *t* for hotel *i*. (Hogan and Lancaster, 2004; Azoulay et al., 2009)

The weights (w_{it}) for the IPTW estimation procedure for each firm *i* at time *t* are computed as follows:

$$w_{it} = \prod_{\tau=0}^{t} \frac{1}{\Pr\left(Z_{i\tau} \mid \bar{Z}_{i\tau-1}, \bar{X}_{i\tau-1}^{TVC}, \bar{X}_{i\tau}\right)} \qquad \textbf{Eq. 4.14}$$

Each element in the denominator of Eq. 4.14 represents the probability that the hotel *i* received it own observed treatment (either subsidized or not subsidized) at time *t*, conditional on past treatment history and its past history of confounder variables. Therefore, the denominator of w_{it} represents the conditional probability that an hotel followed its own treatment history up to time *t*.

The probabilities in the denominator of Eq. 4.14 may vary significantly when time-varying confounders are strongly associated with the receipt of a subsidy, and the resulting IPTW estimator will have a very large variance. Thus we replace the weights with a “stabilised weights” ($sw_{i,t}$) computed, as follows:

$$sw_{it} = \prod_{\tau=0}^{t} \frac{\Pr\left(Z_{i\tau} \mid \bar{Z}_{i\tau-1}, \bar{X}_{i\tau}\right)}{\Pr\left(Z_{i\tau} \mid \bar{Z}_{i\tau-1}, \bar{X}_{i\tau-1}^{TVC}, \bar{X}_{i\tau}\right)} \qquad \textbf{Eq. 4.15}$$

The use of stabilized weights increases IPTW efficiency without influencing its consistency (Hernan et al, 2000).

Let T_1 denote the set of years in which the hotel received at least one subsidy and T_2 the set of years during which the hotel *i* receives no subsidies. The denominator of sw_{it} is then estimated as:

$$\prod_{t \in T_1} \hat{p}_{it}^{den} \prod_{t \in T_2} \left(1 - \hat{p}_{it}^{den}\right) \qquad \textbf{Eq. 4.16}$$

where $\hat{p}_{it}^{den}$ is the probability of being subsidised at time t, conditional on past treatment history and its past history of confounder variables. This probability are obtained by estimating a pooled cross-sectional logistic regression on the whole dataset as follows:

$$\hat{p}_{it}^{den} = \Pr\left(Z_{it} = 1\right) = \gamma_0 + \gamma_1 Z_{it-1} + \gamma_2 Z_{it-2} + \gamma_3 X_{it-1}^{TVC} + \gamma_4 X_{it} + \zeta_t \qquad \textbf{M. 4.5}$$

The numerator of sw_{it} is defined in a similar way, except that the time-varying confounders are omitted from the list of covariates in model M. 4.5.

Lastly, in order to estimate model M. 4.4, the form of function $g(\cdot)$ must be chosen. In this chapter we use two parameterisations (Ko et al., 2003):

$$\textit{Parameterisation } 1: \ \delta g\left(\overline{Z}_{it}\right) = \delta\left(Z_{it} + Z_{it-1} + Z_{it-2}\right) \qquad \textbf{Eq. 4.17}$$

$$\textit{Parameterisation } 2: \ \delta g\left(\overline{Z}_{it}\right) = \delta_1 Z_{it} + \delta_2 Z_{it-1} + \delta_3 Z_{it-2} \qquad \textbf{Eq. 4.18}$$

The estimated causal parameter δ under parameterisation 1 quantifies the direct causal benefit of receiving additional subsidies, regardless of the timing with which subsidies are assigned. For instance, if only one subsidy was received over period t-2 to t, the relative benefit is equivalent, regardless of when it was received. Under parameterisation 2, the timing of subsidisation affects outcomes. In addition, cumulative subsidisation is not assumed to have a linear effect on the current value of the outcome variable analysed. Under both parameterisations, subsidies received before time t-2 have no causal effect on outcomes.

4.8.3 Empirical setting

In this section we used the whole set of subsidised hotels contained in the DBevalHTN database (426 hotels). The hotels can receive one or more subsidy during the observed period (2002-2006). We consider also 372 non-subsidised hotels.[31] Figure 4.3 plots the distribution of number of subsidies for the hotels in our sample.

[31] As in section 4.7, we do not consider non-subsidised hotels that show very low propensity to invest, i.e. we discarded those non-subsidised hotels with negative changes of amortization cost on tangible assets over the entire period under analysis.

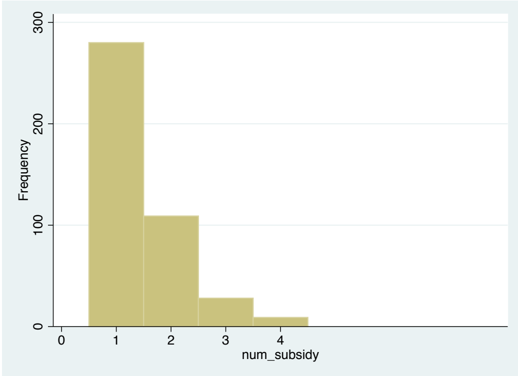


Figure 4.3 Subsidies for hotel in the DBevalHTN database

The figure shows that most of the treated hotels received one subsidy throughout the observed period. However, the number of hotels which obtained two or three was not negligible. In a few cases, more than three subsidies were even granted.

In this section, the treatment is no longer the receipt of a single treatment in a year, but is a history of treatment, i.e. a sequence of 0s and 1s of the treatment status over the years. Accordingly the counterfactual is a differing sequence of 0s and 1s of the treatment status.

We consider as time-varying confounders the pre-treatment value of hotel size (*size*), capital intensity index (*cap_int*), legal form (*legal_form*), hotel category (*cat*) and degree of internationalization (*int*). As control variables in the outcome model we considered the co-location index (*co_loc*), proximity index (*prox*), contemporaneous category, legal form, size, internationalization, and capital intensity, as well as the whole set of destination dummies (see section 4.5.3 for details on these variables). The analysis is carried out on the outcome variables defined in section 4.5.2, i.e., the varying level of capacity utilisation (*occ_var*), average occupation rate (*occ_ratio*), revenue per available room (*revpar*), and the two proxies of labour productivity (*lab_prod* and *lab_prod_2*). Results are obtained under the two parameterisations of functions $g(\cdot)$ for each outcome variable.

4.8.4 Results

This section reports the results of estimating models M.4.4. Table 4.7 lists estimated coefficients when parameterisation 1 of function $g(\cdot)$ is employed. In this case, the difference in the average outcome depends only on cumulative subsidisation over period *t-2* to *t*, and the timing of subsidisation relative to the current outcome level does not play a role: all treatment histories with the same cumulative subsidisation are considered exchangeable, regardless of when the subsidy was received. Accordingly, interpretation of causal parameter δ is the average difference in the outcome between the two versions of treatment history, which differ by one unit in cumulate subsidisation. The results show that δ is positive and statistically significant for the various outcomes considered. The only exception is for labour productivity, where the coefficient is positive but not statistically significant.

Table 4.7. Weighted least square estimates. Model M. 4.4, parameterisation 1.

Variables	*Treatment history parameterisation*		*occ_var*	*occ_ratio*	*revpar*	*lab_prod*	*lab_prod_2*
g(Z)	$\delta(Z_t+Z_{t-1}+Z_{t-2})$						
		(δ)	-0.064***	0.040***	5.285***	1,059.010	623.762
			(0.019)	(0.007)	(0.858)	(1,063.483)	(562.196)
Controls							
co-loc			0.002	0.002**	-0.090	-134.924	-30.707
			(0.003)	(0.001)	(0.145)	(179.448)	(94.863)
prox			0.093**	0.013	2.154	5,646.340**	4,763.340***
			(0.045)	(0.017)	(2.005)	(2,483.858)	(1,313.057)
Legal_form_2			-0.091***	0.036***	5.375***	4,745.117***	2,109.943**
			(0.031)	(0.012)	(1.373)	(1,700.916)	(899.166)
Legal_form_3			-0.054	0.062***	16.364***	8,323.566***	2,297.585*
			(0.046)	(0.017)	(2.050)	(2,540.479)	(1,342.989)
cat			-0.135***	0.065***	5.948***	6,121.176***	3,011.739***
			(0.031)	(0.012)	(1.379)	(1,708.251)	(903.043)
size			-0.014	0.021**	-2.157*	4,233.195***	4,032.608***
			(0.027)	(0.010)	(1.190)	(1,474.064)	(779.243)
ext			-0.095	0.078***	-7.109**	2,963.113	3,175.908*
			(0.062)	(0.024)	(2.789)	(3,456.003)	(1,826.968)
cap_int			0.354***	-0.194***	-28.432***	-6,231.002	4,246.950
			(0.117)	(0.044)	(5.235)	(6,486.397)	(3,428.945)
Observations			798	798	798	798	798
R-squared			0.175	0.346	0.247	0.172	0.263
R_adj			0.151	0.327	0.225	0.148	0.241
F			7.152	17.80	11.05	7.014	12.00

NOTE: Dummy destination are included.

Table 4.8 lists the results when model M. 4.4 is estimated under parameterisation 2 of function $g(\cdot)$. Parameterisation 2 is designed to account both for total subsidisation (within the three-year period) and its timing. Now, δ_1 is the effect of subsidisation during current year *t*, and δ_2 and δ_3 are the (additive) effects of subsidies received during periods t-1 and t-2, respectively. The estimated parameters show a non-linear effect over time. Specifically, the results show the decreasing positive effect of subsidies on the outcome. That is, the positive bearing on the outcome variable of a subsidy received at time t-2 is generally higher than that related to a subsidy received at time t-1 or at the same time at which the outcome level was observed. This suggest that the direct effect of subsidy receipt does stimulate a process of learning plausibly linked to the higher effort exerted by hoteliers to manage the renewed hotel. Alternative cause can be, however, the amount of time necessary for the investment to generate results (e.g. spread of information, branding).

Table 4.8 Weighted least square estimates. Model M. 4.4, parameterisation 2.

Variables	*Treatment history parameterisation*	*occ_var*	*occ_ratio*	*revpar*	*lab_prod*	*lab_prod_2*
g(Z)	$\delta_1 Z_t+\delta_2 Z_{t-1}+\delta_3 Z_{t-2}$					
	(δ_1)	0.016	0.031**	5.282***	290.222	511.757
		(0.033)	(0.012)	(1.465)	(1,815.075)	(959.926)
	(δ_2)	-0.122***	0.034**	4.644***	2,517.655	946.646
		(0.035)	(0.013)	(1.584)	(1,961.564)	(1,037.398)
	(δ_3)	-0.094***	0.054***	5.859***	540.804	449.868
		(0.034)	(0.013)	(1.511)	(1,871.344)	(989.685)
Controls						
co-loc		0.002	0.002**	-0.092	-132.519	-30.122
		(0.003)	(0.001)	(0.145)	(179.614)	(94.991)
prox		0.081*	0.014	2.141	5,777.363**	4,784.870***
		(0.045)	(0.017)	(2.014)	(2,494.490)	(1,319.243)
Legal_form_2		-0.089***	0.036***	5.382***	4,709.859***	2,103.648**
		(0.031)	(0.012)	(1.375)	(1,702.930)	(900.616)
Legal_form_3		-0.055	0.062***	16.361***	8,333.997***	2,299.545*
		(0.046)	(0.017)	(2.053)	(2,542.484)	(1,344.626)
cat		-0.135***	0.065***	5.969***	6,099.083***	3,004.882***
		(0.031)	(0.012)	(1.381)	(1,710.433)	(904.585)
size		-0.016	0.021**	-2.170*	4,270.774***	4,040.240***
		(0.027)	(0.010)	(1.191)	(1,475.835)	(780.514)
ext		-0.086	0.078***	-7.040**	2,772.683	3,136.253*
		(0.062)	(0.024)	(2.798)	(3,465.322)	(1,832.680)
cap		0.358***	-0.191***	-28.270***	-6,491.918	4,181.205
		(0.117)	(0.044)	(5.249)	(6,501.826)	(3,438.575)
Observations		798	798	798	798	798
R-squared		0.185	0.348	0.247	0.173	0.263
R_adj		0.159	0.327	0.223	0.147	0.239
F		7.027	16.46	10.15	6.475	11.02

NOTE: Dummy destination are included.

4.9 Average treatment effect in longitudinal multiple treatments in presence of neighbour interference: Extending the CIA and relaxing the SUTVA

Interactions among hotels may be a major concern, since a subsidy affecting the outcome of one hotel may affect that of others. Hotels operating in the same geographical area (i.e., destination) are in fact likely to interact each other, violating the Stable Unit Treatment Value Assumption (SUTVA; Rubin, 1986). In the following, we focus on the violation of SUTVA due to interference (Hong and Raudenbush, 2006; Verbitsky-Savitz and Raudenbush, 2012), and define a framework aimed at: (a) relaxing the SUTVA assumption, allowing for interference between neighbour treatment assignment and the focal hotel outcome; (b) capable to account for different multiple treatment histories over time.

4.9.1 The extended framework for causal inference in presence of neighbour interference

4.9.1.1 Notation and definitions

Let z_t denote the vector of treatment assignment to hotels in a given period t:

$$\mathrm{z}_t = (z_{1t}, z_{2t},\ldots, z_{Nt}) = (z_{it}, \mathrm{z}_{-it}), \qquad \textbf{Eq. 4.19}$$

where z_{-it} is the vector of treatment assignment when that of hotel i, z_{it}, is removed. In this setting, hotel i has 2^N potential outcomes, $Y_{it}(\mathrm{z}_t)$, corresponding to all possible treatment assignment combinations of N hotels. A contrast between any two of the possible 2^N outcomes is a causal effect. Clearly, the case in which SUTVA is satisfied is special, and:

$$Y_{it}(\mathrm{z}_t) = Y_{it}(z_{it}, \mathrm{z}_{-it}) = Y_{it}(z_{it}). \qquad \textbf{Eq. 4.20}$$

The effect of z_t on the hotel's potential outcome may be viewed as operating through z_{it} and a many-to-one function $v(\mathrm{z}_t)$ (Hong and Raudenbush, 2006). The N-dimensional space is thus reduced to a 2-dimensional space. Hence:

$$Y_{it}\ (\mathrm{z}_t) = Y_{it}\ (z_{it}, \mathrm{z}_{-it}) = Y_{it}\ [z_{it}, v(\mathrm{z}_{-it})]. \qquad \textbf{Eq. 4.21}$$

Two causal effects can be defined (Tchetgen and VanderWeele, 2010): a direct causal effect:

$$DE_{it} = Y_{it}\ [z_{it} = 1,\ v(\mathrm{z}_{-it})] - Y_{it}\ [z_{it} = 0, v(\mathrm{z}_{-it})] \qquad \textbf{Eq. 4.22}$$

as the causal effect of the treatment on a hotel given the treatment status of other hotels; an indirect causal effect or “spillover effect”:

$$IE_{it} = Y_{it}\ [z_{it}\ ,\ v(\mathrm{z}_{-it})] - Y_{it}\ [z_{it}\ , v(\mathrm{z}_{-it}{}')] \qquad \textbf{Eq. 4.23}$$

as the causal effect on one hotel of the treatment received by other hotels in the destination.

The setting can be extended in order to account for the fact that hotels are located in different intra-regional tourist destinations (TDs). Accordingly, we introduce an assignment vector, S = $(s_1, \ldots, s_i, \ldots, s_N)$ where s_i can take values j: $j = 1, \ldots, J$, where J is the number of tourist destinations. The potential outcome becomes $Y_{it}\ [z_{it}, v(\mathrm{z}_{-it}), \mathrm{s}_t]$. In the end, the causal estimand of interest is given by:

$$E\{Y_{it}[z_{it}, v(\mathrm{z}_{-it}), \mathrm{s}_t] - Y_{it}[z_{it}{}', v(\mathrm{z}_{-it}{}'), \mathrm{s}_t{}']\}. \qquad \textbf{Eq. 4.24}$$

4.9.1.2 Assumptions

In order to identify and estimate the average effect of treatment assignment z_t and $v(\mathrm{z}_t)$ we assume[32]:

[32] Assumptions 1-4 stated in previus sections are still valid.

Assumption 5:

Let be $s_t = s_t' = s^*$, where s^* the observed assignment of hotels in the destinations. Therefore, given the current localization of hotels in the destinations, the estimand becomes:

$$E\{[Y_{it}\,(z_{it}, v(\mathrm{z}_{-it}),\ \mathrm{s}^*) - Y_{it}[(z_{it}', \mathrm{v}(\mathrm{z}_{-it}'), \mathrm{s}^*)] \mid \mathrm{S} = \mathrm{s}^*\}. \qquad \textbf{Eq. 4.25}$$

This assumption means that no hotel changed its location as a result of receiving on not receiving subsidies[33].

Assumption 6: Neighbor-level SUTVA

The potential outcome of a hotel *i* belonging to TD *j* is dependent only on its treatment status and that of other hotels within TD *j*. In other word, treatment assignment of hotels in other destinations does not affect the potential outcome of the hotel in question. From the non-interference between destinations we have: $Y_{it}\,[z_{it}, v(\mathrm{z}_{-it}),\ \mathrm{s}^*] = Y_{ijt}[(z_{ijt}, \mathrm{v}(\mathrm{z}_{-ijt})]$.

We also assume that each hotel's subsidy has the same effect on the potential outcome of hotel *i*. Hence, we define $v(\mathrm{z})$ as a function of the share of treated hotels in a destination. Formally, $v(\mathrm{z})$ is as follows:

$$v\left(\mathrm{z}_{-it}\right) = v = \begin{cases} 1 & \text{if } n^{-1}\left(\mathrm{z}_{-it}^{T}\mathrm{z}_{-it}\right) \geq Me \\ 0 & \text{otherwise} \end{cases} \qquad \textbf{Eq. 4.26}$$

where *Me* is the median of the distribution of the intensity of treatment across destinations.

[33] The policy allows the re-location of firms. However, this possibility is empirically irrelevant in the case of hotels.

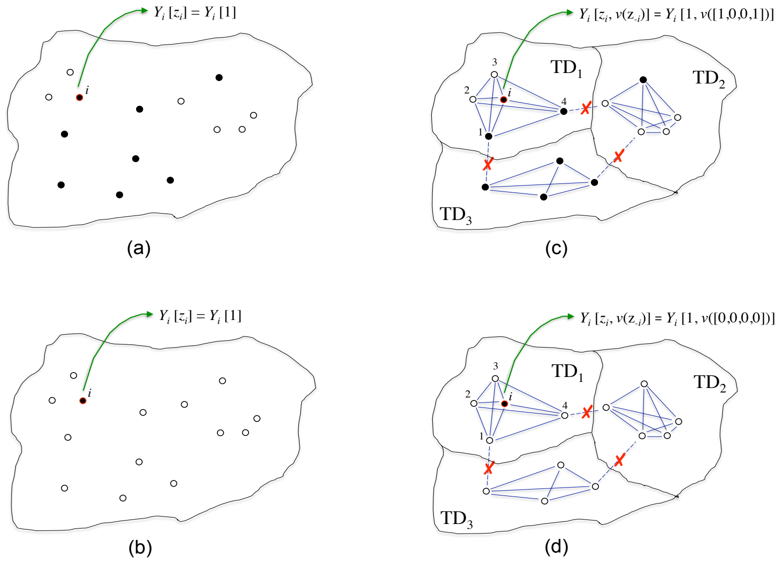


Figure 4.4 Graphical sequence of implications of SUTVA. Black circles: hotels receiving subsidies; white circles: hotels not receiving subsidies. When SUTVA is satisfied (panels (a) and (b)), no influence among units is assumed; outcomes of unit *i* do not vary if treatment status of other hotels varies (e.g., from (a) to (b)); Panels (c) and (d): how SUTVA is relaxed in our framework: hotels in a given destination (TD) are assumed to be connected and outcomes depend on treatment status of all other hotels in same destination. Outcomes of hotel *i* change when treatment status of other hotels changes, although its own treatment status is not changed.

Assumption 7: Strongly ignorable treatment assignment

Let X_t be a hotel-level vector of covariates and W_t a destination-level vector of covariates. Causal inference is possible if treatment assignments are strongly ignorable within the levels of covariates:

$$E[Y_{it}(z_{it}, v_{it}) \mid Z_{it} = z_{it}, V_{it} = v_{it}, X_{it} = x_{it}, W_{it} = w_{it}] =$$

$$= E[Y_{it}\,(z_{it}, v_{it}) \mid X_{it} = x_{it}, W_{it} = w_{it}]. \qquad \textbf{Eq. 4.27}$$

Under the above assumptions, we have a framework with a cluster-level randomised block design, followed by a hotel-level randomized block design within each cluster (i.e. destination). The probability that a TD is assigned to $V = 1$ (highly subsidised TD) given W, is:

$$\Pr(V = 1 \mid W = w) \qquad \textbf{Eq. 4.28}$$

Given a TD assignment to high or low subsidized TD, hotels are assigned at random to $Z = 1$ (subsidy granted). Therefore, the probability for a hotel of receiving a certain treatment is given by:

$$\Pr(Z = z, V = v \mid X = x, W = w) \qquad \textbf{Eq. 4.29}$$

Using the law of probability, Eq. 4.29 can be decomposed into the product of two conditional probabilities as follows:

$$\begin{aligned} &\Pr(Z = z, V = v \mid X = x, W = w) = \\ &\qquad = \Pr(V = v \mid W = w) \cdot \Pr(Z = z \mid V = v, X = x, W = w) \end{aligned} \qquad \textbf{Eq. 4.30}$$

4.9.2 IPTW estimation in a 2-level longitudinal setting and neighbours interference

We aimed to estimate the average treatment effect of subsidies on hotel performance, given the effect of TD exposure to subsidies over time. We, therefore, also had take into account the treatment history at TD level. Although the econometric considerations developed considering longitudinal history of treatment at the hotel level remained applicable to the case of two dichotomous treatments (both at the destination and at the hotel level), the estimation of the final weights was different. Suarez et al. (2008) proposes an extension of the static IPTW estimation to multiple treatment settings, i.e. when subjects in a given time receipt more than one type of treatment. We extended the framework in a two-level longitudinal multiple treatment setting in which at each time t a hotel receives two treatment: one at destination level and the other at hotel level. Specifically, we use the probability of receiving a *2*-dimensional treatment defined in equation Eq. 4.30 to implement the extended IPTW estimator to the dynamic *2*-dimensional treatment setting. Accordingly, we defined stabilized weights as follows:

$$sw_{it}^{2-level} = \prod_{\tau=0}^{t} \frac{\Pr\left(Z_{i\tau}, V_{i\tau} \mid \bar{Z}_{i\tau-1}, \bar{V}_{i\tau-1}, \bar{X}_{i\tau}, \bar{W}_{i\tau}\right)}{\Pr\left(Z_{i\tau}, V_{i\tau} \mid \bar{Z}_{i\tau-1}, \bar{V}_{i\tau-1}, \bar{X}_{i\tau-1}^{TVC}, \bar{W}_{i\tau-1}^{TVC}, \bar{X}_{i\tau}, \bar{W}_{i\tau}\right)}$$
$$= \prod_{\tau=0}^{t} \frac{\Pr\left(V_{i\tau} \mid \bar{V}_{i\tau-1}, \bar{W}_{i\tau}\right) \cdot \Pr\left(Z_{i\tau} \mid \bar{Z}_{i\tau-1}, \bar{V}_{i\tau-1}, \bar{X}_{i\tau}, \bar{W}_{i\tau}\right)}{\Pr\left(V_{i\tau} \mid \bar{V}_{i\tau-1}, \bar{W}_{i\tau-1}^{TVC}, \bar{W}_{i\tau}\right) \cdot \Pr\left(Z_{i\tau} \mid \bar{Z}_{i\tau-1}, \bar{V}_{i\tau-1}, \bar{X}_{i\tau-1}^{TVC}, \bar{W}_{i\tau-1}^{TVC}, \bar{X}_{i\tau}, \bar{W}_{i\tau}\right)} \qquad \textbf{Eq. 4.31}$$

where $\bar{X}_{it}$ and $\bar{X}_{it}^{TVC}$ are hotel-level covariates and time-varying confounder histories up to time t, respectively. Similarly, $\bar{W}_{it}$ and $\bar{W}_{it}^{TVC}$ are TD-level covariates and time-varying confounder histories up to time t. respectively.

Each element in the denominator of Eq. 4.31 is the conditional probability that the hotel i received the 2-dimansional treatment, which is composed by its own observed treatment (either subsidised or not-subsidised) and the treatment received by the destination (either high or low intensity of subsidisation) at time t. Moreover, each element is decomposed as the product of two probabilities. The first, $\hat{p}V_{jt}^{D} = \Pr\left(V_{i\tau} \mid \bar{V}_{i\tau-1}, \bar{W}_{i\tau-1}^{TVC}, \bar{W}_{i\tau}\right)$, is the probability that the destination where the hotel i is located received its own observed treatment (either high or low intensity of subsidisation) at time t conditional on its past treatment history and past history of destination level confounders; the second, $\hat{p}Z_{it}^{D} = \Pr\left(Z_{i\tau} \mid \bar{Z}_{i\tau-1}, \bar{V}_{i\tau-1}, \bar{X}_{i\tau-1}^{TVC}, \bar{W}_{i\tau-1}^{TVC}, \bar{X}_{i\tau}, \bar{W}_{i\tau}\right)$, is the probability that the hotel i received its own observed treatment (either subsidised or non-subsidised) at time t conditional on its own past treatment history and its past history of confounder variables, and the past treatment history and past history of destination confounders.

The aim was to estimate for each hotel the probability of being treated according to one of the four possible treatment statuses in each period: ($Z_t = 1$, $V_t = 1$), ($Z_t = 1$, $V_t = 0$), ($Z_t = 0$, $V_t = 1$), and ($Z_t = 0$, $V_t = 0$). Table 4.9 lists the individual contemporaneous numerator and denominator components for calculating stabilised weights.

Table 4.9. Numerator and denominator for calculating stabilised weights.

Treatment status	*Numerator*	*Denominator*
$(Z_t = 1, V_t = 1)$	$\hat{p}Z_{it}^{N} \cdot \hat{p}V_{jt}^{N}$	$\hat{p}Z_{it}^{D} \cdot \hat{p}V_{jt}^{D}$
$(Z_t = 1, V_t = 0)$	$\hat{p}Z_{it}^{N} \cdot \left(1-\hat{p}V_{jt}^{N}\right)$	$\hat{p}Z_{it}^{D} \cdot \left(1-\hat{p}V_{jt}^{D}\right)$
$(Z_t = 0, V_t = 1)$	$\left(1-\hat{p}Z_{it}^{N}\right) \cdot \hat{p}V_{jt}^{N}$	$\left(1-\hat{p}Z_{it}^{D}\right) \cdot \hat{p}V_{jt}^{D}$
$(Z_t = 0, V_t = 0)$	$\left(1-\hat{p}Z_{it}^{N}\right) \cdot \left(1-\hat{p}V_{jt}^{N}\right)$	$\left(1-\hat{p}Z_{it}^{D}\right) \cdot \left(1-\hat{p}V_{jt}^{D}\right)$

Let T_1 be the set of periods in which the hotel received a subsidy in a destination with high intensity of treatment, T_2 the set of periods in which the hotel received a subsidy in a destination with low intensity of treatment, T_3 the set of periods in which it did not receive any subsidy in a destination with high intensity of treatment, and T_4 the set of periods in which it did not receive any subsidy in a destination with low intensity of treatment. The calculation denominator and denominator for obtaining stabilised weights is reached by multiplying the quantities of interest at time t by their lagged values. Formally, for the denominator we have:

$$\prod_{t \in T_1} pZ_{it}^{D} \cdot pV_{jt}^{D} \prod_{t \in T_2} pZ_{it}^{D} \cdot \left(1 - pV_{jt}^{D}\right) \prod_{t \in T_3} \left(1 - pZ_{it}^{D}\right) \cdot pV_{jt}^{D} \prod_{t \in T_4} \left(1 - pZ_{it}^{D}\right) \cdot \left(1 - pV_{jt}^{D}\right) \qquad \textbf{Eq. 4.32}$$

The probabilities in the above equation were estimated through a logit models as follow:

$$\hat{p}V_{jt}^{D} = \Pr\left(V_{jt} = 1\right) = \gamma_0 + \gamma_1 V_{jt-1} + \gamma_2 V_{jt-2} + \gamma_3 W_{jt-1}^{TVC} + \gamma_4 W_{jt} + \zeta_t \qquad \textbf{M. 4.6}$$

$$\hat{p}Z_{it}^{D} = \Pr\left(Z_{it} = 1\right) = \gamma_0 + \sum_{q=1}^{2} \gamma_q Z_{it-q} \sum_{p=1}^{2} \varphi_p V_{jt-1} + \omega_1 X_{it-1}^{TVC} + \omega_2 X_{it} + \omega_3 W_{jt-1}^{TVC} + \omega_4 W_{jt} + \zeta_t \qquad \textbf{M. 4.7}$$

The numerator of $sw_{it}^{2-level}$ is defined in a similar way, except that one omits the time-varying confounders from the list of covariates

After having obtained the weights, a weighted regression was performed as follows:

$$y_{it} = \beta_0 + \beta_1^{'} X_{it} + \beta_2^{'} W_{it} + \delta g\left(\overline{Z}_{it}\right) + \lambda h\left(\overline{V}_{it}\right) + \varepsilon_{it} \qquad \textbf{M. 4.8}$$

In the empirical estimation we also extended the two parameterisation used in the previous section to function $h(\cdot)$. Specifically, under parameterisation 1 we have:

$$\delta g\left(\bar{Z}_{it}\right) = \delta\left(Z_{it} + Z_{it-1} + Z_{it-2}\right) \quad \textbf{Eq. 4.33}$$

$$\lambda h\left(\bar{V}_{it}\right) = \lambda\left(V_{it} + V_{it-1} + V_{it-2}\right) \quad \textbf{Eq. 4.34}$$

and under parameterisation 2:

$$\lambda h\left(\bar{V}_{it}\right) = \lambda_1 V_{it} + \lambda_2 V_{it-1} + \lambda_3 V_{it-2} \quad \textbf{Eq. 4.35}$$

$$\delta g\left(\bar{Z}_{it}\right) = \delta_1 Z_{it} + \delta_2 Z_{it-1} + \delta_3 Z_{it-2} \quad \textbf{Eq. 4.36}$$

4.9.3 Results

This section reports the results of estimating model M. 4.8. As in section 4.8, we considered time-variant confounders to be the pre-treatment value of the hotel size (*size*), capital intensity index (*cap_int*), legal form (*legal_form*), hotel category (*cat*) and degree of internationalization (*int*). As control variables in the outcome model we considered the co-location index (*co_loc*), proximity index (*prox*), contemporaneous category, legal form, size, internationalization, and capital intensity. Variables at level 2 (i.e. at destination level) may be cluster level variables or cluster aggregates of individual level variables (Hong and Raudenbush, 2006). Here, we used the aggregate value of hotel-level variables at the destination level. In particular, as time varying-confounders we used the aggregated nights spent, the aggregated revenue, the aggregated employment, and the average touristic rate of the destination. As control variables we used the total amount of beds, the average proximity of hotels to attraction points and the average distance among hotels in the destinations. The analysis was carried out on the several outcome variables defined in section 4.5.2, i.e., the varying level of capacity utilisation (*occ_var*), average occupation rate (*occ_ratio*), revenue per available room (*revpar*), and the two proxies of labour productivity (*lab_prod* and *lab_prod_2*). Results were obtained under the two parameterisations of functions $g(\cdot)$ and $h(\cdot)$ for each outcome variable considered.

Although the interpretation of δ is the average direct effect of the receipt of a subsidy on hotel outcome – as discussed in section 4.8 in which neighbours' interference was not considered – λs represent the indirect average effect on hotel outcome linked to belonging to a touristic destination with high instead of low intensity of subsidization. Therefore, it the value of λs differs from zero, violation of SUTVA is indicated. In particular, positive values of λ would be consistent with the hypothesis of positive externality, meaning that the hotels enjoy the positive externalities stemming from being located in a destination, the quality and attractiveness of which is increased by the public subsidisation policy. In this case, hotels enjoy the benefits due to the overall increased quality of the destination even without improving their own quality. Instead, negative values of λ are consistent with the hypothesis that subsidization activates competition among hotels and negative externalities are generated.

Table 4.10 lists the results when parameterisation 1 of both functions $g(\cdot)$ and $h(\cdot)$ is applied. As discussed previously, in this case, it is not the timing but only the cumulative subsidisation which is assumed to play a role. The direct effect of subsidies is still positive and significant. Likewise, there is evidence of SUTVA violation consistent with the competition hypothesis, according to which subsidisation has indirect negative effects on non-subsidised hotels

Estimated coefficients when parameterization 2 is assumed are listed in table 4.11. Now λ_1 represents the contemporaneous effect on the hotel outcome of belonging to a destination where a high proportion of hotels receive subsidies, λ_2 represents the additive indirect effect of the hotel being in a context with high intensity of subsidization during the year prior to outcome evaluation, and λ_3 has the same meaning, but when two time lags are considered.

The results indicate that the contemporaneous (i.e. at time t) indirect effect of being in a destination where many instead of few hotels in are subsidized is positive and statistically significant when *occ_var* and *occ_ratio* are considered as outcomes, and is but not statistically significant for the other outcomes. This evidence is consistent with the hypothesis that the policy activates a process of quality improvement which generates positive externalities. However, the additional effect attributable to past exposure at time t-1 to high density of subsidization is in general lower than the contemporaneous one. This effect become in general negative, and for *occ_var*, *occ_ratio*, and *revpar* also statistically significant, at time t-2. Moreover, the magnitude of λ_3 generally more than counterbalances the positive direct effect (δ_3) on hotel outcomes, leading to a negative net effect of subsidization at time *t*-2. Instead, for *revpar*, the net effect is positive. Overall, This evidence is consistent with the hypothesis of heightened competition.

In summary, it seems that the policy had a positive direct impact on hotel outcomes. The only exception is for labour productivity, in which the sign of the causal parameter is positive but not statistically significant. Less clear is the effect due to potential externalities generated by the different intensity of subsidization of hotel's neighbours in the destination. However, the trend of the indirect effect over time, which is negative at time *t-2*, is consistent with a process in which the policy first generates positive externalities, but after that increases competition among hotels over time.

Table 4.10. Weighted least square estimates. Model M. 4.8, parameterisation 1

Variables	*Treatment history parameterisation*		*occ_var*	*occ_ratio*	*revpar*	*lab_prod*	*lab_prod_2*
g(Z)	$\delta(Z_t+Z_{t-1}+Z_{t-2})$						
		(δ)	-0.081***	0.039***	5.205***	1,098.480	608.719
			(0.019)	(0.007)	(0.811)	(1,135.456)	(575.548)
h(V)	$\lambda(V_t+V_{t-1}+V_{t-2})$						
		(λ)	0.034*	-0.019**	-1.718**	-729.757	-174.052
			(0.020)	(0.008)	(0.871)	(1,220.335)	(618.572)
Controls							
co-loc			0.004	0.001	-0.202	-297.484	-59.890
			(0.003)	(0.001)	(0.134)	(187.479)	(95.031)
prox			0.071	0.036*	3.622*	3,982.847	3,947.330***
			(0.049)	(0.019)	(2.050)	(2,870.403)	(1,454.970)
Legal_form_2			-0.130***	0.042***	5.926***	5,645.511***	1,926.547**
			(0.029)	(0.011)	(1.200)	(1,680.105)	(851.623)
Legal_form_3			-0.040	0.074***	15.408***	9,795.078***	3,070.663**
			(0.044)	(0.017)	(1.844)	(2,582.132)	(1,308.849)
cat			-0.149***	0.059***	5.094***	7,073.073***	3,366.029***
			(0.031)	(0.012)	(1.282)	(1,794.543)	(909.631)
size			-0.016	0.027***	-1.978*	3,356.654**	3,670.209***
			(0.026)	(0.010)	(1.081)	(1,513.446)	(767.146)
ext			-0.054	0.055**	-6.298***	-1,092.897	146.158
			(0.058)	(0.022)	(2.397)	(3,356.775)	(1,701.505)
cap			0.264**	-0.160***	-19.103***	9,548.197	12,783.280***
			(0.117)	(0.045)	(4.880)	(6,833.681)	(3,463.903)
tot_beds			-0.000***	0.000***	0.001***	0.857**	0.976***
			(0.000)	(0.000)	(0.000)	(0.391)	(0.198)
ave_attr			-0.106	-0.129**	1.622	6,495.994	5,713.596
			(0.133)	(0.050)	(5.526)	(7,738.465)	(3,922.527)
ave_alb			-0.017	0.024***	1.170	-1,576.950	-909.040
			(0.022)	(0.009)	(0.935)	(1,309.071)	(663.551)
ave_tur			0.220***	-0.007	-6.564**	2,789.114	-1,237.334
			(0.067)	(0.025)	(2.789)	(3,905.761)	(1,979.779)
Observations			798	798	798	798	798
R-squared			0.147	0.336	0.249	0.142	0.234
R_adj			0.132	0.324	0.236	0.127	0.221
F			9.639	28.30	18.58	9.287	17.11

Table 4.11. Weighted least square estimates. Model M. 4.8, parameterization 2

Variables	*Treatment history parameterization*	*occ_var*	*occ_ratio*	*revpar*	*lab_prod*	*lab_prod_2*
g(Z)	$\delta_1 Z_t+\delta_2 Z_{t-1}+\delta_3 Z_{t-2}$					
	(δ_1)	-0.019	0.039***	5.279***	338.961	503.717
		(0.035)	(0.013)	(1.463)	(2,055.437)	(1,040.697)
	(δ_2)	-0.119***	0.036***	5.019***	1,752.395	874.968
		(0.033)	(0.013)	(1.391)	(1,954.737)	(989.711)
	(δ_3)	-0.105***	0.043***	5.424***	1,217.246	454.374
		(0.034)	(0.013)	(1.409)	(1,978.697)	(1,001.843)
h(V)	$\lambda_1 V_t+\lambda_2 V_{t-1}+\lambda_3 V_{t-2}$					
	(λ_1)	-0.087**	0.045***	1.761	1,395.224	490.217
		(0.041)	(0.016)	(1.725)	(2,423.160)	(1,226.881)
	(λ_2)	0.033	0.007	-2.684	-2,681.575	-1,942.913*
		(0.039)	(0.015)	(1.641)	(2,305.189)	(1,167.150)
	(λ_3)	0.125***	-0.065***	-4.383***	-2,504.492	-825.611
		(0.033)	(0.013)	(1.389)	(1,951.464)	(988.054)
Controls						
co-loc		0.004	0.001	-0.216	-315.163*	-72.454
		(0.003)	(0.001)	(0.134)	(187.943)	(95.158)
prox		0.068	0.035*	3.501*	3,957.926	3,893.919***
		(0.049)	(0.019)	(2.049)	(2,877.748)	(1,457.045)
Legal_form_2		-0.110***	0.032***	5.408***	5,353.317***	1,869.987**
		(0.029)	(0.011)	(1.223)	(1,717.399)	(869.544)
Legal_form_3		-0.031	0.065***	15.207***	9,916.745***	3,270.803**
		(0.044)	(0.017)	(1.861)	(2,613.887)	(1,323.448)
cat		-0.147***	0.055***	5.057***	7,126.378***	3,435.639***
		(0.031)	(0.012)	(1.288)	(1,809.163)	(916.005)
size		-0.014	0.028***	-1.985*	3,320.082**	3,648.710***
		(0.026)	(0.010)	(1.078)	(1,515.024)	(767.078)
ext		-0.111*	0.079***	-4.319*	477.906	972.710
		(0.060)	(0.023)	(2.494)	(3,503.377)	(1,773.810)
cap		0.269**	-0.159***	-18.962***	9,513.090	12,781.818***
		(0.116)	(0.044)	(4.876)	(6,850.025)	(3,468.265)
tot_beds		-0.000**	0.000***	0.001***	0.675*	0.856***
		(0.000)	(0.000)	(0.000)	(0.406)	(0.206)
ave_attr		-0.080	-0.067	-1.940	380.025	473.900
		(0.162)	(0.061)	(6.767)	(9,506.790)	(4,813.423)
ave_alb		0.002	0.005	0.928	-1,294.442	-459.882
		(0.026)	(0.010)	(1.088)	(1,528.437)	(773.870)
ave_tur		0.164**	0.029	-5.088*	3,391.988	-1,272.604
		(0.070)	(0.026)	(2.911)	(4,089.850)	(2,070.749)
Observations		798	798	798	798	798
R-squared		0.164	0.355	0.257	0.146	0.239
R_adj		0.145	0.340	0.240	0.126	0.222
F		8.510	23.83	14.99	7.391	13.60

4.10 Average Treatment Effect on efficiency scores

In this section we examine efficiency scores as outcome variable, obtaining them by means of non-parametric DEA models. Previous research provides us with two possible approaches when DEA scores are considered as outcome variable and the independent external variable of interest (in our case, treatment variable *Z*) is dichotomous.

On one hand, we can frame the estimation strategy within the frontier separation approach based on the seminal paper by Charnes et al. (1981). In this approach, units are divided into two groups (in our case, between treated and non-treated) and different frontiers are estimated for both groups. A bootstrap-based procedure can be used to perform a test on the difference of the average efficiency scores of the two groups (Daraio and Simar, 2007). On the other hand, the two-stage model can be employed, which first estimates efficiency considering only inputs and outputs on the whole set of observations, and then introduces the dichotomous treatment variable as a covariate in a second-stage regression analysis, in which the efficiency score is the dependent variable (Simar and Wilson, 2007; Banker and Natarajan, 2008; McDonald, 2009). The two-stage approach also has the advantage of considering controls, reducing potential bias due to omitted variables. However, in their original formulations, all the above methods are not designed to deal with selection bias, which is a critical issue in evaluation studies. Selection bias arises because observed units have different probabilities of belonging to treated or non-treated groups, due to their different characteristics.

We designed an estimation strategy composed of three steps. In order to reduce problems due to selection bias, a pre-processing step before the outcome analysis was performed (Ho et al., 2007a,b). Therefore, under assumption 1-3 (see section 4.6), we estimated the probability of receiving a subsidy and then employed a matching strategy on the estimated propensity scores, to create a sub-group of treated and control hotels with the same (or as similar as possible) distribution of observed pre-treatment variables. In the second step, in order to explore the effect of subsidies on efficiency measures obtained in the DEA non-parametric framework, we used the two-stage approach (algorithm #2) of Simar and Wilson (2007). Specifically, we first obtained an unbiased measure of efficiency with the CCR-DEA model and then performed a bootstrapped regression, introducing the dichotomous treatment variable as covariate and correcting for a set of factors that were likely to be related to efficiency. The procedure is described in details in section 4.10.1.

4.10.1 Estimation procedure

The details of the estimation procedure employed are as follows:

[1] Preprocessing: matching on the propensity score

[1.1] Perform a logistic regression to obtain an estimate of the probability of treatment using the set of selected pre-treatment covariates;

[1.2] Use nearest neighborhood matching on the propensity scores to construct a sub-sample of hotels;

[2] Regress efficiency (Algorithm #2 in Simar and Wilson (2007))

[2.1] Compute $\hat{\delta}_i = \hat{\delta}\left(x_i, y_i \mid \hat{T}\right) \quad \forall i = 1,...,n$ using the output-oriented DEA model on the matched subsample;

[2.2] Obtain an estimate $\hat{\beta}$ of β as well as an estimate $\hat{\sigma}_\varepsilon$ of σ_ε in the truncated regression $\hat{\delta}_i = Z_i\beta + \varepsilon_i \quad i = 1,...,n$ using the $m < n$ observations where $\hat{\delta}_i > 1$;

[2.3] Loop over the next three steps ([2.2.1] - [2.2.3]) L_1 times to obtain n sets of bootstrap estimates $D_i = \left\{\hat{\delta}^*_{ib}\right\}_{b=1}^{L_1}$ as follows:

[2.3.1] For each $i = 1,...,n$ draw ε_j from the $N\left(0, \hat{\sigma}^2_j\right)$ distribution with left-truncation at $\left(1 - Z_j\hat{\beta}\right)$;

[2.3.2] Compute: $\delta^*_i = Z_i\hat{\beta} + \varepsilon_i \quad i = 1,...,n$;

[2.3.3] Set $\begin{cases} x^*_i = x_i \\ y^*_i = y_i \ \hat{\delta}/\delta^*_i \end{cases} \quad \forall i = 1,...,n$;

[2.3.4] Compute $\hat{\delta}_i = \hat{\delta}\left(x_i, y_i \mid \hat{T}^*\right) \quad \forall i = 1,...,n$ where $\hat{T}^*$ is obtained by replacing Y, X with $Y^* = \left[y^*_i,..,y^*_i\right]$, $X^* = \left[x^*_i,..,x^*_i\right]$;

[2.4] For each i=1,…,n the bias-corrected estimator $\hat{\hat{\delta}}_i = \hat{\delta}_i - bias\left(\hat{\delta}_i\right)$ using the bootstrap estimates in D_i obtained in step [2.3] and the original estimates $\hat{\delta}_i$;

[2.5] Use the method of maximum likelihood to estimate the truncated regression $\hat{\hat{\delta}}_i = Z_i\beta + \varepsilon_i \quad \forall i = 1,...,n$ and obtain $\left(\hat{\hat{\beta}}, \hat{\hat{\sigma}}\right)$;

[2.6] Loop over the steps ([2.6.1]-[2.6.3]) L_2 times to obtain a set of bootstrap estimates $A = \left\{\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*_\varepsilon\right\}_{b=1}^{L_2}$:

[2.6.1] For each i = 1,…,n draw ε_i from the $N\left(0, \hat{\hat{\sigma}}\right)$ distribution with left-truncation at $N\left(1 - Z_i\hat{\hat{\beta}}\right)$;

[2.6.2] Compute $\delta_i^{**} = Z_i\hat{\hat{\beta}} + \varepsilon_i \quad i = 1,...,n$;

[2.6.3] Use the method of maximum likelihood to estimate the truncated regression $\delta_i^{**} = Z_i\beta + \varepsilon_i \quad i = 1,...,n$ and obtain $\left(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*\right)$;

[2.7] Use bootstrap value in A and the estimates $\hat{\hat{\beta}}, \hat{\hat{\sigma}}$ after the bias correction to construct estimated intervals for each element β of the vector of coefficients and for σ_ε

4.10.2 Results

In order to estimate the effect of subsidies on efficiency, measured as DEA scores, we refer to the most restrictive case, considering the same empirical setting as in section 4.7.2.

The first step in the evaluation procedure was specification of the propensity score model. We adopted a logit specification of the treatment dummy variable, which was 1 if the focal hotel received a subsidy and zero otherwise. In the specification of the logit model, we considered the set of control variables presented in section 4.5.3 in their pre-treatment status, i.e., one year before receipt of subsidies. The final specification of the logit model for propensity scores and parameter estimates is shown in Table 4.12

Table 4.12 Logit estimate

Variables	*Est. Coeff.*	*Std Err.*	*z-value*	*Pr(>|z|)*
Constant	-9.996***	3.031	-3.226	0.001
capL1	1.531**	0.612	2.501	0.012
extL1	-0.816	0.529	-1.501	0.123
prox	0.015	0.343	0.043	0.965
Co-loc	-0.033	0.026	-1.261	0.251
sizeL1	-3.894*	2.075	-1.876	0.060
size_sqL1	8.668**	4.098	2.115	0.034
catL1	0.169	0.257	0.658	0.511
Legal_form_2 L1	0.476*	0.263	1.803	0.071
Legal_form_3 L1	0.298	0.418	0.715	0.474
Destination		Yes		
Year		Yes		

NOTE: * , **, and *** indicate statistical significance at 10% , 5%, and 1%

It is important to analyse the overlap between subsamples of treated and control firms. We look at the distributions of the propensity scores for treated and control firms before and after matching (Figure 4.5). Their distributions have a support which overlaps, allowing us to conduct our evaluation exercises. The matching procedure helps us to mitigate the estimation bias further and, after matching, the two distributions do show a greater degree of overlap

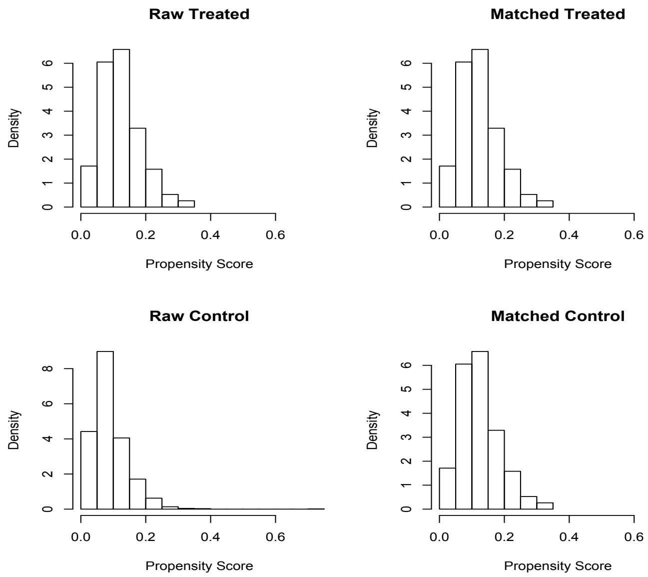


Figure 4.5 Distribution of propensity scores for treated and control subsample

The second step consists of estimating the causal effect of receiving of a subsidy on efficiency. The estimates of the average treatment effect, considering efficiency estimated one year after treatment, are listed in Table 4.13. Receiving a subsidy had a direct positive direct effect on the efficiency of hotels.

Table 4.13 Estimated coefficients and confidence intervals. Outcome after 1 year

		Bounds of bootstrap estimated Confidence Intervals					
		(90%)		*(95%)*		*(99%)*	
	Est. Coeff.[a]	*Lower*	*Upper*	*Lower*	*Upper*	*Lower*	*Upper*
Z	-0.126**	-0.221	-0.041	-0.235	-0.021	-0.264	0.011
Controls							
Cap	0.052	-0.353	0.480	-0.425	0.552	-0.534	0.733
Ext	-0.428**	-0.733	-0.123	-0.780	-0.030	-0.835	0.094
Prox	-0.463***	-0.731	-0.227	-0.774	-0.177	-0.871	-0.057
co-loc	-0.002	-0.017	0.012	-0.019	0.015	-0.025	0.025
Size	-0.058	-0.179	0.068	-0.206	0.103	-0.275	0.158
cat	-0.263***	-0.393	-0.137	-0.425	-0.107	-0.490	-0.070
Legal_form_2	0.029	-0.105	0.153	-0.122	0.176	-0.172	0.222
Legal_form_3	-0.425**	-0.705	-0.163	-0.748	-0.118	-0.813	0.095
Destination				Yes			
Year				Yes			
$\hat{\sigma}_{\varepsilon}$	0.341	0.331	0.399	0.324	0.407	0.313	0.419

NOTE: * , **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively; Efficiency scores expressed according to Farrell (1957), i.e., parameters with negative sign indicate sources of efficiency.

Table 4.14 lists the causal effect on efficiency estimated two years after receipt of a subsidy. Its positive effect even increases in the second year after the receipt.

Table 4.14 Estimated coefficients and confidence intervals. Outcome after 2 years

		Bounds of bootstrap estimated Confidence Intervals					
	Est. Coeff.[a]	*(90%)*		*(95%)*		*(99%)*	
		Lower	*Upper*	*Lower*	*Upper*	*Lower*	*Upper*
Z	-0.412***	-0.619	-0.242	-0.650	-0.211	-0.741	-0.145
Controls							
cap	0.664*	0.042	1.445	-0.093	1.609	-0.434	1.841
ext	-1.002***	-1.672	-0.419	-1.789	-0.307	-1.973	-0.016
prox	-0.818**	-1.357	-0.284	-1.444	-0.190	-1.618	0.040
co-loc	0.016	-0.010	0.044	-0.015	0.051	-0.025	0.071
size	-0.088	-0.304	0.130	-0.351	0.175	-0.456	0.278
cat	-0.421***	-0.659	-0.200	-0.706	-0.157	-0.804	-0.088
Legal_form_2	0.107	-0.144	0.344	-0.188	0.406	-0.324	0.502
Legal_form_3	-0.856*	-1.476	-0.197	-1.533	0.010	-1.711	0.492
Destination				Yes			
Year				Yes			
$\hat{\sigma}_\varepsilon$	0.480	0.466	0.601	0.450	0.613	0.407	0.635

NOTE: * , **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively; Efficiency scores expressed according to Farrell (1957), i.e., parameters with negative sign indicate sources of efficiency.

4.11 Concluding remarks

Whether or not industrial public policies have an effect on private firm performance and eventually on aggregate economic growth is still an open question. The main purpose of this chapter was to contribute to the debate on policy evaluation by assessing the effect of capital subsidies on firms' performance, especially micro and small firms in the hotel industry.

Evaluation with non-experimental data usually relies on two critical assumptions: the similarity of treated and control units (except for their treatment status; the Conditional Independence Assumption), and no interference between unit outcomes, i.e., an individual's outcome should not depend on other individuals' treatment status (the SUTVA assumption). We first estimated the effect of subsidies on hotels treated with these assumptions (i.e., CIA and SUTVA), considering as treated hotels those which received only one subsidy over the period of analysis. We estimated the positive effect of subsidisation on all selected outcomes. With these assumptions, we also found the positive influence of public intervention on productive efficiency, which accounts for multiple inputs and outputs. We then extended analysis to account for the effect of multiple treatments over time. Extending the conditional independence assumption to a dynamic treatment setting, we estimated the positive effect of the sequence of treatment on hotels' final outcomes. The effect was positive but not statistically significant, only for labour productivity.

However, the most important consequence of the SUTVA assumption was that, if the policy generates externalities, their effect on hotel performance cannot be measured and the estimation is therefore biased. We tackled this issue by defining a new estimation framework which allowed for interference between hotels in the dynamic treatment setting. We found that SUTVA may be violated, since a hotel's potential outcomes depend on whether many or few hotels in its own destination are subsidised. In particular, when the proportion of subsidised firms is high, the effect on the potential outcomes of the focal hotel is negative, consistent with increased competition within destinations. This negative dependence strengthens over time.

Our empirical results clearly indicate the need to focus research on interactions and spillovers in industrial public policies directed to private firms.

Some final remarks are necessary. The use of a dichotomous variable to measure the indirect effect of the policy has some limitations. For instance, it can lead to considering as equivalent a TD with treated firms only and a TD with a treated/non-treated ratio slightly above the median. In future works, the framework could be improved by considering continuous variable. Also, it remains open the issue of how to separate the effect due to spatial proximity of the hotels from the spillover effect associated with the subsidies. What should be done is then to clearly identify the net spatial effect of subsides considering spillover effect that cannot be attributed to policy intervention (see e.g. De Castris and Pellegrini, 2012). Lastly, the analysis showed that the effect of time seems to be important: the longer is the period after which the effect is evaluated, the higher is the effect observed. In this regard widening the time-span of the analysis would be beneficial.

4.12 Appendix

4.12.1 4A: Sample representativeness checks

After the merging and balancing process we checked for possible selection due to the discarding of those hotels which lacked data for our evaluation purposes. Table 4A.1 reports data on the variations of the spatial distribution of hotels in our final sample and for the population of hotels in the Trentino province. Data shows that the whole sample as well as the two subsamples of subsidised and non-subsidised hotels contained in the final database (DBevalHTN database) reproduce sufficiently well the spatial distribution observed in the population.

Table 4A.1. Distribution of hotels across destination (year, 2006)

TD	*Population*		*DBevalHTN database*											
			Whole sample			*Subsidised**				*No-subsidised***				
	N. hotels	*(1)[a]*	*N. hotels*	*(2)[a]*	*(1)-(2)*	*N. hotels*	*(3)[a]*	*(3)-(2)*	*(3)-(1)*	*N. hotels*	*(4)[a]*	*(4)-(2)*	*(4)-(1)*
1	49	3.06	16	1.91	1.15	11	2.58	-0.67	0.48	5	1.22	0.69	1.84
2	127	7.94	79	9.45	-1.51	40	9.39	0.06	-1.45	39	9.51	-0.06	-1.57
3	39	2.44	13	1.56	0.88	10	2.35	-0.79	0.09	3	0.73	0.82	1.71
4	103	6.44	54	6.46	-0.02	27	6.34	0.12	0.10	27	6.59	-0.13	-0.15
5	293	18.31	182	21.77	-3.46	102	23.94	-2.17	-5.63	80	19.51	2.26	-1.20
6	91	5.69	46	5.50	0.19	27	6.34	-0.84	-0.65	19	4.63	0.87	1.05
7	118	7.38	56	6.70	0.68	31	7.28	-0.58	0.10	25	6.10	0.60	1.28
8	80	5.00	44	5.26	-0.26	16	3.76	1.51	1.24	28	6.83	-1.57	-1.83
9	45	2.81	17	2.03	0.78	7	1.64	0.39	1.17	10	2.44	-0.41	0.37
10	156	9.75	83	9.93	-0.18	39	9.15	0.77	0.60	44	10.73	-0.80	-0.98
11	34	2.13	17	2.03	0.09	10	2.35	-0.31	-0.22	7	1.71	0.33	0.42
12	135	8.44	71	8.49	-0.06	29	6.81	1.69	1.63	42	10.24	-1.75	-1.81
13	145	9.06	81	9.69	-0.63	41	9.62	0.06	-0.56	40	9.76	-0.07	-0.69
14	77	4.81	30	3.59	1.22	14	3.29	0.30	1.53	16	3.90	-0.31	0.91
n.a.	108	6.75	47	5.62	1.13	22	5.16	0.46	1.59	25	6.10	-0.48	0.65
TOT	1600	100	836	100		426	100			410	100		

NOTE: *hotels that received at least one subsidy over the period 2002-2006; ** hotels that did not receive subsidies over the period 2002-2006; [a] values in percentage.

We further checked the representativeness of our sample by looking at the differences in the average size of the hotels included in the DBevalHTN database compared to the population. We measure firm size as number of rooms, an indicator widely used in the literature (Chung and Kalnins, 2001).

Table 4A.2 shows the number and average size of hotels for the population and for the sample and subsample (subsidised and non-subsidised) of interest, by tourism destination,. For the whole sample and each subsample, the last two columns show, respectively, the differences in the averages with respect to the population and the p-value associated with the t-statistic constructed to test the null hypothesis that the observed differences are not statistically significant. The results suggest that, with the exception of destination 9 (Rovereto area) the average size of hotels in the selected sample is not significantly different from those of the entire population. Table 4A.3 shows how the process of merging with the DBhotelTN did not changed the composition of the sample of subsidised hotels.

Table 4A.2. Comparison of size distribution of hotels in the DBevalHTN database with population (year 2006)

TD	*Population*		*DBevalHTN database*											
			Whole sample				*Subsidised**				*Not-subsidised***			
	N. hotels	*Avg. rooms (1)*	*N. hotels*	*Avg. rooms (2)*	*Diff (2)-(1)*	*p-val*	*N. hotels*	*Avg. rooms (3)*	*Diff (3)-(1)*	*p-val*	*N. hotels*	*Avg. rooms (4)*	*Diff (4)-(1)*	*p-val*
1	49	32.12	16	40.12	7.43	0.34	11	44.54	11.85	0.20	5	30.40	-2.29	0.85
2	127	29.48	79	32.69	3.21	0.18	40	35.82	6.34	0.05	39	29.49	0.01	0.99
3	39	20.77	13	25.23	4.46	0.21	10	25.10	4.33	0.25	3	25.67	4.88	0.49
4	103	27.48	54	29.75	2.27	0.41	27	34.11	6.62	0.07	27	25.41	-2.08	0.56
5	293	25.67	182	27.36	1.68	0.24	102	28.78	3.11	0.06	80	25.53	-0.13	0.95
6	91	21.11	46	29.24	3.13	0.31	27	32.22	6.11	0.11	19	25.00	-1.11	0.80
7	118	28.44	56	31.03	2.59	0.39	31	33.39	4.94	0.20	25	28.12	-0.32	0.94
8	80	24.76	44	26.34	1.58	0.61	16	27.37	2.61	0.56	28	25.75	0.98	0.78
9	45	22.47	17	33.23	10.76	0.02	7	36.28	13.81	0.04	10	31.10	8.63	0.12
10	156	29.85	83	34.08	4.23	0.20	39	35.69	5.83	0.17	44	32.66	2.81	0.51
11	34	27.73	17	26.70	-1.03	0.83	10	23.70	-4.03	0.51	7	31.00	3.26	0.64
12	135	23.99	71	28.29	4.30	0.10	29	32.17	8.17	0.03	42	25.62	1.62	0.60
13	145	34.64	81	32.13	-2.50	0.49	41	36.36	1.72	0.72	40	27.80	-6.84	0.17
14	77	23.28	30	26.63	3.35	0.29	14	25.71	2.42	0.56	16	27.43	4.15	0.31
o.d.	108	17.21	47	17.19	-0.02	0.98	22	18.81	1.60	0.47	25	15.76	-1.45	0.46

NOTE: *hotels that received at least one subsidy over the period 2002-2006 ; ** hotels that did not receive subsidies over the period 2002-2006

Table 4A.3. Impact of data merging and balancing on the distribution of observed subsidized hotels (year, 2006)

TD	*Population*		*Subsidized hotels* Before merge with DBhotelTN*				*Subsidized hotels** After marge with DBhotelTN and balancing*			
	N. hotels	*Avg. rooms (1)*	*N. hotels*	*Avg. rooms (2)*	*Diff (2)-(1)*	*p-val*	*N.*	*Avg. rooms (3)*	*Diff (3)-(2)*	*p-val*
1	49	32.12	15	41.67	-8.97	0.26	11	44.54	2.88	0.81
2	127	29.48	48	37.18	-7.71	0.01	40	35.82	-1.36	0.65
3	39	20.77	18	23.44	-2-67	0.38	10	25.10	1.65	0.62
4	103	27.48	36	32.94	-5.46	0.10	27	34.11	1.17	0.76
5	293	25.67	128	27.11	-1.44	0.35	102	28.78	1.67	0.29
6	91	21.11	35	31.68	-5.57	0.12	27	32.22	0.54	0.88
7	118	28.44	39	30.84	-2.40	0.49	31	33.39	2.54	0.60
8	80	24.76	18	26.72	-1.96	0.64	16	27.37	0.65	0.89
9	45	22.47	11	30.27	-7.81	0.16	7	36.28	6.01	0.53
10	156	29.85	55	35.47	-5.62	0.13	39	35.69	0.22	0.96
11	34	27.73	14	24.00	3.73	0.48	10	23.70	-0.30	0.96
12	135	23.99	41	31.41	-7.42	0.03	29	32.17	0.76	0.87
13	145	34.64	58	36.31	-1.67	0.70	41	36.36	0.05	0.99
14	77	23.28	22	22.50	0.78	0.82	14	25.71	3.21	0.47
o.d.	108	17.21	43	17.41	-0.21	0.90	22	18.81	1.40	0.55
TOT	1600		581				426			

NOTE: * start ups are not considered; ** subsidised hotels in the final database DBevalHTN

5 Conclusions

What is it that supports the wide heterogeneity in productivity among firms? Which factors matter most, and can firms control them, or are they purely external products of the operating environment? These are all primary and challenging questions which still require further research. Indeed, shedding further light on these issues will definitely aid our understanding of how to design effective policies to boost the productivity growth of firms and eventually of nations. In this thesis, we wished to contribute to applied research on firm productivity from both empirical and methodological viewpoints.

We first empirically addressed the issue of what generates and sustains the heterogeneity of firm productivity in manufacturing; with this aim we looked again at the productivity slowdown in Italy which started in the mid-1990s. Consistent with recent studies carried out with varying methods (Antonelli et al. 2013; Bugamelli et al. 2010; Dosi et al., 2012), we obtained evidence of high heterogeneity of firm behaviour lying behind the Italian economic stagnation. In addition, our estimation approach more precisely isolated the component of Total Factor Productivity growth due to technological change. We used a non-parametric method (DEA) to highlight how the technological frontier (of the best-performing firms which lie on it) have moved over time, and how the distance to the frontier of less productive firms has changed. Our results clearly point to growing dualism among firms. Some firms experienced sustained productivity growth; others clearly failed to keep pace with the group of innovators. We questioned whether this dynamic was due to different patterns of strategic adaptation, and obtained evidence that the availability of flexible labour, less expensive but also less skilled, was the easiest solution, the “low road”, to competition for some firms, whereas more efficient and dynamic patterns competed in innovation.

Earlier studies on the Italian economic slowdown pointed to generalised failure on the part of the entire productive system to meet the challenges posed by increased market globalisation. Our results suggest that, even in an advanced economy, ample dispersion of firm performance exists and in some conditions may even widen over time. These findings support the fact that certain strategies and behaviours are more likely in certain firms according to their distance from the industry frontier (see, e.g., Coad, 2011). We likened this fact to the dynamics of firm productivity distribution, which in turn shapes productivity growth at aggregate, industry and country levels. Our evidence may be useful for policy-makers. Designing policy to support "average firms" cannot be effective if the heterogeneity of those firms is wide (Bartelsman, 2010).

The second part of this thesis moved to the services sector. Despite its growing economic weight, there is still little knowledge on the determinants of firm productivity in this sector. We used different methods to distinguish the various factors determining the efficiency of firms in the hotel industry, and found that destination factors play a role: hotels located in better destinations are, on average, more efficient than those in less attractive locations. Although expected, this empirically confirms the role of destination on the performance of tourist businesses (Molina-Azorin et al., 2010) and further extends results, even at the finer intra-regional level.

However, what was surprising was that, even considering a narrowly defined sector in very restricted, compact areas – intra-regional destinations – the dispersion of hotel efficiency remained wide and substantially similar among destinations. This clearly suggested the important role of factors internal to hotels. We proceeded by looking at factors related to manager/owner characteristics and managerial choices, i.e., comparing the human capital of managers and what they do. Our results revealed the predominance of managerial practices on manager characteristics. This supports the view of "management as technology", as recently put forward by Bloom et al. (2013), and also points to the role played by family involvement. To our knowledge, this study is the first providing empirical evidence of the role families play in determining hotel efficiency. Highly motivated, well-trained family members are valuable for hotel efficiency. Conversely, family ownership may lead to over-staffing and slack periods, which depress hotel productivity. These findings are important, given the family nature of the majority of firms in the tourist sector in Italy. The role of internal factors was confirmed even after controlling for fine-grained intra-destination location factors.

Our results offer insights for managers and public policy-makers in designing programmes for improving performance. In particular, we support the view that there is room for improvement within each destination. Significant improvements in performance can be obtained by focusing on the internal operations of hotels, to identify the most important factors which improve efficiency and productivity.

Thus, in the third part of this work (Chapter 4) we studied the effect of public intervention in the tourist sector. In particular, we evaluated the effect of subsidies in supporting capital investments aimed at improving the quality and performance of micro and small hotel businesses. We proceeded in several steps, addressing a series of empirical and methodological issues. On the methodological side, we defined a novel approach which relaxes SUTVA, allowing identification and estimation of indirect effects stemming from the externalities that the policy is likely to generate; we estimated the effect in the case of time-varying treatments. Our main results point to the positive direct bearing of subsidies on several hotel productivity measures, and also empirical evidence of SUTVA violation and indirect effects of subsidies.

We show how the effect of subsidies on hotel performance depend on how those subsidies are assigned to hotels over time and, more importantly, how the net effect of subsidies on a hotel's outcomes depend on whether many or few hotels in its own destination are subsidised. In particular, when the share of subsidised firms is high, the effect on the potential outcomes of the focal hotels appears to be negative, consistent with increased competition within destinations. This negative dependence strengthens over time.

Our results may be of value for policy-makers' decisions on introducing subsidy programmes. Externalities must be an important consideration when deciding how and when to target public policies to firms. Specifically, our results indicate the need to devote more research to the implication of the SUTVA assumption (see Ferracci et al. (2013), for implications in the labour market; Ceruqa and Pellegrini (2013), for the implication of subsidies to firms), in both terms of the need to define proper methodological frameworks and of the implications on the actual effectiveness of policies.

6 Bibliography

Abadie, A., Drukker, D., Herr, J.L., Imbens, G.W., 2004. Implementing matching estimators for average treatment effects in Stata. Stata Journal 4, 290–311.

Abadie, A., Imbens, G.W., 2002. Simple and bias-corrected matching estimators for average treatment effects. NBER Working Paper n. 283.

Abadie, A., Imbens. G.W., 2006. Large aample properties of matching estimators for average treatment effects. Econometrica 74 (1), 235-267.

Acemoglu, D., 2002. Technical change, inequality and the labor market. Journal of Economic Literature 40, 7-72.

Acemoglu, D., Aghion, P., Zilibotti, F., 2006. Distance to frontier, selection, and economic growth. Journal of the European Economic association 4 (1), 37-74.

Acharya, V.V., Baghai, R.P., Subramanian, K.V., 2010. Labor laws and innovation. NBER Working Paper n. w16484.

Adler, P.S., et al., 2009. Perspectives on the productivity dilemma. Journal of Operations Management 27 (2), 99-113.

Aghion, P., 2002. Schumpeterian growth theory and the dynamics of income inequality. Econometrica 70, 855-82.

Aghion, P., Burgess, R., Redding, S.J., Zilibotti, F., 2005. Entry liberalization and inequality in industrial performance. Journal of the European Economic Association 3 (2-3), 291-302.

Aghion, P., Burgess, R., Redding, S., Zilibotti, F., 2008. The unequal effects of liberalization: Evidence from dismantling the license Raj in India. American Economic Review 98 (4), 1397-1412.

Almus, M., Czarnitzki, D., 2003. The effects of public R&D subsidies on firms' innovation activities: the case of Eastern Germany. Journal of Business & Economic Statistics 21 (2), 226-236.

Alvarez-Albelo, A.D., Hernandez-Martin, R., 2012. Congestion and coordination problems in a tourism economy. Tourism Economics 18 (4), 691-710.

Andergassen, R., Candela, G., Figini, P., 2013. An economic model for tourism destinations: Product sophistication and price coordination. Tourism Management 37, 86-98.

Anderson, R. I., Rish, M., Xia, Y., Michello, F., 1999. Measuring efficiency in the hotel industry: a stochastic frontier approach. International Journal of Hospitality Management 18 (1), 45–57.

Antonelli, C., Crespi, F., Scellato, G., 2013. Internal and external factors in innovation persistence. Economics of Innovation and New Technology 22 (3), 256-280.

Arbia, G., Espa, G., 1996. Statistica Economica Territoriale. Cedam, Padua.

Argote L., McEvily B., Reagans, R., 2003. Managing knowledge in organizations: An integrative framework and review of emerging themes. Management Science 49 (4), 571-82.

Arrow, K.J., 1962. The economic implications of learning by doing. The Review of Economic Studies 29 (3), 155–173.

Arvanitis, S., 2005. Modes of labor flexibility at firm level: Are there any implications for performance and innovation? Evidence for the Swiss economy. Industrial and Corporate Change 14 (6), 993–1016.

Assaf A., Kneževic´ Cvelbar, L., 2010. The performance of the Slovenian hotel industry: evaluation post-privatisation. International Journal of Tourism Research 12 (5), 462–471.

Assaf, A., Kneževic´ Cvelbar, L., 2011. Privatization, market competition, international attractiveness, management tenure and hotel performance: Evidence from Slovenia. International Journal of Hospitality Management 30 (2), 391–397.

Asthana, S.C., Zhang, Y., 2006. Effect of R&D investments on persistence of abnormal earnings. Review of Accounting and Finance 5 (2), 124-139.

Azoulay, P., Ding, W., Stuart, T., 2009. The impact of academic patenting on the rate, quality and direction of (public) research output. The Journal of Industrial Economics 57 (4), 637-676.

Bădin, L., Daraio, C., Simar, L., 2012. How to measure the impact of environmental factors in a nonparametric production model. European Journal of Operational Research 223 (3), 818–833.

Baginski, S.P., Lorek, K.S., Willinger, G.L., Branson, B.C., 1999. The relationship between economic characteristics and alternative annual earnings persistence measures. The Accounting Review 74 (1), 105-120.

Baily, M., Hulten, C., Campbell, D., Bresnahan, T., Caves, R., 1992. Productivity dynamics in manufacturing plants. Brookings Papers on Economic Activity. Microeconomics 1992, 187–267.

Baines, T.S., Lightfoot, H.W., Benedettini, O., Kay, J.M., 2009. The servitization of manufacturing: a review of literature and reflection on future challenges. Journal of Manufacturing Technology Management 20 (5), 547–567.

Banker, R.D., Chang, H., 2006. The super-efficiency procedure for outlier identification, not for ranking efficient units. European Journal of Operational Research 175 (2), 1311–1320.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science 30 (9), 1078–1092.

Banker, R.D., Chang, H.H. Majumdar S.H., 1996. A framework for analyzing changes in strategic performance. Strategic Management Journal 17, 693-712.

Banker, R.D., Morey, R.C., 1986a. Efficiency analysis for exogenously fixed inputs and outputs. Operations Research 34 (4), 513-521.

Banker, R.D., Morey, R.C., 1986b. The use of categorical variables in data envelopment analysis. Management science 32 (12), 1613-1627.

Banker, R.D., Natarajan, R., 2008. Evaluating contextual variables affecting productivity using data envelopment analysis. Operations Research 56 (1), 48-58.

Barker, V.L., Mueller, G.C., 2002. CEO characteristics and firm R&D spending. Management Science 48 (6), 782-801.

Barros, C.P., (2004). A stochastic cost frontier in the Portuguese hotel industry. Tourism Economics 10, 177–192.

Barros, C.P., (2005a). Measuring Efficiency in the hotel sector. Annals of Tourism Research 32 (2), 456–477.

Barros, C.P., (2005b). Evaluating the efficiency of a small hotel chain with a Malmquist productivity index. International Journal of Tourism Research 7 (3), 173–184.

Barros, C.P., Botti, L., Peypoch, N., Solonandrasana, B., (2011). Managerial efficiency and hospitality industry: the Portuguese case. Applied Economics 22 (43), 2895–2905.

Barros, C.P., Dieke, U.C., (2008). Technical efficiency of African hotels. International Journal of Hospitality Management 27 (3), 438–447.

Barros, C. P., Peypoch, N., and Solonandrasana, B., 2009. Efficiency and productivity growth in the hotel industry. International Journal of Tourism Research 11 (4), 389–402.

Bartelsman, E.J., 2010. Searching for the sources of productivity from macro to micro and back. Industrial and Corporate Change 19 (6), 1891-1917.

Bartelsman, E.J., Dobbelaere, S., Peters, B., 2013. Allocation of human capital and innovation at the frontier: Firm-level evidence on Germany and the Netherlands. IZA Discussion Papers n. 7540.

Bartelsman, E.J., Doms, M., 2000. Understanding productivity: Lessons from longitudinal microdata. Journal of Economic Literature 38 (3), 569–594.

Bartelsman, E.J., Haltiwanger, J., Scarpetta, S., 2013. Cross-country differences in productivity: The role of allocation and selection. American Economic Review 103 (1), 305–334.

Bassanini, A., Ernst, E., 2002. Labour market regulation, industrial relations and technological regimes. Industrial and Corporate Change 11 (3), 391–426.

Battese, G.E., Coelli, T.J., 1992. Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. Journal of productivity analysis 3 (1-2), 153-169.

Baum, T., Hagen, L., 1999. Responses to seasonality: the experiences of peripheral destinations. International journal of tourism research 1 (5), 299-312.

Baum, J.A., Haveman, H.A., 1997. Love thy neighbor? Differentiation and agglomeration in the Manhattan hotel industry, 1898-1990. Administrative Science Quarterly 42 (2), 304-338.

Baum, J.A., Ingram, P., 1998. Survival-enhancing learning in the Manhattan hotel industry, 1898–1980. Management Science 44 (7), 996-1016.

Baum, J.A.C., Mezias, S.J., 1992. Localized competition and organizational failure in the Manhattan hotel industry. Administrative Science Quarterly 37, 580–604.

Benhabib, J., Spiegel, M., 1994. The role of human capital in economic development: evidence from aggregate cross-country data. Journal of Monetary Economics 34, 143–173.

Bergström, F., 2000. Capital subsidies and the performance of firms. Small Business Economics 14 (3), 183-193.

Beritelli, P., Bieger, T., Laesser, C., 2007. Destination governance: using corporate governance theories as a foundation for effective destination management. Journal of Travel Research 46 (1), 96-107.

Bernard, A.B., Jensen, J.B., Schott, P.K., 2006. Trade costs, firms and Productivity. Journal of Monetary Economics 53 (5), 917-937.

Bertrand, M., Schoar, A., 2003. Managing with style: The effect of managers on firm policies. The Quarterly Journal of Economics 118 (4), 1169-1208.

Bernini, C., Guizzardi, A., 2010. Internal and locational factors affecting hotel industry efficiency: evidence from Italian business corporations. Tourism Economics 16 (4), 883–913.

Bernini, C., Pellegrini, G., 2011. How are growth and productivity in private firms affected by public subsidy? Evidence from a regional policy. Regional Science and Urban Economics 41 (3), 253-265.

Bernini, C., Pellegrini, G., 2013. Is subsidizing tourism firms an effective use of public funds? Tourism Management 35, 156-167

Bianco M., Giacomelli, S., Rodano, G., 2012. Concorrenza e regolamentazione in Italia. Questioni di economia e di finanza Banca d'Italia (Occasional Papers) n. 123.

Birkinshaw, J., Hamel, G., Mol, M.J., 2008. Management innovation. Academy of management Review 33 (4), 825-845.

Blake, A., Sinclair, M.T., Campos, J.A., (2006). Tourism productivity. Evidence from the United Kingdom. Annals of Tourism Research 33 (4), 1099–1120.

Bloom, N., Genakos, C., Sadun, R., Van Reenen, J., 2012. Management practices across firms and countries. Academy of Management Perspectives 26 (1), 12-33.

Bloom, N., Sadun, R., Van Reenen, J., 2012. Americans Do IT Better: US Multinationals and the Productivity Miracle. American Economic Review 102 (1), 167-201.

Bloom N, Sadun R., Van Reenen, J., 2013. Management as technology? Mimeo, March16, 2013 http://cep.lse.ac.uk/textonly/_new/staff/vanreenen/pdf/mat_2012fmar16_ucb.pdf

Bloom, N., Van Reenen, J., 2007. Measuring and explaining management practices across firms and countries. The Quarterly Journal of Economics 122 (4), 1351–1408.

Bloom, N., Van Reenen, J., 2010. Why do management practices differ across firms and countries?. The Journal of Economic Perspectives 102 (1), 203–224.

Blundell, R.W., Bond, S.R., 2000. GMM Estimation with persistent panel data: An application to production functions. Econometric Reviews 19 (3), 321–340.

Boeri T., Garibaldi P., 2007. Two tier reforms of employment protection: A honeymoon effect?. The Economic Journal 117 (521), 357–385.

Bogetoft, P., Lars, O., 2011. Benchmarking with DEA, SFA, and R. Springer.

Bottazzi, G., Cefis, E., Dosi, G., Secchi, A., 2007. Invariances and Diversities in the Evolution of Manufacturing Industries. Small Business Economics 29 (1), 137–159.

Bottazzi, G., Dosi, G., Jacoby, N., Secchi, A., Tamagni, F., 2010. Corporate performances and market selection: some comparative evidence. Industrial and Corporate Change 19 (6), 1953-1996.

Bottazzi, G., Grazzi, M., Secchi, A., Tamagni, F., 2011. Financial and economic determinants of firm default. Journal of Evolutionary Economics 21 (3), 373–406.

Bottazzi, G., Secchi, A., Tamagni, F., 2008. Productivity, profitability and financial performance. Industrial and Corporate Change 17 (4), 711–751.

Botti, L., Briec, W., Cliquet, G., 2009. Plural forms versus franchise and company-owned systems: a DEA approach of hotel chain performance. Omega 37, 566 – 578.

Bourgeois III, L.J., 1981. On measurement of organizational slack. Academy of Management Review 6, 29–39.

Brandolini, A., Bugamelli, M., 2009. Rapporto sulle tendenze nel sistema produttivo italiano. Questioni di economia e di finanza Banca d'Italia (Occasional Papers) n. 45.

Bresnahan, T.F., Brynjolfsson, E. Hitt, L.M., 2002. Information technology, workplace organization, and the demand for skilled labor: firm-level evidence. Quarterly Journal of Economics 117 (1), 339-376.

Brown, J.R., Dev, C.S., 2000. Improving productivity in a service business: evidence from the hotel industry. Journal of Service Research 2 (4), 339–354.

Brynjolfsson, E., Hitt, L.M., 1996. Paradox lost? Firm-level evidence on the returns to information systems spending. Management Science 42 (4), 541-558.

Brynjolfsson, E., Hitt, L.M., 2000. Beyond computation: Information technology, organizational transformation and business performance. The Journal of Economic Perspectives 14 (4), 23-48.

Bugamelli, M., Pagano, P., 2004. Barriers to Investment in ICT, Applied Economics 36 (20), 2275–2286.

Bugamelli, M., Schivardi, F., Zizza, R., 2010. The euro and firm restructuring. In:

Alesina, A., Giavazzi, F. (Ed.), Europe and the euro. University of Chicago Press, Chicago, pp. 99–138.

Buhalis, D., 2000. Marketing the competitive destination of the future. Tourism management 21 (1), 97-116.

Buigues, P.A., Sekkat, K., 2011. Public subsidies to business: an international comparison. Journal of Industry, Competition and Trade 11 (1), 1-24.

Calveras, A., Vera-Hernández, M., 2005. Quality externalities among hotel establishments: What is the impact of tour operators?. Tourism Economics 11 (4), 571-593.

Cameron, G., 2003. Why did UK manufacturing productivity growth slow down in the 1970th and speed up in the 1980s?. Economica 70 (277), 121–141.

Candela, G., Figini, P., Scorcu, A.E., 2008. The Economics of local tourist systems. Tourism and sustainable economic development: Macroeconomic models and empirical methods, 72.

Carpenter, R.E., Petersen, B.C., 2002. Is the growth of small firms constrained by internal finance?. Review of Economics and statistics 84 (2), 298-309.

Carreira C., Silva, F., 2010. No deep pockets: some stylized empirical results on firms' financial contraints. Journal of Economic Surveys 24 (4), 731–753.

Caselli, F,, 1999. Technological Revolutions. American Economic Review 89, 78-102.

Caves, D.W., Christensen, L.R., Diewert, W.E., 1982. The economic theory of index numbers and the measurement of input, output, and productivity. Econometrica 50 (6), 1393–1414.

Cazals, C., Florens, J.P., Simar, L., 2002. Nonparametric frontier estimation: A robust approach. Journal of econometrics 106 (1), 1-25.

Cerqua, A., Pellegrini, G., 2013. Beyond the SUTVA: How Industrial Policy Evaluations Change When We Allow for Interactions Among Firms. Sapienza University of Rome School of Economics Working Paper n. 15.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2 (6), 429–444.

Charnes, A., Cooper, W.W., Rhodes, E., 1981. Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. Management Science 27 (6), 668-697.

Chen, C.F., 2007. Applying the stochastic frontier approach to measure hotel managerial efficiency in Taiwan. Tourism Management 28 (3), 696–702.

Cheng, Q., 2005. What determines residual income?. The Accounting Review 80 (1), 85-112.

Choi, T.Y., Chu, R.K.S., 1999. Consumer perceptions of the quality of services in three hotel categories in Hong Kong. Journal of Vacation Marketing 5 (2), 176 189.

Chrisman J.J., Chua, J.H., Litz, R.A., 2004. Comparing the agency costs of family and non-family firms: conceptual issues and exploratory evidence. Entrepreneurship Theory and Practice 28 (4), 335 – 354.

Chun, H., Kim, J.W., Morck, R., 2011. Varying heterogeneity among US firms: facts and implications. The Review of Economics and Statistics 93 (3), 1034–1052.

Chung, W., Kalnins, A., 2001. Agglomeration effects and performance: A test of the Texas lodging industry. Strategic Management Journal 22 (10), 969-988.

Coad, A., 2011. Appropriate business strategy for leaders and laggards. Industrial and Corporate Change 20 (4), 1049–1079.

Cohen, W.M., Levinthal, D.A. 1990. Absorptive-capacity. A new perspective on learning and innovation. Administrative Science Quarterly 35 (1), 128–152.

Commision of the European Communities, 2007. Agenda for a sustainable and competitive European tourism. Com(2007)-621 final, Brussels, 19.10.2007

Corbett, C., Montes-Sancho, M., Kirsch, D., 2005. The financial impact of ISO 9000 certification: An empirical analysis. Management Science 51 (7), 1046-1059.

Curi, C., Guarda, P., Lozano-Vivas, A., Zelenyuk, V., 2012. Is foreign-bank efficiency in financial centers driven by home or host country characteristics?. Journal of Productivity Analysis 40 (3), 1-19.

Cyert, R., March, J., 1963. A Behavioral Theory of the Firm. Prentice Hall, Englewood Cliffs, NJ.

Daraio, C., Simar, L., 2005. Introducing environmental variables in nonparametric frontier models: a probabilistic approach. Journal of productivity analysis 24 (1), 93-121.

Daraio, C., Simar, L., 2007. Advanced robust and nonparametric methods in efficiency analysis. Springer, New York.

Daraio, C., Simar, L., 2007b. Conditional nonparametric frontier models for convex and nonconvex technologies: a unifying approach. Journal of Productivity Analysis, 28 (1-2), 13-32.

Daraio, C., Simar, L., Wilson, P.W., 2010. Testing whether two-stage estimation is meaningful in non-parametric models of production. ISBA Discussion paper n.

1031.

Daskalopoulou, I., Petrou, A., 2009. Urban tourism competitiveness: networks and the regional asset base. Urban Studies 46 (4), 779–801.

Daveri, F., Jona-Lasino, C., 2005, Italy's decline: getting the facts right. Giornale degli economisti e annali di economia 64 (4), 365–410.

De Castris, M., Pellegrini, G., 2012. Evaluation of spatial effects of capital subsidies in the South of Italy. Regional Studies 46 (4), 525-538.

De Jorge, J., Suárez, C., 2013. Productivity, efficiency and its determinant factors in hotels. The Service Industries Journal (ahead-of-print), 1-19.

Del Gatto, M., Di Liberto, A., Petraglia, C., 2011. Measuring productivity. Journal of Economic Surveys 25 (5), 952–1008.

DeLong, J.B., Summers, L.H., 1991. Equipment investment and economic growth. Quarterly Journal of Economics 106 (2), 445-502.

De Nardis, S., 2010. Imprese italiane nella competizione internazionale. ISAE Working Paper.

Denrell, J., Kovacs, B., 2008. Selective Sampling of empirical settings in organizational studies. Administrative Science Quarterly 53 (1), 109–144.

Dhawan, R., 2001. Firm size and productivity differential: theory and evidence from a panel of U.S. firms. Journal of Economic Behavior & Organization 44 (3), 269–293.

Diaz, M.A, Sanchez, R., 2008. Firm size and productivity in Spain: a stochastic frontier analysis. Small Business Economics 30 (3), 315–323.

Diewert, W.E., 1976. Exact and superlative index numbers. Journal of Econometrics 4 (2), 115–145.

Dolado, J.J., Stucchi, R., 2008. Do temporary contracts affect TFP? Evidence from Spanish manufacturing firms. IZA Discussion Paper n. 3832.

Dosi, G., Grazzi, M., Tomasi, C., Zeli, A., 2012. Turbolence underneath the big calm? Exploring the micro-evidence behind the flat trend of manufacturing productivity in Italy. Small Business Economics 39 (4), 1043–1067.

Dosi, G., Nelson, R.R., 2010. Technical Change and Industrial Dynamics as Evolutionary Processes. In: Hall, B., Rosenberg, N., (Ed.), Handbook of Innovation. Elsevier, Amsterdam/New York, pp. 51–127.

Dunne, T., Foster, L., Haltiwanger, J., Troske, K.R., 2004. Wage and productivity dispersion in US manufacturing: the role of computer investments. Journal of

Labour Economics 22 (2), 397–429.

Duranton, G., Overman, H.G., 2005. Testing for localisation using micro-geographic data. Review of Economic Studies 72, 1077–1106.

Dyer, W.G. Jr., 2006. Examining the "Family Effect" on Firm Performance. Family Business Review 19 (4), 253-273.

Economist, 2009. Secret sauce. November 14th, 88.

Ellison, G., Glaeser, E.L., 1999. The geographic concentration of industry: does natural advantage explain agglomeration?. American Economic Review 89 (2), 311-316.

Fabiani, S., Schivardi, F., Trento, S., 2005. ICT Adoption in Italian Manufacturing: Firm-Level Evidence. Industrial and Corporate Change 14 (2), 225–249.

Faggio, G., Salvanes, K. G., Van Reenen, J., 2010. The evolution of inequality in productivity and wages: panel data evidence. Industrial and Corporate Change 19 (6), 1919–1951.

Fagiolo, G., Luzzi, A., 2006. Do liquidity constraints matter in explaining firm size and growth? Evidence from the Italian manufacturing industry. Industrial and Corporate Change 15 (1), 1-39.

Faini, R., 2003. Fu vero declino? L'Italia degli anni Novanta. il Mulino 52 (6), 1072–1083.

Faini, R., Sapir, A., 2005. Un modello obsoleto? Crescita e specializzazione dell'economia italiana. In: Boeri, T., Faini, R., Ichino, A., Pisauro, G., Scarpa, C. (Ed.), Oltre il declino. il Mulino, Bologna, pp.19–60.

Fallah-Fini, S., Triantis, K., de la Garza, J.M., Seaver, W.L., 2012. Measuring the efficiency of highway maintenance contracting strategies: A bootstrapped non-parametric meta-frontier approach. European Journal of Operational Research 219 (1), 134-145.

Färe, R., Grosskopf, S., 1996. Intertemporal Production Frontiers: With Dynamic DEA. Kluwer-Academic Publishers, Boston.

Färe, R., Grosskopf, S., Lindgren, B., Roos, P., 1992. Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach. Journal of Productivity Analysis 3 (1-2), 85–101.

Färe, R., Grosskopf, S., Norris, M., Zhongyang, Z., 1994. Productivity growth, technical progress and efficiency change in industrialised countries. American Economic Review 84 (1), 66–83.

Farrell, M.J., 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society. Series A (General) 120 (3), 253–290.

Ferracci, M., Jolivet, G., Van den Berg, G J., 2013. Evidence of Treatment Spillovers Within Markets. Review of Economics and Statistics, forthcoming.

Foresti G., Guelpa, F., Trenti, S., 2007. Quali leve per il rilancio dell'industria? La questione dimensionale. Intesa Sanpaolo, Milano.

Foster, L, Haltiwanger, J., Krizan, C.J., 2006. Market selection, reallocation, and restructuring in the U.S. Retail Trade Sector in the 1990s. Review of Economics and Statistics 88 (4), 748–58.

Foster, L., Haltiwanger, J.C., Syverson, C., 2008. Reallocation, firm turnover and efficiency, selection on productivity or profitability?. American Economic Review 98 (1), 394–425.

Fox, J.T., Smeets, V., 2011. Does input quality drive measured differences in firm productivity?. International Economic Review 52 (4), 961–989.

Franch, M., Martini, U., Buffa, F., 2010. Roles and opinions of primary and secondary stakeholders within community-type destinations. Tourism Review 65 (4), 74-85.

Fried, H.O., Lovell, C.A.K., Schmidt, S.S. (Eds.), 2008. The measurement of productive efficiency and productivity growth. Oxford University Press, London.

Fried H.O., Schmidt S.S., Yaisawarng S., 1999. Incorporating the Operating Environment Into a Nonparametric Measure of Technical Efficiency. Journal of Productivity Analysis 12 (3), 249–267.

Galbraith, J., 1995. Designing Organizations . Jossey-Bass, San Francisco, CA.

Gan, L., Hernandez, M.A., 2013. Making friends with your neighbors? Agglomeration and tacit collusion in the lodging industry. Review of Economics and Statistics 95 (3), 1002-1017.

Geroski, P.A., 2000. Models of technology diffusion. Research policy 29 (4), 603-625.

Gomez-Mejia L, Nickel-Nuniez M, Gutierrez I., 2001. The role of family ties in agency contracts. Academy of Management Journal 44 (1), 81 – 95.

Graham, D.J., 2009. Identifying urbanisation and localisation externalities in manufacturing and service industries. Papers in Regional Science 88 (1), 63-84.

Greene, W.H., 2008. The econometric approach to efficiency analysis. The measurement of productive efficiency and productivity growth. In: Fried, H.O., Lovell, C.A.K., Schmidt, S.S., (Ed.), The Measurement of Productive

Efficiency, 2nd edition. Oxford University Press, London, pp. 92-250.

Griffel-Tatjé, E., Lovell, C.A.K., 1999. Profits and productivity. Management Science 45, 1177-1193.

Griliches, Z., Mairesse, J., 1997. Production function: the search for identification. In: S. Strøm (Ed.), Econometrics and Economic Theory in the Twentieth Century: the Ragner Frisch Centennial Symposium. Cambridge University Press, Cambridge, p. 169.

Grönroos, C., Ojasalo, K., 2004. Service productivity: towards a conceptualization of the transformation of inputs into economic results in services. Journal of Business Research 57 (4), 414-423.

Hadlock, C.J., Pierce, J.R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. Review of Financial Studies 23 (5), 1909-1940.

Hall, B.H., Khan, B., 2003. Adoption of new technology. NBER working paper n. w9730.

Hall, B.H., Lotti, F., Mairesse, J., 2009. Innovation and productivity in SMEs. Empirical evidence for Italy. Small Business Economics 33 (1), 13–33.

Hannan, M.T., Freeman, J. 1989. Organizational Ecology. Harvard University Press, Cambridge, MA.

Hanson, A., Rohlin, S., 2013. Do spatially targeted redevelopment programs spillover?. Regional Science and Urban Economics 43 (1), 86-100.

Harris, C.D., 1954. The market as a factor in the localization of industry in the United States. Annals of the association of American geographers 44 (4), 315-348.

Harris, R., Moffat, J., 2011. Plant-level determinants of total factor productivity in Great Britain, 1997-2006. SERC Discussion Papers n. 64.

Harris, R., Trainor, M., 2005. Capital subsidies and their impact on Total Factor Productivity: Firm-level evidence from Northern Ireland. Journal of Regional Science 45 (1), 49-74.

Haugland, S.A., Ness, H., Grønseth, B.O., Aarstad, J., 2011. Development of tourism destinations: an integrated multilevel perspective. Annals of Tourism Research 38 (1), 268-290.

Hernan, M.A., Brumback, B. Robins, J.M., 2000. Marginal structural models to estimate the causal effect of Zidovudine on the survival of HIV-positive men. Epidemiology 11, 561 570.

Herrero, I., 2011. Agency costs, family ties, and firm efficiency. Journal of Management 37 (3), 887-904.

Heshmati, A., 2003. Productivity growth, efficiency and outsourcing in manufacturing and service industries. Journal of Economic Surveys 7 (1), 79–112.

Ho, D., Imai, K., King, G., Stuart, E., 2007a. Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. Political Analysis 15 (3), 199-236,

Ho, D., Imai, K., King, G., Stuart, E., 2007b. Matchit: Nonparametric preprocessing for parametric causal inference. Journal of Statistical Software 42 (8), 1-28.

Hogan, J. W., Lancaster, T., 2004. Instrumental variables and inverse probability weighting for causal inference from longitudinal observational studies. Statistical Methods in Medical Research 13 (1), 17-48.

Holland, P.W., 1986. Statistics and causal inference. Journal of the American statistical Association 81 (396), 945-960.

Hong, G., Raudenbush, S.W., 2006. Evaluating kindergarten retention policy. Journal of the American Statistical Association 101 (475), 901-910.

Hsieh, C.T., Klenow, P.J., 2009. Misallocation and Manufacturing TFP in China and India. Quarterly Journal of Economics 124 (4), 1403–1448.

Hudgens, M.G., Halloran, M.E., 2008. Toward causal inference with interference. Journal of the American Statistical Association 103 (482), 832-842

Huergo, E., Jaumandreu, J., 2004. Firm's age, process innovation and productivity growth. International Journal of Industrial Organization 22 (4), 541-559.

Hwang, S.N., Chang, T.Y., 2003. Using data envelopment analysis to measure hotel managerial efficiency change in Taiwan. Tourism Management 24 (4) 357–369.

Iacovone, L., 2012. The better you are the stronger it makes you: Evidence on the asymmetric impact of liberalization. Journal of Development Economics 99 (2), 474–485.

Ichniowski, C., Shaw, K., Prennushi, G., 1997. The effects of human resource practices on productivity: A study of steel finishing lines. American Economic Review 87 (3), 291-313

Imbens, G.W., 2004. Nonparametric estimation of average treatment effects under exogeneity: A review. Review of Economics and statistics 86 (1), 4-29.

Imbens, G.W., Wooldridge, J.M., 2009. Recent developments in the econometrics of program evaluation. Journal of Economic Literature 47, 5–86.

Inklaar, R., Timmer, M.P., Van Ark, B., 2008. Market services productivity across Europe and the US. Economic Policy 23 (53), 139–194.

Israeli, A., 2002. Star rating and corporate affiliation: their influence on room price and performance of hotels in Israel. Hospitality Management 21, 405–424.

Ito, K., Lechevalier, S., 2009. The evolution of the productivity dispersion of firms: a reevaluation of its determinants in the case of Japan. Review of World Economics 145 (3), 405-429.

Iwai, K., 2000. A contribution to the evolutionary theory of innovation, imitation and growth. Journal of Economic Behavior & Organization 43 (2), 167–198.

Jacobs, J., 1969. The Economy of Cities. Vintage, New York.

Jorgenson, D.W., Ho, M.S., Stiroh, K.J., 2008. A retrospective look at the U.S. productivity growth resurgence. Journal of Economic Perspective 22 (1), 3–24.

Kalnins, A., Chung, W., 2004. Resource-seeking agglomeration: a study of market entry in the lodging industry. Strategic Management Journal 25 (7), 689-699.

Kashyap, R., Bojanic, D.C., 2000. A structural analysis of value, quality, and price perceptions of business and leisure travelers. Journal of Travel Research 39 (1), 45–51.

Kleinknecht, A., 1998. Is labour market flexibility harmful to innovation?. Cambridge Journal of Economics 22 (3), 387–396.

Kleinknecht, A., Oostendorp, R.M., Pradhan, M.P., Naastepad, C.W.M., 2006. Flexible labour, firm performance and the Dutch job creation miracle. International Review of Applied Economics 20 (2), 171–187.

Kneip, A., Park, B., Simar, L., 1998. A note on the convergence of non-parametric DEA efficiency measure. Econometric Theory 14 (6), 783¬–793.

Kneip, A., Simar, L., Wilson, P.W., 2008. Asymptotics and consistent bootstraps for DEA estimators in non-parametric frontier models. Econometric Theory 24 (6), 1663–1697.

Ko, H., Hogan, J.W., Mayer, K.H., 2003. Estimating causal treatment effects from longitudinal HIV natural history studies using marginal structural models. Biometrics 59 (1), 152-162.

König, M., Lorenz, J., Zilibotti, F., 2012. Innovation vs imitation and the evolution of productivity distributions. CEPR Discussion Papers, n. 8843.

Konings, J., Vandenbussche, H., 2007. Antidumping protection and oroductivity of domestic firms: A firm level analysis. LICOS Discussion Paper Series n. 196.

La Ferrara, E., Marcellino, M., 2000. TFP, costs, and public infrastructure: an equivocal relationship. Innocenzo Gasparini Institute for Economic Research.

Law R., Leung R., Buhalis, D., 2009. Information technology applications in hospitality and tourism: a review of publications from 2005 to 2007. Journal of Travel and Tourism Marketing 26 (5-6), 599-623.

Leibenstein, H., 1966. Allocative Efficiency vs. "X-efficiency". American Economic Review 56, 392-415.

Lerner, M., Haber, S., 2001. Performance factors of small tourism ventures: the interface of tourism, entrepreneurship and the environment. Journal of business venturing 16 (1), 77-100.

Lev, B., 1983. Some economic determinants of time-series properties of earnings. Journal of Accounting and Economics 5, 31-48.

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables, Review of Economic Studies 70 (2), 317–342.

Logar, I., 2010. Sustainable tourism management in Crikvenica, Croatia: An assessment of policy instruments. Tourism Management 31 (1), 125-135.

Lotti F., Viviano, E., 2012. Why hiring temporary workers. mimeo, Bank of Italy

Lovell, C.A.K., 1993. Production frontiers and productive efficiency. In: Fried, H.O., Lovell, C.K.A., Schmidt, S.S. (Eds.), The measurement of productivity efficiency: Techniques and applications. Oxford University Press, New York, pp. 3 – 67.

Lucidi, F., Kleinknecht, A., 2009. Little innovation, many jobs: An econometric analysis of the Italian labour productivity crisis. Cambridge Journal of Economics 34 (3), 525–546.

Marcon, E., Puech, F., 2003. Evaluating the geographic concentration of industries using distance-based methods. Journal of Economic Geography 3, 409–428.

Marcon, E., Puech, F., 2010. Measures of the geographic concentration of industries: improving distance-based methods. Journal of Economic Geography 10 (5), 745-762.

Marrocu, E., Paci, R., 2010. The effects of public capital on the productivity of the Italian regions. Applied Economics 42 (8), 989–1002.

Marshall, A., 1920. Principles of Economics. Macmillan, London.

Mas, M., Milana, C., Serrano, L., 2008. Spain and Italy: catching up and falling behind.

Two different tales of productivity slowdown. EU KLEMS Working Paper n. 37.

McCann, B.T., Folta, T.B., 2008. Location matters: where we have been and where we might go in agglomeration research. Journal of Management 34 (3), 532-565.

McCann, B.T., Folta, T.B., 2009. Demand-and Supply-Side Agglomerations: Distinguishing between Fundamentally Different Manifestations of Geographic Concentration. Journal of Management Studies 46 (3), 362-392.

McDonald, J., 2009. Using least squares and tobit in second stage DEA efficiency analyses. European Journal of Operational Research 197 (2), 792-798.

McKinsey Global Institute, 2010. Beyond austerity: a path to economic growth and renewal in Europe. McKinsey Global Institute, Washington, D.C.

Melitz, M.J., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71 (6), 1695-1725.

Michie, J., Sheehan, M., 2001. Labour market flexibility, human resource management and corporate performance. British Journal of Management 12 (4), 287 306.

Michie, J., Sheehan, M., 2003. Labour market deregulation, 'flexibility' and innovation. Cambridge Journal of Economics 27 (1), 123–148.

Mintzberg, H., 1979. The structuring of organizations. Prentice Hall, NJ.

Mion, G., 2004. Spatial externalities and empirical analysis: the case of Italy. Journal of Urban Economics 56 (1), 97-118.

Miller, D.M., 1984. Profitability = productivity + price recovery. Harvard Business Review 62, 145-163.

Miller, D.M., Rao P.M., 1989. Analysis of profit-linked total-factor productivity measurement models at the firm level. Management Science 35, 757-767.

Mohnen, P., Hall, B.H., 2013. Innovation and productivity: An update. Eurasian Business Review 3 (1), 47–65.

Mol, M.J., Birkinshaw, J., 2009. The sources of management innovation: When firms introduce new management practices. Journal of business research 62 (12), 1269–1280.

Molina-Azorin, J.F., Pereira-Moliner, J., Claver-Cortés, E., 2010. The importance of the firm and destination effects to explain firm performance. Tourism Management 31 (1), 22–28.

Morey, R.C., Dittman, D.A., 2003. Evaluating a hotel GM's performance: a case study in benchmarking. The Cornell Hotel & Restaurant Administration Quarterly 44, 53–9.

Morikawa, M., 2011. Economies of density and productivity in service industries: An analysis of personal service industries based on establishment-level data. The Review of Economics and Statistics 93 (1), 179-192.

Morikawa, M., 2012. Demand fluctuations and productivity of service industries. Economics Letters 117 (1), 256-258.

Muñiz, M.A., 2002. Separating managerial inefficiency and external conditions in data envelopment analysis. European Journal of Operational Research 143 (3), 625-643.

Murphy, P., Pritchard, M., Smith, B., 2000. The destination product and its impact on traveler perceptions. Tourism Management, 21, 43–52.

Myers, S.C., Majluf, N.S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. Journal of financial economics 13 (2), 187-221.

Nelson, R.R., 1959. The simple economics of basic science research. Journal of Political Economy 67, 297-306.

Nelson, R.R., 1981. Research on productivity growth and productivity differences: dead ends and new departures. Journal of Economic Literature 19 (3), 1029-1064.

Nelson, R.R., 1991. Why do firms differ, and how does it matter?. Strategic Management Journal 12 (2), 61-74.

Nelson, R.R., Phelps, E.S., 1966. Investment in humans, technological diffusion, and economic growth. American Economic Review 56 (1/2), 69–75.

O'Donnell, C.J., Rao, D.S.P., Battese, G.E., 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratio. Empirical Economics 34 (2), 231–255.

OECD, 2005. Growth in Services: Fostering employment, productivity and innovation. Meeting of the OECD Council at Ministerial Level, 3-4 May 2005.

OECD, 2008. Tourism in OECD Countries 2008: Trends and Policies. Organisation for Economic Co-operation and Development.

Oliner, S.D., Sichel, D.E., Stiroh, K.J., 2007. Explaining a productive decade, Brookings Papers on Economic Activity 1, 81–137.

Olley, G. S., Pakes, A., 1996. The Dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1297.

O'Mahony, M., Timmer, M.P., 2009. Output, input and productivity measures at the industry level: The eu klems database. The Economic Journal 119 (538), F374-F403.

Onida, F., 2004. Se il piccolo non cresce. Le PMI italiane in affanno. Il Mulino, Bologna.

Orfila-Sintes, F., Mattsson, J., 2009. Innovation behavior in the hotel industry. Omega 37 (2), 380-394.

Oulton, N., 1998. Competition and the dispersion of labour productivity amongst UK companies. Oxford Economic Papers 50 (1), 23-38.

Pellegrino, G., Piva, M., Vivarelli, M., 2011. Young firms and innovation: a microeconometric analysis. Structural Change and Economic Dynamics 23 (4), 329–340

Pérez-Rodríguez, J. V., Acosta-González, E., 2007. Cost efficiency of the lodging industry in the tourist destination of Gran Canaria (Spain). Tourism Management 28 (4), 993–1005.

Piva, M., Santarelli, E., Vivarelli, M., 2005. The skill bias effect of technological and organisational change: Evidence and policy implications. Research Policy 34 (2), 141-157.

Portela, S.M.C.A., Thanassoulis, E., 2001. Decomposing school and school-type efficiency. European Journal of Operational Research 132 (2), 357-373.

PAT – Servizio Statistica, 2006. L'imprenditoria alberghiera nella provincia di Trento, Provincia Autonoma di Trento, Trento.

Peng, D.X., Schroeder, R.G., Shah, R., 2008. Linking routines to operations capabilities: a new perspective. Journal of Operations Management 26, 730–748.

Puga, D., 2010. The Magnitude and causes of agglomeration economies. Journal of Regional Science 50 (1), 203-219.

Ramalho, E.A., Ramalho, J.J., Henriques, P.D., 2010. Fractional regression models for second stage DEA efficiency analyses. Journal of Productivity Analysis 34 (3), 239-255.

Ray, S.C., 1991. Resource-use efficiency in public schools: A study of Connecticut data. Management Science 37 (12), 1620-1628.

Redding, S.J., 2011. Theories of Heterogeneous Firms and Trade. Annual Review of Economics 3 (1), 77-105.

Rigby, D.L., Essletzbichler, J., 2006. Technological variety, technological change and a geography of production techniques. Journal of Economic Geography 6 (1), 45-70.

Ritchie, J.R.B., Crouch, G.I., 2000. The competitive destination: A sustainability perspective. Tourism Management 21 (1), 1-7.

Robins, J.M., Hernán, M.Á., Brumback, B., 2000. Marginal structural models and causal inference in epidemiology. Epidemiology 11 (5), 550-560.

Rodriguez-Clare, A., 2005. Coordination failures, clusters and microeconomic interventions. Inter-American Development Bank Working paper n.544

Rodrik, D., 2007. Industrial development: some stylized facts and policy directions. Industrial development for the 21st century: sustainable development perspectives, 7-28.

Rosenbaum, P., 2007. Interference Between Units in Randomized Experiments. Journal of the American Statistical Association 102 (477), 191–200

Rosenthal, S.S., Strange, W.C., 2004. Evidence on the nature and sources of agglomeration economies. Handbook of regional and urban economics 4, 2119-2171.

Rossi, S., 2006. La regina e il cavallo. Quattro mosse contro il declino. La Terza, Bari.

Rubin, D., 1974. Estimating Causal Effects of Treatments in Randomized and Non randomized Studies. Journal of Educational Psychology 66 (5), 688-701.

Rubin, D., 1986. Statistics and Causal Inference: Which Ifs Have Causal Answers. Journal of the American Statistical Association 81, 961-2.

Ruggiero, J., 1998. Non-discretionary inputs in data envelopment analysis. European Journal of Operational Research 111 (3), 461-469.

Sabirianova, K., Svejnar, J., Terrell, K., 2005. Distance to the efficiency frontier and foreign direct investment spillovers. Journal of the European Economic Association 3 (2‑3), 576–586.

Sainaghi, R., 2010. Hotel performance: state of the art. International Journal of Contemporary Hospitality Management 22 (7), 920-952.

Sampaio de Sousa, M.C., Stosic, B., 2005. Technical efficiency of the Brazilian municipalities: correcting nonparametric frontier measurement for outliers. Journal of Productivity Analysis 24 (2), 157–181.

Scarpetta, S., Hemmings, P., Tressel, T., Woo, J., 2002. The Role of Policy and Institutions for productivity and firm dynamics: Evidence from micro and industry data. OECD Working Paper n. 329.

Scarpetta, S., Tressel, T., 2004. Boosting productivity via innovation and adoption of new technologies: any role for labor market institutions?. World Bank Working Paper n. 3273.

Schimitz, J.A. Jr., 2005. What determines productivity? Lessons from the dramatic recovery of the US and Canadian iron ore Industries following their early 1980s crisis. Journal of Political Economy 113 (3), 582-625.

Schwab, K., 2012. The global competitiveness report 2012–2013. World Economic Fourum, Geneva, Switzerland.

Shang, J.K., Wang, F.C., Hung, W.T., 2010. A stochastic DEA study of hotel efficiency. Applied Economics 42 (19), 2505–2518.

Shephard, R.W., 1970. Theory of cost and production functions. Princeton University Press, Princeton.

Schubert, S.F., Brida, J.G., 2008. Dynamic effects of subsidizing the tourism sector. Tourism Economics 14 (1), 57-80.

Schuler, R.S., Jackson, S.E., 1987. Linking competitive strategies with human resource management practices. The Academy of Management Executive 1 (3), 207-219.

Schumpeter, J.A., 1934. The Theory of Economic Development. Harvard University Press, Cambridge, Mass.

Sigala, M., Airey, D., Jones, P. Lockwood, A., 2004. ICT Paradox Lost? A stepwise DEA methodology to evaluate technology investments in tourism settings. Journal of Travel Research 43 (2), 180–192.

Simar, L., 2003. Detecting outliers in frontier models: a simple approach. Journal of Productivity Analysis 20 (3), 391–424.

Simar, L., Wilson, P.W., 1998. Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. Management science 44 (1), 49–61.

Simar, L., Wilson, P.W., 1999. Estimating and bootstrapping Malmquist indices. European Journal of Operational Research 115 (3), 459–471.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics 136 (1), 31–64.

Simar, L., Wilson, P.W., 2008. Statistical inference in nonparametric frontier models: recent development and perspectives. In: Fried, H., Lovell, C.A.K., Schmidt, S., (Ed.), The Measurement of Productive Efficiency, 2nd edition. Oxford University Press, London, pp. 421–521.

Simar, L., Wilson, P.W., 2013. Statistical approaches for nonparametric frontier models: A guided tour. ISBA Discussion papers n. 47.

Skuras, D., Tsekouras, K., Dimara, E., Tzelepis, D., 2006. The Effects of Regional Capital Subsidies on Productivity Growth: A Case Study of the Greek Food and Beverage Manufacturing Industry. Journal of Regional Science 46 (2), 355-381.

Smith, J.A., Todd, P.E., (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. Journal of econometrics 125 (1), 305-353.

Solow, R.M., 1957. Technical change and the aggregate production function. The Review of Economics and Statistics 39 (3), 312-320.

Stuart, E.A., 2010. Matching methods for causal inference: A review and a look forward. Statistical science: a review journal of the Institute of Mathematical Statistics 25 (1), 1-21.

Suarez, D., Haro, J. M., Novick, D., Ochoa, S., 2008. Marginal structural models might overcome confounding when analyzing multiple treatment effects in observational studies. Journal of clinical epidemiology 61 (6), 525-530.

Syverson, C., 2004. Product substitutability and productivity dispersion. Review of Economics and Statistics 86 (2), 534–550.

Syverson, C., 2011. What determines productivity?. Journal of Economic Literature 49 (2), 326–365.

Tambe P., Hitt L.M., Brynjolfsson, E., 2012. The extroverted firm: How external information practices affect innovation and productivity. Management Science 58 (5), 843–859

Tchetgen, E.J.T., VanderWeele, T.J., 2010. On causal inference in the presence of interference. Statistical Methods in Medical Research 21 (1), 55-75.

Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strategic Management Journal 18 (7), 509–533.

Thanassoulis, E., Portela, M.C., Despic, O., 2008. Data envelopment analysis: the mathematical programming approach to efficiency analysis. In: Fried, H., Lovell, C.A.K., Schmidt, S., (Ed.), The Measurement of Productive Efficiency, 2nd edition. Oxford University Press, London, pp. 251-420.

Topalova, P., 2004.Trade Liberalization and Firm Productivity: the Case of India. IMF Working Papers n. 28.

Tsai, H., Song, H., Wong, K.K., 2009. Tourism and hotel competitiveness research. Journal of travel & tourism marketing 26 (5-6), 522-546.

Tulkens, H., Vanden Eeckaut, P., 1995. Non-parametric Efficiency, Progress and Regress Measures for Panel Data: Methodological Aspects. European Journal of Operational Research 80 (3), 474–499.

Tundis, E., Zaninotto, E., Gabriele, R., Trento, S., 2012. Crescita della produttività, progresso tecnico e impiego del lavoro nelle imprese manifatturiere italiane: 1996-2006. Economia e Politica Industriale 39 (4), 25-61.

Tveteras, R., Battese, G.E., 2006. Agglomeration externalities, productivity, ad technical efficiency. Journal of Regional Science 46 (4), 605-625.

Tzelepis, D., Skuras, D., 2004. The effects of regional capital subsidies on firm performance: an empirical study. Journal of Small Business and Enterprise Development 11 (1), 121-129.

Tzelepis, D., Tsekouras, K., Skuras, D., Dimara, E., 2005. The effects of ISO 9001 on firms' productive efficiency. International Journal of Operations & Production Management 26 (10), 1146–1165.

Van Ark, B., O'Mahony, M., Timmer, M.P., 2008. The productivity gap between Europe and the United States: trends and causes. Journal of Economic Perspective 22 (1), 25-44.

Van Biesebroeck, J., 2007. Robustness of productivity estimates. Journal of Industrial Economics 55 (3), 529–569.

Vandenbussche, J., Aghion, P., Meghir, C., 2006. Growth, distance to frontier and composition of human capital. Journal of Economic Growth 11, 97–127.

Van Reenen, J., 2011. Does competition raise productivity through improving management quality?. International journal of industrial organization 29 (3), 306-316.

Verbitsky-Savitz, N., Raudenbush, S.W., 2012. Causal Inference Under Interference in Spatial Settings: A Case Study Evaluating Community Policing Program in Chicago. Epidemiologic Methods 1 (1), Article 6.

Wagner, J., 2007. Exports and productivity: a survey of the evidence from firm-level data. The World Economy 30 (1), 60-82.

Wagner, J., 2012. International trade and firm performance: a survey of empirical studies since 2006. Review of World Economics 148 (2), 235-267.

Wheelock, D.C., Wilson, P.W., 1999. Inefficiency and productivity change in U.S. banking. 1984-1993. Journal of Money, Credit and Banking 31 (2), 212–234.

Wilson, P.W., 1993. Detecting outliers in deterministic nonparametric frontier models with multiple outputs. Journal of Business & Economic Statistics 11 (3), 319–323.

Wilson, P.W., 1995. Detecting influential observations in data envelopment analysis. Journal of Productivity Analysis 6 (1), 27–45.

Wilson, P.W., 2008. FEAR: A software package for frontier efficiency analysis with R. Socio-economic planning sciences 42 (4), 247–254.

Woodward, J., 1958. Management and technology. Cambridge University Press, Cambridge.

Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. The MIT Press.

WTO, 2006. World trade report. Exploring the links between subsidies, trade, and the WTO. World Trade Organization, Geneva.

Wu, J., Tsai, H., Zhou, Z., 2011. Improving efficiency in international tourist hotels in Taipei using a non-radial DEA model. International Journal of Contemporary Hospitality Management 23 (1), 66–83.

Yu, M.M., Lee, B.C., 2009. Efficiency and effectiveness of service business: Evidence from international tourist hotels in Taiwan. Tourism Management 30 (4), 571-580.

Zanetti, G., Alzona G.L., 2004. Europa e Italia: la sfida della competitività. Il Mulino, Bologna

Zelenyuk, V., 2006. Aggregation of Malmquist productivity indexes. European Journal of Operational Research 174 (2), 1076–1086.

Zelenyuk, V., 2009. Power of significance test of dummy variables in two-stage efficiency analysis model. Applied Economics Letters, 16, 1493–1495.

Zirulia, L., 2009. Competition between and within Tourist Destinations. RCEA Working Papers series n. 39-09.

7 General appendix

7.1 A: Detection strategy for outliers

To detect outliers we used a method based on the concept of leverage, that is, the effect produced on the efficiencies of all other firms when the observed firm is removed from the dataset (Stosic and Sampaio de Souza, 2005). The underlying concept is that outliers are expected to display leverage far above the mean. The leverage measure is then calculated for each firm, and used to detect and automatically eliminate outliers from the dataset.

Formally, leverage is measured as the standard deviation of the efficiency estimates relative to the full sample, without the observation in question, and the inefficiency estimates for the full sample. In order to calculate leverage, the most straightforward way is to use jackknife resampling. DEA is first applied to each of the firms, the unaltered, original dataset being used to obtain the set of efficiencies $\{\theta_k,\ k=1,...,K\}$. A "leave-one-out" strategy is then employed: one by one, each firm is removed, and each time the set of efficiencies $\{\theta^*_{ki},\ k=1,...,K,\ k\neq i\}$ is recalculated, where i=1,…,K indexes the removed firm. Lastly, the leverage of the i-th firm is defined as:

$$leverage_i = \sqrt{\frac{\sum_{k=S_L,k\neq i}\left(\theta^*_{ki}-\theta_k\right)}{K-1}}$$

A higher leverage value provides evidence for an influential observation.

We performed the outlier procedure with respect to the technological frontier at industry level in each year, although this approach is, computationally, extremely intensive. Therefore, as in Stosic and Sampaio de Sousa (2005), we used a more efficient stochastic procedure, which combines bootstrap resampling with the above jackknife strategy. We reduced the computational burden and calculated the leverage only for those firms which were efficient, given the extracted subsample; for inefficient firms, leverage was set at zero. This was because the elimination of an inefficient firm from the dataset under analysis has no effect on the efficiency of any other firm. The procedure was implemented with the R statistical package. The details are as follows:

[1] Loop the following steps ([1.1]–[1.5]) B times and obtain estimates of leverage $A = \{l_{bi}\}_{b=1}^{B} \quad \forall i \in S_L^{Eff}$

[1.1] extract randomly, without re-emission, a subset S_L of cardinality L from the original data et S of cardinality K

[1.2] calculate efficiency $\theta_k \quad \forall k \in S_L$

[1.3] partition $S_L = S_L^{Eff} \cup S_L^{Ineff}$

[1.4] loop the following step ([1.3.1]) $\forall j \in S_L^{Eff}$

[1.4.1] remove the current firm $j \in S_L^{Eff}$ and calculate efficiency $\left\{\theta_{ki}^{*}:\ k = 1,\ldots,L^{Ineff}\right\}$, where i is the removed firm.

[1.5] calculate the leverage

$$l_i = \begin{cases} \sqrt{\dfrac{\sum\limits_{k=S_L,k\neq i}\left(\theta_{ki}^{*} - \theta_k\right)}{K-1}} & \forall i \in S_L^{Eff} \\ 0 & \forall i \in S_L^{Ineff} \end{cases}$$

[2] calculate the average leverage $\bar{l}_i = \sum_{b=1}^{B} l_{bi} \Big/ n_i$, where n_i is the number of times firm i is extracted.

[3] calculate the global average leverage: $\bar{l} = \sum_{i=1}^{K} \bar{l}_i \Big/ K$

The procedure requires choice of the cardinality of the subsample extracted in each iteration and the number of repetitions. Stosic and Sampaio de Sousa (2005) suggest a cardinality which is 10-20% that of the entire dataset S and a number of repetitions greater than or equal to 1000. In this paper, we chose L=0.2 and B=1000. In order to take into account the number of observations used, we defined quantity

$\bar{l}\log(K)$ as the threshold leverage. Observations with average leverage greater than the threshold were omitted.