Essays in Efficiency and Productivity Analysis under Technology Heterogeneity Regimes

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[…] if a man will be content to begin with doubts he shall end in certainties.

Francis Bacon¹

¹English philosopher (1561-1626) who has been called the father of the Empiricism and has been a practitioner of the Scientific Method during the Scientific Revolution.
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Chapter 1 Introduction

1.1 The urge to understand technological heterogeneity

Undoubtedly, the mechanisms surrounding the notion and role of technology in the production process are at best vaguely defined not only in terms of theoretical foundations grounded on the Economic Theory of production but in the context of empirical research as well.

The common practice to address technological heterogeneity in the context of benchmarking was to put the blame, without further wise justification, on a set of factors responsible for causing distortions in the benchmarking process such as managerial ability, size of the production entity, resource endowments and so on, while no sophisticated suggestions regarding how to accommodate for additional aspects had arisen. A new era begun with the pioneering work of O’Donnell et al., (2008), who reshaped previous work of Hayami (1969) and Hayami and Ruttan (1971), with the introduction of the metafrontier, which envelops the different production (or cost) frontiers and accounts for all the possible heterogeneity among the Decision Making Units (DMU) exists. Since then, a growing wave of empirical applications employing the metafrontier to account for more aspects of technological heterogeneity and calculate the technology gap values has disseminated its concept.

Apparently, the fact that the metafrontier embraces aspects of heterogeneity otherwise would have been neglected, does not guarantee that heterogeneity has been entirely captured. This brings to the forefront the importance of the research design so as to reveal as much heterogeneity as possible. Depending which aspects the researcher aspires to shed light on, the choice of the means to do so should be guided by the prospect of unravelling and identifying the underlying drivers triggering heterogeneous patterns in performance. The main objective of the subsequent analysis is to study the notion of technological heterogeneity, its distorting role in the benchmarking process and the how alternative technological regimes i.e. hierarchical structures, are responsible and to what extent for the heterogeneous patterns in performance observed.

Along the above line of argument we find the rationale behind the sample selection of the analysis followed in the present thesis. Since the objective is to study the impact of different technological hierarchies and whether those affect the benchmarking process in ways the latter identifies aspects of the technological heterogeneity, we collected data on industries of the European manufacturing and transportation sector in order to study the different patterns in performance. Those sectors operate within the European context meaning that those share regulations, restrictions and opportunities. Besides that, the two sectors employ different production technology in order to produce output utilizing inputs of the same quality, given
context. At this point, we should focus on the idea of alternative technological structures. Every industry of manufacturing and transportation sector in the sample operates under the production technology of the (European) countries we have collected – this constitutes the country frontiers dominated technology hierarchy - but viewed from another standpoint, we also have countries employing the available technology of each industry – this constitutes the industry frontiers dominated technology hierarchy.

Therefore, two major sources of heterogeneity arise, (i) the choice to consider technologies of the manufacturing and transportation sector is ground on the fact that we aim to include heterogeneous units in order to account for more aspects of technological heterogeneity so as to be able to identify heterogeneous patterns in performance and (ii) the choice to consider country and industry frontiers (we also consider hierarchical structures based on the level of competitiveness in a different setting) pave the way to identify the performance pattern of each DMU under alternative technological regimes but also allows for examining the impact of the structure on the performance of the units examined.

1.2 Conceptual Issues; Endogeneity concerns in Efficiency Analysis

The above discussion incites endogeneity concerns within the context of performance evaluation. First and foremost, the theoretical foundations of the concept of metafrontier stimulate endogeneity between the productive performance and technology gap values. More precisely, the metafrontier is an overall frontier which is used to evaluate the performance of all the units under examination as it takes into consideration the full production (i.e. technology) set. The partition of the metafrontier with respect to a particular factor e.g. by country or industry technology set, gives rise to the individual frontiers. Then, we evaluate the performance of each unit under examination against each frontier while the distance between each individual frontier and the metafrontier is captured by the technology gap value. Therefore, the endogeneity between the productive performance and technology gap values (used to capture technological heterogeneity) occurs since those are defined over the same technology set. That is productive performance scores and technology gap values share the same technological characteristics embodied in the corresponding technology sets which are latent in nature. We only observe how the bundle of inputs, given technology, produces output which is projected on the performance outcome with respect both to the metafrontier and the individual frontiers. The same rationale applies to derivative measures such as energy efficiency which share the same technology set with the one used to calculate the productive performance scores.

An additional endogeneity concern is raised by the existence of the alternative technological hierarchies examined herein, that is the country and industry frontiers dominated
technology hierarchies since both are defined over the same technology set and are evaluated against the same European technology level. Since we aspire to study the existence of any heterogeneous patterns in performance under different technological hierarchies, we also need to account for the possibility that heterogeneous behaviour originates from the structure itself. Such being the case, we need an index to measure to what extent the alternative hierarchies trigger performance’s heterogeneous patterns for the same units. That is the quest for identifying the drivers of heterogeneous performance within a group, pinpoints towards the structure of technology those units operate under. In other words, changes in the production structure i.e. technology, may be associated with heterogeneous performance and we have to take that into consideration.

Another factor provoking endogeneity within the context of performance evaluation, is the fact that productive performance is not (or should not be considered as) a static notion despite the fact that the vast majority of studies treat it that way. Productive performance is in fact a dynamic notion which evolves through time horizon since more and more information, technological advancements, technical opportunities occur. Production entities respond to these changes by improving their performance at therefore approach the best available technology represented by the metafrontier. The moral from the aforementioned is that productive performance is or better yet, should be considered as time persistent meaning that past levels of productive performance affect the current ones. The importance of time persistence or in other words, path dependence has been acknowledged by the pioneering work of David (1985, 1986). Framed differently, beyond the high dependence of with current levels, past values of productive performance and/or technology gap might be associated with unobserved or hard to quantify factors affecting current performance levels. Along with this line, we find the omitted selection rules governing the relations we aspire to reveal such as the resource endowments, the human capital, the different national policies, priorities and regulations which are not homogeneous across countries and industries, the different technological opportunities each industry faces and so on.

Last but not least, we should also acknowledge that there are additional factors associated with the performance of a DMU which cannot be explicitly identified and measured empirically in an appropriate and acceptable manner, which underlines the fact that the significance of the measurement errors cannot be overlooked as those distort the investigation of the relationship we aspire to explore by supressing the observed magnitude. Also, the omitted variables bias is an undeniable anchor every empirical study has to find a coping mechanism against.
1.3 Contribution of the thesis at hand

The contribution of this thesis is multifocal and can be found along the lines of the following facts. More precisely, each chapter examines a novel research question which extends our understanding as far as the effect of technological heterogeneity in the benchmarking process is concerned but also contributes to the existing literature of efficiency analysis.

In Chapter 2, we describe how we collected and combined data from distinct but complementary specialized databases in order to devise a unique dataset which will allow examining our research questions. We also describe the process on how we managed to overcome some data deficiencies and limitations using all the information available at that time. To the best of our knowledge, this dataset is unique and it has not been employed so far to examine any research questions similar to the ones cover herein.

In Chapter 3, which is the first essay of this thesis, we use the concept of metafrontier in order to relax the technological isolation assumption to allow for inter-industry pure technical spillover effects among three industry specific technologies from the European transportation sector, that is the Air Transport, Land Transport and Water Transport. Moreover, we discern the spillover effects into outgoing (originating from the industry-specific frontiers to the metafrontier) and incoming (originating from the metafrontier to the industry-specific frontiers) so as to be able to study their impact separately by specifying two models to study the drivers affecting the productive performance of the units with respect to the industry specific frontier and the overall technology. An additional contribution also is that we study the time persistent pattern of technological heterogeneity by introducing the path dependence of productive performance (capturing the outgoing spillover effects) and technology gap values (capturing the incoming spillover effects) and the fact that we study these issues through a causality setting offers additional insight to the mechanisms driving productive performance improvement.

In Chapter 4, we partition the metafrontier to study whether the alternative technological hierarchies have emerge in the literature, that is the country frontiers dominated technology hierarchy and the industry frontiers dominated technology hierarchy, affect the probability of being identified as technologically heterogeneous -in production terms- within a group of DMUs. In order to identify the heterogeneous units, we introduce an iterative algorithm based on the relative position and variance of the productive performance of each DMU with respect to the metafrontier, while when a unit hit its threshold it is being identified as exhibiting DMU-specific heterogeneous behavior while at the same time, the present framework allows us to introduce a measure of sensitivity of a DMU’s performance, labeled as Hierarchical Structure Heterogeneity –HSH-, when the latter operates under the two hierarchies we consider, while
when it hits a threshold calculated by a measure of concentration is characterized as HSH. More precisely, we decompose the notion of technological heterogeneity into the heterogeneity attributed to the characteristics attached to the DMU per se (DMU-specific heterogeneity) and into the heterogeneous behavior attributed to the technological structure under which each DMU operates (Hierarchical Structural Heterogeneity) and we aspire to unravel the mechanisms connecting those types of heterogeneity. Issues of time persistence of technological heterogeneity are also examined in conjunction to the initial condition of productive performance volume that is the state dependence. In other words, we investigate the drivers triggering heterogeneous performance under an endogeneity framework as the HSH is endogenously associated with the productive performance of each DMU since both are defined on the same technology sets.

In Chapter 5 we take the advantage of the nested (or clustered) nature of the dataset in order to include the significance of the level of aggregation into the investigation of the drivers affecting heterogeneous performance. To do so, we extended the notion of the metafrontier to that of the meta-metafrontier so as to interpose two additional levels of heterogeneity and since we prove that those intermediate levels exist and are indeed distinct, we depart to study source of spillover effects originating from different levels of aggregation which among the main contributions of the study. Additional contributions are found on the grounds that we integrate into the analysis the role of absorptive capacity (as captured by the global competitiveness index) in conjunction the magnitude of the spillover effects originating from different levels of aggregation. Moreover, we found evidence that the technological heterogeneity is found on lower aggregation levels but it can only be revealed and studied in higher aggregation levels where there is found the maximum amount of heterogeneity among the units under examination. It goes without saying that endogeneity concerns have also been accounted for since higher levels of absorptive capacity can be associated with higher productive performance levels and higher ability to absorb new technical knowledge i.e. spillover effects. To the best of our knowledge no study has taken into consideration the above issues.

Finally, in Chapter 6 we make another contribution, to the field of energy studies this time. Employing another unique dataset compounded for this thesis which concerns countries around the globe, we study under a causality framework the relationship between the productive performance and energy efficiency levels accounting for the moderating effect of alternative competitiveness regimes. That is, we partition the metafrontier with respect to the competitiveness levels to study the drivers of the energy efficiency levels of the Less Competitive and the Competitive group of countries which had not been attempted before. The latter allows
us to focus on the non-linear relationship characterizing the energy efficiency and productive performance which is clear only for the competitive cluster while the lower competitiveness countries seem to exploit the effect of absorptive capacity and spillover effects to catch-up. Furthermore, we incorporate the effect of time persistence of technological heterogeneity framed into a causality setting. This is also a contribution of the present chapter.

1.4 Methodological Strategy at a Glance

The empirical analysis followed in order to answer the research questions raised in this thesis has been developed in two stages. In the first stage, adopting the metafrontier framework (O’Donnell et al., 2008) and employing the variable returns to scale – to account for the size of different units’ production capabilities - input oriented (input contraction) bootstrap version of the Data Envelopment Analysis technique introduced by Simar and Wilson (1999; 2007) - in order to introduce statistical noise to the efficiency scores so as to be able to conduct hypotheses testing - we calculated the technology gap values along with the productive performance scores for each and every Decision Making Unit (DMU) under each production frontier, whether it is a country or an industry frontier, on an annual basis. We also extended the concept of the metafrontier to that of the meta-metafrontier as in Kontolaimou (2014), so as to further partition the overall technology with the ultimate goal to draw inferences regarding the sources of technological heterogeneity and identify whether it nests in lower or in higher levels of aggregation. Furthermore, we used quantities produced by the Data Envelopment Analysis technique in order to calculate the slack-based energy efficiency scores (Hu and Wang, 2006) for the DMUs of two distinct production frontiers based on the $k$-means clustering procedure with respect to their competitiveness level on an annual basis as well.

At the second stage, in order to investigate the causal effects between the productive performance and technology gaps, energy efficiency, absorptive capacity among other quantities of interest, a variety of econometric methodologies such as dynamic panel binary response models with one endogenous regressor (Giles and Murtazashvili, 2013), (System) Generalized Method of Moments (Holtz-Eakin et al., 1988, Arellano and Bond, 1991, Roodman, 2009) and hierarchical models (Hox et al., 2010) with random slopes and coefficients have been employed. As mentioned above, the primary focus of this thesis is the endogenous relation of productive performance, technology gap, energy efficiency since those are defined over the same technology set, however, have a different role to play in the process of unravelling the sources and effects of technological heterogeneity and this is the reason why we relied on methodologies designed to tackle with the challenging issue of endogeneity, pertinent to almost every empirical economic analysis. A detailed and more technical presentation of the methodologies adopted herein along
with the rationale behind this choice, can be found in the respective sections of Chapters 3, 4, 5 and 6 further on.

1.5 Main Findings

The empirical investigation presented in this thesis has led to some coherent results in terms of the behaviour of the key issues examined. Below, we provide a look forward on the most prominent ones before we explicitly address the latter in full detail further on.

First and foremost, the most robust and hard to neglect finding was the significance of the time persistence of productive performance in the context of technological heterogeneity. Put it another way, productive performance, energy efficiency, and technology gap levels are heavily influenced by past levels which highlights the fact that any of the kinds of performance examined exhibit sticky behaviour implying that improvements in performance do not happen instantly or from one year to another. Instead, a considerable amount of time is necessary to accumulate the new knowledge as shown the significance of the absorptive capacity introduced into the analysis.

Another significant finding that came up is the significance of the spillover effect in the improvement of productive performance whether those are incoming, outgoing or running among the entities of the same group. Also, it appears that competitiveness levels affect the absorption of the new technical knowledge produced and disseminated across the production entities with the less competitive entities to be beneficiated more as those appear to catch-up by responding to the developments relatively smoother due to the fact that there is room for further improvements in performance for the underachievers. Spillover effects able to penetrate the thick walls of alternative technological structures and/or competitiveness regimes are translated into improvements in the levels of (productive) performance (or energy efficiency) in a systematic way. Focusing on high performance DMUs and despite the fact that spillovers are responsible for performance improvements up to a certain extent for all the units, a trade-off in the form of non-linear effects is documented for the units exhibiting high competitiveness due to capacity limitations most likely. Even high performance units, need time to adjust their technology and coping mechanisms.

The effects of technological heterogeneity and how it has shaped the European scenery regarding both the industries operating within but also as regards to the countries per se, has also arose in the present analysis. The existence of alternative technological hierarchies provided the following insights. First, technologically heterogeneous behaviour is documented in countries with incomplete market mechanisms and fragmented and deprived industries across Europe and second highlights the importance of the first period that is the state dependence which concerns
the bundle of characteristics a unit embraces in the initial period of the study. These determine its evolution and in conjunction to the stickiness of productive performance determine the future trajectory of the system. Moreover, the initial conditions act as the missing link to understand the way the two hierarchical structures are connected.

Last but not least, moving beyond the causality framework, and since we have disaggregated the level of technological heterogeneity to account for more levels in order to study both the source of heterogeneous behaviour and the significance of the aggregation level, we find evidence that disaggregating the overall technology does not necessarily provides the insights we expected. More precisely, even though the technological disaggregation so as to break down the level of heterogeneity and control for its impact on the performance of the units under examination appears to be possible, it turned out that further disaggregation is not the golden key in the quest of understanding how technological heterogeneity distorts the benchmarking. In contrast, the moral was that technological heterogeneity is addressed in low levels of aggregation where it is hard to be disentangled; its investigation is only possible in production environments embracing as much as heterogeneity possible. That is, in order to draw inferences regarding technological heterogeneous behaviour of the units, the latter should be in full interaction with each other.

1.6 Structure

The present thesis is a compound of seven chapters including this introductory chapter. A brief description of each chapter can be found below.

In Chapter 2, we present, to the most possible and coherent way, the data collection process which was developed in a multi-piece procedure. More precisely, we justify the selection of the particular European countries along with countries of the globe, industries of the Manufacturing and Transportation sector and time window. The matching and harmonization of several and distinct but complementary databases where the variables of interest collected from is also described along with the undertaking of calculating the series for capital from the investments series using the perpetual inventory method, is also described in order to underline the uniqueness of the datasets employed in the analysis developed further on. Moreover, additional data related issues along with some deficiencies regarding the raw data series are also discussed.

In Chapter 3, adopting a metafrontier framework and a second stage System Generalized Method of Moments estimation procedure, the technology isolation assumption is relaxed and the role of technological spillovers and path dependence on the productive performance of Air, Land and Water Transportation industries of seventeen European countries from 1999 through
2006 is explored. The main findings suggest that path dependence is a major determinant of the productive performance of the European Transportation Systems while the technological spillovers are in full operation when the technological advancements are taken into account. Grounded in the empirical results, divergence and clustering processes are sketched out in the productive performance of European transportation systems.

In Chapter 4, partitioning the metafrontier to examine the effect of alternative technological structures on the patterns of heterogeneous behaviour and employing a control function approach with one endogenous regressor, we investigate the factors triggering such behavior using data on seventeen European countries and thirteen industries from manufacturing and transportation from 1999 through 2006. Empirical results suggest that the types of technological heterogeneity examined, that is the Decision Making Unit-specific heterogeneity and the hierarchical structural heterogeneity, are endogenously related via the role of the state dependence while the path dependence phenomenon is a major catalyst for future technological achievements and productivity improvements. Transition economies and fragmented industries exhibit persistent technological heterogeneity regardless of the technological structure adopted since further development is mostly affected by past characteristics of the economic environment implying low subsequent competitiveness.

In Chapter 5, we extend the metafrontier framework to that of the meta-metafrontier to investigate whether or not the decomposition of the overall technology supports the existence of distinct disaggregated hierarchical technologies employing the technology gap ratio to test if the latter are absorbed by the former. We use data on seventeen European Union countries on nine manufacturing and four transportation industries from 1999 through 2006. In the first stage, we partition the overall technology to sector and industry technological structures to introduce more structure to the analysis and calculate the productive performance and technology gap associated to each layer of technological heterogeneity. At the second stage, we gain insight from the estimation of a two level hierarchical model while we use the Generalized Method of Moments estimator to account for the endogeneity issues arose. Results support the existence of distinct sector specific technologies while the drivers of the European technology for this period appear to be the sectors of the transportation industry. Findings also point towards the fact that technological heterogeneity is found on low aggregation levels while is it the catalyst for further improvement at higher aggregation levels. Intermediate levels of technological heterogeneity, yet existed; do not appear to exert any significant influence on the improvement or shed light to the quest for the determinants of heterogeneous patterns of productive performance which are
found to be absorptive capacity levels, pure technical spillover effects and path dependence phenomena.

In Chapter 6, we aspire to unravel the relationship between energy efficiency and productive performance in distinct competitiveness regimes at a global level. The adopted empirical approach employs a unique dataset concerning seventy eight countries from 2002 through 2011. The examined countries are clustered in two groups based on the Global Competitiveness Index while inter-country flows irrespectively of the class membership are allowed. In the first stage, we adopt a slack-based efficiency measure and a metafrontier approach to estimate the energy efficiency, productive performance and technology gaps. Then the Generalized Method of Moments estimator is employed to investigate the endogenous relationship between energy efficiency and productive performance and the role of the implied overall technology as it is conveyed by the level of competitiveness. Empirical results reveal significantly different patterns of productive performance and energy efficiency determinants among the different clusters. Absorptive capacity levels seem to be the golden key to the less competitive countries to improve their energy efficiency while a non-linear relationship of a U-shape for the competitive cluster is identified between the levels of energy efficiency and productive performance. Inter-countries spillover effects in conjunction to the absorptive capacity and group identity do matter. Path dependence phenomenon is present as performance is sticky in nature and is determined by past technological, institutional, regulatory trajectories and decisions from the angle of the policy maker.

Finally, Chapter 7, concludes this thesis by providing the main conclusions drawn, the policy implications and lessons to be learned from the investigation of the research questions examined, the limitations and weaknesses of the analysis and the potential for further research.
References

Arelano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*, 277-297.

David, P. A. (1985). Clio and the Economics of QWERTY. *The American economic review*, 332-337.

David, P.A. (1986). Understanding the economics of QWERTY: the necessity of history. *Economic History and The Modern Economics* eds W.N. Parker. Oxford, Blackwell.

Giles, J., & Murtazashvili, I. (2013). A Control Function Approach to Estimating Dynamic Probit Models with Endogenous Regressors. *Journal of Econometric Methods, 2*(1), 69-87.

Hayami, Y. (1969). Sources of agricultural productivity gap among selected countries. *American Journal of Agricultural Economics, 51*(3), 564-575.

Hayami, Y., & Ruttan, V. W. (1970). Agricultural productivity differences among countries. *The American Economic Review, 895*-911.

Holtz-Eakin, D., Newey, W. and Rosen, H.S. (1988) Estimating Vector Autoregressions with Panel Data. *Econometrica, 56*(6), 1371-1395.

Hox, J. J., Moerbeek, M., & van de Schoot, R. (2010). Multilevel analysis: Techniques and applications. Routledge.

Hu, J. L., & Wang, S. C. (2006). Total-factor energy efficiency of regions in China. *Energy policy, 34*(17), 3206-3217.

Kontolaimou, A. (2014). An efficiency analysis of European banks considering hierarchical technologies. *Applied Economics Letters, 21*(10), 692-696.

O'Donnell, C.J., Rao, P. and Battese, G. (2008) Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics 34*, 231-225.

Roodman, D. (2009) How to xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal, 9*(1), 86-136.

Simar, L., & Wilson, P. W. (1999). Of course we can bootstrap DEA scores! But does it mean anything? Logic trumps wishful thinking. *Journal of Productivity Analysis, 11*(1), 93-97.

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.
Chapter 2 Data Handling

The present chapter is devoted to the description of the data collection process so as to give prominence to the uniqueness of the datasets employed herein. The quality of the data is of great importance to any empirical study to draw credible and robust inferences. Below, we will provide insights regarding the type of the data collected, the sources and nature of the variables employed, the time frame selected along with the obstacles we had to tackle with during the construction of the database.

2.1 Data Design: sectors, industries and countries

It has become apparent from the previous chapter that the main theme this thesis is developed around is the technological heterogeneity and to which extent it distorts the benchmarking process. Therefore, in order to study the effect on technological heterogeneity along with the impact of different technological hierarchies i.e. alternative technological structures, we head to collect data on industries operating under the Manufacturing and Transportation sector within the European context. The choice of the aforementioned sectors was not random, instead, it was intended so as to study the effects of heterogeneous regimes on productive performance on two intrinsically -yet interconnected- technologies. Below, we will present the selected industries of the Manufacturing and Transportation sector along with the European countries compound the dataset.

As far as the industries are concerned, we relied on nine industries of the Manufacturing sector that is Food, Beverages and Tobacco (15 to 16 ISIC), Textiles, Textile, Leather and Footwear (17 to 19 ISIC), Wood and of Wood and Cork Products (20 ISIC), Pulp Paper, Paper, Printing and Publishing (21 to 22 ISIC), Chemical, Ruber, Plastics and Fuel (23 to 25 ISIC), Other Non-Metallic Mineral Products (26 ISIC), Basic Metals and Fabricated Metal (27 to 28 ISIC), Transport Equipment (34 to 35 ISIC) and Construction (41 to 43 ISIC) and on all the industries constituting the Transportation sector that is, Land Transport and Transport via Pipelines (49 ISIC), Water Transport (50 ISIC), Air Transport (51 ISIC) and Warehousing and Supporting and Auxiliary Transport Activities (52 ISIC).

Regarding the countries examined herein, we collected data on seventeen countries participating in the European Union under the technology of which the industries just mentioned operate. In particular, the countries included in the dataset are the following: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Poland, Slovak Republic, Slovenia, Spain, Sweden and the United Kingdom. The above countries and industries are studied for an eight year period from 1999 through 2006. Neither the selection of this particular period was unintentional. The aim was to collect data...
from one year prior to the millennium to study the evolution of technological achievements within Europe as more countries were becoming part of the European community and how the latter had been disseminated and embodied to the selected industries up until to the year the present analysis begun (2012). The diminution took place eventually, is attributed to two interconnected facts. First and foremost, one of the side effects of the financial depression diffused in Europe from August 2007 onwards, made the updating of the data on the respective databases a hard task for the authorities despite their remarkable efforts to provide the research institutions with accurate and credible data series. Secondly, in conjunction to the difficulty in maintaining the databases up to date, some data deficiencies were already existed. Taking these facts under serious consideration along with our priority to include as robust data as possible, we responded to that trade-off by narrowing the time window along with the set of the countries and industries included.

Moreover, the enquiry why more countries within Europe, more industries and years were not considered, given the above, emerges quite fluently. At the time of the data collection, matching databases and selection of units to be included in the final database, we had to deal with a rather divisive trade-off. The competing features of that trade-off were on the one hand the inclusion of more countries of the European Union and more industries for more years with severely incomplete and inconsistent data series while one the other, pursuing such a path we need to confront that issue by creating data which was undesirable not to mention that it was not the our purpose. All in all, we decided to include less countries and industries for a smaller time period but with consistent information and more reliable reported rather than manufactured data points. This is what would make the conclusions of this thesis more reliable according to our perspective.

Last but not least, the construction of the second unique dataset analysed herein, was guided by a differentiated perspective compared to the one just described. The first database’s intention was to shed light at the heterogeneous production mechanisms of industries and countries in conjunction to the source of the driving forces of productive performance improvement within the European context in order to provide insights regarding the situation during the years prior to the economic recession. In contrast, the rationale of the second database was to increase the aggregation level by focusing only on country-level analysis while at the same time aspiring to study the role of heterogeneous technologies from a global perspective. By this contrast, we aim at providing a broader view of the effects of technologically heterogeneous regimes on the productive performance of the countries under examination not only at a European level –which to some extent one could argue that it might exhibit limited
heterogeneity due to the Union’s setting- but at a global one to account for as much heterogeneity as possible.

2.2 Data sources, variables and coverage

In order to perform an efficiency analysis to evaluate the relative productive performance of the units under examination, given technology, we need to have data on inputs and outputs. Throughout this thesis, we followed a single output and multi-inputs analysis. More precisely, Chapters 3, 4 and 6 share the same dataset while for Chapter 5 an additional database using a different aggregation level was devised.

Regarding the former database, the gross value added of each industry in each and every country was considered as the output while the set of inputs was comprised by the total hours worked by employees as a proxy for labour, the energy consumption of each industry in each and every country as a proxy for energy usage, the intermediate inputs as a proxy to other inputs included in the production process affecting the output and the gross fixed capital formation of each industry in each and every country as a proxy to the investment. In other words, this unique database has been comprised by combining district but complementary databases. It should be mentioned that in order to compound the final database, several distinct and complementary specialized databases should be matched and harmonized. More precisely, data on gross value added, total hours worked by employees and intermediate inputs were collected through the Groningen Growth and Development Centre (GGDC) database, energy consumption series was collected through the Enerdara-Odyssey database while data on the global competitiveness index was collected from various annual reports of the World Economic Forum. An additional challenge we had to cope with was that during the collection of data, was related to the series on gross fixed capital formation via the Structural Analysis database integrated at the database of the Organization of Economic Cooperation and Development, where many more deficiencies regarding the series were addressed. Potentially, this could act as an interception in devising a dataset forcing us to reduce the dimension of the panel to size not sufficient enough. To overcome this difficulty, we matched and harmonized the missing data on the series of gross fixed capital formation provided by the Structural Analysis database to those contained in the capital input files provided by the EU KLEMS Growth and Productivity Accounts\(^2\) (ISIC Rev. 3, Release 2009) keeping track with the two-digit industries. More precisely, we relied on the nominal gross fixed capital formation for the Computing equipment and Communications equipment files which acted as complements for the cases where missing data were observed. In rare cases, data were available only for sub-sectors of the selected ones, so in order to summation

\(^2\)Austria, Czech Republic, Denmark, Finland, Germany, Italy, Netherlands, Slovenia, Spain, Sweden and the United Kingdom.
was needed to get the value for the principal sector. Since we aspire to study the productive performance of industries operating under the technology of manufacturing and transportation sectors’, we considered capital the most basic input to the production process and as such, our main priority was to interfere into the reported data as less as possible to get the best approximation to reality possible. Needless to say it was a demanding task but we managed to cover all the vacancies matching the above databases with officially reported data, eventually.

It should be mentioned that gross fixed capital formation is a major block of the capital used in the production function. This brings to the forefront the most severe obstacle in every empirical study within the field of efficiency and productivity analysis which is the lack thereof of a consistent series for the capital stock. In other words, the databases, do not provide data on capital itself, at an industry level, but only data on gross fixed capital formation which can be used to calculate the capital series. In this line, the most used method in efficiency analysis is the Perpetual Inventory Method (PIM), which as its name declares is based upon the inventories which in our case are proxied by the gross fixed capital formation. According to the PIM, the following formula is used to calculate the series for the capital of the current period:

\[ K_{i,t} = (1 - \delta)K_{i,t-1} + I_{i,t}, \quad (2.1) \]

where \( K_{i,t} \) is the capital series we aspire to calculate and corresponds to each period, \( K_{i,t-1} \) is the capital of the previous period, \( \delta \) is the depreciation factor while \( I_{i,t} \) is the gross fixed capital formation which as already mentioned is the proxy for the investments series. At this point we have to address two additional issues surrounding the calculation of capital. The first one concerns the choice of the value for the depreciation factor. It is commonly accepted that different production activities have different technological idiosyncrasies, characteristics, equipment requirements etc. Therefore, each case should be treated accordingly, namely, a different depreciation factor should be picked for different production activities. Indeed, at first, different depreciation factors were chosen (3.5%, 5%, 8%, 10%) but the resulting differences were insignificant and eventually in order to suppress the technical confusion the final rate was decided to be 10% which is the most used rate in capital calculation without distorting the actual series. The second point we need to address is the calculation of the initial period for the capital series. In order to calculate the capital for the initial period, we moved five years back, by solving the equation 2.1 backwards, which is found to be given by the following formula:

\[ K_{1999} = \frac{I_{1999}}{\delta + g} \quad (2.2) \]
where $g$ is estimated as the average growth rate in gross fixed capital formation-investments for the preceding five years for each of the examined industries and countries. More precisely, data on gross fixed capital formation was collected from 1995, opposed to any other variable in the database, so as to calculate the growth rate of investments for the past five years to value of capital for the initial period that is 1999. Needless to mention that along with the gross fixed capital formation, the series for the industry specific deflators was extended to cover the period from 1995 through 1998 so as to calculate the growth rate of the investments using the real values instead of the nominal ones also using 2000 as the base year. The past five-year period is considered as a descent time period to affect current value of capital. That said, we also have to mention that the dimension of the final database, that is the selection upon countries, industries and years, was also determined by the data availability on the gross fixed capital formation.

Another peculiarity of the variables collected is the fact that Czech Republic, Denmark, Poland, Slovak Republic, Slovenia, Sweden and the United Kingdom that is seven out of the seventeen European countries, considered report the monetary variables in national currency and in euros for the whole period of study. At the same group, we also find Greece for 1999 and 2000 where the reported values were in drachmas, the national currency before the adoption of Euro. That complicated things up since we had to follow a different route to harmonize the values provided with the rest of the database. First, we had to collect the respective exchange rates from 1999 (1995 for the case of the gross fixed capital formation) through 2006 provided by the European Commission (Directorate General- DG- for Budget) to express the local currency in Euros and then to deflate the values using the specific deflators we had already collected, to convert the nominal into real values.

Moreover, data on the Global Competitiveness Index, which is a country and year varying measure provided by the World Economic Forum on an annual basis consisting of twelve pillars\(^3\), is not available through a database, therefore, we had to collect the values by the annual reports of the Forum, for all the countries and years of the database. Data on energy consumption by industry and country were collected through the Enerdata-Odyssey database.

As far as the database used for the analysis presented in Chapter 6 of the thesis at hand, it is comprised by different variables. More precisely, the database comprises of seventy eight countries around the globe for a decade that is from 2002 through 2011. In this case, a single output multi-outputs approach was adopted to calculate the relative productive performance of the examined units. The output is captured by the Gross Domestic Product measured in millions

\(^3\) Institutions, Infrastructure, Macroeconomic Environment, Health and Primary Education, Higher Education and Training, Goods Market Efficiency, Labor Market Efficiency, Financial Market Development, Technological Readiness, Market Size, Business Sophistication and Innovation.
United States dollars in constant 2005 prices provided by the Groningen Growth and Development Centre while the input set consists of the Labour input as captured by millions of persons engaged, the Capital input as captured by the capital stock in millions of United states dollars both collected through the database of Groningen Growth and Development Centre. The input set also contains the Energy input as captured by the Energy use measured in kilo tons of oil equivalent collected through the International Energy Agency. Also, data on carbon dioxide emissions, measured in kilo tons of oil equivalent, were also drawn from the International Energy Agency. In addition, the Global Competitiveness index was also included in the database, and consequently it narrowed down the total number of the countries and years covered.

2.3 Missing values

Although the database was built upon the idea of reducing the missing values, unfortunately, this is something that every empirical study has to deal with. In our case, we treated the missing values with great caution so as to achieve the best possible approximation to the real values. Different statistical and mathematical methods were applied so as to fill the missing values in the series examined. The first attempt, and the preferred strategy, was to use a simple linear model to predict the missing values ahead in the series because we were handling economic variables which are affected by unobserved random shocks included in the disturbance term. In such case, the predicted value was only included in the dataset if and only if the prediction was statistically significant. In case it was not the case or there were not sufficient points available (e.g. the missing value was that of the third period), the value was interpolated. In some cases, neither of the aforementioned methods produced a reasonable outcome then the last resort was the moving average technique, using as inputs the values of the previous time periods.

Apart from the missing values in the time series of the collected variables, we had to cope with those at the series of the deflators employed to convert the nominal values into real ones using the year 2000 as the base year which is was selected as the starting year of the millennium. In order to get the real values of the monetary variables we collected country and industry specific deflators as already mentioned. In this case the missing values were treated in a rather different way. The industries selected were 2-digit level industries according to the International Standard Industrial Classification (ISIC) and so were the corresponding deflators. In cases, the series of the deflators were either incomplete or not available by the database. In such cases, the strategy was as follows. Due to insignificant differences in the deflators between the sub-industries of the principal industries, we filled the series with the former. More precisely, suppose
a two-level industry, according to the ISIC, that does not have a value for the deflator of the year 2003. In this case, in order to fill the entry, we kept constant the identity of the industry but we used the deflator of the three-level sub-industry to get the most representative value possible. The main priority was to stay in the particular industry by all means using the information provided by the less aggregated level. In contrast to the above methods in filling the voids in the series, this was the main strategy adopted for the case of the deflators with all the possible variants of the procedure applied.

At this point, we need to mention that the missing values of the final database were no more than 5% of the resulting panel points, so the credibility of the database is not compromised or doubted.
References

Enerdata. http://www.enerdata.net/ (accessed on 25.02.2013).

EU-KLEMS Growth and Productivity Accounts. http://www.euklems.net/ (accessed on 02.03.2013)

European Commission, Financial Programming and Budget Directorate. http://ec.europa.eu/budg…infoeuro_en.cfm (accessed on 12.03.2013)

Groningen Growth and Developing Centre, GGDC Productivity Level Database. http://www.rug.nl/research/ggdc/data/ggdc-productivity-level-database (accessed on 08.03.2013)

International Energy Agency, IEA Statistics. http://www.iea.org/ (accessed on 08.03.2013).

Organization for Economic Cooperation and Development, Structural Analysis Database. http://www.oecd.org/industry/ind/stanstructuralanalysisdatabase.htm (accessed on 08.03.2013)
Chapter 3 Spillovers, Path Dependence and the Productive Performance of European Transportation sectors in the presence of Technology Heterogeneity*

* A revised version of this chapter has been published to the Technological Forecasting and Social Change co-authored with Tsekouras, K., Kounetas, K., and Broadstock, D.

3.1 Introduction

Technology homogeneity has always been a very crucial precondition in efficiency and productivity analysis and the transportation sector is not an exception. Engineers, economists, operational researchers, and scholars from the management disciplines who have been engaged in this line of research are always very cautious to ensure that Decision Making Units (DMUs) are benchmarked against rivals who employ almost identical production technology. Although technology homogeneity is not a very clear situation, since “heterogeneity of several types is everywhere” (O’Donnell et al., 2008, Dosi et al., 2010), the urge to ensure as much technology homogeneity as possible, may result in a peculiar type of “technological isolation” of the examined DMUs. Technological isolation may be defined as the situation where even close neighbouring, in technological terms, production units are considered as completely distinct and no technological flows, the so-called technological spillovers, between them are taken into account. In the case where technological isolation is not imposed during productive efficiency analysis -and hence technological spillovers are allowed to exist- the role of General Purpose Technologies, technological modularity, lumpiness and non-irreversibility, idiosyncrasies, absorptive capacity and network effects may be explored (Syverson, 2011). On the other hand, previous studies which acknowledge the existence of technological inter-linkages and inter-industry flows focus either on specific types of flows which may arise from R&D activities (Cainelli and Iacobucci, 2012, Del Bo, 2013), or those which are closely attached to factors related to the spatial or cognitive distance distribution of production entities, as the different types of variety (e.g. Frenken et al., 2007; Del Bo, 2013) or breadth and relatedness of technological linkages associated to international trade.

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4 Tsekouras, K., Chatzistamoulou, N., Kounetas, K., & Broadstock, D. C. (2016). Spillovers, path dependence and the productive performance of European Transportation sectors in the presence of technology heterogeneity. Technological Forecasting and Social Change, 102, 261-274.
(Boschma and Iammarino, 2009). None of these studies however explicitly consider the possible bidirectional nature of effects, distinguishing between the source and the target of technological and knowledge flows.

A decade ago, Battese et al., (2004) introduced the notion of the metafrontier, which allows technological heterogeneity to be incorporated in productive efficiency analysis and therefore relax restrictive technological isolation conditions. In the framework of technological heterogeneity any positive influence of technological spillovers onto productive performance may be completely eliminated, if the production units are locked-in, or in other words, if they exhibit path dependence of the evolution of their productive performance. Regarding path dependence, the major arguments are that the accumulated competencies, capabilities and irreversible structures, more or less the full operational process of a firm as well as a number of contingent and localized conditions that exert significant effects on the non-ergodic dynamics of the process and change its path, its speed and its duration (Antonelli, 2008). Although within the evolutionary economics strand, the path dependence phenomenon is a cornerstone of the investigation of productive performance (David, 1993, 2001), the interdependence between neighbouring technologies is a rather neglected issue.

In this chapter we introduce a theoretical and methodological framework which allows the co-examination of (i) technology heterogeneity, (ii) any inter-linkages and flows between the heterogeneous technologies, incorporating a plethora of differentials, observed or not as well as the multidirectional nature of such kind of flows and (iii) the path dependence of productive performance. This analytical framework is applied to three European transportation sub-sectors revealing interesting patterns of productive performance which have not been traced by previous seminal papers on transportation efficiency (Brons et al., 2005).

The European Commission has during the last 25 years or so, actively established a number of initiatives/bodies aimed directly at fostering Europe-wide transport sector integration and development. In 2011 a White Paper was released by the European Commission (2011) setting out a roadmap towards a ‘single European transport area’ by 2020, one which has the underpinnings of a ‘competitive and resource-efficient transport system’. In this line, the issues of technological spillovers and path dependence are of primary importance in the case of European Transportation Sector, where policies are

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5 Indicatively one could mention the Trans-European Transport Network initiative (TEN-T) adopted in 1996 and the Innovation & Networks Executive Agency (INEA) established by the European Commission in 2014.
increasingly aimed at supporting EU wide convergence/cohesion in the transport sectors across the European members States.

In this chapter we distinguish between Air, Land and Water Transportation Systems, contrary to previous studies which focus only on niches of these transportation systems, we allow for spillover effects among these industry-specific technologies while at the same time we test for path dependent regimes of their productive efficiency. Relationships between the efficiency of transportation-industry specific frontiers and a unified transportation meta-frontier, enveloping them all together, can be a conceptually challenging notion.

The productive capacity and efficiency of all parts of the transport industry embed a much wider range of attributes and characteristics which lay behind how they are used. These may include General Purpose Technologies, with IT infrastructures being the most prominent, quality of human resources which are pumped from the same labor markets, safety and environmental regulations, financial schemes, managerial competencies and capabilities, operational procedures, institutions, etc. All of these may be considered as nodes of the transportation system network and links of the corresponding value chain. As a result, severe questions are posed on the validity of the technological isolation hypothesis in the transportation sector case. Subsequently, the necessity to evaluate the performance of transportation systems in a technology heterogeneity framework becomes apparent. On the other hand, given the heavy infrastructure requirements of transport industries, path dependencies may arise due to slow adjustments and therefore narrow the influence of the any spillovers. Arguably path dependency is more likely to exist in transport than many other sectors due to the heavy infrastructure.

In this chapter we employ a unique panel dataset for the Air, Land and Water transportation industries from seventeen European countries covering the period from 1999 to 2006. A two stage analysis is followed. In the first stage we estimate -employing bootstrapped Data Envelopment Analysis (DEA)- the productive efficiency both with respect to transportation industry-specific technologies and the European transportation metatechnology. In the second stage, we employ the system Generalized Methods of Moments (GMM) procedure in order to test for technological spillovers between the three industry-specific transport technologies, the European transportation metatechnology, and simultaneously for the influence of any path dependence regime on the productive performance of the European transportation industries. An additional feature of our approach is that we distinguish the spillover effects in to two types: ‘outgoing’, which are those generated from the individual frontiers moving towards the European transportation metatechnology and form the localized technical change; and
‘incoming’ ones, which represent the technological advancements generated from the best practices in the metatechnology being diffused towards the individual frontiers. Moreover, tracing technological spillovers and path dependence of European transport industries allows the sketching of “catching up” or “falling behind” phenomena, and the identification of their drivers, within and between transportation technologies in terms of performance.

The chapter is ordered as follows: The Section 3.2 discusses related literature; Section 3.3 outlines the theoretical and methodological framework introduced and applied in this chapter, Section 3.4 presents the data; Results and discussion are given in Section 3.5 while Section 3.6 concludes the chapter.

3.2 Review of the Literature

Efficiency analysis is a widely used tool in transport. Regulators and other transport network analysts use efficiency analysis tools most often for the purpose of benchmarking the operational cost efficiency of public transport operators (see for example Holvad et al., 2004; Farsi et al., 2005; Margari et al., 2007 among others), with a view to providing information relevant to passenger fare-setting decisions. Brons et al., (2005) conducted a meta-analysis reviewing a large number of efficiency studies prior to 2005, highlighting among other things that two thirds of studies focused on productive efficiency, rather than their dual problem of cost efficiency. Their meta-analysis includes only 30 studies, suggesting the area has attracted reasonable levels of research attention, but there probably remain opportunities to further contribute to our understanding.

The existing studies have generally evaluated productive efficiency for a specific mode of transport such as: water/sea ports (Cullianane et al., 2005, 2006; Gonzales and Trujillo, 2009; Odeck and Brathen, 2012; Baired and Rother, 2013), urban transit systems (Holvad et al., 2004; Garcia-Sanchez, 2009; Pinna and Torres, 2001; Margari et al., 2007; Roy and Yvandre-Billon, 2007; Karlaftis and Tsamboulas, 2012); airports (Adler and Golany, 2001; Martin and Roman, 2001; Merkert and O’Fee, 2013); or railways (Cantos and Maudos, 2001; Growitsch and Wetzel, 2009). The technological isolation assumption has been adopted, explicitly or implicitly, by all of the abovementioned studies which focus on specific segments (modes/niches) of the transportation industry and do not attempt to account for any interaction between transportation technologies or for possible path dependence regimes.

There is a smaller number of studies considering more than one area of the transportation industry at the same time, such as that of Koroneos and Nanaki (2008)
who conduct an energy/exergy efficiency analysis of the Greek highway, railway, marine and civil aviation sectors, indicating that road transport is the most efficient. In the same line, Krautzberger and Wetzel (2012) jointly consider productivity growth along with environmental protection targets for four subsectors of the transportation industry (Land, Water, Air transport and also Supporting and auxiliary activities) for the EU-27 and Norway for the period 1995-2006. However, neither of these studies take a clear account of the potential inter-industry spillovers from one transport sector to another, nor examining the path dependence of their productive performance. Unlike the previous studies, Del Bo (2013) argues about the intra- (horizontal) and inter- (vertical) industry spillovers which are reinforced by foreign direct investment effects but without considering the role of technology gap. Additional developments focus on the sources of inefficiency in transportation activities (Albalate and Bel, 2010) and on the role of incomplete contracts.

The quantitative tools used to model efficiency historically are either parametric, such as Stochastic Frontier Analysis (SFA) or non-parametric via the Data Envelopment Analysis (DEA) technique. Brons et al., (2005) offer a broad overview of the methodologies in efficiency analysis while Karlaftis and Tsamboulas (2012) using a wide range of methodologies (DEA, SFA, neural networks) conclude that efficiency scores may be affected by the methodology used. DEA places an exact envelope around a set of data points, but does not parameterize the production function per se, which in some cases is of interest in its own right. Stochastic frontier models on the other hand, offer the advantage of explicitly parameterizing the production function allowing at the same time for idiosyncratic error to exist. In cases of technology heterogeneity SFA may be rather problematic since a common functional form is assumed to hold for any one of the heterogeneous production units. It is worthwhile to mention one of the developments within the DEA strand of literature in recent years due to Simar and Wilson (1998, 2000, 2007), who introduced the bootstrapped version of DEA. This methodological advancement offered a way to handle adequately the white noise and inference problems associated with this linear-programming based technique.

Battese et al., (2004) and O’ Donnell et al., (2008) brought to the fore the metafrontier framework for efficiency analysis. In the concept of metafrontier, and given three groups of heterogeneous production units e.g. Air, Land and Water Transport industries, a frontier will exist for each group, but in addition there will be a metafrontier, which is a separate frontier that envelopes each of the individual group frontiers.
By its definition, the meta-frontier encapsulates the separate frontiers and creates the appropriability conditions for the exploitation of any spillover effects among the decision making units in the case of non-convex technologies (Battese et al., 2004, O’Donnell et al., 2008).

There is a burgeoning and growing literature surrounding the issue of spillover effects and its multiple dimensions, since spillovers are relevant to a wide variety of disciplines including regional economists, evolutionary economic geographers, innovation and/or industrial economists among others. These disciplines have rather differentiated viewpoints regarding the mechanisms of inter-industry spillovers. Regional economists and economic geographers have dedicated much effort on the concepts of related and unrelated variety, linking the former to the idea of technological-relatedness and the latter to the degree of industry variety (Cainelli and Iacobucci, 2012). In addition to the promising field of spatial growth analysis, the cognitive approach has been introduced which brings to the fore the regional (or industry in some cases) receptivity of the achievements generated at a higher level so as to enhance the productivity of a DMU (Capello, 2009). Moreover, special attention has been devoted to the vertical integration of industries and their relationship to the technological relatedness (e.g. Cainelli and Iacobucci, 2009) while two significant studies by Anselin et al., (1997; 2000) tried to shed some light, taking into account an aggregate perspective, on local geographical spillovers generated by universities research and high technology innovation. Although this strand of research challenges the technological isolation assumption it does not seem to internalize its full potential, since it does not account for/differentiate among the whole spectrum of technological and knowledge spillovers that may be present.

Moreover and beyond the transportation sector, regarding the inter-industry technological spillovers, Bernstein (1988), Gifford and Garrison (1993), Nadiri (1993) and Verspagen and De Loo (1999) among others, discuss the potential flows which can occur not just within an industry but also across different industries. The underlying rationale, suggests that technologies, processes, regulations and legislations adopted or developed in one industry may be able to carry over to another with little or maybe even no significant modifications. Thus, if one is able to account for the technological heterogeneity among the individual modes of transport (e.g. Air, Land and Water) and consider the characteristics of the transportation sector in a broader perspective, then the opportunities for technological spillovers are not only a feasible possibility, but are intuitively likely in reality. In this direction one could argue that the physical and
operational technologies in each of the transport sectors derive often from common components but put together in differing ways. Moreover, Fai and von Tunzelmann (2001) pay particular attention to the notion of technological convergence that may arise when spillovers are possible.

Along these lines, there exist attempts to quantify and measure the amount of knowledge that is spread from one sector to another in the form of spillover effects, which as discussed above include the important contributions of Bernstein (1988), Nadiri (1993) and Verspagen and De Loo (1999). The findings indicate that the trade and transportation sector was one of the engines of growth for the U.S economy for more than four decades (Quella, 2009). Keller (2004) argues that small and poor countries are more likely to exploit technology diffusion compared to bigger and richer ones, while R&D investments and international openness could explain to some extent their accomplishments.

Some scholars have presented the idea that productive efficiency can be considered as a learning and dynamic process of accumulated competencies and capabilities (Dutta et al., 2005). The majority of them treat efficiency in a temporal manner that fluctuates only as a function of time, but so far the literature lacks a systematic attempt to quantify how the past accumulated competencies and capabilities are being projected on to current efficiency performance. To this direction, one should account for the path dependence of efficiency i.e. to what extent productive performance of previous periods has an impact on the current performance. Path dependence and its significance have been acknowledged long ago in the pioneering works of David (1985, 1986). The notion and significance of path dependence primarily concerns the impact of past decisions, states, choices not only on the current but also on the future path, though there are studies that move beyond this definition and try to further disentangle the notion into more specific areas such as state or path dependence where the attention is focused on the events themselves and not their order (Page, 2006). More precisely, path dependence is considered as a causal relationship within a system in which the current values are associated with past ones and together affect the future ones and is a view widely supported by empirical observation (Kasy, 2011). Similarly, Martin and Sunley (2006), highlight the fact that path dependence is “a probabilistic and contingent process” where future paths or technologies are based upon the current and past states of the system at hand. If we also consider productive efficiency as a dynamic notion, then the
concept of path dependence could be easily extended to technological trajectories which will inevitably lead to technological full or partial “lock-in” (i.e. Heinrich, 2014).

From the above review, it is apparent that modelling the productive efficiency of European transport industries under a meta-frontier framework allows for the relaxation of the technological isolation assumption and therefore it becomes possible to shed light on the path dependence of productive efficiency, inter-industry spillover effects emanating both from the industry specific technology and the overall technological advancements of the European transportation sector. The next section outlines a two-stage empirical procedure which will first model the productive efficiency scores and technology gap values of the European transport industries, and in the second stage will explicitly model the existence and nature of path dependence and hence technological lock-in effects.

Inarguably, there is a plethora of ways to assess the influence of spillovers in the existing literature but so far none of them has attempted to assess the spillovers emanating by the productive performance of the industries per se and integrate to the analysis the process of path dependence and here lies one of the contributions of this thesis.

3.3 Theory, Tested Hypotheses and Modelling Issues

We discern three transportation technologies, namely Air (AT), Land (LT) and Water (WT) which correspond to three distinct productive frontiers. Each one of these frontiers envelops the corresponding transportation technologies of the seventeen European countries. In the framework of $k$ frontiers ($k=AT, LT, WT$) a transportation industry of each country employs a vector of inputs $x \in {\mathbb{R}}^n$ to produce a vector of outputs $y \in {\mathbb{R}}^m$. The production possibility set is given as $S = \{(x,y): x \text{ can produce } y\} \subseteq {\mathbb{R}}^{n+m}$ with the input set, which is defined as $L(y) = \{x \in {\mathbb{R}}^n : (x,y) \in S\}$. The input-oriented efficiency associated with $S$ can be measured with respect to the input set through the direct input distance function $D_1(x,y) = \sup \{\theta > 0 : x \theta \in L(y)\}$. Thus the productive efficiency for a given transportation industry $(x, y)$ in each one of the examined European countries is given as in Equation 3.1 below:
In the case where multiple technologies are possible, each transportation industry is considered as operating under exactly one of those. The assumption of technological isolation is imposed for each one of the three transportation frontiers. Although technological flows are permitted vertically, or within, each one of the examined transportation technologies, no interactions may take place between, or horizontally, across the three transportation frontiers. Technological isolation is grounded on complete heterogeneity. Such being the case the definition of the European Transportation Sector, as a synthesis of AT, LT and WT makes no sense.

Relaxing the hypothesis of technological isolation, the notion of the metafrontier comes into play. Given the three transportation technologies \( T^{AT}, T^{LT}, T^{WT} \), the metatechnology set, denoted as \( T^M \), can be defined as the convex hull of the jointure of all technology sets represented as \( T^M = \{ (x, y : x \geq 0, y \geq 0, \ x \ can \ produce \ y \ in \ at \ least \ one \ of \ T^{AT}, T^{LT}, T^{WT} \} \) (Battese et al., 2004) - i.e. a global frontier that envelopes each of the three individual transportation frontiers. The input set \( I^M (x) \) associated with the metatechnology is defined in the same way as for a single technology, while the corresponding efficiency of each industry with respect to homogeneous boundary for all heterogeneous industries can be measured by the input-oriented metatechnical efficiency score \( MTEff_i \) and is easily obtained by solving an analogous LP problem as in Equation 3.1 above.

Thus, the metafrontier framework (Hayami and Ruttan 1970; Battese and Rao, 2002; Battese et al., 2004; O’Donnell et al., 2008) adopted in this analysis, is intended to account for all the possible heterogeneity in the production technology among the individual frontiers and compare them to an available state of technology-knowledge by calculating not only the efficiency scores of each DMU but the technology gap of each group frontier relative to the meta-technology (metafrontier). In the framework of productive efficiency analysis under technology heterogeneity, many studies consider that the latter has been attributed to environmental factors (i.e. size, ownership scheme, classification, regulation, staff education) which affect the efficiency of the units under
examination (i.e. Matawie and Assaf 2008, Assaf et. al., 2012). Such factors are considered as exogenous, influencing the performance in a broader sense and not exclusively the technology. In a series of papers based on the definition of the metafrontier (as an envelope of the individual group frontiers) such heterogeneity may exist due to differences in the available resource endowments, economic infrastructure (O’Donnell et al., 2008), and other characteristics of the physical, social and economic environment in which production takes place (O’Donnell et al., 2008; Kontolaimou et al., 2012; Kounetas, 2015). Moreover, additional sources of heterogeneity can be attributed to the structure of national markets, national regulations, legal and institutional frameworks and even cultural profiles (Halkos and Tzeremes, 2011; Kontolaimou and Tsekouras, 2010) and diverse managerial schemes (Wang et al., 2013). Finally, technological heterogeneity may also be dependent on characteristics related the capacity, to absorbed knowledge, the core competences and the development of dynamic capabilities (Cohen and Levinthal, 1989; Kontolaimou and Tsekouras, 2010).

Each productive efficiency score obtained from the estimation with respect to the common technology can be used to define the so-called metatechnology ratio $MTR_{ik}$ which is considered as a measure of proximity of the $k$-th group individual frontier to its metafrontier. For a given point $(x, y)$, the latter could be defined as in Equation 3.2 below:

$$MTR_{ik}(x, y) = \frac{MTE_{ik}(x, y)}{E_{ik}(x, y)}$$

(3.2)

$MTR_{ik}(x, y)$ depicts the ratio of the minimum inputs attained by a DMU employing the superior metatechnology to the minimum inputs used by the group technology to produce a given level of outputs. Taking advantage of the $MTR_{ik}$ notion, the technology gap $T_{g_{ik}}$ of the $i$-th DMU in the $k$-th group frontier is defined as the distance of the group frontier to the metafrontier, weighted with the minimum inputs which are attainable employing the group-specific technology that is Equation 3.3 below:

$$T_{g_{ik}}(x, y) = 1 - MTR_{ik}(x, y)$$

(3.3)

For a DMU exhibiting a $T_{g_{ik}}$ value equal to zero, it is evident that the group frontier, at the input level of the specific DMU, is tangent to the metafrontier and thus
no efficiency losses are due to inferiority of the group technology compared to the metatechnology. However productive inefficiency with respect to the group frontier is still a possible situation.

In handling the technological heterogeneity, one should acknowledge that bidirectional technological flows may exist between the metatechnology and the three industry-specific transportation technologies. Considering the industry specific technology from the one hand and the European metatechnology from the other, two kinds of spillover effects could be identified; the 'outgoing' and the 'incoming' ones. More specifically, the former concerns the flow from the industry-specific technology towards the European Transportation metatechnology while the latter encapsulates the flows that are directed from the European Transportation Metatechnology towards the transportation industry-specific technologies. Simple but informative illustrations of the two types of spillovers are presented in Figure 3.1 below.

Figure 3.1 Meta-frontier, individual frontiers, Incoming and Outgoing Spillovers for the single output-single input case

\[
E_{\text{eff*}}(x, y) = \frac{BD}{AD}, \quad MTE_{\text{eff*}}(x, y) = \frac{CD}{AD}, \quad Tg_{\Phi}(x, y) = BC
\]
Therefore, it is quite reasonable to assume that this technological interdependence affects the productive performance both with respect to the industry frontiers, as well as with respect to the metafrontier. Along this line, we argue that the Transportation Sector Metafrontier depicts a production possibilities set where transportation technology idiosyncrasies and lumpiness (Cooper et al., 2006), appropriability conditions (Winter, 2006), absorptive capacity (Cohen and Levinthal, 1990), and localized technical change\(^6\) (Atkinson and Stiglitz, 1969; Acemoglu, 2014), are not significant. Such being the case, incoming spillovers influence the productive performance with respect to the industry specific technology. This gives rise to the following hypothesis which will be tested within the additional econometric specification discussed further below:

\[
H_1: \text{Productive performance with respect to the overall transportation technology } \left(T_{g_{i,t-1,k}}\right) \text{exerts an influence over productive performance with respect to the transportation industry specific frontier } \left(Eff_{i,t-1,k}\right). \text{ Incoming spillovers from the transportation metatechnology to the transportation industry-specific technologies are significant in the case of European countries.}
\]

If the above hypothesis holds, the role of General Purpose Technologies (Jovanovic and Rousseau, 2005), innovation openness (Cassiman and Veugelers, 2006; van Zuylen and Weber, 2002) and technological modularity (Fixson, 2007) are dominant, and the metatechnology proves to be a crucial node of the transportation production system. Following the above rationale, it equally stands to reason that technology flows of the outgoing spillovers type might also exist and which would exert influence on the productive performance with respect to the European transportation metatechnology. The following testable hypothesis can be put forward:

\[
H_2: \text{Productive performance with respect to the transportation industry specific frontier } \left(Eff_{i,t-1,k}\right) \text{exerts an influence over productive performance with respect to the overall transportation technology } \left(T_{g_{i,t-1,k}}\right). \text{ Outgoing spillovers from industry specific technology to the transportation metatechnology are significant in the case of European countries.}
\]

\(^6\)In this chapter the term “localized technical change” is employed following the definition of Atkinson and Stiglitz (1969) and the recent further elaboration of the same term by Acemoglu (2014). Antonelli (2001, p. 47-52) although focuses on the spatial dimension of the “localized technical change”, which is not the primary case of interest here, he acknowledges the industrial roots of the “localized technical change” mentioning as primary sources the learning by doing and learning by using processes. We owe this clarification to an anonymous referee’s comment.
The introduction of a testable framework for bidirectional spillovers in the analysis of productive performance of the European transportation industries allows for illustration of the existing spillover possibilities that may potentially be exploited. In this direction it is questionable if all of the European transportation technologies are equally benefited from the technological flows between the industry-specific technologies and the metatechnology. A first indication is that in a plethora of cases where productive performance has been investigated, strong time persistence and therefore performance dispersion and volatility has been found. Time persistence of productive performance or “path dependence” or “lock-in” does not cancel out the significance of outgoing and incoming spillovers, but affects the allocation of the benefits that the spillovers convey. This is to say that the potential for spillovers is very likely to differ across industries, and over time.

Subsequently “catching-up” or “falling behind” phenomena may be generated/explored through the path dependence processes. In addition, we should note that time persistence in productive performance is path dependent rather than past dependent: irreversibility shapes the process together with a number of contingent and localized conditions that exert significant effects on the non-ergodic dynamics of the process and change its path, its speed and its duration (David, 2007; Antonelli, 2008). In this line two additional testable hypotheses, related to path dependence of the productive performance, both with respect to the European transportation metatechnology and the industry-specific technology, could be formulated:

**H₃:** The Technology gap \( \left( T_{\text{g}_{i,t,k}} \right) \) exhibits path dependence patterns. The already developed competencies and capabilities affect current distance from the metatechnology.

**H₄:** Productive performance under technology isolation conditions \( \left( E_{\text{f}_{i,t,k}} \right) \), exerts path dependence patterns. The industry-specific past developed technological competencies and capabilities exert influence on the current productive performance with respect to the group frontier.

The two basic theoretical arguments introduced above, that is the path dependence of both efficiency and the technology gap, and also technological spillovers from the metatechnology to the country-specific technology and vice versa, may be modelled in the context of the following two equations (Equations 3.4 and 3.5):

\[
T_{\text{g}_{i,t,k}} = b_0 + b_1T_{\text{g}_{i,t-1,k}} + b_2E_{\text{f}_{i,t-1,k}} + \Gamma T_{\text{g}_{i,t-1,k}} + \Delta X_{i,t,k} + \Delta Z_{i,t,k} + \nu_{i,t,k} \quad (3.4)
\]
\[ E_{\text{Eff}_{i,t-1k}} = \xi_{i,t} + \gamma_{i,t} T_{g_{i,t-1k}} + \theta_{i,t} E_{\text{Eff}_{i,t-1k}} + \Gamma_{k} X_{i,k} + \Delta_{k} Z_{i,k} + \mu_{i,t} \quad (3.5) \]

In Equation (3.4) above, \( T_{g_{i,t-1k}} \) is the technology gap of the \( i \)-th European transportation industry in time \( t \), as it was defined in Equation 3.3 above, \( T_{g_{i,t-1k}} \) is its lagged value, capturing path dependence. \( E_{\text{Eff}_{i,t-1k}} \) is the efficiency of the \( i \)-th transportation industry with respect to the \( k \left( k = \text{Air, Land, Water} \right) \) transportation sector specific frontier, capturing any incoming technological spillovers. A time lag here is devoted to allowing the necessary diffusion period for the technological spillovers which need to be absorbed. \( X_{i,k} \) is a matrix of exogenously determined industry-specific characteristics associated to the productive performance of the transportation industry, \( Z_{i,k} \) is matrix of instruments whose presence in Equations 3.4 and 3.5 is to help handle the statistical consequences that can arise from the endogeneity across the two equations, discussed further in Section 3.5, and \( \mu_{i,t} \) is the usual disturbance term. Equation 3.4 includes both the outgoing technological spillovers through the inclusion of \( E_{\text{Eff}_{i,t-1k}} \) variable (Hypothesis H1) and path dependence of productive performance thorough the inclusion of \( T_{g_{i,t-1k}} \) variable (Hypothesis H4). In Equation 3.5, \( E_{\text{Eff}_{i,t-1k}} \) is the efficiency of the \( i \)-th transportation industry with respect to the \( k \left( k = \text{Air, Land, Water} \right) \) transportation sector specific frontier in time \( t \), as it was defined in Equation 1.1, \( E_{\text{Eff}_{i,t-1k}} \) is its lagged value capturing path dependence (Hypothesis H4) and \( T_{g_{i,t-1k}} \) is the technology gap of the \( i \)-th transportation industry with respect to the European Transportation metatechnology, capturing any incoming technological spillovers originated from the metatechnology towards the transportation sector specific technology (Hypothesis H2). Again the time lag here is devoted to capturing the diffusion period of the technological spillovers which need to be generated and absorbed and \( \mu_{i,t} \) is the corresponding error term. \( b, \xi_{i}, \gamma_{i,k}, \Delta_{k}, \Gamma_{k} \) and \( \Delta_{\text{Eff}_{i}} \) are vectors of parameters to be estimated.

The econometric estimation of the above system of two equations raises several issues. Since the technological spillovers may run in both directions, that is from the metafrontier to the industry specific frontier and vice versa, the regressors \( E_{\text{Eff}_{i,t-1k}} \) in
Eq. (4) and $T_{g,i,t-1}$ in Equation 1.5 may be correlated with the corresponding error term, and therefore endogeneity issues embrace both equations. Second, time invariant characteristics, industry- and country-specific of the fixed-effects type, such as geography, climate conditions, infrastructures and demographics, may be correlated with the explanatory variables. The fixed effects are contained in the $u_{g,i,t}$ in Equation 3.4 and $u_{g,eff}$ in Equation 3.5 respectively. In other words, each one of these two error terms consists of unobserved industry-specific effects as well as observation-specific errors.

Third, the presence of the lagged dependent variables, $T_{g,i,t-1}$ and $Eff_{i,t-1}$, as explanatory variables makes the equations prone to autocorrelation issues. Finally, our dataset is comprised of a relative small number of time periods ($t = 1,...,8$) and rather large number of Transportation industries ($i = 1,...,51$). Details of how these issues are handled are given in Section 3.5.

### 3.4 Data Sources and Variable Definitions

In order to investigate the issues surrounding our main research questions we have devised a unique dataset by employing and matching distinct, but complementary, information sources. The resulting dataset is a balanced panel consisting of three transportation industries. More specifically, we take into consideration Air Transport, Land Transport and transport via pipelines and Water Transport from seventeen European Union member states\(^7\) for an eight year period, from 1999 to 2006. Accordingly, the sample will not be affected by the events of the global financial crisis that manifested from August 2007 onwards. It is worth adding that the sample period was chosen purely on the basis of availability of key variables, some of which become unavailable after 2006. The final panel dimension comprises of 408 observations.

For the estimation of productive efficiency with respect to each transportation industry frontier and the European transportation metafrontier as well, we employ a single-output, multi-input frontier. More specifically, we approximate the output variable ($Y$) by the gross valued added of each industry, whilst the inputs include the capital stock ($K$) in million Euros, the labour input ($L$) which is captured by the total hours worked by employees, expenditure on intermediate inputs ($M$) in million Euros and the total energy consumption ($E$) measured in million tons (Mt) of oil equivalent. For several of the

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\(^7\) Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Poland, Slovak Republic, Slovenia, Spain, Sweden and the United Kingdom.
countries in this dataset, certain variables are reported in local currency, and need to be converted into Euro’s, relying on the exchange rates reported by the European Commission regarding each particular country and year of the dataset, before being used in the analysis while all the monetary variables are expressed in Euros in constant 2000 prices.

In the second stage of the analysis, we have employed as additional explanatory variables, the industry specific productive characteristics captured by the corresponding input ratios, and variables which capture any ambient technological discrepancies. These include the variables EURO, which is a dummy variable indicating membership of the European Monetary Union (EMU), and GCI, which reflects the Global Competitiveness Index value of each country in the given year. The former is intended to control for any heterogeneity owing to transaction cost advantages accruing to the countries participating in the EMU, while the latter was introduced in order to reflect differences in productive performance that may derive from each countries’ relative advantages in infrastructure, human capital, technological achievements and other developments related to the production process (Sala-i-Martin et al., 2008). Tables 3.1 and 3.2 below, provide the definition, measurement and basic descriptive statistics for each of the variables.

| Variable                  | Units of measurement | Source                        |
|---------------------------|----------------------|-------------------------------|
| Output \((Y)\)            | million euros        | GGDC                          |
| Capital \((K)\)           | million euros        | OECD STAN, EUKLEMS            |
| Labor \((L)\)             | million hours worked by employees | GGDC                      |
| Intermediate inputs \((M)\) | million euros   | GGDC                          |
| Energy consumption \((E)\) | million tons of oil equivalent | Enerdata - Odyssey   |
| Global Competitiveness Index | pure number | World Economic Forum         |
| EURO                      | -                   | European Commission          |

All the monetary values are in constant 2000 prices using industry and country specific deflators.

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8 Czech Republic, Denmark, Poland, Slovak Republic, Slovenia, Sweden and the United Kingdom.
Table 3.2 Descriptive statistics by industry and variable for the European Transportation sector from 1999 to 2006

| Industry       | Air Transport | Land Transport | Water Transport | TOTAL  |
|----------------|---------------|----------------|-----------------|--------|
| Y              | 1,772         | 10,660         | 1,464           | 4,632  |
| (2,318)        | (11,065)      | (1,887)        | (7,861)         |        |
| K              | 14,577        | 10,660         | 5,488           | 20,306 |
| (17,313)       | (42,929)      | (9,849)        | (31,095)        |        |
| L              | 35,514        | 435,456        | 19,543          | 163,504|
| (39,422)       | (369,681)     | (16,283)       | (288,178)       |        |
| M              | 4,053         | 12,086         | 2,987           | 6,375  |
| (4,792)        | (14,544)      | (3,814)        | (9,957)         |        |
| E              | 2,585         | 16,268         | 0,272           | 6,375  |
| (3,173)        | (17,472)      | (0,354)        | (12,433)        |        |
| $GCI$          | 4.156         |                |                 |        |
|                | (1.655)       |                |                 |        |
| $EURO$         | 58.82%        |                |                 |        |

Note 1: Numbers indicate the mean value while parentheses correspond to the standard deviation.

Note 2: Euro is a dummy variable indicating whether the country has the common currency or not. Here, 58.82% (10 out of 17 countries) share the same currency.

Note 3: The Global Competitiveness Index ($GCI$) refers to the whole sample of countries and industries for the period 1999-2006.

As already mentioned, the data were drawn by combining several distinct sources of information. Data for Gross Value Added, total hours worked by employees and intermediate inputs were obtained from the database of Groningen Growth and Development Centre (GGDC), Enerdata-Odyssey database was used to collect data on energy consumption, data on gross fixed capital formation and capital input files were acquired through Organization for Economic Cooperation and Development (OECD) Structural Analysis (StAn), and EU-KLEMS Growth and Productivity Accounts databases respectively. The deflators used to convert the current into constant 2000 prices are specific to each particular industry, country and year of the dataset and were acquired through OECD StAn database. The Global Competitiveness Index data were collected from various editions of the Global Competitiveness Report published by the World Economic Forum.

Very often, the most severe obstruction in the assessment of productive efficiency for a group of DMUs is the lack of a consistent variable reflecting capital stock. To overcome this stumbling block, we draw on the Perpetual Inventory Method (PIM) (see Krautzberger and Wetzel, 2012) to create a consistent measure of capital stock. The initial condition for the capital stock is given by $K_{1999} = \frac{I_{1999}}{\delta + g}$, where g is estimated as the average growth rate in capital investments for the preceding 5 years for each of the examined industries and countries. Given this initial value, the capital stock for each subsequent year is constructed using the formula in Equation 3.6 below:

$$K_{t+1} = (1 - \delta)K_{t+1} + I_{t+1}, \quad (3.6)$$
where $K_{i,t,k}$ and $I_{i,t,k}$ represent the capital stock and investment of the $i$-th country on the $k$-th industry for the year $t$ respectively, where $\delta$ is the depreciation rate which is assumed to be equal to 10% yearly.\(^9\)

### 3.5 Econometric Strategy, Empirical Results and Discussion

The presentation and discussion of the empirical results follows the two stage structure of the analysis. The industry-specific transportation efficiency scores and technology gaps (which arise in the context of the metafrontier) are firstly presented and discussed. Subsequently, and having justified a number of choices regarding econometric issues, we present and discuss the estimation results of Equations 1.4 and 1.5 focusing on the core issues of path dependence and technological spillovers.

#### 3.5.1 Efficiency and Technology Gap Estimates

The estimation of $E_{i,t,k}^{\text{Eff}}$, and $T_{i,t,k}^{\text{g}}$ have been carried out using the bootstrap DEA approach\(^10\) in order to overcome weaknesses of traditional DEA and also reveal the statistical properties for our measures, employing the FEAR package (Wilson, 2008). An analytical presentation of this approach can be found in Simar and Wilson (1999, 2000, 2007) and Tsekouras et al., (2010). At this point it is crucial to note that both the $E_{i,t,k}^{\text{Eff}}$ and $T_{i,t,k}^{\text{g}}$ estimation is grounded on a cross-section basis, estimated separately for each year in the sample. Therefore, the successive values of the estimated productive efficiency and technology gap for each DMU encompasses two factors which by nature are dynamic. The first one is the change of the distance of the DMU from the (meta-)frontier, which may be a movement towards (improvement) or backwards (deterioration) from the frontier. The second one is the movement outwards (technical change) or inwards (technical regress) of the metafrontier itself. In this sense the estimated time-series for efficiency and technology gaps reflect the diachronic evolution of productive performance of the examined DMU, taking into direct account any technological developments either in the industry-specific frontier or in the metatechnology.

Tables 3.3, 3.4 and 3.5 display the estimated values of (i) the productive efficiency with respect to the industry-specific (Air, Land, Water) transportation technology and (ii)

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\(^9\) The estimated capital series do not change in a significant manner when different levels of depreciation rates were considered.

\(^10\) We have also estimate the Free Disposal Hull efficiency estimators testing for the validity of the convex hull (Simar and Wilson, 2000). Our results indicate that the metafrontier behaves as a convex frontier in our case and are available upon request.
the technology gap with respect to the European transportation metatechnology for each country between from 1999 to 2006. The distributions of the productive efficiency and technology gaps are also given below in Figure 3.2 and Figure 3.3 which show kernel density estimates for the first period of the sample (1999), the middle (2003), and the last (2006).

We begin by looking at the estimated productive efficiency and technology gap values for Air Transport Industries (ATI). From the full sample averages (e.g. across all years) in the final columns of Table 3.3, the Finnish, Swedish and German ATIs exhibit the highest scores for productive efficiency, while in the metafrontier case Slovenian and Dutch ATIs present the smallest technology gaps.

The time evolution of the productive efficiency scores, depicted in Figure 3.2a, reflect a process of continuous and quite significant divergence, reflected in the increased deviation of the distribution in each of the years. The corresponding time evolution of the European ATIs technology gap (Figure 3.3a) depicts that, although the overall picture in 2006 is quite similar to the one sketched in 1999, a significant but temporary increase of the technology gap took place in 2003. Notwithstanding this, the technology gap distribution remains almost steady with no apparent divergence or convergence processes in operation. Fig.3.4a offers a scatterplot of the productive efficiency scores and the corresponding technology gap values of the European Air Transport industries. A left truncated inverted U-shaped relationship arises.

Shifting attention towards the Land Transportation Industries (LTI) given in Table 3.4, the sample average productive efficiency scores reveal Germany and the Netherlands as the countries with the highest efficiency on average. In Figure 3.2b kernel densities of the estimated productive efficiency scores of the LTIs for the years 1999, 2003 and 2006 are illustrated. It is noticeable that a left shift in the mean distribution is accompanied with a drastic increase of the variance: thus a progressive process of divergence is apparent. In terms of technology gap values, the Finnish, and Dutch LTIs exhibit the best performance in terms of the metatechnology while Great Britain and the Dutch have the LTIs which most often define the transportation metafrontier. From Figure 3.3b, where kernel densities of the estimated technology gaps of the European LTIs are depicted, it is evident that technology gaps as well as their deviations are diachronically increasing. As in the case of the efficiency scores a cluster of ‘falling behind’ LTIs seems to emerge. In Figure 3.4b the scatter plot of technical efficiency against technology gap of the LTIs roughly illustrates the underlying relationship.
between these two performance measures: the significant conglomeration of LTIs in the lower right quadrant indicates a pattern of high productive efficiency and low technology gap.

Water Transportation Industries (WTIs) efficiency scores, presented in Table 3.5, reveal that the Irish and UK WTIs exhibit on average the highest scores. Significant fluctuations regarding the estimated efficiency scores are noticeable for the Belgian and especially the French WTIs. In terms of the metatechnology, the German and Danish WTIs exhibit the worst productive performance, compared to the rest of the European WTIs. Figure 3.2c mirrors a rather different, compared to the LTI case, pattern of the European WTIs productive performance. More specifically, it seems that between 1999 and 2003 a significant increase of technical efficiency scores and a convergence of the WTIs productive performance with respect to the industry-specific technology have occurred. In the same direction, but more dramatic, is the picture of the WTIs technology gap distribution presented in Figure 3.3c. The technology gap increases drastically from 1999 to 2003 and decreases in 2006, but in 2006 remains quite distant from its 1999 level. The relationship between productive efficiency and technology gap of the WTIs, for the whole examined period, is presented in the scatter plot of Figure 3.3b. Similarly to the LTI case, a conglomeration of highly efficient WTIs, both with respect to industry-specific technology and the metatechnology, is present. A left truncated U-shaped relationship is apparent.
| Country                  | 1999    | 2000    | 2001    | 2002    | 2003    | 2004    | 2005    | 2006    | Mean  | St. Dev. |
|-------------------------|---------|---------|---------|---------|---------|---------|---------|---------|-------|----------|
| Austria (AUS)           | 0.873   | 0.403   | 0.752   | 0.609   | 0.422   | 0.568   | 0.507   | 0.647   | 0.588 | 0.644    |
| Belgium (BEL)           | 0.431   | 0.320   | 0.587   | 0.622   | 0.585   | 0.340   | 0.732   | 0.536   | 0.877 | 0.590    |
| Czech Rep. (CZE)        | 0.878   | 0.661   | 0.841   | 0.772   | 0.829   | 0.750   | 0.870   | 0.733   | 0.862 | 0.545    |
| Denmark (DNK)           | 0.880   | 0.296   | 0.856   | 0.486   | 0.867   | 0.272   | 0.823   | 0.539   | 0.691 | 0.417    |
| Finland (FIN)           | 0.897   | 0.141   | 0.858   | 0.347   | 0.866   | 0.296   | 0.895   | 0.428   | 0.887 | 0.393    |
| France (FRA)            | 0.865   | 0.295   | 0.687   | 0.585   | 0.713   | 0.557   | 0.859   | 0.712   | 0.867 | 0.665    |
| Germany (DEU)           | 0.879   | 0.073   | 0.844   | 0.381   | 0.852   | 0.159   | 0.889   | 0.450   | 0.877 | 0.280    |
| Greece (GRC)            | 0.848   | 0.584   | 0.913   | 0.600   | 0.884   | 0.587   | 0.937   | 0.675   | 0.724 | 0.555    |
| Ireland (IRL)           | 0.929   | 0.448   | 0.858   | 0.557   | 0.750   | 0.543   | 0.934   | 0.495   | 0.799 | 0.497    |
| Italy (ITA)             | 0.616   | 0.433   | 0.550   | 0.620   | 0.912   | 0.600   | 0.934   | 0.691   | 0.803 | 0.704    |
| Netherlands (NLD)       | 0.871   | 0.002   | 0.844   | 0.452   | 0.842   | 0.130   | 0.880   | 0.150   | 0.880 | 0.273    |
| Poland (POL)            | 0.370   | 0.631   | 0.170   | 0.544   | 0.099   | 0.418   | 0.381   | 0.592   | 0.566 | 0.502    |
| Slovak Rep. (SLK)       | 0.874   | 0.080   | 0.835   | 0.129   | 0.833   | 0.073   | 0.878   | 0.141   | 0.879 | 0.116    |
| Slovenia (SVL)          | 0.877   | 0.087   | 0.841   | 0.099   | 0.832   | 0.005   | 0.878   | 0.151   | 0.879 | 0.083    |
| Spain (ESP)             | 0.820   | 0.559   | 0.792   | 0.672   | 0.802   | 0.652   | 0.782   | 0.739   | 0.784 | 0.726    |
| Sweden (SWE)            | 0.889   | 0.240   | 0.856   | 0.474   | 0.910   | 0.565   | 0.898   | 0.508   | 0.879 | 0.353    |
| United Kingdom (GBR)    | 0.873   | 0.095   | 0.832   | 0.286   | 0.836   | 0.101   | 0.879   | 0.243   | 0.877 | 0.113    |
| Mean                    | 0.804   | 0.315   | 0.760   | 0.484   | 0.755   | 0.389   | 0.821   | 0.496   | 0.807 | 0.439    |
| St. Dev.                | 0.166   | 0.215   | 0.182   | 0.185   | 0.210   | 0.153   | 0.210   | 0.105   | 0.209 | 0.155    |
| Max                     | 1RL     | CZE     | GRC     | CZE     | ITA     | CZE     | GRC     | ESP     | ESP   | ESP      |
| Min                     | POL     | NLD     | POL     | SLV     | POL     | SLV     | POL     | SLV     | POL   | SLV      |
Table 3.4 Productive Performance scores (Eff) and Technology gap (Tg) values for the Land Transport and transport via pipelines for 1999-2006

| Country        | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | Mean | St. Dev. |
|----------------|------|------|------|------|------|------|------|------|------|----------|
| Austria (AUS)  | 0.917| 0.043| 0.937| 0.143| 0.923| 0.168| 0.860| 0.244| 0.807| 0.270    |
| Belgium (BEL)  | 0.856| 0.161| 0.824| 0.266| 0.829| 0.213| 0.832| 0.417| 0.840| 0.458    |
| Czech Rep. (CZE)| 0.597| 0.351| 0.532| 0.396| 0.580| 0.247| 0.672| 0.218| 0.591| 0.174    |
| Denmark (DNK)  | 0.926| 0.324| 0.873| 0.518| 0.870| 0.422| 0.897| 0.464| 0.843| 0.434    |
| Finland (FIN)  | 0.906| 0.066| 0.912| 0.146| 0.900| 0.101| 0.896| 0.096| 0.889| 0.096    |
| France (FRA)   | 0.913| 0.065| 0.920| 0.138| 0.916| 0.120| 0.904| 0.145| 0.888| 0.134    |
| Germany (DEU)  | 0.903| 0.101| 0.910| 0.160| 0.904| 0.132| 0.903| 0.142| 0.900| 0.111    |
| Greece (GRC)   | 0.745| 0.191| 0.738| 0.299| 0.591| 0.231| 0.468| 0.462| 0.452| 0.475    |
| Ireland (IRL)  | 0.901| 0.277| 0.918| 0.504| 0.927| 0.537| 0.911| 0.690| 0.896| 0.605    |
| Italy (ITA)    | 0.899| 0.108| 0.910| 0.251| 0.899| 0.148| 0.897| 0.178| 0.885| 0.155    |
| Netherlands (NLD)| 0.906| 0.065| 0.917| 0.133| 0.917| 0.096| 0.911| 0.092| 0.911| 0.081    |
| Poland (POL)   | 0.703| 0.070| 0.862| 0.274| 0.881| 0.089| 0.816| 0.093| 0.726| 0.081    |
| Slovak Rep. (SLK)| 0.900| 0.144| 0.910| 0.204| 0.901| 0.153| 0.893| 0.174| 0.882| 0.147    |
| Slovenia (SLV) | 0.905| 0.594| 0.907| 0.616| 0.904| 0.606| 0.894| 0.631| 0.884| 0.624    |
| Spain (ESP)    | 0.770| 0.048| 0.773| 0.127| 0.773| 0.086| 0.798| 0.096| 0.833| 0.080    |
| Sweden (SWE)   | 0.937| 0.199| 0.923| 0.363| 0.799| 0.289| 0.801| 0.416| 0.767| 0.374    |
| United Kingdom (GBR)| 0.907| 0.078| 0.907| 0.094| 0.900| 0.150| 0.916| 0.139| 0.843| 0.110    |

| Year | Eff | Tg | Eff | Tg | Eff | Tg | Eff | Tg | Eff | Tg |
|------|-----|----|-----|----|-----|----|-----|----|-----|----|
| 2000 | 0.858| 0.168| 0.863| 0.272| 0.848| 0.223| 0.839| 0.276| 0.814| 0.259|
| 2003 | 0.856| 0.161| 0.824| 0.266| 0.829| 0.213| 0.832| 0.417| 0.840| 0.458|
| 2006 | 0.856| 0.161| 0.824| 0.266| 0.829| 0.213| 0.832| 0.417| 0.840| 0.458|

Mean | 0.858 | 0.168 | 0.863 | 0.272 | 0.848 | 0.223 | 0.839 | 0.276 | 0.814 | 0.259 |
St. Dev. | 0.096 | 0.146 | 0.102 | 0.158 | 0.107 | 0.157 | 0.115 | 0.196 | 0.123 | 0.193 |
Max | SWE | SLV | AUS | SLV | IRL | SLV | GBR | IRL | NLD | SLV |
Min | CZE | AUS | CZE | GBR | CZE | ESP | GRC | NLD | GRC | ESP |

Mean | 0.858 | 0.168 | 0.863 | 0.272 | 0.848 | 0.223 | 0.839 | 0.276 | 0.814 | 0.259 |
St. Dev. | 0.096 | 0.146 | 0.102 | 0.158 | 0.107 | 0.157 | 0.115 | 0.196 | 0.123 | 0.193 |
Max | SWE | SLV | AUS | SLV | IRL | SLV | GBR | IRL | NLD | SLV |
Table 3.5 Productive Performance scores (Eff) and Technology gap (Tg) values for the Water Transport for 1999-2006

| Country         | 1999  | 2000  | 2001  | 2002  | 2003  | 2004  | 2005  | 2006  | Mean  | St. Dev. |
|-----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------|
| Austria (AUS)   | 0.892 | 0.093 | 0.916 | 0.194 | 0.906 | 0.126 | 0.913 | 0.168 | 0.947 | 0.196    |
| Belgium (BEL)   | 0.891 | 0.061 | 0.929 | 0.372 | 0.713 | 0.093 | 0.918 | 0.133 | 0.949 | 0.203    |
| Czech Rep. (CZE)| 0.891 | 0.085 | 0.945 | 0.302 | 0.837 | 0.112 | 0.913 | 0.189 | 0.953 | 0.180    |
| Denmark (DNK)   | 0.923 | 0.055 | 0.870 | 0.655 | 0.782 | 0.106 | 0.654 | 0.142 | 0.915 | 0.150    |
| Finland (FIN)   | 0.890 | 0.103 | 0.919 | 0.242 | 0.909 | 0.154 | 0.913 | 0.186 | 0.948 | 0.209    |
| France (FRA)    | 0.853 | 0.056 | 0.855 | 0.522 | 0.907 | 0.129 | 0.936 | 0.126 | 0.955 | 0.157    |
| Germany (DEU)   | 0.889 | 0.094 | 0.920 | 0.357 | 0.903 | 0.150 | 0.914 | 0.190 | 0.946 | 0.207    |
| Greece (GRC)    | 0.891 | 0.089 | 0.920 | 0.192 | 0.905 | 0.149 | 0.915 | 0.186 | 0.944 | 0.205    |
| Ireland (IRL)   | 0.898 | 0.063 | 0.950 | 0.481 | 0.939 | 0.098 | 0.912 | 0.140 | 0.966 | 0.149    |
| Italy (ITA)     | 0.649 | 0.065 | 0.934 | 0.270 | 0.909 | 0.135 | 0.722 | 0.136 | 0.929 | 0.164    |
| Netherlands (NLD)| 0.768 | 0.047 | 0.699 | 0.343 | 0.793 | 0.095 | 0.725 | 0.118 | 0.736 | 0.140    |
| Poland (POL)    | 0.889 | 0.087 | 0.918 | 0.318 | 0.903 | 0.149 | 0.913 | 0.185 | 0.948 | 0.211    |
| Slovak Rep. (SLK)| 0.890 | 0.100 | 0.922 | 0.245 | 0.906 | 0.160 | 0.915 | 0.188 | 0.946 | 0.205    |
| Slovenia (SLV)  | 0.891 | 0.100 | 0.915 | 0.239 | 0.901 | 0.156 | 0.912 | 0.189 | 0.944 | 0.206    |
| Spain (ESP)     | 0.747 | 0.057 | 0.908 | 0.272 | 0.920 | 0.115 | 0.929 | 0.146 | 0.977 | 0.157    |
| Sweden (SWE)    | 0.545 | 0.045 | 0.501 | 0.325 | 0.529 | 0.085 | 0.684 | 0.108 | 0.647 | 0.130    |
| United Kingdom (GBR) | 0.895 | 0.099 | 0.932 | 0.387 | 0.916 | 0.119 | 0.938 | 0.123 | 0.951 | 0.163    |

Mean 0.841 0.076 0.880 0.836 0.858 0.125 0.866 0.156 0.918 0.178 0.890 0.166 0.785 0.129 0.813 0.138
St. Dev. 0.104 0.021 0.113 0.122 0.036 0.025 0.099 0.030 0.088 0.028 0.082 0.034 0.127 0.029 0.139 0.026
Max DNK FIN IRL DNK IRL SLK GBR DEU ESP POL ESP GRC IRL GRC DNK CZE
Min SWE SWE SWE GRC SWE SWE DNK SWE SWE NLD SWE BEL BEL FRA BEL
Figure 3.2 Kernel densities of the Productive Performance for each transportation industry in 1999, 2003 & 2006.

2a. Air Transport

2b. Land Transport

2c. Water Transport

Legend:
- 1999
- 2003
- 2006
Figure 3.3 Kernel densities of the Technology gap for each transportation industry in 1999, 2003 & 2006
3.5.2 Second Stage Analysis

3.5.2.1 Econometric Strategy

In order to estimate Equations 3.4 and 3.5 above, we have to deal with the econometric problems mentioned above and more specifically with the issues of endogeneity between $T_{g_{it}}$ and $Eff_{it}$, the inclusion of lagged dependent variables among the set of explanatory ones, fixed effects, autocorrelation issues and also the short time dimension of the panel dataset. One plausible choice would be the Arellano-Bond (1991) or difference Generalized Method of Moments (GMM) estimator first proposed by Holtz-Eakin et al., (1988). Concerns about endogeneity, due to the possible bi-directional nature of spillover effects, are reduced since the difference GMM estimator instruments any endogenous variables (including lagged endogenous terms) to eliminate any possible correlation with error terms. We have also to note that we have included in each econometric model country dummies to account for wider aspects of country level unobservable heterogeneity such as economic infrastructure, human capital, corruption level etc. The specific country dummies due to their strictly exogenous characteristics have been treated as predetermined as far as the econometric specification is concerned. Apparently, their impact has been both embedded in the model’s parameters\(^{11}\).

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\(^{11}\) We owe this clarification to an anonymous referee.
The short time dimension of our panel does not allow any shocks on fixed effects to decline with time, and may also, in conjunction with the lagged dependent variable, be a source of autocorrelation problems. The Arellano-Bond estimator has been designed to cope with such kind of situations (Roodman, 2006). However, some additional econometric issues should be handled in the case of the system of Equations 3.4 and 3.5. More specifically, (i) in both equations the issue of over-identification arises since the chosen number of instruments is greater than the respective number of the explanatory variables, (ii) orthogonality conditions across equations are not ensured, due to the fact that incoming and outgoing spillover effects may be in operation and (iii) the form of heteroskedasticity is not known a priori. Therefore, Equations 3.4 and 3.5 are estimated employing the System Generalized Method of Moments (GMM) as proposed by Roodman (2009). System GMM performs at least as good as its reduced form counterpart (of difference GMM) in situations where $T$ is small and $N$ is large in dimension, and where lagged dependent variables are included, but in addition System GMM deals with the issues of over-identified restrictions, the non-orthogonality conditions across equations and heteroscedasticity (Hayashi, 2000). In our case, system GMM equation is asymptotically more efficient than the difference GMM estimator for the reasons already mentioned.

This choice is further justified by the following facts. Firstly, the rule of thumb according to which the number of instruments should be smaller than the number of groups in the panel is satisfied, and additionally the Sargan/Hansen tests (which are mirror tests) for robustness are quite satisfactory both indicating the absence of heteroskedasticity at a 5% level of significance. At this point, it would be of particular interest to highlight the fact that in the case of difference GMM with robust standard errors the Sargan test for instruments’ identification is not available and thus no test of instruments exogeneity is possible. On the contrary, in the case of the system GMM estimator, the mirrored tests of Hansen J-statistic and Sargan are computable. The results regarding these tests are reported in the lower part of Table 3.6 and both indicate a quite satisfactory handling of heteroscedasticity and instruments’ exogeneity.

### 3.5.2.2 Technological Spillovers and Path Dependence

Table 3.6 presents the System GMM estimation results for two variants of the efficiency and technology gap equations. The first version includes the time trend variable $T$ accounting for general linear time effects on the mix of productive performance and technology evolution, both with respect to the industry-specific frontier and the metafrontier. The second does not include $T$. In the framework of the system GMM estimation a formal test for nested models is currently
unavailable. Therefore, we choose to focus on the more general versions with the time variable included (Models 1a and 2a), though also present and highlight any differences in comparison from the versions which do not include the T variable (Models 1b and 2b). A more detailed discussion on the influence of the T variable is provided later in this section.

Examining the first core issue of spillovers running from the transportation metatechnology to the industry-specific technology (incoming) and vice versa (outgoing), the coefficients of interest are for the influence of the lagged technology gap variable $T_{g_{i,t-1}}$ in the efficiency equation (Table 3.6, column 1a), and the influence of the lagged productive efficiency variable $(E_{i,t-1}^{\phi,k})$ in the technology gap equation.

The incoming spillovers i.e. the influence of the technology gap on the productive performance with respect to the industry specific technology are captured by the $\xi_i$ parameter in Equation 3.4 which is found to be negative and statistically significant. Accordingly, as the technology gap increases for a given DMU, on average the productive efficiency of the same DMU will be decreasing, but by a smaller amount. Elaborating further, empirical findings reveal that the transportation industries which attain low technology gaps, that is which are “close” to the metafrontier, are benefited from technological spillovers from the metatechnology and improve their efficiency in terms of the transportation industry-specific technology. Hypothesis $H_1$ can therefore not be rejected. Not trapping in technological idiosyncrasies and the subsequent lumpiness, overcoming barriers that result from appropriability conditions linked to general purpose technologies (Jovanovic and Rousseau, 2005), exploiting the potentials of technological modularity (Fixson, 2007), low adjustment costs associated to the compliance with European regulations, and forming adequate absorptive capacity (Cohen and Levinthal, 1990, 1991) ensure on the one hand small technology gaps which fuels productive performance with respect to the industry-specific technology. We should not overlook the fact that incoming technological spillovers are almost completely indifferent to time heterogeneity.

Turning next to the case of outgoing spillovers, as captured by the parameter $b_j$, the picture is slightly less clear. It is only in the case where the time variable ($T$) is included in the technology gap equation, that past productive performance levels will exert a significant (and negative) influence on the current level of the technology gap. Arguably however, localized technical change in the form of industry specific technological trajectories, are transformed to technological flows that comprise, to an extent, the transportation metatechnology. Product, process and organizational innovations which are produced and implanted within the transportation-industry specific frontier, are transformed to ingredients that compose the
transportation metatechnology through the inter-industry diffusion processes. On the other side, transportation industries which fail to follow the outward shift of the industry-specific frontier, and therefore exhibit low efficiency scores, fall behind from the metatechnology as well.

The second of the two core issues examined in this paper regards the nature and existence of path dependence in productive performance and technology gap, captured by the parameters $\xi_2$ and $b_1$ respectively. A positive and significant influence on the productive performance and technology gap from the previous period is found on current productive performance and technology gaps respectively. Path dependence is in operation, that is, transportation industries perform better, both with respect to the industry frontier and the metafrontier, if they have accumulated significant competencies and capabilities (e.g. high competence in the previous period sustains a guaranteed minimum level of competence in the present period irrespective of other drivers). Thus Hypotheses H$_3$ and H$_4$ cannot be rejected, and it must be concluded that path dependence is a salient feature of the European transport industries. However this finding when considered carefully highlights an additional concern which is that, European transportation industries exhibiting low productive performance and/or high technology gap in the past period are effectively handicapped regarding their current productive performance and technology gap level. This follows from the fact that the coefficient precluded a sharp shift (increase) away from the existing low levels of productive performance.

Pursuing this train of logic further, one could argue that among the European Transportation Industries and the European metatechnology, clustering processes are taking place. In the long run, the cluster of champions will be more distant from the cluster of laggards both with respect to the industry-specific technology and the metatechnology. The same applies for the emerging ‘falling behind’ phenomena of followers with respect to the champions, and the laggards with respect to the followers. That is, an ongoing polarization is being shaped.

In addition to the above, the tests presented in the lower part of Table 1.6 reveal that spurious path dependence is also in operation both in the efficiency and technology gap equations, that is, past unobserved heterogeneity negatively affects the current level of unobserved heterogeneity of efficiency and technology gap of the examined European transportation industries. In other words factors included in the unobserved heterogeneity, for instance infrastructure, institutional issues, country and industry specific technological and geographical idiosyncrasies, are not easily reversible and reinforce the stickiness of productive performance both with respect to industry specific frontiers and the metafrontier.

The Time heterogeneity variable ($T$) appears to be statistically significant only in the case of efficiency equation. A negative coefficient appears on the time-trend variable in the
efficiency equation which, keeping all other factors constant at their average level, reflects that the distance of the specific DMU from the corresponding frontier is increasing over time either by an outward shift of the frontier, either by the backward movement of the DMU or both. Accordingly, similar inferences could be drawn in the case of the technology gap equation for a positive influence of the time-trend variable. That is, the time trend variable reflects either the “catching up” (negative coefficient implying convergence) or the “falling behind” (positive coefficient suggesting divergence) phenomena, taking into consideration that the frontier itself may experience turbulence due to technical progress or technical regress. In the case examined herein, significant divergence processes are identified within the industry-specific frontiers. On the other hand no significant catching-up or falling behind phenomena are traceable with respect to the metatechnology case.

It is not worthless to mention that specific productive characteristics, captured by the ratios of the inputs, affect neither the productive performance with respect to the industry-specific frontier nor with respect to the metatechnology. Instead, in the present paper the time persistence or lock-in, and the multidirectional technological spillovers seem to have the most influential stirring role. More specifically the crucial factors determining productive performance are associated with the accumulated competencies, capabilities and other idiosyncrasies such as, innovative capacity, institutional quality, regulatory environment, resource endowments, geographical and surface topographical specificities (e.g. hilliness, localized weather etc.), cultural and social characteristics. The significant irreversibility of all the above reinforce the stickiness of the efficiency and technology gap.

According to the Global Competitiveness Report (WEF, 2015) “competitiveness is defined as the set of institutions, policies, and factors that determine the level of productivity of a country” consisting of twelve pillars. These pillars are institutions, infrastructure, health and primary education macroeconomic environment, higher education and training, labour market efficiency, goods market efficiency, financial market development, technological readiness, market size, innovation and business sophistication. All these features of national economies have been summarized and incorporated into the GCI index. Thus one could argue that GCI offers a sophisticated representation of the micro- and macro-economic foundations of individual countries’ competitiveness, accounting for a significant magnitude of possible heterogeneity for each individual country (Sala-i-Martin and Artadi, 2004). Extending this towards the direction of convergence’s issues, from the econometric results which imply a positive influence in the efficiency equation and a negative influence over the technology gap it seems there may exists a “curse of low competitiveness”. More precisely improved competitiveness is consistent with
moving closer to the group frontier but at the same time falling behind the European transportation metatechnology. Therefore, (i) to the best of our knowledge, there is not available a solid theoretical framework which would imply explicitly which exogenous variables should be employed in the second stage of the analysis, and (ii) that a huge number of such kind of time varying country specific variables could be considered as potential determinants of the multifaceted productive performance, in this paper we opt for the time invariant country fixed effects in conjunction with the time varying GCI and EURO variables. It is worthy to mention that GCI encompasses several time varying dimensions of the country characteristics (e.g. infrastructure, human capital, institutional quality, macroeconomic environment and financial conditions, innovativeness etc.). However, we should acknowledge that it is a limitation of the adopted research approach. For the time being, the lack of a solid theoretical and empirical framework does not allow enlighten such kind of considerations which appear to be very interesting future research issues which is out of the scope of the present chapter.\(^\text{12}\)

Finally, the EURO variable is not significant in either of the productive efficiency or technology gap equations. The EURO variable used as an additional explanatory variable in our econometric estimation and provides the opportunity to encapsulate, in a way, the level of heterogeneity that arises from the countries’ participation in the Eurozone or not. More specifically, monetary unification is thought to boost intra-euro area trade (Baldwin, 2006), and lead to trade integration (“Rose effect”) due to the reduction of transaction costs (Frankel and Rose, 1997; Rose, 2000) reducing incentives to undertake structural reforms of labour and product markets. Moreover, enhanced financial integration (Baele et. al., 2004) leads concentration of the banking system (Eiling et al., 2005) increasing the possibility of having gradual reforms (Duval and Elmeskov, 2006) but having an ambiguous effect on risk sharing (Giannone and Reichlin, 2006) and specialization (Giannone and Reichlin, 2006) at a national level.

Either the transaction costs reduction attained within the Eurozone are very low, or they are eliminated due to the ‘easy and quiet life’ behaviour grounded on low interest rates and fiscal expansions especially in the Southern European Countries which are Eurozone members. Although the introduction of the Euro currency does not seem to boost the productive performance of European transportation industries, we should proceed with caution regarding its extension leads due to the rather limited time window which is covered by the post-euro period (e.g. that some of the benefits may take longer to be realized in the data).

\(^{12}\) We own this clarification to an anonymous referee.
### Table 3.6 Results of the System Generalized Method of Moments Estimation

| Explanatory Variables | Productive Performance equation | Technology gap equation |
|-----------------------|---------------------------------|-------------------------|
|                       | With Time Trend | No Time Trend | With Time Trend | No Time Trend |
|                       | (1a)            | (1b)            | (2a)            | (2b)            |
| $E_{i,t-1}^{eff-k}$   | Path Dependence | -               | -               | -               |
|                       | .284 (+.004)    | .386 (+.000)    | -               | -               |
| Outgoing Spillovers   | -               | -               | -3.25 (-.003)  | -4.20 (-.212)  |
| $T_{i,t-1}^{g-k}$     | Path Dependence | -               | .321 (+.004)    | .309 (+.023)    |
|                       | -1.80 (-.008)   | -1.78 (-.004)   | -               | -               |
| $K / L$               | .000+ (-.955)   | .000+ (-.952)   | .000+ (-.492)   | .000+ (-.277)   |
| $K / E$               | .000+ (-.602)   | .000+ (.555)    | .000+ (.990)    | .000+ (.732)    |
| $K / M$               | .001 (-.863)    | .000+ (-.966)   | .010 (-.432)    | .010 (-.450)    |
| $L / E$               | -0.000+ (-.691) | -0.000+ (-.654) | -0.000+ (-.424) | -0.000+ (-.441) |
| $E / M$               | -7.09 (-.441)   | -1.408 (-.308)  | -7.48 (-.353)   | -0.001 (-.999)  |
| $L / M$               | .026 (-.317)    | .046 (-.245)    | .029 (-.271)    | .007 (-.768)    |
| $T$                   | Time Heterogeneity | -               | -.002 (-.502)   | -               |
| $EURO$                | -0.00 (-.998)   | -0.003 (-.887)  | -0.018 (-.632)  | -0.043 (-.340)  |
| $GCI$                 | .017 (-.042)    | -0.000+ (-.976) | -.055 (-.000)   | -.081 (-.024)   |
| Constant              | 32.697 (-.000)  | .545 (-.000)    | 6.655 (-.477)   | .889 (-.025)    |

**Note 1:** Numbers in parentheses for the estimated coefficients correspond to the associated p-values of the estimation.

**Note 2:** Regarding the Arellano-Bond AR(1) test, the numbers correspond to the z-values while the parentheses indicate the p-values.

**Note 3:** The values of the Hansen test of over-identified restrictions and that of the instruments exogeneity correspond to the chi-square value whilst the parentheses indicate the respective probabilities.

**Note 4:** As far as the coefficients of the productive characteristics are concerned, those are not actually zero but correspond to a very small number, i.e. smaller than .0001. This is captured by the symbol "+".

At this point we should notice that including the productive performance scores and the ratios of the productive characteristics of the industries considered, does not induce any multicollinearity concerns, since the majority of the coefficients is quite low (Table 3.7 below). In
the opposite case this could be a problem in explaining the productive performance variability using the productive characteristics ratios. Also, the ratios do not exhibit high levels of dependence to each other.

**Table 3.7 Correlation matrix between the productive performance and the productive characteristics**

| Productive Performance | $K/L$ | $K/M$ | $K/E$ | $L/E$ | $L/M$ | $E/M$ |
|------------------------|-------|-------|-------|-------|-------|-------|
| $K/L$                  | 1.000 |       |       |       |       |       |
| $K/M$                  | -0.210| 1.000 |       |       |       |       |
| $K/E$                  | -0.148| 0.524 | 1.000 |       |       |       |
| $L/E$                  | 0.025 | 0.496 | 0.092 | 1.000 |       |       |
| $L/M$                  | 0.144 | -0.128| -0.196| -0.149| 1.000 |       |
| $E/M$                  | 0.116 | -0.164| -0.058| -0.097| -0.044| 1.000 |
| $K/L$                  | 0.106 | -0.150| -0.051| -0.090| -0.055| 0.941 |

3.6 Conclusions

In this chapter we question the validity of the technological isolation assumption which is dominant in the investigation of the productive efficiency of the European Transportation System. We argue that the three main transportation industries, Air, Land and Water, are interlinked, through technological spillovers under a metatechnology framework, yet they also remain technologically heterogeneous in principle. Metatechnology is built by flows originated from the industry-specific frontiers mainly in the form of the localized technical change, and General Purpose Technologies, and in turn fuel industry-specific technologies. The introduction of spillovers elevates the role of path dependence which may be considered as a driving force towards a different orientation that is of the spillovers' shrinkage and dominance of technological isolation. In this contextual framework, a pattern of technological and performance networking is introduced for the three European transportation systems. Employing a dataset for seventeen EU countries for the period 1999 to 2006 we estimate productive efficiency scores with bootstrapped DEA technique and highlight different patterns of the productive performance with respect to both the industry-specific technologies and the European transportation metatechnology. The initial and unrefined picture reveals that technological isolation, and hence the absence of any spillovers, is rather questionable, although the patterns of technological interdependence of the transportation industry specific frontiers and the metafrontier, are not identical across all the three transportation systems.

At a second stage devising a dynamic panel model, which accounts for endogeneity of spillovers and path dependence, by employing an appropriate system GMM estimator we find
that both incoming and outgoing spillovers effects are in operation, and that the path
dependence is a crucial characteristic of productive performance both with respect to the
industry specific frontiers and the metafrontier. In other words, our findings indicate that two
counterbalancing drivers seem to fight each other in terms of catching up or falling behind in
European transportation. Although, spillovers reinforce convergence of the European
transportation Industries productive performance, at the same time path dependence triggers the
divergence and clustering situation. Importantly, these contrasting effects are only revealed when
the co-evolution of transportation industries productive performance and the technological
advancements are examined simultaneously. That is, the productive performance in a non-static
technological context highlights the role of the inter-industry technological flows and in this case
the technological isolation framework is rather obscuring. On the contrary, when the
technological developments are not of major concern and the productive performance is
examined in sterilized environment, the technological isolation assumption is not so costly and
the path dependence becomes the major driver of productive performance.

EU countries’ competitiveness has proven to be a major driver of the productive
performance of the corresponding transportation industries. This finding reaffirms the need for
future research to explore the nature of clustering processes within the European Transportation
system more closely with further exploration of country level heterogeneity being an obvious
direction in the presence of richer data. In doing so, the exploration of spillovers among
countries transportation systems as well as the technological isolation hypothesis could be
explored across different dimensions. Pooling together countries and transportation sectors i.e.
when multiple sources of technology heterogeneity are simultaneously taken into account would
be of great interest, but such a research route demands for very rich datasets at a low aggregation
level which to the best of our knowledge do not yet exist. In addition, future research could be in
the line of developing a solid theoretical and empirical framework which would allow the
investigation and identification of the exact origins, sources, and drivers triggering inter-industry
spillover effects.
References

Acemoglu, D. (2014) Localized and Biased Technologies: Atkinson and Stiglitz’s New View, Induced Innovations, and Directed Technological Change. N.B.E.R. (DOI): 10.3386/w20060.

Adler, N. and Golany, B. (2001) Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to Western Europe. Eur. J. Oper. Res. 132(2), 260-273.

Albalate, D. and Bel, G. (2010) What shapes local public transportation in Europe? Economics, mobility, institutions, and geography. Transp. Res. Part E 46(5), 775-790.

Anselin, L., Varga, A. and Acs, Z. (1997). Local geographic spillovers between university research and high technology innovations. J. Urb. Econ. 42(3), 422–448.

Anselin, L., Varga, A., and Acs, Z. (2000). Geographic and sectoral characteristics of academic knowledge externalities. Pap. Reg. Sci. 79(4), 435–443.

Antonelli, C. (2001). The Microeconomics of Technological Systems. Oxford University Press.

Antonelli, C. (2008) Localized Technical Change: Towards the economics of complexity. Routledge, London.

Arelano, M. and Bond, S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58, 277-297.

Assaf, A., Gillen, D. and Barros, C. (2012) Performance assessment of UK airports: Evidence from a Bayesian dynamic frontier model. Transp. Res. Part E 48(3), 603–615.

Atkinson, A.B. and Stiglitz, J.E. (1969) A New View of Technological Change. Econ. J., 573-578.

Baele, L., Ferrando, A., Hördahl, P., Krylova, E., and Monnet, C. (2004) Measuring financial integration in the euro area (No.14). European Central Bank.

Baldwin, R. (2006) “The euro’s trade effects,” ECB Working Paper Series, No.594, March (https://www.ecb.europa.eu/pub/pdf/secwpsecwp594.pdf , accessed on 15.06.2015)

Baired, A. and Rother, D. (2013) Technical and Economic Evaluation of the floating container storage and transshipment terminal (FCSTT). Transp. Res. Part C 30, 178-192.

Battese, G. E., and Rao, D. P. (2002). Technology gap, efficiency, and a stochastic metafrontier function. Int. J. Bus. Econ., 1(2), 87-93.

Battese, G.E., Rao, D.S.P., O’Donnell, C.J. (2004) A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. J. Prod. Anal., 21, 91-103.

Bernstein, J.I. (1988) Costs of production, intra-and interindustry R&D spillovers: Canadian evidence. Can. J. Economics, 324-347.
Boschma, R., & Iammarino, S. (2009). Related variety, trade linkages, and regional growth in Italy. Econ. Geogr., 85(3), 289-311.

Brons, M., Nijkamp, P., Pels, E. and Rietveld, P. (2005) Efficiency of urban public transit: a meta analysis. Transportation 32(1), 1-21.

Cainelli, G., & Iacobucci, D. (2012). Agglomeration, related variety, and vertical integration. Econ. Geogr., 88(3), 255-277.

Cainelli, G., & Iacobucci, D. (2009). Do agglomeration and technology affect vertical integration? Evidence from Italian business groups. Inter. J. Econ. Bus., 16(3), 305-322.

Cantos, P. and Maudos, J. (2001) Regulation and efficiency: the case of European railways. Transp. Res. Part A 35(5), 459-472.

Capello, R. (2009). Spatial spillovers and regional growth: a cognitive approach. Eur. Plan. Stud., 17(5), 639-658.

Cassiman, B., and Veugelers, R. (2006) In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition. Manage Sci. 52, 62-82.

Cohen, W. M., & Levinthal, D. A. (1989) Innovation and learning: the two faces of R & D. The Economic Journal, 99(397), 569-596.

Cohen, W.M. and Levinthal, D.A. (1990) Absorptive capacity: A new perspective on learning and innovation. Admin. Sci. Quart. 35(1), 128-152.

Cooper, R. W. and Haltiwanger, J.C. (2006) On the nature of capital adjustment costs. Rev. Econ. Stud. 73(3), 611-633.

Cullinane, K., Ping J. and Wang, T. (2005) The relationship between privatization and DEA estimates of efficiency in the container port industry. J.Econ. Bus. 57(5), 433-462.

Cullinane, K., Wang, T., Song, D. and Ping, J. (2006) The technical efficiency of container ports: comparing data envelopment analysis and stochastic frontier analysis. Transp. Res. Part A 40(4), 354-374.

David, P.A. (1985) Clio and the Economics of QWERTY. Am. Econ. Rev. 75, 332-337.

David, P.A. (1993) Why are institutions the “carriers of history”? Path dependence and the evolution of conventions, organizations and institutions. Struct. Change Econ. Dynam. 5(2), 205-220.

David, P.A. (2001) Path dependence, its critics and the quest for ‘historical economics’. Evolution and path dependence in economic ideas: Past and present eds P. Garrouste and S. Ioannides, pp. 15-40. In Association with the European Association for Evolutionary Political Economy (EAEPE).
David, P.A. (2007) Path dependence: A foundational concept for historical social science. Cliometrica, 1(2), 91-114.

Del Bo, C. F. (2013). FDI spillovers at different levels of industrial and spatial aggregation: Evidence from the electricity sector. Energy Policy, 61, 1490-1502.

Dosi, G., Lechevalier, S. and Secchi, A. (2010) Interfirm heterogeneity: nature, sources and consequences for industrial dynamics. An introduction. Ind. Corp. Change, 19(6), 1867-1890.

Dutta, S., Narashimhan, O. and Rajiv, S. (2005) Conceptualizing and measuring capabilities: Methodological and empirical application. Strateg. Manage. J. 26(3), 277-285.

Duval, R., and Elmeskov, J. (2006) The effects of EMU on structural reforms in labour and product markets (http://papers.ssrn.com/sol3/papers.cfm?abstract_id=887083 accessed on 16.06.2015).

Eiling, E., Gerard, B., and De Roon, F. (2005) International diversification in the Euro-zone: The increasing riskiness of industry portfolios. In Working Paper.

Enerdata. http://www.enerdata.net/ (accessed on 25.02.2013).

EU-KLEMS Growth and Productivity Accounts. http://www.euklems.net/ (accessed on 02.03.2013).

European Commission, Financial Programming and Budget Directorate. http://ec.europa.eu/budget/contracts_grants/info_contracts/inforeuro/inforeuro_en.cfm (accessed on 12.03.2013).

European Commission (2011), “Roadmap to a single European transport area - Towards a competitive and resource efficient transport system.” White Paper, COM (2011) 144, March 2011.

Fai, F. and von Tunzelmann, N. (2001) Industry-specific competencies and converging technological systems: evidence from patents. Struct. Change Econ. Dynam, 12(2), 141-170.

Farsi, M., Filippini, M. and William, G. (2005) Efficiency measurement in network industries: application to the Swiss railway companies. J. Regul. Econ. 28(1), 69-90.

Fixson, S.K. (2007) Modularity and Commonality Research: Past Developments and Future Opportunities. Concurrent Eng.-Res. A, 15, 85-111.

Frankel, J.A., and Rose, A.K. (1997) Is EMU more justifiable ex post than ex ante?. Eur. Econ. Rev., 41(3), 753-760.

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. Reg. Stud., 41(5), 685-697.
García-Sánchez, I.M. (2009) Technical and scale efficiency in Spanish urban transport: estimating with data envelopment analysis. Adv. Oper. Res. 98(2), 175-212.

Giannone, D., and Reichlin, L. (2006) Trends and cycles in the euro area: how much heterogeneity and should we worry about it? (No. 0595). European Central Bank.

Gifford, J.L. and Garrison, W.L. (1993) Airports and the Air Transportation System: Functional Refinements and Functional Discovery. Technol. Forecast. Soc. Change 43, 103-123.

González, M.M., and Trujillo, L. (2009) Efficiency measurement in the port industry: a survey of the empirical evidence. J. Transp. Econ. Policy, 43(2), 157-192.

Groningen Growth and Developing Centre, GGDC Productivity Level Database. [http://www.rug.nl/research/ggdc/data/ggdc-productivity-level-database](http://www.rug.nl/research/ggdc/data/ggdc-productivity-level-database) (accessed on 08.03.2013).

Growitsch, C. and Wetzel, H. (2009) Testing for economies of scope in European railways: an efficiency analysis. J. Transp. Econ. Policy, 43(1), 1-24.

Halkos, G.E. and Tzeremes, N.G. (2011) Modelling the effect of national culture on multinational banks performance: A conditional robust nonparametric frontier analysis. Econ. Mod., 28, 515-525.

Hayami, Y., and Ruttan, V.W. (1970). Agricultural productivity differences among countries. Am. Econ. Rev., 895-911.

Hayashi, F. (2000) Econometrics, Princeton, NJ: Princeton University Press.

Heinrich, T. (2014) Standard wars, tied standards, and network externality induced path dependence in the ICT sector. Technol. Forecast. Soc. Change, 81, 309-320.

Hol vad, T., Hougaard, L., Kronborg, D. and Kvist, H.K. (2004) Measuring inefficiency in the Norwegian bus industry using multi-directional efficiency analysis. Transportation, 31(3), 349-369.

Holtz-Eakin, D., Newey, W. and Rosen, H.S. (1988) Estimating Vector Autoregressions with Panel Data. Econometrica, 56(6), 1371-1395.

Jovanovic, B. and Rousseau, P. (2005) General purpose technologies. Handbook of Economic Growth eds Philippe Aghion & Steven Durlauf, pp. 1181-1224. Elsevier.

Karlaftis, M.G. and Tsamboulas, D. (2012) Efficiency measurement in public transport: Are findings specification sensitive?. Transp. Res. Part A. 46(2), 392-402.

Kasy, M. (2011) A nonparametric test for path dependence in discrete panel data. Econ. Lett. 113(2), 172-175.

Keller, W. (2004) International technology diffusion. J. Econ. Lit. 42(3), 752-782.
Kontolaimou, A., and Tsekouras, K. (2010). Are cooperatives the weakest link in European banking? A non-parametric metafrontier approach. J. Bank. Financ. 34(8), 1946-1957.

Kontolaimou, A., Kounetas, K., Mourtos, I. and Tsekouras, K. (2012) Technology gaps in European banking: Put the blame on inputs or outputs?. Econ. Modell. 29(5), 1798-1808.

Koroneos, C.J. and Nanaki, E.A. (2008) Energy and exergy utilization assessment of the Greek transport sector. Resour. Conserv. Recy. 52(5), 700-706.

Kounetas, K. (2015). Heterogeneous technologies, strategic groups and environmental efficiency technology gaps for European countries. Energy Policy. 83, 277-287.

Krautzberger, L. and Wetzel, H. (2012) Transport and CO2: Productivity Growth and Carbon Dioxide Emissions in the European Commercial Transport Industry. Environ. Resour. Econ. 53(3), 435-454.

Matawie, K.M. and Assaf, A. (2008). A metafrontier model to assess regional efficiency differences. J. Mod. Management. 3(3), 268-276.

Margari, B., Buzzo, F.E., Petraglia, C. and Piacenza, M. (2007) Regulatory and environmental effects on public transit efficiency: a mixed DEA-SFA approach. J. Regul. Econ. 32(2), 131-151.

Martin, J.C. and Roman, C. (2001) An application of DEA to measure the efficiency of Spanish airports prior to privatization. J. Air Transp. Manage. 7(3), 149-157.

Martin, R. and Sunley, P. (2006) Path dependence and regional economic evolution. J. Econ. Geogr. 6(4), 395-437.

Merkert, R. and O’Fee, B. (2013) Efficient procurement of public air services—Lessons learned from European transport authorities’ perspectives. Transp. Policy. 29, 118-125.

Nadiri, M.I. (1993) Innovations and technological spillovers. National Bureau of Economic Research, (DOI): 10.3386/w4423

Odeck, J. and Bråthen, S. (2012) A meta-analysis of DEA and SFA studies of the technical efficiency of seaports: A comparison of fixed and random-effects regression models. Transp. Res. Part A 46(10), 1574-1585.

O'Donnell, C.J., Rao, P. and Battese, G. (2008) Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empir. Econ. 34, 231-225.

Organization for Economic Cooperation and Development, Structural Analysis Database. http://www.oecd.org/industry/ind/stanstructuralanalysisdatabase.htm (accessed on 08.03.2013).

Page, S.E. (2006) Path dependence. Q.J. Polit. Sci. 1(1), 87-115.
Pinna, V. and Torres, L. (2001) Analysis of the efficiency of local government services delivery. An application to urban public transport. Transp. Res. Part A 35, 929-944.

Quella, N. (2009) Knowledge Spillovers and TFP Growth Rates. http://www.stonybrook.edu/economics/research/papers/2009/nuriaquella09.pdf (accessed on 08.02.2014).

Roodman, D. (2006). An introduction to “difference” and “system” GMM in Stata. Working Paper no.103, Center for Global Development, http://www.cgdev.org/publication/how-do-xtabond2-introduction-difference-and-system-gmm-stata-working-paper-103 (accessed on 16.04.2014).

Roodman, D. (2009) How to xtabond2: An introduction to difference and system GMM in Stata. Stata J. 9(1), 86-136.

Rose, A.K. (2000) One money, one market: the effect of common currencies on trade. Econ. Policy. 15(30), 7-46.

Roy, W., and Yvrande-Billon, A. (2007) Ownership, contractual practices and technical efficiency: The case of urban public transport in France. J. Transp. Econ. Policy. 41(2), 257-282.

Sala-i-Martin, X., Blanke, J., Drzeniek Hanouz, M. Geiger, T; Mia, I. and Paua, F. (2008) The Global Competitiveness Index: Prioritizing the Economic Policy Agenda. The Global Competitiveness Report 2008-2009 eds PORTER, M.E. and SCHWAB, K. (Geneva, World Economic Forum).

Sala-i-Martin, X. and Artadi, E. (2004), ‘The Global Competitiveness Index’, in The Global Competitiveness Report: 2004–05, M. Porter et al. (eds), Oxford: Oxford University Press.

Simar, L., and Wilson, P.W. (1998) Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. Manage. Sci. 44, 49-61.

Simar, L., and Wilson, P.W. (1999) Estimating and bootstrapping Malmquist indices. Eur. J. Oper. Res. 115, 459-471.

Simar, L., and Wilson, P.W. (2000) A general methodology for bootstrapping in nonparametric frontier models. J. Appl. Stat. 27, 779–802.

Simar, L. and Wilson, P.W. (2007) Estimation and inference in two-stage, semi-parametric models of production processes. J. Econometrics. 136(1), 31-64.

Syverson, C. (2011) What Determines Productivity?. J. Econ. Lit. 49, 326–365.

Tsekouras, K., Papathanassopoulos, F., Kounetas, K. and Pappous, G. (2010) Does the adoption of new technology boost productive efficiency in the public sector? The case of ICUs system. Int. J. Prod. Econ. 128(1), 929-951.
van Zuylen, H.J. and Weber, K.M. (2002) Strategies for European Innovation policy in the transport field. Technol. Forecast. Soc. Change, 69, 215-235.

Verspagen, B. and De Loo, I. (1999) Technology spillovers between sectors. Technol. Forecast. Soc. 60, 215-235.

Winter, S. (2006) The logic of Appropriability: from Schumpeter to Arrow to Teece. Res. Policy. 35, 1100-1106.

Wilson, P. (2008) FEAR: A software package for frontier efficiency analysis with R. Socio. Econ. Plan. Sci. 42(4), 247-254.

World Economic Forum. http://www.weforum.org/ (accessed on 5.04.2013).

Wang, Q., Zhao, Z., Zhou, P., and Zhou, D. (2013) Energy Efficiency and Production Technology Heterogeneity in China: A meta-frontier DEA approach. Econ. Model. 35, 283-289.
Chapter 4 Productive Performance, Technology Heterogeneity and Hierarchies: should all be treated equally?13

4.1 Introduction

Technology homogeneity has always been a very crucial precondition in efficiency and productivity analysis. Engineers, economists, operational researchers, and scholars from the management disciplines who have been engaged in this line of research are always very cautious to ensure that Decision Making Units (DMUs), that is the examined production entities, are benchmarked against peers who employ identical production technology. In principle, each DMU is technologically comparable (i.e. strongly identical) only to itself. Viewed from this standpoint, it could be argued that achieving perfect technology homogeneity is a utopia, since “heterogeneity of several types is everywhere” (O’Donnell et al., 2008, Dosi et al., 2010). In other words, the urge to find commonalities among the examined DMUs and ensure as much technology homogeneity as possible, may lead instead in an idiosyncratic type of “technological isolation” of the examined DMUs (Tsekouras et al., 2015). The case at which a DMU is benchmarked exclusively against itself so as to achieve absolute technology homogeneity seems to be unreasonable if not schizophrenic. It is also undeniable that absolute technology homogeneity abolishes the very nature of the benchmarking process. In practice, when productive performance is evaluated, the examined DMUs, constituting the benchmarking set, are most of the times aggregated according to some a priori and based on the intuition of the researcher, shared characteristics (e.g. countries, sectors, industries, technological trajectories and business clusters). However, the lack of identifying DMU idiosyncratic productive performance characteristics may has a severe impact in defining the frontier and subsequently on the outcome of the benchmarking process in general. The idiosyncratic productive performance may be attributed to a number of specificities and peculiarities, observed or not, such as differences in the technical and managerial skills available to production entities, differences in the available resource endowments, economic infrastructure and any other characteristics of the physical, social, institutional and economic environment in which production process takes place (Asaftei et al., 2008). In this paper, we introduce and define the DMU-specific heterogeneity (DSH) on the basis of the isomorphic production sets and we present an algorithm for identifying DSH production units on the basis of a highly aggregated frontier.

13 This paper is co-authored with Tsekouras, K and Kountas, K whilst a revised version has been submitted for publication and is under the review process.
The handling of technology heterogeneity in the frontier analysis context, has been greatly benefited by the introduction (Hayami & Ruttan, 1970) and subsequent developments of the metafrontier approach (Battese & Rao, 2002; Battese et al., 2004; O’Donnell et al., 2008) which allows the incorporation of technology heterogeneity and measurement of the resulting key-note of the technology gap and metatechnology ratio. Although these developments may serve for the examination of the magnitude and direction of spillovers (Casu et al., 2014, Tsekouras et al., 2015) between neighboring yet distinct technologies, such an investigation raises questions regarding the sources of heterogeneity. The issue of heterogeneity sources brings to the fore the concept of the technology hierarchy. On the one hand, a technology hierarchy dominated by country frontiers is a structure which assumes that the country specific characteristics ensure the higher attainable level of technology homogeneity. In the paper at hand, we call this structure as Country Frontiers Dominated Technology Hierarchy (CFDTH). On the other hand, in the case where a structure is dominated by sector frontiers we call it Sector Frontiers Dominated Technology Hierarchy (SFDTH) once one adopts this assumption, at least implicitly, that sector characteristics endure the maximum level of homogeneity.

CFDTH is prevailing in the analysis of Bartelsman et al., (2013) and attributes the idiosyncratic productive performance, also called as productivity differentials, to country-specific market and institutional mechanisms which result in (in-)efficient resources allocation mainly through turbulence and industrial dynamics. In a different economic rationale, SFDTH attributes the idiosyncratic productive performance in the asymmetric effects of the emerging technologies, or technological opportunities, on different industrial structures (Los & Verspagen, 2006, Castellacci, 2007, Castellacci & Zheng, 2010, Castellacci et al., 2014). In this perspective, a production entity which exhibits significant volatility of its productive performance under different considerations of technology hierarchy, is identified as structurally heterogeneous. In this direction, we also define the Hierarchical Structural Heterogeneity (HSH) and we introduce a measure of HSH in the frontier-metafrontier context. For the case examined herein, HSH reveals to what extent the productive performance of a production entity is affected by the intra-sectorial life-cycle patterns, the sectorial patterns of innovation and the resulting technological regimes (Castellacci, 2007).

Both DSH and HSH are defined in the context of the technology set, the antecedent of any technology heterogeneity. In this line of argument, it is reasonable to assume that any technology heterogeneity patterns, and thus DSH and HSH, are endogenously related. More specifically, the main research question of the present paper is to examine if the probability that a DMU exhibiting idiosyncratic productive performance of the DSH type -at a technologically homogeneous
environment, is endogenously related to the HSH type-in an environment where hierarchical technology heterogeneity is taken into consideration-associated to the former. In a nutshell, we investigate if the adopted, and most of the times imposed, technological hierarchy distorts the benchmarking process and is responsible for the idiosyncratic behavior of some of the corresponding production entities. We employ a balanced panel dataset corresponding to seventeen European countries and thirteen industries from Manufacturing and Transportation sectors covering the period from 1999 to 2006. Although the co-examination of European Manufacturing and Transportation Sectors is mainly adopted for experimentation reasons-since the imposed a priori heterogeneity is apparent-it allows us to derive interesting findings regarding the impact of the imposed level of aggregation of any benchmarking process. Furthermore, we exploit the potential of a recent econometric technique, proposed by Giles & Murtazashvili (2013), estimating a dynamic panel probit model with one endogenous regressor which allows us to examine issues of multifaceted technology heterogeneity, in conjunction with time persistent characteristics and the role of the initial conditions. The empirical results reveal that DSH production entities exhibit two kinds of heterogeneous patterns and HSH production entities are mainly traced in the right tail of the productive performance distribution. Moreover, a type of weak endogeneity between the two types of heterogeneity is revealed. Finally, path dependence and initial conditions prove to be the catalysts provoking technological heterogeneity and endogenous interdependence between the DSH and HSH.

The remaining of the chapter is structured as follows: Section 4.2 provides a review of the related literature, Section 4.3 presents the theoretical and methodological underpinnings, Section 4.4 describes the dataset employed in the analysis, Section 4.5 presents the discussion of the results while Section 4.6 concludes the chapter.

4.2 Review of the Literature

Both theoretical and empirical work in the field of efficiency and productivity analysis, have pointed out the importance of heterogeneity and its distorting role to the benchmarking process. To this end, recent achievements in handling the multifaceted issue of heterogeneity could be categorized into three strands.

According to the first strand, any heterogeneity might exists is included into the disturbance term of a parametric model which could be further disentangled to inefficiency and noise as Greene (2005) has pointed out. Orea and Kumbhakar (2004) adopting a latent class stochastic frontier approach, argued that inappropriate handling of unobserved differences in the production technology, may mislead the researcher to label those production differentials as inefficiency. Their approach heavily relies on the fact that the model identifies the optimal number of “homogeneous”, yet latent, technological groups i.e. frontiers and proceeds to the
evaluation of their productive performance. The third strand is the one of the metafrontier framework, which was introduced by the seminal papers of Hayami (1969) and Hayami and Ruttan (1970). The metafrontier framework was renewed and further developed by the contributions of Battese and Rao (2002), Battese et al., (2004) and O’Donnell et al., (2008). In this respect, Kounetas et al., (2009) introduced input- and output- invariant measures of technology heterogeneity, incorporating issues of scale efficiency and introducing technology hierarchies. One appealing feature of the metafrontier framework is that it is applicable to non-parametric models as well as to parametric ones. The key issue of the metafrontier context is the creation of a new frontier which envelops the individual ones, accounting for heterogeneity to the most possible extent and introducing bidirectional technological flows between the individual frontiers and the metafrontier (Casu et al., 2014, Tsekouras et al., 2015). The production entities are benchmarked against the overall technology, while it allows for the calculation of technology gaps between the individual frontiers and the metafrontier. A growing and burgeoning literature surrounds the usage the metafrontier context since it moves beyond capturing the productivity differentials at an individual level providing the ground to study the effect of different technological structures per se, or in other words to consider the impact of alternative technological hierarchies, on the productive performance of the DMUs under evaluation.

In the last fifteen years, two approaches have attempted to investigate the productive performance differentials considering different technological and economic structures. More specifically, the first assumes that the country frontiers have a dominant role and the productive performance differentials are due to country-specific mechanisms which result in (in-) efficient resources allocation mainly through turbulence (Bartelsman et al., 2013; Chen & Irarrazabal, 2014; Melitz & Polanec, 2015; Collard-Wexler & De Locker, 2015; Dobbelaere et al., 2015). The second approach focuses on the asymmetric effects of the emerging technologies on different industrial structures and the resulting productive performance differentials (Aghion et al., 2015; Los & Verspagen, 2006, Castellacci, 2007, Castellacci & Zheng, 2010, Castellacci et al., 2014). In this case, the dominant technological hierarchy is the one reflected on industrial frontiers and innovation as well as technological opportunities are the driving forces of technology heterogeneity.

The above approaches bring to the fore different factors affecting productive performance of a set of production entities. Augmenting this argument, studies on the distorting role of heterogeneity on productive performance focus on the production entities themselves along with a set of candidate factors (e.g. Lee et al., 2009) provoking heterogeneous patterns in performance. DMUs’ homogeneity considerations are of central interest in efficiency analysis.
and has been attempted by the use of advanced and complex quantitative techniques (Dai & Kuosmanen, 2014). Efforts to distinguish the dimensions of heterogeneity and perform tests for the homogeneity of the technologies across production entities, are not scarce in the literature of efficiency analysis since it has been employed in several studies of banking efficiency (Brown & Glennon, 2000; Altunbas et al., 2001; Elysiani & Rezvanian, 2002; Isik & Hassan, 2002; Bos et al., 2009) where in all of the cases the homogeneity assumption was rejected. The latter highlighted the importance of considering different structure of the production frontiers to be able to shed light and get indications of what heterogeneity really embraces or put it another way; what are the “ingredients” that formulate a frontier with less distortions in the performance of the respective DMUs. Moreover, Cazu and Girardone (2010) calculate the efficiency scores using production frontiers and proceed to second stage System-GMM to study the beta and sigma convergence within the European banking sector.

4.3 Theoretical and Methodological Underpinnings
Our methodological framework is developed in three interconnected stages. In the first stage, we present the theoretical and methodological underpinnings regarding the DSH, the presentation of the corresponding approach for the HSH follows, and finally the interrelation of the two types of heterogeneity is theoretically and methodologically developed.

4.3.1 Definitions, notation and individual heterogeneity
A production entity is generally regarded as a Decision Making Unit (DMU) which transforms \( N \) inputs \( N = \{1,...,n\} \) into \( M \) outputs \( M = \{1,...,m\} \). The underlying production process is described by the technology set \( S = \{ (x, y) : x \text{ can produce } y \} \subseteq R^{m+n}_+ \) which actually is the set of both physically and technologically attainable points \( (x, y) \) where \( x \in R^n_+ \) is the input and \( y \in R^m_+ \) is the output vector respectively.

- **Definition 1.** \( K \) production entities which are benchmarked against each other, under a common technology set \( S \), define the **Benchmarking Set**, \( B_K \).

The input-oriented frontier \( F = \{(x, y) \in S : D_I (x, y) = 1\} \) associated with the technology set \( S \), can be characterized as the upper boundary or the “technology frontier” for the \( K \) production entities. The **input distance function**, \( D_I (x, y) = \sup \{x \in R^n_+ : (x, y) \in S\} \), represents the smallest input quantity vector on the ray from the origin through \( x \) that can produce output \( y \), that is, \( L(y) = \{x \in R^n_+: (x, y) \in S\} \).
For a given production entity \((x, y)\), the productive performance is defined as:

\[
\hat{\text{Eff}}_{n}(x, y) = \hat{\theta}(x, y) = \min \left\{ \theta \left| \theta > 0, y_j \leq \sum_{i=1}^{n} y_i \theta_i, \sum_{i=1}^{n} x_i \theta_i \geq \sum_{i=1}^{n} x_i n_i \right\} ,
\]

(4.1)

for \(y_j\) such that \(\sum_{i=1}^{n} y_i = 1, y_j \geq 0, i = 1, 2, \ldots, n\)

where \(\theta\) is a scalar and the value obtained denotes the technical efficiency score for the \(i-th\) production entity while \(\gamma\) is a \(N \times 1\) vector of constants.

Data Envelopment Analysis (DEA) is one of the most known approaches used in numerous applications related to performance evaluation (Ulucan & Baris Atici, 2010; Demirbag et al., 2010), employing mathematical programming techniques, to form the piece-wise linear frontier and estimate the productive efficiency scores corresponding to all production entities in the benchmarking set \(B_K\). Simar and Wilson (1999; 2007) has focused on the bias of the efficiency estimates occurring from the way the piece-wise frontier is being shaped by the DEA and introduced the concept of bootstrapping the DEA efficiency scores. Following Simar and Wilson’s procedure\(^{\text{14}}\), we are able to estimate the bias\(^{\text{15}}\) and the sigma for the original DEA estimators for the \(i-th\) production entity as:

\[
\text{bias}\{\hat{\theta}_i(x, y)\} = \frac{1}{B} \sum_{b=1}^{B} (\hat{\theta}_{i,b}^*(x, y) - \hat{\theta}_i(x, y)) \quad \text{(4.2)}
\]

and

\[
\text{sigma}^2 \{\hat{\theta}_i(x, y)\} = \frac{1}{B} \sum_{b=1}^{B} (\hat{\theta}_{i,b}^*(x, y) - \left\{ \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{i,b}^*(x, y) \right\})^2 ,
\]

(4.3)

where \(B\) is the number of the total bootstrap replications, here \(b = 1, 2, \ldots, 2000\).

Thus, a common and “homogeneous” benchmarking set occurs for evaluating the efficiency scores of the \(K\) production entities participating in the former. However, common sense suggests that this is not the case for the majority of real-life situations since every production entity is tied to individual heterogeneity.

- **Definition 2** We define as \(w_i\) the ratio of bias correction to the sigma of the bootstrap estimated productive efficiency scores for each \(i-th\) production entity as:

\[w_i = \frac{\text{bias}\{\hat{\theta}_i(x, y)\}}{\text{sigma}^2 \{\hat{\theta}_i(x, y)\}}\]

\(^{\text{14}}\) The FEAR package (Wilson, 2008) was employed to get the bootstrapped efficiency scores.

\(^{\text{15}}\) Bias is a bias-corrected estimator of \(\hat{\theta}_{i,b}^*(x, y)\) given as \(2\hat{\theta}_{i,b}^*(x, y) - \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{i,b}^*(x, y)\).
\[ w_i = \frac{\hat{\text{bias}}_i}{\text{sigma}_i}, i = 1, 2, ..., K \tag{4.4} \]

The above ratio incorporates and internalizes the combined effect of bias and variance resulting from the heterogeneous nature of the transformation of inputs into outputs along with the noise from the iterative process of the bootstrap technique, while at the same time aspires to shed light on the entity that is less likely to belong to a certain benchmarking set of production entities. Then, the one exhibiting the minimum ratio is being excluded from the benchmarking set and this is how the new \( B_{K-i} \) associated to the input-oriented frontier \( F_{K-i} \), set is defined. The productive efficiency scores of the remaining \( K-i \) production entities are being evaluated again under the new technology set \( S_{K-i} \) which does not contain the unit employing the combination \((x_i, y_i)\).

The \( i \)-th production entity is heterogeneous with respect to the \( B_k \) benchmarking set, if \( w_i < w^* \), where \( w^* \) is a latent critical value which ensures that the benchmarking set does not contain DSH production entities. Therefore, the \( i \)-th production entity is characterized as DSH according to the following binary variable:

\[
\text{DSH} = \begin{cases} 
1, & \text{if } w^* > w_i \\
0, & \text{otherwise}
\end{cases}
\tag{4.5}
\]

- **Proposition 1.** Let \( B_k \subseteq \mathbb{R}_+^N \times \mathbb{R}_+^M \) be the benchmarking set of the production entity’s and \( B^*_k \subseteq \mathbb{R}_+^{N+M} \) be the set of the bootstrapped estimates mapped with the following function \( f(\cdot), f : B_k \rightarrow B^*_k \). Consider the \( B_{K-i} \) set accompanied by a function \( g(\cdot) \) associating the two sets, \( g : B^*_k \rightarrow B_{K-i} \) including production entities exhibiting delinquent, -in production technology terms- behaviour captured by the \( w_i \) ratio. The \( i \)-th production entity is characterized as DSH, if the \( B_{K-i} \) set is not isomorphic to \( B_k \) set or in other words, if its exclusion, based on the value of \( w_i \) from the benchmarking set does not result to an isomorphic set.

\[ \text{DSH} = \begin{cases} 
1, & \text{if } w^* > w_i \\
0, & \text{otherwise}
\end{cases}
\tag{4.5}
\]

---

\[ \text{Proposition 1.} \text{ Let } B_k \subseteq \mathbb{R}_+^N \times \mathbb{R}_+^M \text{ be the benchmarking set of the production entity’s and } B^*_k \subseteq \mathbb{R}_+^{N+M} \text{ be the set of the bootstrapped estimates mapped with the following function } f(\cdot), f : B_k \rightarrow B^*_k \text{. Consider the } B_{K-i} \text{ set accompanied by a function } g(\cdot) \text{ associating the two sets, } g : B^*_k \rightarrow B_{K-i} \text{ including production entities exhibiting delinquent, -in production technology terms- behaviour captured by the } w_i \text{ ratio. The } i \text{-th production entity is characterized as DSH, if the } B_{K-i} \text{ set is not isomorphic to } B_k \text{ set or in other words, if its exclusion, based on the value of } w_i \text{ from the benchmarking set does not result to an isomorphic set.} \]

---

\[ \text{The numerator in formula (4.4) reflects the uncertainty about the true value of the productive efficiency score of the specific production entity operating at } (x, y) \text{ compared to its peers and it is associated with its position in the space } \mathbb{R}_+^N \times \mathbb{R}_+^M \text{ denoting the precision of the efficiency score (Daraio & Simar, 2007). The denominator of this ratio represents the dispersion of each production entity taking into account every single value or in other words, indicates how “tight” are the values of the efficiency scores around the mean compared to their peers after the implementation of the bootstrap technique. All in all, it accounts for the noise associated to the } i \text{-th examined production entity (Efron & Tibshirani, 1993).} \]

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Computational Algorithm. The algorithm developed at this stage in order to identify the associated with the minimum $w_i$ ratio DMUs, can be outlined as follows:

i. Apply to the $B_k$ set, the bootstrap algorithm to obtain, for each production entity, the bias-corrected efficiency scores, the bias and the sigma as well.

ii. Compute the ratio $w_i$ for each production entity in the benchmarking set, i.e.

$$\forall \ i = (1, 2, \ldots, K)$$

iii. Identify the $i-th$ production entity exhibiting the minimum value of the $w_i$ ratio.

iv. Exclude the respective production entity so as to get a purged out from the sampling noise benchmarking set $B_{k-i}$.

   a. Test the hypothesis: $B_k$ is isomorphic to $B_{k-i}$ or $B_k \equiv B_{k-i}$.

   b. If the null hypothesis is not rejected the production entity $i$ is not $DSH$ and the procedure terminates\(^{17}\). The $B_k$ set is homogeneous in terms of $DSH$.

   c. If the null hypothesis is not accepted, repeat steps (1) to (4) for the next production entity which exhibits the lower value of the $w_i$ ratio between the $K-1$ remaining production entities. The $B_k$ set is not homogeneous in terms of $DSH$, since $i$-th production entity is $DSH$, and we have to test for the existence of additional $DSH$ production entities in the $B_{k-i}$ set.

4.3.2 Technology heterogeneity and hierarchy structure

In the case that at least one a priori known characteristic is attributed only to a subset of the benchmarked production entities, the benchmarking set encompasses distinct technological sets. However, these distinct technological sets may be associated via, known or unknown, characteristics which are common to all the elements of $B_k$.

In this perspective, and given $p$ distinct but still associated technologies $S^1, S^2, \ldots, S^p$, the metatechnology set\(^{18}\), denoted as $S^M$, is defined as the convex hull of the jointure of all

\(^{17}\) The rationale behind the previous procedure is that after the removal of a given production entity, the deviation of the variances of the efficiency scores of the rest production entities in the benchmarking set, compared to the situation before the removal, can be used in order to improve its extent of technology “homogeneity”. In this paper we employ the non-parametric statistics tests of Mann-Whitney Wilcoxon for independent and unequal sample sizes in order to test the equality of means of the meta-efficiency scores distribution before and after the exclusion of the $DSH$ suspect production entities.
technology sets represented as

\[ S^M = \{(x, y) : x, y \geq 0 : x \text{ can produce } y \text{ in at least one of } S^1, S^2, ..., S^p \} \].

- **Definition 3.** Technology hierarchy structure is the production frontiers’ hierarchy dominated by the \( h \)-th \((h = A_1, A_2, ..., A_j)\) differential characteristic of the \( S^1, S^2, ..., S^p \) distinct technologies and is reflected on the \( S^M \) convex hull of the jointure of the \( p \) technology sets.

Hereafter, we consider two technology hierarchies. In the first one, the *Country Frontiers Dominated Technology Hierarchy (CFDTH)*, the technology set corresponds to European countries while in the second case, we consider the *Sector Frontier Dominated Technology Hierarchy (SFDTH)*, which is formed by different industrial sectors. The hierarchy is not *a priori* known. Actually, there are alternative hierarchies which may share some common technological opportunities and restrictions while at the same time are differentiated with respect to some other factors. The shared commons are represented by \( S^M \) technology while technological differentials are embodied in \( S^p \) technologies.

The productive efficiency of a production entity with respect to the metafrontier, is measured by the input-oriented *metatechnical efficiency score*\(^{19}\) \( \left( MTEff_{i,h} \right) \) and it is easily estimated by solving an analogous LP problem as in (1). Metafrontier analysis is an approach that accounts for technology differentials of heterogeneous technologies whilst the particular characteristic of the metafrontier as an envelope of all the respective hierarchy structures, provides the opportunity to account for all the possible existing heterogeneity among the production entities participating in a dataset (O’Donnell et al., 2008; Kounetas et al. 2009).

O’Donnell et al., (2008) have employed conventional Shepard distance functions to estimate technical efficiency with respect to that metatechnology and individual technology sets as well. Each efficiency score obtained from the estimation with respect to the common technology, can be used to define the *metatechnology ratio* \( \left( MTR_{i,j} \right) \) which is considered as a measure of proximity of the \( l-th \) group under a hierarchy structure to the its metafrontier and

---

\(^{18}\) Accordingly, the *metaproduction* input set for \( S^M \) is and the input distance function with respect to \( S^M \) is \( D_{l} \left( MF: (x, y) \right) = \sup \{ \theta > 0 : \gamma_{\theta} \in L^M (y) \} \) where the metafrontier associated with \( S^M \) is represented by the set \( MF = \{(x, y) \in S^M : D_{l}^M (x, y) = 1 \} \).

\(^{19}\) Metatechnical efficiency, by its definition, is a measure that works irrespective of the hierarchy under which a production entity operates and corresponds to an identical initial homogeneous status.
for a given point \((x, y)\) of the \(i-th\) production entity under \(h_s = A_1, A_2, \ldots, A_s, s = 1, 2, \ldots, l\) hierarchy can be defined as:

\[
MTR_{i,h_s}(x, y) = \frac{MTEff_{i,h_s}(x, y)}{Eff_{i,h_s}(x, y)}
\]  

(4.6)

Conceptually, the technology gap is defined as the distance of the group frontier to the metafrontier, weighted with the minimum inputs which are attainable employing the group-specific technology is given by:

\[
Tg_{i,h_s}(x, y) = 1 - MTR_{i,h_s}(x, y)
\]  

(4.7)

- **Definition 4.** We define hierarchical structural heterogeneity (HSH) as the absolute value of technology gaps under the alternative hierarchies that the \(i-th\) production entity operates and adopted herein, that is \(|Tg^{CFDTH}_{i,h_j} - Tg^{SFDTTH}_{i,h_j}|\), and captures the “sensitivity” of the productive performance the \(i-th\) entity exhibits under different technological hierarchies, \(h_j\). It is worth-noting that, unlike in the DSH case which is defined in the framework of complete homogeneity via the usage of meta-technical efficiency, the HSH is defined in a framework that technology heterogeneity has been encompassed through the frontier-metafrontier context.

It should be noted that the context of technology gap has captured the attention of scholars who are engaged in research where technology heterogeneity is of high importance (Lozano-Vivas & Pastor, 2010). Although the DEA technique is well-established in performance evaluation studies through production frontiers, the way of calculating the technology gaps moves beyond the concept of metafrontier (O’Donnell et al., 2008) neglecting for some aspects of the pervasive heterogeneity.

### 4.3.3 The combined effect of DMU-specific and structural heterogeneity

Exploiting the potential of a recent methodological contribution introduced by Giles and Murtazashvili (2013), we investigate the factors affecting the determinants of the probability of being DSH and the inter-linkage with the effect of HSH by the estimation of two dynamic models which are explicitly described in equations (4.8) and (4.9) below.

Before we proceed to the presentation of the econometric models employed in this analysis, it is not worthless to make an observation based on Tables 4.1 and 4.2 below which present the frequency of occurrence, under both hierarchical structures, for the DSH production entities of the sample. Taking into consideration the number of deletions under each hierarchy, we construct the idiosynratic group variable applying the formula of the Florence median. The
The idiosyncratic group variable ($IG$) includes the production entities (either countries or industries) which exceeded the threshold indicated by the Florence median. More precisely, for the $CFDTH^{20}$, the threshold was 35 deletions while for the $SFDTH^{21}$ case, was 27 deletions. The threshold indicated by the Florence median is in line with the results of the algorithm presented in Section 4.3.1, since those complement each other. Transition economies (e.g. Ryzhenkov, 2016) and fragmented industries exhibiting intensive turbulence due to globalization which participate in the idiosyncratic group are expected to affect positively the odd of being $DSH$ irrespective of the technological structure adopted.

Table 4.1 Frequency of occurrence of the DSH production entities, on an annual basis, under the Country Frontiers Dominated Technology Hierarchy (CFDTH)

| Countries          | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | Total |
|-------------------|------|------|------|------|------|------|------|------|-------|
| Austria           | 0    | 1    | 2    | 2    | 4    | 3    | 3    | 3    | 18    |
| Belgium           | 2    | 3    | 7    | 6    | 5    | 3    | 4    | 2    | 32    |
| Czech Republic    | 5    | 7    | 6    | 6    | 7    | 5    | 4    | 6    | 46    |
| Denmark           | 0    | 2    | 2    | 3    | 4    | 1    | 2    | 0    | 14    |
| Finland           | 0    | 2    | 1    | 2    | 2    | 2    | 1    | 0    | 10    |
| France            | 0    | 2    | 2    | 3    | 3    | 3    | 1    | 1    | 17    |
| Germany           | 0    | 0    | 2    | 1    | 1    | 0    | 0    | 0    | 4     |
| Greece            | 4    | 5    | 4    | 5    | 6    | 5    | 4    | 4    | 38    |
| Ireland           | 1    | 2    | 2    | 4    | 4    | 3    | 3    | 2    | 21    |
| Italy             | 1    | 1    | 1    | 2    | 2    | 1    | 1    | 1    | 10    |
| Netherlands       | 1    | 1    | 2    | 5    | 5    | 1    | 1    | 1    | 17    |
| Poland            | 6    | 7    | 7    | 8    | 8    | 9    | 7    | 9    | 61    |
| Slovakia          | 1    | 4    | 1    | 1    | 1    | 2    | 0    | 0    | 10    |
| Slovenia          | 8    | 10   | 11   | 6    | 9    | 10   | 9    | 7    | 70    |
| Spain             | 1    | 5    | 4    | 6    | 7    | 5    | 5    | 2    | 35    |
| Sweden            | 0    | 1    | 1    | 3    | 3    | 1    | 1    | 0    | 10    |
| United Kingdom    | 0    | 1    | 0    | 0    | 0    | 0    | 0    | 0    | 1     |
| Total             | 30   | 54   | 55   | 63   | 70   | 55   | 49   | 38   | 414   |

20 Czech Republic, Greece, Poland, Slovenia and Spain.

21 Air Transport, Basic metals, Chemicals and chemical products, Food and Beverages, Other non-metallic minerals, Textiles and Transport Equipment.
Eq. (4.8) employs a dynamic binary response random effects panel data model for the probability that a production entity has been identified $DSH$ which is given by:

$$DSH_{i,j,t} = \alpha_0 + \sum_{g=1}^{G} \beta_g X_{g,i,j,t} + \rho DSH_{i,j,t-1} + \lambda I_{j,i,t} + c_{i,j,t} + u_{i,j,t}$$

(4.8)

where $i = 1,2,\ldots,K$, $j = 1,2,\ldots,J$, $t = 1,2,\ldots,T$, $h_s = h_{CFTDH}, h_{SFDTH}$, $g = 1,2,\ldots,G$

where, $X_{g,i,j,t}$ is the matrix of the $G$ exogenous repressors, $\rho$ is a parameter of particular interest since it captures the time persistence of $DSH$ phenomenon (Tsekouras et al., 2015; Bartelsman et al., 2013; Bartelsman and Doms, 2000; Syverson, 2011) or the path dependence of the DMU-specific heterogeneous behavior endogenously associated with the current behavior, that is the $DSH_{i,j,t-1}$. The parameter $\lambda$ captures the effect of the idiosyncratic group to the probability of being $DSH$, the source of spurious path dependence attributable to unobserved heterogeneity across production entities is represented by the $c_{i,j,t}$ term while $u_{i,j,t}$ denotes the usual unobserved errors.

Regarding the $HSH$, we argue that time persistence, country-, sector- and industry- specific characteristics are the major determinants. Therefore, a pooled cross section linear regression of the type depicted in Eq. (4.9) had to be estimated:

$$HSH_{i,j,t} = \left[ T_{g,i,t}^{CFTDH} - T_{g,i,t}^{SFDTH} \right] = \sum_{q=1}^{Q} \theta_q Z_{q,i,j,t} + c_{i,j,t} + \phi \left[ T_{g,i,t}^{CFTDH} - T_{g,i,t}^{SFDTH} \right] + \delta D_{g,i,t} + u_{i,j,t}$$

(4.9)

where $i = 1,2,\ldots,K$, $j = 1,2,\ldots,J$, $t = 1,2,\ldots,T$, $h_s = h_{CFTDH}, h_{SFDTH}$, $q = 1,2,\ldots,Q$

where $Z_{q,i,j,t}$ is a matrix of $Q$ time varying exogenous repressors, $\bar{Z}_{i,j}$ is a matrix containing invariant (averages) exogenous repressors captured by the ratios of the productive
characteristics by country and industry respectively and occurs by relying to the Mundlak’s (1978) device. The coefficient $\phi$ of the lagged value of the dependent variable captures path dependence characteristics. In addition, $c_{2i,j}\varepsilon_{i,j}$ is an unobserved effect while $D_{i-t}^T$ represents the time heterogeneity effect on the absolute difference of the structural heterogeneity. The term $u_{2i,j}\varepsilon_{i,j}$ denotes the usual unobserved errors.

The dependent variable of Eq. (4.9) along with other factors of this model in conjunction to its underlying relation with Eq. (8), gives rise to severe endogeneity concerns. More specifically, endogeneity issues arise due to (i) the endogenous relationship between $DSH$ and $HSH$ which implies that $HSH$ is an endogenous covariate in the $DSH$ equation, (ii) the inclusion as an explanatory variable of the time lagged dependent variables in both the $DSH$ and $HSH$ equations in order to capture the path dependence of productive performance differentials, (iii) the fact that $DSH$ and $HSH$ equations are not identified within a solid theoretical framework, which to the best of our knowledge is not available, and therefore several issues of the omitted variables type may arise and (iv) the fact that $DSH$ may arise from an omitted “selection” rule mirroring policy orientation, and targeting. The estimation of Eqs (8) and (9) requires a dynamic panel probit with one endogenous regressor estimator. To the best of our knowledge, such an estimator is not yet available. In this direction, we heavily rely, undertaking some minor but necessary modifications, on the econometric strategy introduced by Giles and Murtazashvili (2013). The complete form of the equation to be estimated is the following:

$$DSH_{i,j}\varepsilon_{i,j} = \xi_0 + \sum_{g=1}^G \beta_g X_{g,i,j}\varepsilon_{i,j} + \sum_{q=1}^Q \delta_q Z_{q,i,j}\varepsilon_{i,j} + \phi HSH_{i,j} + \rho DSH_{i,j-1}\varepsilon_{i,j} + u_{2i,j}\varepsilon_{i,j} + \psi I\varepsilon_{i,j} + \hat{t}_{2i,j}\varepsilon_{i,j} + \bar{V}_{2i,j}\varepsilon_{i,j} + \Delta DSH_{i,j-1}\varepsilon_{i,j} + \nu_{i,j}\varepsilon_{i,j} + u_{3i,j}\varepsilon_{i,j}$$

(4.10)

where $i = 1,2,\ldots,K$, $j = 1,2,\ldots,J$, $t = 1,2,\ldots,T$, $h_5 = h_{CFDTH}$, $h_{SFDTTH}$, $g = 1,2,\ldots,G$, $q = 1,2,\ldots,Q$.

The inclusion of the residuals from Eq. (4.9), $\hat{t}_{2i,j}\varepsilon_{i,j}$, as a predictor intents to account for endogeneity arising from one of its components (Eq.(4.9)), the matrix $\overline{V}_{2i,j}\varepsilon_{i,j}$ contains the industries’ cumulative residuals in each of the hierarchies adopted herein. Such being the case, for the $CFDTH^{23}$, represents a total time-invariant, yet unobserved effect, which encompasses the year heterogeneity in the use of the input ratios along with other factors affecting

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22 Additional assumptions concerning the dependent variable have to be established considering that $E[I_t h_{CFDTTH} - T_{h_{CFDTTH}}] = 0$ while the inter-linkage between Eq. (4.8) and Eq. (4.9) structural errors assumes that $Cov(u_{i,j}\varepsilon_{i,j}, u_{2i,j}\varepsilon_{i,j}) = 0$.

23 For the $CFDTTH$ case, the time averages of the residuals were calculated, taking into account the industries while for the case of industry frontiers, $SFDTTH$, country averages of the residuals should be calculated accordingly.
heterogeneous behavior and have not been included in the specification and \( \nu_{i,j,t} \), is a reduced form of the unobserved heterogeneity term. Finally, the inclusion of the initial conditions i.e. whether or not a production entity had been identified as heterogeneous in the first year of the sample, \( DSH_{i,j,t=1} \), aims to capture the effect of the state dependence of each production entity and how it impacts its future productive performance achievements while the impact of the participation into the idiosyncratic group is also considered and captured by the parameter \( \psi \).

4.4 Data and variables

In order to test our methodological approach we employ a dataset that allows (i) introducing some apparent, nevertheless meaningful DMU associated heterogeneity (ii) examining different technology hierarchies without involving any micro-level idiosyncrasies but in conjunction to DMU-specific heterogeneity and (iii) minimizing measurement errors that would increase DMU-specific heterogeneity. In this direction, we have devised, the employed in this paper dataset, by combining information provided by four distinct publicly available sources resulting in a unique balanced panel comprising of thirteen 2-digit industries\(^{24}\) according to the International Standard Industrial Classification (ISIC) in seventeen EU countries\(^{25}\) over an eight-year period from 1999 to 2006. It is not worthless to note that the basic unit of analysis is the European industries of Manufacturing and Transportation sectors. Thus, the employed dataset contains 1,768 observations in the panel dimension. The dataset used to estimate the productive performance via the corresponding production frontiers embraces five variables; one output and four input variables.

More specifically, we approximate the produced output \((Y)\), by the gross valued added of each industry, whilst the inputs include the capital stock \((K)\) in million Euros, the labor input \((L)\) which is captured by the total hours worked by employees, expenditure on intermediate inputs \((M)\) in million Euros and the total energy consumption \((E)\) measured in million tons (Mtoe) of oil equivalent. For several of the countries\(^{26}\) in this dataset, certain monetary variables are reported in local currency and needed to be converted into Euros, using the currency provided by the European Commission, before being used in the analysis.

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\(^{24}\) More specifically, 9 of them belong to the Manufacturing (Food and Beverages, Textiles, Wood and Wood Products, Pulp Paper, Chemicals and Chemical Products, Other non-metallic Minerals, Basic Metals, Transport Equipment and Construction) and 4 to the Transportation sector (Land Transport and Transport via Pipelines, Water Transport, Air Transport and Supporting and Auxiliary Transport Activities).

\(^{25}\) In particular, Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Poland, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom.

\(^{26}\) Czech Republic, Denmark, Poland, Slovak Republic, Slovenia, Sweden and the United Kingdom.
In the second stage of the analysis, where we investigate the drivers of the two types of technological heterogeneity and their underlying connection as well, we have employed as additional exogenous explanatory variables, the productive characteristics of the production entities captured by the corresponding input ratios, and variables which capture additional ambient technological discrepancies. These include the *EURO* variables, a dichotomous variable indicating membership in the European Monetary Union (EMU), and the *GCI* variable, which reflects the Global Competitiveness Index’s value of each of the examined countries on a yearly basis. The former is intended to control for any heterogeneity owing to transaction cost and pooled input markets advantages accruing to the countries participating in the EMU and was introduced in the analysis to test the European market integration hypothesis. The latter was introduced in order to reflect differences in productive performance. Those differences may derive from each country’s relative advantages in infrastructure, human capital, technological achievements and other developments related to the production process (Sala-I-Martin et al., 2008) in conjunction to the fact that the productive performance is linked to the level of the differential competitive characteristics. Tables 4.3, 4.4 and 4.5, below, provide the definition, measurement and basic descriptive statistics for each variable included in the final dataset corresponding to both technology hierarchies, respectively.

### Table 4.3 Variables, units of measurement and sources

| Variable                          | Units of measurement | Source                                |
|-----------------------------------|----------------------|---------------------------------------|
| Gross Value Added (*Y*)           | million euros        | GGDC                                  |
| Capital (*K*)                     | million euros        | OECD STAN, EUKLEMS                    |
| Labor (*L*)                       | million hours worked by employees | GGDC                                  |
| Intermediate Inputs (*M*)         | million euros        | GGDC                                  |
| Energy Consumption (*E*)          | million tons of oil equivalent | Enerdata - Odyssey                    |
| Global Competitiveness Index (*GCI*) | pure number       | World Economic Forum                  |
| EURO                              | -                    | European Commission                   |

All the monetary values are in constant 2000 prices using industry and country specific deflators.
Table 4.4 Descriptive statistics of the inputs and output for the Country Frontiers Dominated Technology Hierarchy (CFDTH) for the period 1999-2006

| Country       | Y     | K     | L     | E     | M     |
|---------------|-------|-------|-------|-------|-------|
| Austria       | 3,749 | 20,426| 107,975| 1.153 | 5,786 |
|               | (3,732)| (22,744)| (114,683)| (1.859)| (3,953)|
| Belgium       | 4,320 | 19,861| 99,815 | 1.647 | 11,439|
|               | (3,234)| (14,373)| (77,534)| (2.346)| (8,060)|
| Czech Rep.    | 1,614 | 10,976| 189,263| 1.080 | 4,491 |
|               | (1,231)| (12,844)| (169,705)| (1.782)| (9,052)|
| Denmark       | 2,401 | 9,159 | 65,533 | 589   | 4,746 |
|               | (1,971)| (6,941)| (62,069)| (1.016)| (4,417)|
| Finland       | 2,555 | 9,159 | 64,115 | 1.383 | 4,577 |
|               | (2,173)| (6,941)| (59,790)| (2.225)| (3,813)|
| France        | 19,716| 63,842| 558,171| 6.659 | 42,524|
|               | (17,284)| (69,373)| (580,158)| (11.052)| (35,394)|
| Germany       | 31,995| 96,897| 928,138| 9.296 | 60,768|
|               | (24,969)| (98,318)| (812,794)| (14.818)| (51,865)|
| Greece        | 2,055 | 9,796 | 101,646| 892   | 2,665 |
|               | (2,678)| (10,279)| (115,950)| (1.505)| (3,218)|
| Ireland       | 2,664 | 9,468 | 54,229 | .541  | 4,316 |
|               | (3,563)| (9,462)| (76,510)| (0.972)| (4,992)|
| Italy         | 18,739| 103,214| 569,381| 6.404 | 41,557|
|               | (14,874)| (96,987)| (476,815)| (10.194)| (26,641)|
| Netherlands   | 6,033 | 30,423| 161,328| 2.225 | 12,643|
|               | (5,169)| (30,802)| (158,568)| (2.629)| (11,723)|
| Poland        | 3,092 | 24,270| 348,803| 1.981 | 7,091 |
|               | (3,099)| (28,651)| (316,457)| (2.795)| (6,287)|
| Slovak Rep.   | 572,215| 131,896| 62,433| .464  | 1,560 |
|               | (509,262)| (207,664)| (55,152)| (.652)| (1,851)|
| Slovenia      | 1,612 | 15,147| 30,837 | .235  | 3,807 |
|               | (1,249)| (16,361)| (26,980)| (.344)| (2,911)|
| Spain         | 12,423| 87,914| 574,034| 4.686 | 26,571|
|               | (13,799)| (60,901)| (818,315)| (7.440)| (24,214)|
| Sweden        | 4,343 | 20,976| 120,009| 1.627 | 7,888 |
|               | (2,981)| (22,553)| (102,452)| (2.258)| (5,384)|
| United Kingdom| 22,006| 102,949| 636,169| 6.502 | 37,581|
|               | (18,635)| (75,459)| (566,057)| (11.035)| (31,475)|
| TOTAL         | 8,137 | 36,336| 274,934| 2.786 | 16,194|
|               | (13,651)| (59,419)| (460,343)| (6.782)| (26,434)|
As already mentioned, the data were drawn by combining several distinct sources. Data for Gross Value Added, total hours worked by employees and intermediate inputs were obtained from the database of Groningen Growth and Development Centre (GGDC), Enerdata-Odyssey database was used to collect data on energy consumption. Data on gross fixed capital formation were acquired through the Organization for Economic Cooperation and Development Structural Analysis (OECD StAn) database whilst wherever necessary, the Capital input files which were acquired through the EU-KLEMS Growth and Productivity Accounts database were employed. Industry specific deflators were acquired through OECD StAn database. The Global Competitiveness Index data were collected from various editions of the Global Competitiveness Report published by the World Economic Forum.

The most severe obstruction in the assessment of productive efficiency of a group of DMUs is the lack of a consistent series representing the capital stock. To overcome this stumbling block, we draw on the Perpetual Inventory Method (PIM) (see Krautzberger and Wetzel, 2012 as an example) to create a consistent measure of capital stock. The initial condition

| Industry                          | \( Y \)    | \( K \)    | \( L \)    | \( E \)    | \( M \)    |
|-----------------------------------|------------|------------|------------|------------|------------|
| Food & Beverages                  | 9,723      | 39,685     | 376,588    | 1,723      | 29,302     |
|                                   | (10,450)   | (56,861)   | (369,075)  | (1,603)    | (29,588)   |
| Textiles                          | 2,049      | 6,843      | 97,338     | .464       | 7,425      |
|                                   | (2,860)    | (8,638)    | (105,939)  | (.631)     | (11,590)   |
| Wood & wood products              | 2,009      | 13,158     | 93,422     | .382       | 4,118      |
|                                   | (2,072)    | (26,899)   | (74,893)   | (.358)     | (4,020)    |
| Pulp Paper                        | 8,380      | 37,809     | 230,451    | 2.180      | 29,302     |
|                                   | (9,351)    | (64,412)   | (244,461)  | (2.380)    | (29,588)   |
| Chemicals                         | 9,653      | 60,933     | 163,996    | 3.211      | 21,590     |
|                                   | (11,421)   | (74,900)   | (179,805)  | (3.319)    | (24,983)   |
| Other non-metallic minerals        | 3,966      | 16,490     | 136,646    | 5.439      | 6,727      |
|                                   | (4,549)    | (17,278)   | (129,576)  | (5.714)    | (7,925)    |
| Basic Metals                      | 12,007     | 67,863     | 427,353    | 23,616     |
|                                   | (15,316)   | (95,229)   | (437,768)  | (28,194)   |
| Transport Equipment               | 9,716      | 50,245     | 271,373    | .616       | 31,959     |
|                                   | (16,310)   | (61,519)   | (341,160)  | (.830)     | (49,353)   |
| Construction                      | 26,479     | 62,010     | 1,031      | .366       | 40,162     |
|                                   | (28,530)   | (87,707)   | (1,047)    | (.344)     | (42,332)   |
| Land Transport                    | 10,660     | 10,660     | 435,456    | 12,086     |
|                                   | (11,065)   | (42,929)   | (369,681)  | (14,544)   |
| Water Transport                   | 1,464      | 5,548      | 19,543     | 2,987      |
|                                   | (1,887)    | (9,849)    | (16,283)   | (3,814)    |
| Air Transport                     | 1,772      | 14,577     | 35,514     | 4,053      |
|                                   | (2,318)    | (17,313)   | (39,422)   | (4,792)    |
| Supporting Activities             | 7,899      | 56,414     | 254,907    | 12,019     |
|                                   | (9,318)    | (63,513)   | (329,467)  | (13,716)   |
| TOTAL                             | 8,137      | 36,336     | 274,934    | 16,194     |
|                                   | (13,651)   | (59,419)   | (460,343)  | (26,434)   |
for the capital stock is given by \( K_{1999} = \frac{I_{1999}}{\delta + g} \), where \( g \) is estimated as the average growth rate in capital investments for the preceding 5 years for each of the examined industries and countries. Given this initial value, the capital stock for each subsequent year is constructed using the inventory formula:

\[
K_{t+k} = (1 - \delta) K_{t+k} + I_{t+k},
\]

where \( K_{t+k} \) and \( I_{t+k} \) represent the capital stock and gross capital investment respectively, as captured by the gross fixed capital formation, of the \( i \)-th country on the \( k \)-th industry for the year \( t \) respectively, and \( \delta \) is the depreciation rate which is assumed to be equal to 10% yearly.

### 4.5 Results and discussion

#### 4.5.1 Identifying DSH and HSH industrial structures

**4.5.1.1 DSH production entities**

Implementing the methodological approach presented in Sections 4.3.1 and 4.3.2, we have identified the *DMU-specific* heterogeneous entities (*DSH*) for both the technological structures (i.e. hierarchies). Empirical results for the case where the hierarchical structure is dominated by the country frontiers (*CFDTH*) are presented in Table 4.1. The benchmarking sets set with respect to the metafrontier (i.e. the European Technology Level), becomes isomorphic when 414 idiosyncratic production entities, corresponding to the 23.4% of the total number of observations in the panel (1,768 observations), have been excluded from the latter. When the hierarchies come into play, in the case of *CFDTH* the greater number of *DSH* entities are identified in the frontiers of the Czech Republic, Poland and Slovenia with apparent institutional heterogeneity and incomplete market mechanisms ([Ryzhenkov, 2016](#)) while the country frontiers with the less *DSH* production entities correspond to those of Germany and United Kingdom. The corresponding results for the *DSH* entities, but under the *SFDTH* structure that is the when the technological structure is dominated by the sector frontiers, are presented in Table 4.2. In this case, the most capricious industrial structures which prevent the metafrontier from becoming isomorphic, or in other words the industries which exhibit the higher frequency regarding *DSH* behavior are those of the Textiles, the Non-Metallic Minerals and of the Air Transport. On the contrary, Construction and Water Transport industries are identified as the production entities with the lowest frequency as *DSH*.

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27 In fact, the estimated capital series did not exhibit significant differences when different levels of depreciation rates were considered.
All in all, considering the characteristics of the production entities which have been identified as DSH we could argue that in the case of the CFDTH type of technology structure, transition economies with less developed market mechanisms and incomplete shakeouts (Driffield et al., 2013) exhibit (i) higher possibility to be idiosyncratic and (ii) are located at the left-tail of the productive performance with respect to the metafrontier, that is are the laggards of the productive performance. At a first glance, the approach of Bartlesman et al., (2013) seems to be confirmed in this case. When the SFDTH structure is considered, the identified DSH production entities are those industries which face low levels of technological opportunities and which fail to exploit the new technological paradigm and the prevailing general natural trajectories. According to Castellacci (2007) and Verspagen and Los (2000), the role of appropriability conditions, the degree of openness to foreign competition, mainly via globalization, and the size of the market, could be considered as the crucial factors of the shrinking phenomenon of the productive performance of such type of industries. Table 4.6 below provides a simple but useful insight regarding the differential productive performance associated with the alternative technology structures and the metatechnology as well. The average technology gap value under the CFDTH appears to be greater than the corresponding one under the SFDTH. We should also note, that the country frontiers (CFDTH) encompass tangled and folded aspects of the economic environment, compared to the sector ones (SFDTH), which due to the high aggregation proves difficult to be approximated and measured in a more direct manner.

|                      | CFDTH        | SFDTH        |
|----------------------|--------------|--------------|
| **Productive Efficiency w.r.t. individual frontier** |              |              |
| Mean                 | 0.866        | 0.816        |
| Std.Dev.             | 0.133        | 0.144        |
| Max                  | 0.989        | 0.985        |
| Min                  | 0.213        | 0.099        |
| **Productive Efficiency w.r.t. Meta-frontier**      | Mean         | 0.478        |
| Std.Dev.             | 0.194        |              |
| Max                  | 0.902        |              |
| Min                  | 0.053        |              |
| **Technology gap**   | Mean         | 0.447        |
| Std.Dev.             | 0.209        | 0.419        |
| Max                  | 0.940        | 0.889        |
| Min                  | 0.000        | 0.000        |

A quite interesting feature of the DSH distribution, which we should recall that is identified irrespectively to the technology hierarchies, is revealed by the transition probability matrix, illustrated in Table 4.7 below. The information depicted in the transition probability matrix provides strong evidence in favor of the time persistence of heterogeneous behavior which points towards the direction of the characterization of a production entity as DSH.
Pursuing this finding, a significant -statistically speaking- path dependence phenomenon is being unraveled, since the probabilities at the main diagonal are greater than the threshold of 33.33%. It is also interesting to note that DMUs which had not been identified as DSH in the past it is almost certain (90.87%) that those will not exhibit heterogeneous behavior in the subsequent years. The same logic applies for the counterfactual case but the probability appears to be significantly lower (73.4%). However, we have to attempt to establish a more robust empirical relationship regarding the extent and the role of the persistence of heterogeneous behavior. We proceed with such an analysis, in Section 4.5.1.3 of this chapter.

Table 10 Transition probability matrix of the DSH units for the period 1999-2006

| DSH | No  | Yes |
|-----|-----|-----|
| No  | 90.87 | 9.13 |
| Yes | 26.40 | 73.60 |
| Total | 75.24 | 24.76 |

Figure 4.1 below, presents for both technological hierarchies, the productive efficiency scores’ distribution for both DSH and the non-DSH production entities. It is noticeable that the DSH group exhibits inferior productive performance, with respect to the metafrontier, and smaller intra-group variation compared to the non-DSH group. Additionally, it is interesting to note the bimodal pattern of the meta-efficiency scores’ distribution of the non-DSH group.

Figure 4.1 Distribution of the productive performance of the DSH and non-DSH production entities with respect to the metafrontier, for the years 1999-2006

The time dimension of the productive performance densities for both the DSH and the non-DSH production entities are presented in Figures 4.2 and 4.3 respectively.

For the DSH case, depicted in Figure 4.2 below, it is evident that despite some turbulence in 2002 and 2003, the distributions exhibit time persistence.
Figure 4.2 Distribution of the productive performance of the DSH production entities for with respect to the metafrontier for selected years of the sample

Note: The rationale behind the selection of the years 1999, 2002 and 2006 is that those represent the initial period, the middle and the end of our sample. The year 2003 is also displayed, since at that year most of the deletions have occurred.

For the non-DSH case, depicted in Figure 4.3 below, it is interesting to note that two distinct, in terms of productive performance, groups emerge which also exhibit time persistent behavior.

Figure 4.3 Distribution of the productive performance of the non-DSH production entities for with respect to the metafrontier for selected years of the sample

Note: The rationale behind the selection of the years 1999, 2002 and 2006 is that those represent the initial period, the middle and the end of our sample. The year 2003 is also displayed, mostly for reasons of comparison with Figure 2.2.
4.5.1.2 Hierarchical Structural Heterogeneity (HSH) considerations

The Hierarchical Structural Heterogeneity (HSH), as mentioned in Section 4.3.3, is captured by the absolute difference of the technology gap value of each production entity under the two alternative hierarchies, CFDTH and SFDTH, examined here. That is, 

\[ HSH_{i,j} = |Tg_{i,j}^{CFDTH} - Tg_{i,j}^{SFDTH}| \]

The threshold for a production entity to be identified as HSH is defined as the Florence median of the HSH variable distribution. Figure 4.4 below depicts the density of the HSH variable along with the Florence median line. It is evident, that a significant proportion of the probability mass of the HSH variable corresponds to values lower than the threshold the Florence median indicated.

Figure 4.4 Distribution of the HSH production entities and the Florence median threshold for the period 1999-2006

Table 4.8 below, illustrates the number of production entities exceeding the threshold of the Florence median over the study period based on the values of the HSH measure. It is evident that from the standpoint of the CFDTH, Czech Republic, Greece, and Poland are the countries which are prone to structural heterogeneity. From the viewpoint of the SFDTH, the industries of Chemicals, Construction and Pulp paper are those which are associated with high HSH values and consequently exceed the threshold. It is not worthless to note that Czech Republic, Greece and Poland have been identified within the DSH group under the CFDTH, while Chemicals and Construction have been identified as DSH under that of the SFDTH. Although, until now, the DSH and HSH patterns have been presented in detail for both the CFDTH and the SFDTH cases, the relationship between DSH and HSH remains rather vague and unexplored in several dimensions which we disentangle in the following section.
Table 11: Number of production entities with HSH value greater than the Florence median threshold for the period 1999-2006

| Countries | BM | CHM | CNST | FB | OMM | PP | TXT | TE | WP | AT | LT | WT | SA | TOTAL |
|-----------|----|-----|------|----|-----|----|-----|----|----|----|----|----|----|-------|
| AUT       | 0  | 1   | 0    | 0  | 0   | 0  | 0   | 0  | 0  | 2  | 0  | 0  | 0  | 0 (0.6%) |
| BEL       | 0  | 2   | 0    | 0  | 0   | 0  | 0   | 0  | 0  | 2  | 0  | 2  | 0  | 6 (3.6%) |
| CZE       | 0  | 1   | 1    | 0  | 6   | 0  | 2   | 1  | 4  | 1  | 5  | 0  | 4  | 29 (17.4%) |
| DNK       | 0  | 1   | 0    | 0  | 0   | 0  | 2   | 1  | 4  | 0  | 0  | 0  | 0  | 2 (1.2%)  |
| FIN       | 0  | 0   | 0    | 0  | 0   | 0  | 0   | 0  | 0  | 0  | 0  | 2  | 0  | 3 (1.8%)  |
| FRA       | 0  | 0   | 0    | 0  | 0   | 0  | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 0 (0.0%)  |
| DEU       | 0  | 0   | 0    | 0  | 0   | 0  | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 0 (0.0%)  |
| GRC       | 0  | 3   | 6    | 8  | 8   | 1  | 0   | 0  | 0  | 8  | 8  | 0  | 0  | 45 (26.9%) |
| IRL       | 0  | 1   | 8    | 8  | 0   | 0  | 0   | 0  | 0  | 1  | 0  | 0  | 0  | 10 (6.0%) |
| ITA       | 0  | 8   | 0    | 0  | 0   | 0  | 1   | 0  | 0  | 1  | 0  | 1  | 0  | 12 (7.2%) |
| NLD       | 0  | 8   | 0    | 0  | 0   | 0  | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 8 (4.8%)  |
| POL       | 0  | 5   | 4    | 0  | 0   | 0  | 0   | 0  | 0  | 6  | 0  | 0  | 2  | 17 (10.2%) |
| SVK       | 0  | 0   | 0    | 0  | 2   | 6  | 2   | 0  | 0  | 0  | 0  | 1  | 0  | 12 (7.2%) |
| SVN       | 0  | 0   | 0    | 0  | 0   | 0  | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 0 (0.0%)  |
| ESP       | 0  | 8   | 0    | 0  | 0   | 0  | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 13 (7.8%) |
| SWE       | 0  | 0   | 0    | 0  | 0   | 0  | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 3 (1.8%)  |
| GBR       | 1  | 2   | 0    | 0  | 0   | 0  | 1   | 0  | 0  | 0  | 0  | 0  | 0  | 4 (2.4%)  |
| **TOTAL** | 9  | 36  | 16   | 14 | 10  | 19 | 8   | 7  | 3  | 11 | 15 | 12 | 7  |       |

Note 1: Countries: AUT: Austria, BEL: Belgium, CZE: Czech Republic, DNK: Denmark, FIN: Finland, FRA: France, DEU: Germany, GRC: Greece, IRL: Ireland, ITA: Italy, NLD: Netherlands, POL: Poland, SVK: Slovak Republic, SVN: Slovenia, ESP: Spain, SWE: Sweden, GBR: United Kingdom.

Note 2: Manufacturing Sector: BM: Basic Metals, CHM: Chemicals and Chemical Products, CNST: Construction, FB: Food & Beverages, OMM: Other non-Metallic Minerals, PP: Pulp Paper, TE: Transport Equipment, TXT: Textiles, WP: Wood Products. Transportation Sector: AT: Air Transport, LT: Land Transport, WT: Water Transport, SA: Supporting and Auxiliary Transport Activities.
4.5.1.3 DSH and HSH relationship under alternative technological structures

In order to investigate the determinants and the underlying relationship between the two types of technology heterogeneity, that is \( DSH \) and \( HSH \), under both the \( CFDTH \) and the \( SFDTH \) hierarchies, Equations 4.8, 4.9 and 4.10 have been estimated. Empirical results are presented in Table 4.9a below, while Table 4.9b at the Appendix of the chapter displays the full version of the estimations which are not presented here for the sake of simplicity. The latter table presents the estimation results of (i) a dynamic panel probit model when the \( DSH \) is the dependent variable, (ii) a pooled cross-section linear model when the \( HSH \) is the dependent variable and (iii) a dynamic panel probit model with one endogenous regressor which corresponds to the case where the \( DSH \) is the left hand variable and the \( HSH \) is included among the set of regressors, that is, when an endogenous relationship between \( DSH \) and \( HSH \) is assumed. As additional regressors, we have considered the ratios of the time varying productive characteristics to capture the production possibilities under the alternative hierarchical structures, the idiosyncratic group variable to investigate its effect on heterogeneous behavior, the \( EURO \) variable to test for the market integration hypothesis, the \( GCI \) to capture multiple aspects of the production environment since it is a composite index of twelve pillars, the time averages of the input ratios to control for variations in production throughout the study period and the year effect to account for time heterogeneity.

Although the \( HSH \) variable does not exert statistically significant influence on the probability that a DMU is identified as \( DSH \) neither in the \( CFDTH \) nor in the \( SFDTH \) case, a simple nested models test along with the statistical significance of the variable which captures the impact of initial conditions, allows us to argue that the endogeneity is not a negligible issue. In other words, the employment of the augmented model (Equation 4.10) is by no means trivial since the inclusion of the additional variables in the endogenous model proves not to be redundant. Therefore, despite the fact that the endogenous regressor appear to be statistically insignificant, the use of the model in Equation 4.10 is recommended so as to mitigate the endogeneity concerns. Put it another way, one could rather safely argue that \( DSH \) and \( HSH \) are endogenously related via the initial conditions. The latter is known as state dependence (David 1985; 1986) and may be interpreted as the way conditions and characteristics of the economic environment along with a set of institutional (Driffield et al., 2013) and regulatory factors of the starting period affect the future productive performance of a production entity. This result is also supported by the estimated coefficients of the introduced time dummies since only the first year is statistically significant in both technology hierarchies.
In the same context, empirical results indicate that the most influential determinant of both types of heterogeneity, irrespective the technology hierarchy imposed, is the path dependence phenomenon. Factors which are not, at least easily in the short-run, modifiable emerge as the major sources of heterogeneity. According to the theoretical framework introduced in the present paper, such kind of factors are mainly associated to institutional, social and cultural characteristics of the countries’ frontiers (CFDTH) on the one hand, and stages of the life cycle and trajectories of the sector technologies (SFDTH) on the other. It is not worthless to mention that path dependence along with the role of initial conditions indicates that the technology possibility sets in Europe are rather lumpy and therefore the spillovers rather limited.

In this line, it is not surprising the fact that the productive characteristics, as they are captured by the input ratios in their time varying or time invariant version, defined at the corresponding period-industrial average, level only in very rare cases influence the DSH and HSH variables. Input ratios should be considered as the mediators between the above mentioned “quasi-fixed” institutional, social, cultural and technological sources of heterogeneity and the DMUs’ idiosyncratic productive performance. The lumpiness of these sources of heterogeneity does not exert any influence on input ratios and therefore no direct effect of the latter on the types of technology heterogeneity is identified. The significance of the idiosyncratic group variable is prevailing in both hierarchies validating the consistency of the developed algorithm presented in herein.

Quite interesting are the empirical results regarding the influence of the country’s competitiveness level as it captured by the GCI variable (Sala-i-Martin et al., 2008) in both the DSH and HSH under both the CFDTH and the SFDTH. In any case, higher values of the GCI result in a smaller probability that a production entity is identified as DSH and also in a more modest value of the HSH variable. Taking into account that the GCI index synthesizes institutional, financial, social, infrastructure and knowledge conditions (Sala-i-Martin et al., 2008), it is absolutely reasonable to argue that heterogeneity of the DSH and HSH type, concerns countries with less developed market mechanisms and incomplete shakeouts and sectors with low levels of technological opportunities and vulnerable to the effects and consequences of globalization and markets’ integration. Finally, surprisingly enough the participation in the Euro area, captured by the dichotomous variable EURO, of some of the examined European economics, has not affected in a positive way the homogenization of the production possibility sets of the examined countries and technological sectors, at least for the particular time window adopted in this study.
As a final remark, it is worth-noting, that the rho (\(\rho\)) parameter (at the last part of Table 2.9a), representing the intra-class correlation of the panel (i.e. the percentage of the variance attributed to the differences across panels), borne out that the data structure is indeed of panel type since its value differs significantly from zero.

Table 2.9a Estimation results for both technological structures

| Dependent variable | HSH | CFDTH | DSH | DSH with endogenous HSH | HSH | SFDTH | DSH | DSH with endogenous HSH |
|-------------------|-----|-------|-----|-------------------------|-----|-------|-----|-------------------------|
| Regressors         | Coefs | APE | Coefs | APE | Coefs | APE | Coefs | APE |
| constant           | .039*** | (.015) | .064*** | (.013) | .049 | (.108) |
| HSH                | - | - | - .093 | (1.113) | - | - |
| Path & State       | HSH\(_{t-1}\) | .813*** | (.014) | .823*** | (.014) | .197*** | (.040) |
| dependence         | DSH\(_{t-1}\) | - | .252*** | .186*** | - | .321*** | (.048) |
| Initial conditions | - | - | .354*** | (.070) | - | - |
| Initial conditions | - | - | - | - | .433*** | (.076) |
| Input ratios       | Time-varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time-invariant     | Yes | No | Yes | Yes | No | Yes | Yes |
| Year dummies       | Yes | No | No | Yes | No | No |
| Idiosyncratic Group | - | .262*** | .144** | - | .109*** | (.033) |
| GCI                | -.005* | (.002) | -.018* | (.009) | -.010*** | (.002) |
| EURO               | .003 | (.003) | -.010 | (.026) | -.200 | (.161) |
| Residuals          | - | - | .124 | (.166) | - | - |
| Cumulative residuals | - | - | -.060 | (.038) | - | - |
| R\(^2\)            | .746 | - | - | .741 | - | - |
| Log-Likelihood     | - | -514.89 | -492.691 | - | -526.538 | -498.963 |
| LR test of H\(_0\): \(\rho=0\) | - | .000 | .000 | - | .001 | .000 |

H\(_0\): HSH endogenous in DSH

Note 1: Numbers in parentheses, for the estimated coefficients, correspond to the associated standard errors.
Note 2: As far as the coefficients and estimated standard errors of the productive characteristics are concerned, those are not actually zero but correspond to a very small number, i.e. smaller than .0001. This is captured by the symbol “\(\ast\)”.
Note 3: Stars indicate statistical significance at different significance levels i.e. ***=1%, **=5%, *=10%.
Note 4: The abbreviation APE stands for Average Partial Effects.
4.6 Conclusions

The results of the benchmarking process are facing severe risks when technology heterogeneity issues are not handled appropriately. In the last fifteen years, two not necessarily rival, approaches have emerged in the literature aspiring to investigate technology heterogeneity issues which result in productive performance idiosyncrasies. Each approach assumes a rather different technology hierarchy. More specifically, the first assumes that the country frontiers have a dominant role and the productive performance differentials are due to country-specific mechanisms which result in (in)efficient resource allocation mainly through turbulence. The second approach focuses on the asymmetric effects of the emerging technologies on different industrial structures and the resulting productive performance differentials which finally facilitate the differentiation of technologies of the examined industrial structures. In this case the dominant technological hierarchy is the one reflected from the sector frontiers.

In this paper, we have defined the two abovementioned dimensions of technology heterogeneity and we have developed a computational approach -based on bootstrapped DEA technique and the notion of isomorphism of consecutive sets of the DMUs under investigation- which allows the identification of the production entities which exhibit production entity-specific heterogeneity. Furthermore, exploiting the potentials of the metafrontier context and the technology gap notion, we have defined and estimated the measure of heterogeneity which arises when we consider alternative technological structures, that is the hierarchical structure heterogeneity. To do so, we employed a unique balanced panel dataset of thirteen industries of Manufacturing and Transportation in seventeen EU countries over an eight-year period.

The empirical results indicate that with respect to the hierarchy dominated by the country frontiers, transition economies with incomplete market mechanisms exhibit idiosyncratic performance; concerning the hierarchy dominated by the sector frontiers, it becomes evident that European industrial structures with low technological opportunities, labor intensive, heavily influenced by globalization and environmental regulatory policies are those which misfit to the corresponding benchmarking set.

In the second stage analysis and employing a recent econometric approach which allows the estimation of a dynamic panel probit model with one endogenous regressor, we explore the inter-relationships between the two-faceted idiosyncratic productive performance and alternative technological hierarchies. This quest reveals that the two types of technological heterogeneity are endogenously related via the initial conditions of the capricious performance of the examined European industrial structures. In the same line, path dependence becomes an influential
characteristic of both types of technology heterogeneity irrespectively to technological hierarchy considerations.

Finally, although high levels of the multidimensional competitiveness imply low technology heterogeneity, it is quite interesting that the input ratios, the conventional measures of industrial structures’ technological characteristics, fail to predict idiosyncratic productive performance in both the examined technology hierarchies. It seems that institutional, cultural and infrastructure characteristic, not depicted in the input bundles, are the main determinants of the idiosyncratic performance both at country and sector level.
References

Altunbaş, Y., Gardener, E. P., Molyneux, P., & Moore, B. (2001). Efficiency in European banking. *European Economic Review, 45*(10), 1931-1955.

Asaftei, G., Kumbhakar, S. C., & Mantescu, D. (2008). Ownership, business environment and productivity change. *Journal of Comparative Economics, 36*(3), 498-509.

Bartelsman, E. J., & Doms, M. (2000). Understanding productivity: Lessons from longitudinal microdata. *Journal of Economic Literature, 569-594.

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

Battese, G. E., & Rao, D. P. (2002). Technology gap, efficiency, and a stochastic metafrontier function. *International Journal of Business and Economics, 1*(2), 87-93.

Battese, G. E., Rao, D. P., & O'Donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis, 21*(1), 91-103.

Bos, J. W., Koetter, M., Kolari, J. W., & Kool, C. J. (2009). Effects of heterogeneity on bank efficiency scores. *European Journal of Operational Research, 195*(1), 251-261.

Brown, J. A., & Glennon, D. C. (2000). Cost structures of banks grouped by strategic conduct. *Applied Economics, 32*(12), 1591-1605.

Castellacci, F. (2007). Technological regimes and sectoral differences in productivity growth. *Industrial and Corporate Change, 16*(6), 1105-1145.

Castellacci, F. and Zheng, J. (2010). Technological regimes, Schumpeterian patterns of innovation and firm-level productivity growth. *Industrial and Corporate Change, 19*(6), 1829-1865.

Castellacci, F., Los, B., & de Vries, G. J. (2014). Sectoral productivity trends: convergence islands in oceans of non-convergence. *Journal of Evolutionary Economics, 24*(5), 983-1007.

Casu, B., & Girardone, C. (2010). Integration and efficiency convergence in EU banking markets. *Omega, 38*(5), 260-267.

Casu, B., Girardone, C., Ferrari, A., & Wilson, J. O. (2014). Integration, productivity and technological spillovers: Evidence for eurozone banking industries. *Productivity and Technological Spillovers: Evidence for Eurozone Banking Industries (February 20, 2014).*

Chen, K., & Irarrazabal, A. (2014). The role of allocative efficiency in a decade of recovery. *Review of Economic Dynamics, 18*(3), 523-550

Collard-Wexler, A. & Loecker, J. D. (2015). Reallocation and Technology: Evidence from the US Steel Industry. *The American Economic Review, 105*(1), 131-171.
Dai, X., & Kuosmanen, T. (2014). Best-practice benchmarking using clustering methods: Application to energy regulation. *Omega, 42*(1), 179-188.

David, P. A. (1985). Clio and the Economics of QWERTY. *The American economic review, 332*-337.

David, P.A. (1986). Understanding the economics of QWERTY: the necessity of history. *Economic History and The Modern Economics* eds W.N. Parker. Oxford, Blackwell.

Daraio, C., & Simar, L. (2007). Conditional nonparametric frontier models for convex and nonconvex technologies: a unifying approach. *Journal of Productivity Analysis, 28*(1-2), 13-32.

Demirbag, M., Tatoglu, E., Glaister, K. W., & Zaim, S. (2010). Measuring strategic decision making efficiency in different country contexts: A comparison of British and Turkish firms. *Omega, 38*(1), 95-104.

Dobbelaeere, S., Kiyota, K., & Mairesse, J. (2015). Product and labor market imperfections and scale economies: Micro-evidence on France, Japan and the Netherlands. *Journal of Comparative Economics, 43*(2), 290-322.

Dosi, G., Lechevalier, S., & Secchi, A. (2010). Introduction: interfirm heterogeneity—nature, sources and consequences for industrial dynamics. *Industrial and Corporate Change, 19*(6), 1867-1890.

Driffield, N. L., Mickiewicz, T., & Temouri, Y. (2013). Institutional reforms, productivity and profitability: From rents to competition?. *Journal of Comparative Economics, 41*(2), 583-600.

Efron, B., & Tibshirani, R. J. (1993). An Introduction to the Bootstrap, Monographs on Statistics and Applied Probability, Vol. 57. *New York and London: Chapman and Hall/CRC.*

Elyasiani, E., & Rezvanian, R. (2002). A comparative multiproduct cost study of foreign-owned and domestic-owned US banks. *Applied Financial Economics, 12*(4), 271-284.

Enerdata. [http://www.enerdata.net/](http://www.enerdata.net/) (accessed on 25.02.2013).

EU-KLEMS Growth and Productivity Accounts. [http://www.euklems.net/](http://www.euklems.net/) (accessed on 02.03.2013).

European Commission, Financial programming and budget directorate. [http://ec.europa.eu/budget/contracts_grants/info_contracts/inforeuro/inforeuro_en.cfm](http://ec.europa.eu/budget/contracts_grants/info_contracts/inforeuro/inforeuro_en.cfm) (accessed on 12.03.2013).

Giles, J., & Murtazashvili, I. (2013). A Control Function Approach to Estimating Dynamic Probit Models with Endogenous Regressors. *Journal of Econometric Methods, 2*(1), 69-87.

Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics, 126*(2), 269-303.
Groningen Growth and Developing Centre, GGDC productivity level database. http://www.rug.nl/research/ggdc/data/ggdc-productivity-level-database (accessed on 08.03.2013).

Hayami, Y. (1969). Sources of agricultural productivity gap among selected countries. American Journal of Agricultural Economics, 51(3), 564-575.

Hayami, Y., & Ruttan, V. W. (1970). Agricultural productivity differences among countries. The American Economic Review, 895-911.

Isik, I., & Hassan, M. K. (2002). Technical, scale and allocative efficiencies of Turkish banking industry. Journal of Banking & Finance, 26(4), 719-766.

Kounetas, K., Mourtos, I., & Tsekouras, K. (2009). Efficiency decompositions for heterogeneous technologies. European Journal of Operational Research, 199(1), 209-218.

Krautzberger, L., & Wetzel, H. (2012). Transport and CO2: productivity growth and carbon dioxide emissions in the european commercial transport industry. Environmental and Resource Economics, 53(3), 435-454.

Lozano-Vivas, A., & Pastor, J. T. (2010). Do performance and environmental conditions act as barriers for cross-border banking in Europe?. Omega, 38(5), 275-282.

Lee, H., Park, Y., & Choi, H. (2009). Comparative evaluation of performance of national R&D programs with heterogeneous objectives: A DEA approach. European Journal of Operational Research, 196(3), 847-855.

Los, B., & Verspagen, B. (2006). The evolution of productivity gaps and specialization patterns. Metroeconomica, 57(4), 464-493.

Los, B., & Verspagen, B. (2000). R&D spillovers and productivity: evidence from US manufacturing microdata. Empirical economics, 25(1), 127-148.

Melitz, M. J. & Redding, S. J. (2015). New Trade Models, New Welfare Implications. The American Economic Review, 105(3), 1105-1146.

Mundlak, Y. (1978). On the pooling of time series and cross section data. Econometrica: journal of the Econometric Society, 69-85.

O'Donnell, C. J., Rao, D. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empirical Economics, 34(2), 231-255.

Orea, L., & Kumbhakar, S. C. (2004). Efficiency measurement using a latent class stochastic frontier model. Empirical Economics, 29(1), 169-183.

Organization for Economic Cooperation and Development, Structural analysis database. http://www.oecd.org/industry/ind/stanstructuralanalysisdatabase.html (accessed on 08.03.2013).
Ryzhenkov, M. (2016). Resource misallocation and manufacturing productivity: The case of Ukraine. *Journal of Comparative Economics, 44*(1), 41-55.

Sala-i-Martin, X., Blanke, J., Drzeniek Hanouz, M., Geiger, T., Mia, I., Paua, F., 2008. The Global Competitiveness Index: prioritizing the economic policy agenda. In: PORTER, M.E., SCHWAB, K. (Eds.), *The Global Competitiveness Report 2008–2009*. World Economic Forum, Geneva.

Simar, L., & Wilson, P. W. (1999). Of course we can bootstrap DEA scores! But does it mean anything? Logic trumps wishful thinking. *Journal of Productivity Analysis, 11*(1), 93-97.

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.

Syverson, C. (2011). What determines productivity?. *Journal of Economic Literature, 49*(2), 326-365.

Tsekouras, K., Chatzistamoulou, N., Kounetas, K., & Broadstock, D. C. (2016). Spillovers, path dependence and the productive performance of European Transportation sectors in the presence of technology heterogeneity. *Technological Forecasting and Social Change, 102*, 261-274.

Ulucan, A., & Atci, K. B. (2010). Efficiency evaluations with context-dependent and measure-specific data envelopment approaches: An application in a World Bank supported project. *Omega, 38*(1), 68-83.

Wilson, P. W. (2008). FEAR: A software package for frontier efficiency analysis with R. *Socio-economic planning sciences, 42*(4), 247-254.

World Economic Forum. [http://www.weforum.org/](http://www.weforum.org/) (accessed on 05.04.2013).
## Appendix of Chapter 4

### Table 4.9b Estimation results for both technological structures (all the variables included)

| Dependent variable | HSH | DSH | DSH with endogenous HSH | HSH | DSH | DSH with endogenous HSH |
|--------------------|-----|-----|-------------------------|-----|-----|-------------------------|
|                     | Coefs | APE | Coefs | APE | Coefs | APE |
| **Path & State dummies** |     |     |     |     |     |     |
| Year dummies        |     |     |     |     |     |     |
| 2000                |     |     |     |     |     |     |
| 2001                |     |     |     |     |     |     |
| 2002                |     |     |     |     |     |     |
| 2003                |     |     |     |     |     |     |
| 2004                |     |     |     |     |     |     |
| 2005                |     |     |     |     |     |     |
| Idiosyncratic Group |     |     |     |     |     |     |
| GCI                 |     |     |     |     |     |     |
| EURO                |     |     |     |     |     |     |
| Residuals           |     |     |     |     |     |     |
| Cumulative Residuals|     |     |     |     |     |     |

### Table 4.9b: Estimation results for both technological structures (all the variables included)

| Dependent variable | HSH | DSH | DSH with endogenous HSH | HSH | DSH | DSH with endogenous HSH |
|--------------------|-----|-----|-------------------------|-----|-----|-------------------------|
|                     | Coefs | APE | Coefs | APE | Coefs | APE |
| **Path & State dummies** |     |     |     |     |     |     |
| Year dummies        |     |     |     |     |     |     |
| 2000                |     |     |     |     |     |     |
| 2001                |     |     |     |     |     |     |
| 2002                |     |     |     |     |     |     |
| 2003                |     |     |     |     |     |     |
| 2004                |     |     |     |     |     |     |
| 2005                |     |     |     |     |     |     |
| Idiosyncratic Group |     |     |     |     |     |     |
| GCI                 |     |     |     |     |     |     |
| EURO                |     |     |     |     |     |     |
| Residuals           |     |     |     |     |     |     |
| Cumulative Residuals|     |     |     |     |     |     |
|                  |        |       |        |        |
|------------------|--------|-------|--------|--------|
| $R^2$            | .746   |       | .741   |        |
| Log-Likelihood   | -      | -14.89| -492.69| -      |
| LR test of $H_0: \beta=0$ | - | .000 | .000 | - |
| LR test $H_0$: DSH nested in Endogenous model | - | .000 | .000 | .000 |

**Note 1:** Numbers in parentheses, for the estimated coefficients, correspond to the associated standard errors.

**Note 2:** As far as the coefficients and estimated standard errors of the productive characteristics are concerned, these are not actually zero but correspond to a very small number, i.e. smaller than .0001. This is captured by the symbol “+”.

**Note 3:** Stars indicate statistical significance at different significance levels i.e. ***=1%, **=5%, *=10%.

**Note 4:** The abbreviation APE stands for Average Partial Effects.
Chapter 5 Dimensionality considerations of Technological Heterogeneity and the impact on Productive Performance; the role of Absorptive Capacity and Spillover Effects

5.1 Introduction

An important aspect of any study in Efficiency and Productivity analysis is how the unobserved heterogeneity is treated by the researcher. Therefore, the researcher makes clear from the outset which aspect of the pertinent heterogeneity (Dosi et al., 2010) has been accounted for and why. This has led to a literature proliferation as different aspects of heterogeneity (such as region of study, managerial skill, ownership status etc.) shed light to different interpretations and affect economic policy in so many ways. Despite the factor against which the researcher attempts to downsize the heterogeneity bias, the use of metafrontier (O’Donnell et al., 2008) allows to account for the existing heterogeneity since it envelops all the individual production functions including the specificities and idiosyncrasies of the latter as well as those of the Decision Making Units operating under each frontier. Such being the case, the concept of the metafrontier has been used to accommodate for numerous aspects, frequently unobserved or hard to quantify, and lead to distortions of the benchmarking process. As Tsekouras et al., (2015) argue, the metafrontier allows for the relaxation of the technological isolation assumption so as to account for pure productive performance or pure technical spillover effects running among different production technologies.

Needless to acknowledge the fact that influential studies (Casu et al., 2014; Del Bo, 2013, Nadiri, 1993; Verspagen & De Loo, 1999) in every field in Economics, including that of Efficiency Analysis, exploring the nature of spillover effects with numerous ways have made significant contributions to the literature which grows in an exponential manner. Attached to the concept of the spillover effects, we find that of the absorptive capacity i.e. the ability of a DMU to identify new available sources of external generated knowledge to improve its performance, to assimilate technological developments, ability to exploit technical opportunities avoiding trapping in lumpy regimes or perpetuate inefficient performance. Alternatively framed, the amount of knowledge a DMU is capable to absorb, as introduced by Cohen & Levinthal in a series of papers (1989; 1990).

Combining the aforementioned concepts, those of spillover effects and absorptive capacity along with the concept of metafrontier, we find ourselves in the threshold of a quite interesting and realistic aspect of productive performance measurement since we take into consideration all the existing heterogeneity among the units under consideration as well as their production and
absorptive capabilities. In the broad sense, absorptive capacity is a multifaceted notion and every attempt to disentangle it would lead to omitted variables bias. Pursuing this train of logic, the use of a single and units free index, as a product of multiple aspects of the operating environment, proves to be an appealing and plausible choice. To this end, the global competitiveness index proposed and developed by Sala-i-Martin and Artadi (2004) and is used to rank “how efficiently a country uses the available resources so as to produce high levels of prosperity to its citizens” while it “integrates the micro and macro-economic aspects of competitiveness” as it accounts for the same the set of institutions, policies, regulations, infrastructure and so on, for every single country which paves the way for meaningful comparisons and inferences. That said, disentangling that index or choosing to focus on selected aspects of its constructs, directly leads to selection bias since the researcher decides to focus on a single pillar which affects the robustness of the analysis and the implications of the results as well since the bulk of heterogeneity has intentionally been left out of the radar.

Studies employing the concept of the metafrontier to ease heterogeneity concerns despite the fact that have elevate our understanding, often neglect dimensionality issues. More precisely, the production technology of the metafrontier may encapsulates additional structure - in technological terms, which can only be revealed in case we partition the overall technology into lower aggregation levels and then proceed to less aggregated structure up to the point we reach the lowest level of analysis possible. Engaging in this line of research, we get a stair-wise reduction of technological heterogeneity which otherwise would have been neglected affecting the performance evaluation. Moreover, revealing more layers of technological hierarchy becomes possible to identify the sources of spillover effects and eventually how the learning process occurs and diffuses. Pulling the pieces together, it comes to the forefront the nested nature of production sets as the latter are integrated in the overall production set. In this line of argument, two issues arise. First, it is reasonable to assume that the units belong to a certain group would have correlated errors which means that if we lack information (i.e. additional variables) for one unit in the group, most likely we lack for the rest as well which violates one of the fundamental assumptions of the rich regression family techniques. Moreover, supressing for the hierarchy of the technology i.e. the level of heterogeneity, the performance evaluation may be distorted to a great extent. All in all each level of technological heterogeneity has its own characteristics, affects differently the exploitation of technological opportunities and therefore should be treated accordingly.

Considering all the above, in this chapter we extend the concept of metafrontier (O’Donnell et al., 2008) to that of the meta-metafrontier (Kontolaimou, 2014) to investigate
whether or not the decomposition of the overall technology supports for the existence of distinct disaggregated technologies employing the technology gap ratio to test if the latter are absorbed by the former. At a second stage and acknowledging the nested nature of our dataset, we employ variants of multilevel (or hierarchical or mixed effects) models to investigate the significance the combined effect of absorptive capacity level, as captured by the global competitiveness index, and spillover effects when the level of technological heterogeneity has been accounted for but also, what are the differences when a different level of technological heterogeneity is accounted for. To do so, we use data on seventeen European Union countries on nine industries of the manufacturing and four industries of the transportation sector from 1999 through 2006. We should mention that in this chapter we follow Castellacci’s (2007) approach studying industries' production technology in order to draw inferences regarding the underlying learning mechanisms in Europe while the DMUs are the European countries.

The present chapter is structured as follows. Section 5.2 presents the methodological strategy and research questions, Section 5.3 describes the dataset, Section 5.4 concerns the discussion of the estimation results while Section 5.5 concludes the chapter.

5.2 Methodological underpinnings and research questions

This section consists of two interconnected pieces. In the first one we extent the metafrontier framework of O'Donnell et al., (2008) building upon the works of Hayami (1969) and Hayami and Ruttan (1970), as has been presented in previous chapters, to that of the meta-metafrontier as in Kontolaimou (2014) in order to disentangle the technology heterogeneity at the European level. To do so, we partition the overall level to two distinct and disaggregated sector-level technologies to (i) identify the drivers of the overall technology level and (ii) investigate for potential spillover effects between the levels of technology heterogeneity and (iii) figure out where the industries learn and improve their performance from. The latter brings us to the second piece presented herein. At the second stage of the analysis we aim at measuring the magnitude and the direction of the effect of spillover effects i.e. whether the industries are benefited by the technological advancements taking place under the sector technology or at the European level.

5.2.1 Productive performance and technology gap calculation under multiple hierarchical technologies

Assume we observe multiple technology sets, \( S', S^2, S^3, \ldots, S^k \) corresponding to distinct industries belonging to the European manufacturing and transportation sectors associated with production frontiers \( F', F^2, F^3, \ldots, F^k \). Then a metatechnology \( S^\text{Europe} \) applies representing the

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28 The FEAR package (Wilson, 2008) was employed.
European state of technology achievements, that is the $MMF^{\text{Europe}}$ enveloping all the lower level production frontiers. In case of clustered data with a hierarchical structure, that is industries operating under distinct sector technologies, the European metafrontier can be partitioned to multiple yet distinct metatechnologies $MF^1, MF^2, MF^3, \ldots, MF^l$, based on a criterion which in our case is the fact that we observe industries from the manufacturing and transportation sector, to separate metatechnologies corresponding to distinct technology sets, $S^{MF^1}, S^{MF^2}, S^{MF^3}, \ldots, S^{MF^l}$ enveloping the corresponding, to that particular sector, industry technology sets, $S^{F^1}, S^{F^2}, S^{F^3}, \ldots, S^{F^k}$.

More formally, the meta-metatechnology set refers to the convex hull of the jointure of all the metatechnology sets of the lower level of technology hierarchy and can be represented by the production possibility set

$$S^{MMF} = \{(x, y : x \geq 0, y \geq 0), x \text{ can produce } y \text{ in at least one of } S^{MF_1}, S^{MF_2}, \ldots, S^{MF_l}\}$$

while the meta-technology, in this case the sector technology, can be represented by the production possibility set

$$S^{MF} = \{(x, y : x \geq 0, y \geq 0), x \text{ can produce } y \text{ in at least one of } S^{F^1}, S^{F^2}, \ldots, S^{F^k}\} \subseteq S^{MMF}.$$

Additionally, the meta-metafrontier, $MMF^{\text{Europe}}$, associated with $S^{MMF}$ can be defined as

$$MMF^{\text{Europe}} = \{(x, y) \in S^{MMF} : D_i\left(MMF^{\text{Europe}}; (x, y)\right) = 1\},$$

where $D_i\left(MMF^{\text{Europe}}; (x, y)\right)$ is the input distance function with respect to $MMF^{\text{Europe}}$. By definition the meta-metafrontier envelopes all the individual metafrontiers.

Figure 4.1 below illustrates the above two-level technology heterogeneity framework on a single-input, single-output case. Consider a country, represented by the combination $(x, y)$ operating under each individual industry frontier, $F^1, F^2, F^3, \ldots, F^k$ which is enveloped by the sector metafrontier, $MF^1, MF^2$ and the meta-metafrontier $MMF^{\text{Europe}}$. The minimum input quantity that this country can use to produce the observed output, $y$, under the industry technology is $X^I = \frac{X}{D_i(F^I; (x, y))}$, where $D_i(F^I; (x, y))$ is the input distance function with respect to the frontier $F^I$. In case that the country adopts the best available technology provided by the sector technology level, i.e. the metatechnology, it can further reduce the minimum input required to produce $y$ to level $X^{MF^I} = \frac{X^I}{D_i(MF^I; (x, y))}$ where $D_i(MF^I; (x, y))$ is the input distance function with respect to the metafrontier, $MF^I$. The maximum input reduction that the
country can achieve is up to level $X^{MMF} = \frac{x}{D_1 \left( MMF^{Europe}; (x, y) \right)}$ by employing the available meta-metatechnology.

Thus the productive efficiency for a given country $(x, y)$ in each one of the examined industries is given as in Equation 5.1 and is represented by the green solid line at the Figure 5.1 below:

$$E\hat{f}_{ik}(x, y) = \min \left\{ \theta > 0, \gamma \leq \sum_{i=1}^{n} y_i \gamma_i ; \theta \gamma \geq \sum_{i=1}^{n} y_i \lambda_i \right\}$$

for $y_i \geq 0, i = 1, 2, \ldots, n$ such that

$$\sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, 2, \ldots, n \right\}$$  \hspace{1cm} (5.1)

Each productive efficiency score obtained from the estimation with respect to the common technology can be used to define the so-called metatechnology ratio $MTR_{ik}$ which is considered as a measure of proximity of the $k$-th group individual frontier to its metafrontier. For a given point $(x, y)$, the latter could be defined as in Equation 5.2 below:

$$MTR_{ik}(x, y) = \frac{MTE\hat{f}_{ik}(x, y)}{E\hat{f}_{ik}(x, y)}$$  \hspace{1cm} (5.2)

Accordingly, the distance between the sector technology and the European meta metafrontier can be expressed as:

$$MMTR_{ik}(x, y) = \frac{MMTE\hat{f}_{ik}(x, y)}{MTE\hat{f}_{ik}(x, y)}$$  \hspace{1cm} (5.3)

$MTR_{ik}(x, y)$ depicts the ratio of the minimum inputs attained by a DMU employing the superior metatechnology to the minimum inputs used by the group technology to produce a given level of outputs. The definition for the $MMTR_{ik}(x, y)$ results accordingly.

Taking advantage of the $MTR_{ik}$ and that of the $MMTR_{ik}(x, y)$ notion, the first level technology gap that is the technology gap with respect to the sector technology, $T_{ik}^{factor}$ of the $i$-th DMU in the $k$-th group frontier is defined as the distance of the industry frontier to the metafrontier (manufacturing or transportation), weighted with the minimum inputs which are
attainable employing the group-specific technology that is Equation 5.4 below (red dashed line at Fig. 5.1):

$$T_{g_{\text{sector}}}^{\text{Sector}}(x, y) = 1 - \text{MTR}_{g_{\text{sector}}}(x, y)$$

(5.4)

while the second level technology gap, representing the distance between the sector and the European technology is captured by the blue dashed line as shown at the Fig. 5.1 below, and can be calculated as:

$$T_{g_{\text{EU}}}^{\text{EU}}(x, y) = 1 - \text{MMTR}(x, y)$$

(5.5)

For a DMU exhibiting a $T_{g_{\text{sector}}}^{\text{Sector}}(x, y)$ value equal to zero, it is evident that the group frontier, at the input level of the specific DMU, is tangent to the sector metafrontier and thus no efficiency losses are due to inferiority of the group technology compared to the metatechnology. However productive inefficiency with respect to the group frontier is still a possible situation. The same logic applies to the case of the European technology.

According to the above, in order to test whether the presence of the intermediate levels of technology contributes to the reduction of technology heterogeneity, we should compare the technology gap values resulting with and without those disaggregated levels of technology. To do so, we will use the expression $\left( \frac{T_{g_{\text{Sector}}}^{\text{Sector}}}{T_{g_{\text{EU}}}^{\text{EU}}} \right) = 1$, both for the manufacturing and transportation technologies. In the form of testable hypothesis, the above could be stated as follows:

$H_1$: There existence of the disaggregated levels of technology does not contribute to the reduction of technology heterogeneity as those are absorbed by the higher level of technology i.e. the meta-metafrontier.

In other words, the sector specific meta-frontiers are meaningless.

More specifically, in case we do not fail to reject the above hypothesis could probably point towards the direction that the distinct technologies are not absorbed by the overall technology. Furthermore, we can examine the contribution of each particular sector technology to the European technology level by testing the equality of the ratios, that is

$$\left( \frac{T_{g_{\text{Sector}}}^{\text{Sector}}}{T_{g_{\text{EU}}}^{\text{EU}}} \right)_{\text{Manufacturing}} = \left( \frac{T_{g_{\text{Sector}}}^{\text{Sector}}}{T_{g_{\text{EU}}}^{\text{EU}}} \right)_{\text{Transportation}}$$

, with respect to each sector. The equality of the ratios is associated to the relative position of the sector frontiers with respect to the European one. More formally, this could be stated as follows:

$H_2$: The industry specific technologies equally contribute and shape the overall technology in the European level and thus there are no sector specific technologies in operation.
If the null is rejected, then one sector technology is closer to the European state of technology and thus is relatively more beneficiated by technological advancements at that level. In this line of argument, this paves the way to identify the technological drivers and address the origins of the most influential technological structure in the EU for the period 1999-2006.

All in all, the rationale behind the hypotheses presented above is to examine the significance, if any, of the introduction of the sector technologies contribute to the heterogeneity reduction and to figure out their importance as an analytical tool, when we have clustered data, so as to create a homogeneous frontier to evaluate the performance of similar DMUs. It goes without saying that ideally, the level-wise reduction of heterogeneity sheds light on the underlying mechanisms at each distinct technological level.

Figure 5.1 Two level technology hierarchy

5.2.2 Econometric strategy and initial results

5.2.2.1 Theoretical justification for the use of multilevel modelling

Before we proceed to the formal specification of the econometric models we are going to apply in order to investigate the research questions examined herein, it is not worthless to move a step backwards, and build upon the concept of the choice of the methodology we are employing.

As described in the previous section, the nature of the data at hand is by all means nested, since countries operating under the industry technology, industries share the characteristics of the sector technology those belong and the sectors operate under the European production technology. A this stage, we should mention that the focus of this chapter and therefore the research questions, concern the improvement of the productive performance of the country operating under each industry’s production technology since the countries across Europe
contribute at a different degree to the technological advancements at the industry level. That said, we can argue rather safely that the sector and the European technological achievements as well can be projected on the performance of the industry and consequently on that of each country. The latter has significant policy implications as the identification of the effect could motivate the authorities and European Agencies to promote the improvement of productivity through the exploitation of the technological advancements which spill over between industries within Europe.

From a conceptual standpoint, DMUs under the same technological hierarchy i.e. production technology will likely have correlated errors as it is reasonable to assume that those have at least some characteristics in common. Also, developments, technological achievements and opportunities occurring at sector (i.e. higher) level are influencing the productive performance of each country in each industry (i.e. characteristics at the lower level). Also, there are relationships e.g. the impact of spillover effects or the degree of absorptive capacity, which are defined and influenced by the structure across different levels. In other words, we can study relationships across different hierarchical levels which otherwise would have been neglected as the effect of the level would not had been properly evaluated. This can be accounted for in a precise way by the multilevel modelling via maximum likelihood estimation. For instance, some countries operating in a particular industry are more technologically advanced or capable of incorporating the spillover effects generated within Europe compared to others for a variety of reasons (e.g. regulation, human capital etc.). Therefore, the latter is projected on the performance of the industry.

In order to handle the complexity of technological hierarchies, the use of graphical methods is recommended in order to collect evidence of any underlying associations in the data and afterwards to proceed with statistical methods to evaluate the significance of the identified relationships. Such being the case and acknowledging the structure of the dataset which is clustered in nature, it is of no surprise that there is significant degree of heterogeneity among every level of technological hierarchy, i.e. the industry, the sector and the European level of technology. Having a closer look, more layers of heterogeneity are being revealed. That is there is technological heterogeneity among the industries themselves but also between the manufacturing and transportation sector technology. It goes without saying that leaving unmodeled the extent of heterogeneity could mislead the interpretation of the results and this is why the method chosen should account for the heterogeneity among the different levels.

For all the aforementioned reasons, the investigation of the issues at hand should move beyond the well-established family of ordinary least squares technique as the latter is a simplistic
single-level technique neglecting for the effect of the level. The latter pinpoints towards the
direction of ruling out a considerable amount of heterogeneous patterns occurring from the
dimension or technological level a variable is determined (Hox et al., 2010; Luke, 2004).
However, in case one attempts to disaggregate group (or higher level) information and attribute
it directly to the individual level, the unmodeled contextual information ends-up pooled into the
single individual error term of the model. This is problematic because individuals belonging to
the same context (e.g. industry or sector) will presumably have correlated errors. In addition,
ignoring the context, the model assumes that the regression coefficients apply equally to all
contexts thus propagating the notion that processes work in the same way in different contexts
(Luke, 2004).

More precisely, a hierarchical model is a statistical model applied to data collected at more
than one level in order to elucidate relationships at more than one level. To avoid any
interpretational pitfalls, we should clarify two common fallacies frequently appointed in the
literature. From the one hand, the *ecological fallacy* concerns the viewpoint that relationships
observed in groups are assumed to hold for individuals (Friedman, 1999) whilst on the other
hand, we have the *atomistic fallacy* according to which inferences about groups are incorrectly
drawn from individual-level information (Hox et al., 2010). All in all, it turns out that fallacies are
a problem of inference rather than a problem of measurement. Even if the situation we are
dealing with shares all the above characteristics, there might be some concern about the
suitability of the modelling approach but in this case where the data are nested in more than one
category (countries operating under the industry technology, industries belonging to different
sectors within the European Union). The hierarchical models allow us to study effects that vary
by entity or groups and estimate group level averages the moment where regular regression
techniques ignore the average variation between the entities and that single regression may face
sample problems and lack of generalization.

For all the aforementioned conceptual as well as technical reasons, seems that the
appropriate methodology to investigate our research questions is that of multilevel modelling.
Needless to say that, in spite of the modelling advantages of the hierarchical modelling, it does
not come at no cost. As the levels of the analysis increase and therefore the aggregation is
increased, finding variables attached to higher levels becomes a challenging task. Moreover, the
inclusion of more variables at the higher levels results to interaction terms hard to interpret
adding more degrees to the model complexity which might result to violation of orthogonality
conditions.
5.2.2.2 Modelling considerations and research questions

It should be clear from the outset that the overarching concern is to examine how a country’s productive performance, employing the technology of a given industry, is influenced by characteristics tied to that country (e.g. the Global Competitiveness Index) as well as by characteristics of the production technology of the sector that the industry operates under or the European level of technology. Framed differently, we are interested in investigating whether the role of spillover effects occurring from sector and European technological achievements improve the productive performance of the country and therefore the performance at the industry level. Spillover effects occur at a higher level of technology hierarchy and we need to take this into consideration by employing the appropriate statistical tool which is the hierarchical modelling approach, as mentioned in the previous section. Other factors, such as the label of the industry or that of the sector –manufacturing or transportation- which are defined at a different level of production technology other than that of the country, will be incorporated in the analysis.

The next step to be made is to decide upon the type of the multilevel model which best describes the situation we are interested in exploring. In the case examined herein where the performance of each country exhibits heterogeneous patterns through the industries considered along with the fact that it is reasonable to assume that any spillover effects generated at the sector or the European level (both reduced to Level 2) affect the performance of each country (Level 1), the use of the random intercepts and slopes model seems to be a plausible choice. At this point, we have to justify the use of multilevel modelling from one additional viewpoint, that of the apparent heterogeneity and the significance of the technological hierarchy which is incorporated into the analysis. It is by any means undeniable that the data are clustered in groups.

Provided that we are after exploring the significance of spillover effects and the significance of the sector’s production technology –all are defined at a higher level than that of the country level- including variables in a single level equation and estimating with ordinary least squares (OLS) techniques would result in neglecting for both the heterogeneity among the different levels and the effect of the level itself. Additionally, with multilevel modelling we can investigate entity-varying effects (or groups) and/or estimate group level averages. Not to mention that any cross terms included would downsize the effect of the technology regime since those would not have been occurred by the interaction between variables tied to different levels of analysis. Moreover, the fact that there are interactions to be studied between alternative levels along with the nested structure of the data, would result in correlated errors and violation to the non-correlated errors of the OLS. In contrast to the single level OLS regression estimation,
hierarchical modelling relaxes this independence assumption and allows for correlated error structures (Luke, 2004). Otherwise, the OLS underestimate the standard errors leading to accept a null which is not correct (Type I error) but this is not the case for the multilevel models.

In what follows, we specify different hierarchical models of two levels where the lowest level variable (Level 1 dependent variable) is the productive performance of each country while the level two units are the industries and the sector respectively. This specification will give rise to alternative research questions and interpretations.

Every empirical study employing multilevel analysis departs from the estimation of a null model i.e. with no Level 1 or Level 2 predictors so as to calculate the intra class coefficient to establish the appropriability of the methodology. The null model takes the following form:

Level 1: \( \text{Eff}_{ij} = \beta_{0j} + r_{ij} \)
Level 2: \( \beta_{0j} = \bar{\text{Eff}} + u_{0j} \)

The mixed model takes the form:

\[
\text{Eff}_{ij} = \bar{\text{Eff}} + u_{0j} + r_{ij}
\] (5.6)

the productive performance \( \text{Eff}_{ij} \) of the \( i \)-th country employing the technology of the \( j \)-th industry in time \( t \) (time subscript has been suppressed for the sake of simplicity) is affected by the (grand) mean of productive performance \( \bar{\text{Eff}} \) of all the countries under each individual industry in Europe for the study period. Note that we allow intercepts to vary according to the industry which is a reasonable assumption to make as we acknowledge the different performance patterns of the countries under each industry (Table 5.1 below) while the random terms \( r_{ij} \) and \( u_{0j} \) represent the un-modelled variability tied to the country and industry respectively. The latter are not statistical parameters to be estimated but are latent random variables with an expected mean of zero and variance equal to \( \sigma_u^2 \). This is further justified by the fact that the random effects parts of the model is concerned with the variance components which should not by any means interpreted as effects in the model (Luke, 2004).
Table 13 Mean Productive Performance by industry

| Industry                  | Average Productive Performance |
|----------------------------|--------------------------------|
| Air Transport              | 0.750                          |
| Basic Metals               | 0.870                          |
| Chemicals                  | 0.688                          |
| Construction               | 0.871                          |
| Food & Beverages           | 0.792                          |
| Land Transport             | 0.834                          |
| Other Non-Metallic         | 0.844                          |
| Pulp                       | 0.802                          |
| Supporting Activities      | 0.863                          |
| Textiles                   | 0.803                          |
| Transport Equipment        | 0.770                          |
| Water Transport            | 0.856                          |
| Wood                       | 0.865                          |
| **Grand Mean**             | **0.816**                      |

Next, we calculate the intra class coefficient (ICC) as the ratio using the following formula:

\[
\varrho = \frac{\sigma_{\mu}^2}{\sigma_{\mu}^2 + \sigma_{r}^2}
\]  

(5.7)

The intra class coefficient tells us about the correlation of the observations within a group. More precisely, the indicator measures the proportion of the industry level variance of the productive performance between the countries, in a given industry, in the total variance. For instance an ICC is of .095 means that 9.5% of the variability in the productive performance is explained by the presence of the industry technology. As Britto & McCombie (2008) argue, an ICC over 8% is sufficient for productivity studies implying that the introduction of group-level variables is justified, although there is not a formal threshold.

Overall, we aim at explaining the productive efficiency of each European country employing the production technology of each individual industry using the absorptive capacity of each country, the role of pure technical spillover effects whether the latter are generated at the level of the sector or European level of technology) and the role of the sector’s identity as well from 1999 through 2006. In this line, it is reasonable to assume that the ability to absorb new technical knowledge is influenced by the intensity of spillover effects generated at the sector and the European technology level as well.

We specify the following model to investigate the research questions presented below:
Level 1 (country): 
\[ E_{ij}^{\text{eff}} = \beta_0 + \beta_{ij}^{sector} GCI_{ij,t-1} + \beta_{ij}^{sector} GCI_{ij,t-1} + \beta_{ij}^{sector} Sector_{ij,t-1} + r_{ij} \]

Level 2 (industry): 
\[ \beta_{ij} = \gamma_{00} + u_{ij} \]
\[ \beta_{ij}^{sector} = \gamma_{10}^{sector} + \gamma_{11}^{sector} Tg_{ij,t-1} + u_{ij} \]
\[ \beta_{ij}^{Europe} = \gamma_{20}^{Europe} + \gamma_{21}^{Europe} Tg_{ij,t-1} + u_{ij} \]

The mixed model takes the form:
\[ E_{ij}^{\text{eff}} = \gamma_{00} + \gamma_{10}^{sector} GCI_{ij,t-1} + \gamma_{11}^{sector} Tg_{ij,t-1} * GCI_{ij,t-1} + \gamma_{20}^{sector} Sector_{ij,t-1} + \gamma_{21}^{Europe} Tg_{ij,t-1} * Sector_{ij,t-1} + u_{ij} + r_{ij} * GCI_{ij,t-1} + \mu_{ij} * Sector_{ij,t-1} \]

\[ \text{(5.8)} \]

At this point we should mention that the lagged value of the global competitiveness index captures the absorptive capacity levels that is the already accumulated knowledge a country has incorporated in its production technology, Sector is a binary outcome variable indicating participation in the manufacturing sector while the lagged values of the technology gap are introduced in the analysis to capture any spillover effects, with one year lag to diffuse among the DMUs, originating from the sector technology (\( Tg_{ij,t-1}^{sector} \)) and the European technology (\( Tg_{ij,t-1}^{Europe} \)) as well. The disturbance terms \( u_{ij} \) and \( r_{ij} \) indicate industry and country unobserved characteristics while the \( u_{ij}, u_{ij}^{sector}, u_{ij}^{Europe} \) are the variance components tied to the levels of the estimation procedure and are to be estimated. Also the parameters of interest are the \( \gamma_{00}, \gamma_{10}, \gamma_{11}, \gamma_{20}, \gamma_{21} \). Due to the small number of the DMUs under each frontier and small group number, i.e. both below 30, the recommendable method is that of the restricted maximum likelihood. Also we have to mention that in this case we have a balanced design consisting of seventeen DMUs at each industry.

The rationale behind the particular specification is the following. Productive performance improvements are attached to the absorptive capacity of each country as captured by the global competitiveness index which is a composite index incorporating twelve pillars. In addition, GCI is country and year-varying variable, directly comparable across countries. It is reasonable to assume that the impact of absorptive capacity on each country is influenced by the sector technology as each country employs the industry technology attached to the sector identity, the spillover effects of the sector technology and is also influenced by the technological advancements within Europe. In other words, the impact of absorptive capacity is affected by the volume of spillover effects which is different according to the sector’s technology each industry employs. The above specification sheds light to the following research questions:

**H:** Past competencies, capabilities and accumulated knowledge does not exert any significant influence on the current levels of productive performance. In other words, the absorptive capacity levels of a country are
not time persistent and do not contribute to the improvement of current levels of productive performance (\(GCI_{ij,t}, \gamma_{10} = 0\)).

**H_2**: The combined effect of absorptive capacity and sector spillover effects production technology and absorptive capacity of the country does not lead to productive performance improvements. In other words, the ability of the country to adopt and incorporate into its own production process the best available technology provided by the sector each industry operates under, does not play a crucial role in the improvement of its performance (\(GCI_{ij,t} \cdot T_{gij,t-1}^{Sector}, \gamma_{11} = 0\)).

**H_3**: The production technology of the manufacturing sector does not exert a significant influence of the productive performance of the country adopting it under the respective industry. In other words, the fact that a country is oriented towards manufacturing industries is not associated with higher productive performance. In other words, the identity of the industry i.e. the sector it belongs to, is not sufficient to guarantee high performance levels pinpointing that relying exclusively on the intermediate level of technology hierarchy to shed light to the mechanism of performance assessment provides no insight for the investigation of the drivers of a country’s productive performance (\(Sector = 1, \gamma_{20} = 0\)).

**H_4**: The technical knowledge produced at the European level in conjunction to the sector technological capabilities do not contribute to improvement of the productive performance of the industry technology employed by each country. In a nutshell, the industries are equally capable of exploiting any technological opportunities arise (\(Sector \cdot T_{gij,t-1}^{Europe}, \gamma_{21} = 0\)).

From a conceptual perspective, we should clarify that, from the surface, a part of the spillover effects originating from the European technology, has already been projected on each sector’s production technology. However, reflecting under the meaning of spillover effects and technological opportunities, the degree of accumulation is rather different between levels of technology hierarchy and it is affected by the ability of the sector each industry belongs to exploit the technological capabilities available highlighting the potential of the sector technology. This is done by the above interaction which “adjusts” the European technological opportunities.

Table 5.2 below presents the estimation results for the case of the null model. Focusing on the first column, that of the industry level, the (grand) mean of productive performance score of all the countries at all industries throughout the period of study is .816 (as shown in Table 4.1) and significant. The ICC is 14.03% so we can study the effect of spillover effects originating from a level other than the country one. We should mention that if the indicator is close to 0 then the grouping variable (industry technology) is of no use and we could run a simple regression as the significance of the level heterogeneity is not important while if the indicator approaches 1, there is no variance to explain at the individual level (country level) which implies
that every DMU is the same, i.e. it pinpoints no heterogeneity. In our case, 14.03% of the variability in the productive performance among the countries is explained by the heterogeneous industry technologies. The last row of the table below tests the null hypothesis that there are no random effects ($H_0$: Random Effects=0) and a simple regression suffice over multilevel modelling. Here, we do not accept the null, so there is level variability to explain by the particular approach.

Moving forward, we estimate the model in Equation 5.8 and the results are illustrated in Table 5.3 below. Results indicate that high levels of attained absorptive capacity influence in a positive manner the current levels of productive performance (Hypothesis 1 is not accepted) while the combined effect of absorptive capacity and sector spillovers representing the ability and potentiality to absorb the best available (and new) technical knowledge exerts a negative and significant influence on the current levels of productive performance indicating that countries with incomplete market mechanisms, low human capital levels, and fragmented industries characterized by low technological opportunities i.e. low absorptive capacity, cannot be benefited or accumulate the spillover effects running from the sector’s technology (Hypothesis 2 is not accepted). Industries employing the technology of the manufacturing do not seem to be in a better position compared to those employing the transportation technology (Hypothesis 3 is not rejected). Therefore the identity of the industry itself is not sufficient to guarantee high performance levels pinpointing that relying exclusively on the intermediate level of technology hierarchy we cannot draw inferences about the drivers of the productive performance at a lower level, i.e. at the country level. Industries of the manufacturing sector appear to be less capable, compared to the ones of the transportation, to incorporate new technical knowledge produced within Europe by all industries and consequently the latter fail to exert a positive influence on the mean productive performance of the country so as to improve its performance score with respect to the industry technology (Hypothesis 4 is accepted).

The most basic model evaluation tool in the form of post-estimation diagnostics regarding the mixed models is that of the test for non-equal variance of the DMUs under evaluation. The heteroskedasticity test is simply a quantile-quantile plot of the standardized residuals which is presented below (Fig. 5.2). The Q-Q plot is meant to compare the empirical values of the variable of interest to standard normal distribution. It is obvious that the (standardized) residuals do not fall on the straight line so the assumption of homogeneity is violated. This implies that our estimates are biased and as such we cannot place any confidence on the latter.

Shifting the attention to the case where the Level 2 corresponds to the sector technology, we seek to investigate whether the effect of the characteristics associated to the industry
technology exerts a significant influence on the productive performance of the country. The moral here is that we will get a direct measurement of the effect of each industry technology acknowledging the importance of the level heterogeneity along with the moderating effect of absorptive capacity and level spillover effects. Again, we have to estimate a null model similar to the one in equation 5.6 above but in this case the heterogeneity level of interest (Level 2) will be that of the sector technology. The results are illustrated at the second column of Table 5.2 below. This is a case according to which different indications pinpoint towards the same direction.

From the one hand, the ICC value is very low to support the use of the hierarchical modelling approach. On the other hand, the likelihood ratio test fails to accommodate for the significance of the intermediate level of technology heterogeneity. Either ways, we are not allowed proceed to further modelling. Although the former is quite straightforward, we need to elaborate more on the latter to be sure we draw the right inferences from the perspective of the Economic theory.

From a set theory standpoint, the overall (i.e. the European) production set can be partitioned into sub-sets with respect to a characteristic shared to the units consist the former. The resulting sub-sets are mathematically justified but in doing so and from the perspective of the Economic Theory, the sub-sets carry less (but perhaps more compact) information and as a consequence the ability to explain the phenomena of interest seems to be negatively associated to the number of levels interposing between the lowest and the higher level of aggregation. The fact that the intermediate levels exist is a logical and hard to neglect issue. But the very existence of the level seems that does not have any interpretable ability. This might be an indication that technological heterogeneity islands are mostly appo inted in low aggregation levels rather than in higher ones. In this line, it seems that the fact that a large group of DMUs is considered to be technologically heterogeneous is not a property of the group per se but it is an specific or a combination of inherited characteristic(s) of the entities which arise every time the latter considered as a group or are brought together. Interposing additional levels of technology hierarchy, i.e. lowering the aggregation level, we might force the data to reveal a story cannot be supported by the nature of the latter. The clustered or nested nature is by any means an indication that an analysis ought to consider the levels in the data as a high priority but it appears that one should not follow that nested nature and sub-sequenced analysis blindfolded. In our case, that fact that the hierarchical approach does not work can be considered as an opportunity to dig deeper in order to better understand the phenomena and relationships we aspire to explain so as to provide credible results. Simply put, it does not work for some reason. Sector level technological heterogeneity may not be the appropriate disaggregation level to explain the improvement of the (mean) productive performance at the (mean) industry level. As a matter of
fact, the characteristics along with the overall behaviour of each particular industry but also as a
group appear to be important. The source of technological opportunities and technical
knowledge are not exclusively the industries employing similar technology because of the fact the
latter are part of a particular sector. Framed differently, evolution and performance improvement
are products of technologically heterogeneous, yet compatible, production environments. The
technological heterogeneity is attached to the DMU and is being projected on the next higher
level of aggregation (i.e. country characteristics are projected on industry’s performance). From
that point onwards, the label of the aggregation level does not seem to matter significantly but
the characteristics of the DMUs per se are at the end of the day imprinted on the higher level, i.e.
the European level. As should be inferred from the context, that we do not disgrace the
importance of the lower aggregation heterogeneity levels or that there is no nested heterogeneity
in those, but rather we are stressing that despite the fact that those exist and contribute to the
technological improvement of the participating units, the amount of heterogeneity the latter
entail may not be sufficient to provide ample evidence to explain the variability in the lower
levels. Therefore, the particular heterogeneity regime can be neglected whilst in conjunction to
the outcome of Hypothesis 1 in section 5.2.1 for 2006 in favour of technological convergence of
the two distinct metatechnologies, we can argue that the latter are absorbed by the overall
frontier, i.e. European level, as the interposed levels of heterogeneity –in this case sectors- do
not seem to contribute methodologically but the characteristics associated to the lower levels –
industry and eventually DMUs- appear to be of great importance. The decomposition of the
technological heterogeneity level is feasible but is not quite illuminating. The latter is in favour of
the very nature of spillover effects which are running from and to every possible direction.
Primarily, the concern is placed on the level of absorptive capacity of the country boosted by the
spillover effects and not on the identity of the sector the technology level of which each DMU,
i.e. country, can claim.

Apparently, the most appropriate level to draw inferences from is that of the industry
where the greater volume of heterogeneity is found. Therefore, we should target high levels of
aggregation –in terms of heterogeneity- such as industry level, European level etc. Focusing on
the industry level, as it can support a certain level of heterogeneity and aggregation, the
idiosyncrasies and peculiarities tied to the industry’s technology seem to matter the most as those
are closely related to its performance and not its identity (manufacturing, transportation,
services).

All in all, the missing piece of the puzzle of improving the productive performance of a set
of heterogeneous DMU proves to be technological heterogeneity itself since it encapsulates all
the potential for further development. Technologically heterogeneous regimes oriented towards high aggregation levels appear to be the cornerstone for the performance improvement of the participating DMUs due to the unlimited opportunities to exploit from seemingly unrelated sources.

Table 14 Estimating the null model (ANOVA random effects)

| Level 2 variable | Industry Level | Sector Level |
|------------------|----------------|-------------|
| **Fixed parameters** |                |             |
| Grand mean       | .816***        | .817***     |
|                  | (.015)         | (.007)      |
| **Variance**     |                |             |
| Country level    | .018           | .208        |
| Industry level   | .003           | .000        |
| **Observations** | 1,768          | 1,768       |
| **Groups**       | 13             | 2           |
| **ICC**          | 14.03%         | 3.23%       |
| **Log-Likelihood** | 1015.092      | 910.500    |
| **LR test vs. Linear Regression** | .000 | .136 |

**Note:** Even if it is intrinsically different model, at the estimation of the sector level null model, we tried to explain the productive performance of the country with respect to the sector technology directly i.e. ignoring the level of the industry, the ICC value does not support the use of the hierarchical modelling (5.95%), the outcome of the likelihood ratio test was in favour of the approach. Following the related literature, we considered the intra-class coefficient.

Table 5.3 Industry level results

| Level 2 variable | Industry Level |
|------------------|----------------|
| **Fixed parameters** |                |
| $GCI_{jt}$       | .015***        |
|                  | (.004)         |
| $Sector = 1$     | .052           |
|                  | (.034)         |
| $GCI_{jt} \ast T_{Sector}^S_{jt-1}$ | -.023*** |
|                  | (.005)         |
| $Sector \ast T_{Europe}^S_{jt-1}$ | -.059** |
|                  | (.027)         |
| Constant         | .750***        |
|                  | (.030)         |
| **Variance**     |                |
| L1: GCI          | .018           |
| L2: Industry level | .003        |
| **Obs**          | 1,547          |
| **Groups**       | 13             |
| **Log Restricted-Likelihood** | 890.900       |
| **LR test vs. Linear Regression** | .000          |
5.2.2.3 Econometric specification

The findings above place concern about the appropriability of the multilevel modelling to investigate the relationships of interest. Another issue which had been suppressed up to this point is that the different technological regimes are endogenously related as the technology sets defined at an industry and sector level are sub-sets of the overall (i.e. European) production set implying that there is (potentially) an endogenous relationship between the spillover effects emanating from the different technology regimes and the productive performance. Such a relationship violates the assumption about strict exogeneity yielding to biased estimators. Moreover, in the previous chapters, the time persistence of heterogeneous patterns in the productive performance has proved itself as a significant driver of its current levels, so it would be unwise to neglect it. The latter, raises additional endogeneity concerns as has been supported in chapters 3 and 4 in more detail.

Such being the case, in order to deal with the theoretical concerns, an alternative method should be followed instead to accommodate for the abovementioned issues and at the same time to provide insights to the basic research questions of this chapter which is the effect of the technological heterogeneity regime in the productive performance of each country and the role of spillover effects and absorptive capacity. The underlying idea of the specifications following is that in order to give prominence to the technological heterogeneity regime (or level) we should include in the specification of each level, characteristics (variables) defined at the other levels so as to assess their impact. To do so, we will employ the Generalized Method of Moments or difference estimator of Arellano & Bond (1991) as introduced by Holtz-Eakin et al., (1988). The appropriability of the method along with the problems it can cope with has been extensively described and justified in chapters 1 and 3, and for the sake of brevity it will not be presented again. We will proceed to the model specifications and research questions instead.
We specify three different econometric models according to the technological heterogeneity regime we need to focus on. More precisely, we specify the industry level model, the sector level model and the European level model respectively, as shown below:

\[
\text{Eff}_{i,t} = a_{0i} + \beta_{1i}\text{Eff}_{i,t-1} + \beta_{2i}\text{GCI}_{i,t-1} + \beta_{3i}\text{GCI}_{i,t-1}\times T_{\text{Sector}} + \gamma_{i}\text{T}_{\text{Sector}} + \gamma_{i}\text{T}_{\text{Europe}} + u_{i,t},
\]

\(i = 1, \ldots, 17, j = 1, \ldots, 13, k = \text{Manufacturing, Transportation technology}, t = 1, \ldots, 8\)  (5.9)

\[
\text{Eff}_{j,k} = \beta_{0j} + \delta_{1j}\text{Eff}_{j,k-1} + \delta_{2j}\text{GCI}_{j,k-1} + \delta_{3j}\text{GCI}_{j,k-1}\times T_{\text{Sector}} + \lambda_{j}\text{T}_{\text{Sector}} + \lambda_{j}\text{T}_{\text{Europe}} + u_{j,k},
\]

\(i = 1, \ldots, 17, k = \text{Manufacturing, Transportation technology}, t = 1, \ldots, 8\)  (5.10)

\[
\text{Eff}_{l,t} = \gamma_{0l} + \theta_{1l}\text{Eff}_{l,t-1} + \theta_{2l}\text{GCI}_{l,t-1} + \theta_{3l}\text{GCI}_{l,t-1}\times T_{\text{Sector}} + \psi_{l}\text{Transportation} + \psi_{l}\text{T}_{\text{Sector}} + u_{l,t},
\]

\(i = 1, \ldots, 17, k = \text{Manufacturing, Transportation technology}, t = 1, \ldots, 8\)  (5.11)

The dependent variable of each specification is the productive performance with respect to each level of technological heterogeneity, i.e. the industry, the sector and the European level as well. Regarding the independent variables included in the above models, the lagged values of the dependent variable capture the time persistence of productive performance, the lagged value of the GCI captures the level of absorptive capacity, the lagged values of the technology gap with respect to the sector and European technology respectively capture the magnitude of spillover effects originating from the sector and the European level respectively with one year lag as the necessary period to incorporate any technological breakthroughs in the production process, the variable called Transportation is a binary variable indicating whether the industry belong to the transportation sector. The terms \(u_{i,t}, u_{j,t} \text{ and } u_{k,t}\) are the error terms including factors which affect productive performance of each level and have not been introduced into the specifications. Finally, \(a_{0i}, \beta_{1i}, \beta_{2i}, \beta_{3i}, \gamma_{i}, \lambda_{j}, \psi_{j}\) where \(i = 1, 2, 3, j = 1, 2\) is the vector of parameters to be estimated. The research questions we are after could formally be stated as follows:

\(H_1\): The productive performance of each country does not exhibit time persistent behaviour across the technological heterogeneity levels considered. In other words, the path dependence phenomenon can be neglected since it does not exert any significant effect on current levels of productive performance.

\((\beta_1 = 0, \delta_1 = 0, \theta_1 = 0)\).

\(H_2\): Absorptive capacity is not considered as an important driver of productive performance implying that all the countries irrespective of the level of absorptive capacity are equally capable to absorb new knowledge

\((\beta_2 = 0, \delta_2 = 0, \theta_2 = 0)\)

\(H_3\): Spillover effects generated at the sector level are not significant and do not affect significantly the productive performance of the country \((\gamma_1 = 0, \lambda_1 = 0)\).
\( H_{3b} \): Spillover effects generated at the European level are not significant and do not affect significantly the productive performance of the country \( (\gamma_2 = 0, \lambda_2 = 0) \).

\( H_4 \): The exploration of spillover effects generated at a higher level is associated to the level of the absorptive capacity of each unit. Framed differently, productive performance is connected with the ability of each country to absorb new technical knowledge conveyed by spillover effects \( (\beta_j = 0, \delta_j = 0, \theta_j = 0) \).

\( H_5 \): The two sectors are equally capable to supply technological advancements in the form of spillover effects to the European level. The sector-specific production technology does not exert any significant effect on the productive performance of the country. In other words, the sector-specific spillover effects contribute in a similar manner the European production technology irrespective of the sector-specific technology they drawn upon \( (\psi_j = 0) \).

### 5.3 Data and variables

In order to test our research questions we employ a dataset that allows (i) introducing some apparent but meaningful DMU associated heterogeneity (ii) setting a structured dataset which provides the opportunity to draw inferences from the clustered nature of the data (iii) examining different sector technologies and their linkage to the overall level of technology without involving any micro-level idiosyncrasies but in conjunction to DMU specific heterogeneity (iv) minimizing measurement errors that would increase DMU specific heterogeneity. In this direction we have device, the employed in this chapter dataset, combining information provided by four distinct publicly available sources resulting in a unique balanced panel comprising of 13 2-digit industries\(^{29}\) according to the International Standard Industrial Classification (ISIC) in 17 EU countries\(^{30}\) over an 8-year period from 1999 through 2006. Thus, the employed dataset contains 221 observations on the cross section dimension and 1,768 observations on a panel data dimension. The final dataset embraces five variables; one output and four input variables.

More specifically, we approximate the output variable \( (Y) \) by the gross valued added of each industry, whilst the inputs include the capital stock \( (K) \) in million Euros, the labor input \( (L) \) which is captured by the total hours worked by employees, expenditure on intermediate inputs \( (M) \) in million Euros and the total energy consumption \( (E) \) measured in million tons (Mt) of oil

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\(^{29}\) More specifically, 9 of them belong to the Manufacturing (Basic metals, Chemicals and chemical products, Construction, Food & Beverages, Other non-metallic minerals, Pulp paper, Transport equipment, Textiles, Wood Products) and 4 to the Transportation sector (Air transport, Land transport, Supporting and auxiliary transport activities and Water transport).

\(^{30}\) In particular, Belgium, Czech Republic, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Netherlands, Austria, Poland, Slovenia, Slovakia, Finland, Sweden, United Kingdom.
equivalent. For several of the countries\textsuperscript{31} in this dataset, certain variables are reported in local currency, and need to be converted into Euro’s before being used in the analysis.

In the second stage of the analysis we have employed as additional explanatory variables, the industry specific productive characteristics captured by the corresponding input ratios, and variables which capture any ambient technological discrepancies. These include the variables EURO, which is a dummy variable indicating membership of the European Monetary Union (EMU), and GCI, which reflects the Global Competitiveness Index value of each country in the given year. The former is intended to control for any heterogeneity owing to transaction cost advantages accruing to the countries participating in the EMU, while the latter was introduced in order to reflect differences in productive performance that may derive from each countries’ relative advantages in infrastructure, human capital, technological achievements and other developments related to the production process (Sala-i-Martin et al., 2008). Tables 5.4 and 5.5 below provide the definition, measurement and basic descriptive statistics for each of the variables.

As already mentioned, the data were drawn by combining several distinct sources of information. Data for Gross Value Added, total hours worked by employees and intermediate inputs were obtained from the database of Groningen Growth and Development Centre, Enerdata-Odyssey database was used to collect data on energy consumption, data on gross fixed capital formation and capital input files were acquired through OECD Structural Analysis and EU-KLEMS databases respectively. Industry specific deflators were acquired through OECD STAN. The Global Competitiveness Index data were collected from various editions of the Global Competitiveness Report published by the World Economic Forum.

Very often, the most severe obstruction in the assessment of productive efficiency for a group of DMUs is the lack of a consistent variable reflecting capital stock. To overcome this stumbling block, we draw on the Perpetual Inventory Method (PIM) (see Krautzberger and Wetzel, 2012 as an example) to create a consistent measure of capital stock. The initial condition for the capital stock is given by $\frac{K_{1999}}{1999} = \frac{I_{1999}}{1999} + \frac{g}{\delta}$, where $g$ is estimated as the average growth rate in capital investments for the preceding 5 years for each of the examined industries and countries. Given this initial value, the capital stock for each subsequent year is constructed using the formula in Eq.(4.12):

\[
K_{t|k} = (1 - \delta)K_{t-1|k} + I_{t|k}
\]  
(5.12)

\textsuperscript{31} Czech Republic, Denmark, Poland, Slovak Republic, Slovenia, Sweden and the United Kingdom.
where $K_{it}$ and $I_{it}$ represent the capital stock and investment of the $i$-th country on the $k$-th industry for the year $t$ respectively, where $\delta$ is the depreciation rate which is assumed to be equal to 10% yearly.\footnote{In fact, the estimated capital series did not change in a significant manner when different levels of depreciation rates were considered.}

### Table 5.4 Variables, units of measurement and sources

| Variable                        | Units of measurement | Source                          |
|---------------------------------|----------------------|---------------------------------|
| Gross Value Added ($Y$)         | million euros        | GGDC                            |
| Capital ($K$)                   | million euros        | OECD STAN, EUKLEMS              |
| Labor ($L$)                     | million hours worked by employees | GGDC                      |
| Intermediate Inputs ($M$)       | million euros        | GGDC                            |
| Energy Consumption ($E$)        | million tons of oil equivalent | Enerdata - Odyssey            |
| Global Competitiveness Index ($GCI$) | pure number        | World Economic Forum            |

**EURO**

- European Commission

All the monetary values are in constant 2000 prices using industry and country specific deflators.

### Table 5.5 Descriptive Statistics of the inputs and output for the Sector Frontiers Dominated Technology Hierarchy (SFDTH) for the period 1999-2006

| Industry                        | $Y$   | $K$   | $L$   | $E$   | $M$   |
|---------------------------------|-------|-------|-------|-------|-------|
| Food & Beverages                | 9,723 | 39,685| 376,588| 1,723 | 29,302|
| (10,450)                        | (56,861)| (369,075)| (1,603) | (29,588)|
| Textiles                        | 2,049 | 6,843 | 97,338| .464  | 7,425 |
| (2,860)                         | (8,638)| (105,939)| (.631)  | (11,590)|
| Wood & wood products            | 2,009 | 13,158| 93,422| .382  | 4,118 |
| (2,072)                         | (26,899)| (74,893)| (.358)  | (4,020)|
| Pulp Paper                      | 8,380 | 37,809| 230,451| 2.180 | 14,473|
| (9,351)                         | (64,412)| (244,461)| (2.380)| (14,492)|
| Chemicals                       | 9,653 | 60,933| 37,809| 92.422| 21,590|
| (11,421)                        | (74,900)| (179,805)| (3.319)| (24,983)|
| Other non-metallic minerals     | 3,966 | 16,490| 136,646| 2.374 | 6,727 |
| (4,549)                         | (17,278)| (129,576)| (2.889)| (7,925)|
| Basic metals                    | 12,007| 67,863| 427,353| 5.439 | 23,616|
| (15,316)                        | (95,229)| (437,768)| (5.714)| (28,194)|
| Transport equipment             | 9,716 | 50,245| 271,373| .616  | 31,959|
| (16,310)                        | (61,519)| (341,160)| (.830)  | (49,353)|
| Construction                    | 26,479| 67,863| 427,353| 5.439 | 23,616|
| (28,530)                        | (87,707)| (437,768)| (5.714)| (28,194)|
| Land transport                  | 10,660| 67,863| 427,353| 5.439 | 23,616|
| (11,065)                        | (42,929)| (346,681)| (17.472)| (14,344)|
| Water transport                 | 1,464 | 5,548 | 19,543| .272  | 2,897 |
| (1,887)                         | (9,849)| (16,283)| (0.354)| (3,814)|
| Air transport                   | 1,772 | 14,577| 35,514| 2.885 | 4,053 |
| (2,318)                         | (17,315)| (39,422)| (3.173)| (4,792)|
| Supporting activities           | 7,899 | 56,414| 254,907| .338  | 12,019|
| (9,318)                         | (63,513)| (329,467)| (.517)  | (13,716)|
| TOTAL                           | 8,137 | 36,336| 274,934| 2.786 | 16,194|
| (13,651)                        | (59,419)| (460,343)| (6.782)| (26,434)|

\footnote{In fact, the estimated capital series did not change in a significant manner when different levels of depreciation rates were considered.}
5.4 Results and discussion

5.4.1 Sector-specific technology considerations

Before the formal examination of our research questions, let us examine what inferences could be drawn by the technological structure adopted so far. We use the industries of the manufacturing and transportation industries to achieve a higher level of technology heterogeneity so as to examine the two distinct sectors allowing us to focus on the multi-dimensional technology structures. Tables 5.6 and 5.7 below present the productive performance scores and the technology gap values for the different levels of technology hierarchy that is the technology corresponding to the industry, sector and European level respectively for the industries of the manufacturing and transportation sector respectively.

Firstly, we will consider the case the sector technologies do not interpose between the industry frontiers and the European technology level. More precisely, Table 4.6 below concerns the industries of the manufacturing sector. The average country seems to perform quite well under each industry’ technology (.812) but at the same time, a rather poor performance with respect to the European level of technology (.452) is found. Notably, the industries of the manufacturing in the EU for the years 1999-2006, do not seem to perform quite well within the European level which might be a rough indication regarding their absorptive capacity levels in terms of accumulation of technical advancements and exploitation of spillover effects generated at the EU level. Unlike the case just mentioned, a differentiated picture arises when the sector technology is taken into account. As far as the case of manufacturing is considered, the reduction of technological heterogeneity reveals a different scheme. The mean productive performance of all the industries has experienced spectacular increase and we can now identify two distinct groups based on their mean productive performance score with respect to the sector specific technology. Fig. 5.3 provides a graphical illustration of what we just described in a more dynamic manner since it depicts the begging of the period (1999), the middle (2003) and the end (2006) of the period. Panel (a) in Fig.5.3 shows that (i) there is not significant turbulence over the period of study as regards the performance scores and (ii) that most of the industries perform quite well as densities appear to be left skewed without experiencing severe changes. Panel (c) in Fig.5.3 depicts the behavior of the industries of the manufacturing sector compared to all industries i.e. those of the transportation sector included on a European level. We notice that over the period of study, the performance of the manufacturing in the EU has declined. What is really illuminating is the panel (c) in Fig.5.3 which depicts the kernels for the productive performance of the industries of manufacturing when the latter are evaluated against the manufacturing sector technology. We notice that throughout the distribution remains bimodal indicating two distinct groups of industries within the manufacturing sector which we were able to identify after the
sector technology has been taken into account. The moral up to here is that the reduction of
technological aggregation restrains the degree of heterogeneity by (i) ensuring homogeneity in
the benchmarking process and (ii) identifying groups of DMUs sharing similar performance
characteristics. Focusing on the technology gap values resulting from different aggregation levels,
one gets a similar picture, i.e. that the industries of manufacturing underachieve at the European
level (.445). However, when the manufacturing-specific technology is considered an improved
performance is documented implying that the reduction of the degree of heterogeneity makes
the benchmarking process smoother since the latter takes into consideration only similar (or
homogeneous) -in technological terms- DMUs. Particularly, the technology gap of the average
industry operating under the manufacturing sector with respect to the sector-specific technology,
is .318 contrasted to 0.444 in the case of the EU-technology itself. In accordance to the above
discussion, Fig. 5.4 depicts the technology gap distributions resulting from different aggregation
levels. Panel (a) in Fig. 5.4 refers to the technology gap with respect to the sector technology. It
is evident that there is turbulence over the years while the distributions are also bimodal
indicating the existence of two underlying groups exhibiting different performance. When we do
not account for the sector-specific technology, as depicted in panel (b) in Fig. 5.4, besides the
form of the distribution itself, we are not able to identify any groups as the latter seem to be
absorbed by the overall technological structure. Framed otherwise, disaggregating the overall
level of technology, we move towards a less mixed picture which provides the opportunity to
identify hidden technological groups sharing the same characteristics.
Table 5.6 Descriptive statistics of the manufacturing industries for the period 1999-2006

| Industry Performance | Sector Performance | European Performance | Sector Technology Gap | European Technology Gap | Overall Technology Gap |
|----------------------|--------------------|----------------------|-----------------------|------------------------|------------------------|
| Basic Metals         | .870               | .534                 | .459                  | .389                   | .479                   | .148                   |
|                      | (.132)             | (.158)               | (.170)                | (.146)                 | (.162)                 | (.167)                 |
| Chemicals and        | .688               | .582                 | .468                  | .152                   | .317                   | .205                   |
| chemical products    | (.168)             | (.175)               | (.200)                | (.138)                 | (.227)                 | (.201)                 |
| Construction         | .871               | .675                 | .630                  | .223                   | .274                   | .076                   |
|                      | (.131)             | (.133)               | (.158)                | (.110)                 | (.149)                 | (.121)                 |
| Food and Beverages   | .792               | .470                 | .431                  | .418                   | .466                   | .082                   |
|                      | (.144)             | (.176)               | (.158)                | (.168)                 | (.163)                 | (.088)                 |
| Other non-metallic   | .844               | .618                 | .422                  | .270                   | .501                   | .312                   |
| minerals             | (.106)             | (.141)               | (.168)                | (.128)                 | (.181)                 | (.227)                 |
| Pulp paper           | .802               | .596                 | .510                  | .263                   | .372                   | .156                   |
|                      | (.129)             | (.152)               | (.187)                | (.119)                 | (.185)                 | (.177)                 |
| Textiles             | .803               | .488                 | .318                  | .402                   | .603                   | .276                   |
|                      | (.138)             | (.203)               | (.094)                | (.202)                 | (.091)                 | (.212)                 |
| Transport equipment  | .770               | .506                 | .437                  | .354                   | .445                   | .131                   |
|                      | (.163)             | (.206)               | (.192)                | (.202)                 | (.187)                 | (.138)                 |
| Wood and wood products | .865             | .527                 | .394                  | .395                   | .546                   | .237                   |
|                      | (.104)             | (.146)               | (.133)                | (.134)                 | (.136)                 | (.183)                 |
| Total                | .812               | .555                 | .452                  | .318                   | .445                   | .180                   |
|                      | (.147)             | (.178)               | (.184)                | (.176)                 | (.196)                 | (.190)                 |

Figure 5.3 Productive performance and technological hierarchy for the Manufacturing sector over the period 1999-2006
Shifting the attention to the industries of the transportation sector, the picture is about the same regarding both the productive performance and the technology gaps. Table 5.7 below illustrates that each transportation sector performs quite well under its own technology but compared to the European technology the productive performance seems to decrease dramatically (0.535 compared to 0.826 on average). After the introduction of the transportation sector specific technology, we notice that the mean performance increases (0.635) since the latter is evaluated only against the transportation sector specific technology. A more informative picture is depicted by the panels of the Fig. 5.5 below. Particularly, in panel (a), the productive performance distribution under each transportation technology does not experience any intense turbulence throughout the sample period. The distributions are consistently left skewed indicating high performance. Panel (b) in Fig. 5.5 depicts the case where the sector specific technology has been considered providing weak evidence for the existence of distinct groups under the sector-specific technology. The latter might be an indication that the industries of transportation sector employ and share similar technological opportunities and that those, despite their differentiated nature, do perform alike when benchmarked against the sector technology in contrast to the industries of manufacturing which form technological clubs under the sector technology. In a nutshell, industries of the manufacturing sector could be divided into
groups due to the technologically heterogeneous performance while this is not the case for the industries of the transportation sector which appear to be technologically comparable. In contrast to the case of the manufacturing industries, those of the transportation appear to form two technological groups under the European level, as panel (c) in Fig. 5.5 pinpoints. There are two groups contributing to the European level of technology as shown by the bimodal distribution. As regards the technology gap values, the transportation industries seem to perform quite well both with respect to the European and the sector specific level (.360 and .254 respectively as opposed to .445 and .318) compared to the industries of manufacturing. The panels (a) and (b) in Fig.4.3 confirm the above observations regarding the performance of the transportation sectors with respect to alternative technological aggregation levels.

Let us now focus on the last column of Tables 5.6 and 5.7 and on the panel (c) of the Figs. 5.5 and 5.6 below. The overall technology gap corresponds to the distance between the sector specific technology and the European technology level. The overall technology gap provides a rough indication about the relative position of the two sector technologies compared to the overall technology that is the European level. The average gap of the manufacturing is .180 with a standard deviation of .190 while the corresponding values for the case of the transportation are .142 and .141 respectively indicating that the transportation technology is closer to the European one and consequently can be more benefited by the technological advancements at that level. The above discussion regarding the performance of the transportation industries provides support for this finding. Moreover, the distributions depicted in panel (c) in the Figs. 5.4 and 5.6 indicate that both distributions are right skewed while the probability mass of the manufacturing remains unchanged throughout the period of study whilst that of the transportation experiences changes and shifts with might be an indication that the sector accumulates technical knowledge and exploits technological advancements in a most rigorous manner compared to the manufacturing.
Table 5.7 Descriptive Statistics of the Transportation industries for the period 1999-2006

|                     | Industry Performance | Sector Performance | European Performance | Sector Technology Gap | European Technology Gap | Overall Technology Gap |
|---------------------|----------------------|--------------------|----------------------|-----------------------|------------------------|------------------------|
| Air Transport       | 0.750 (.176)         | 0.475 (.222)       | 0.384 (.180)         | 0.381 (.221)          | 0.496 (.185)           | 0.173 (.139)           |
| Land Transport      | 0.834 (.107)         | 0.619 (.197)       | 0.572 (.194)         | 0.262 (.200)          | 0.319 (.199)           | 0.178 (.095)           |
| Supporting Transport Activities | 0.863 (.111) | 0.656 (.200)       | 0.585 (.207)         | 0.242 (.199)          | 0.323 (.214)           | 0.115 (.121)           |
| Water Transport     | 0.856 (.113)         | 0.742 (.090)       | 0.598 (.152)         | 0.131 (.042)          | 0.303 (.144)           | 0.201 (.165)           |
| Total               | 0.826 (.137)         | 0.623 (.208)       | 0.535 (.204)         | 0.254 (.201)          | 0.360 (.203)           | 0.142 (.141)           |

Figure 5.5 Productive performance and technological hierarchy for the Transportation sector over the period 1999-2006
Moving towards the formal examination of our main research questions, Table 5.8 below presents the results regarding the first research hypothesis examined herein. It is noticeable that $H_1$ is rejected in all levels of significance for both sectors in the three selected years and in total as well. Therefore, the sector specific technologies exist, are distinct and are not absorbed by the overall level technology. This finding supports the argument that the disaggregation of technological heterogeneity gives rise to technological constructs which otherwise would have been neglected as non-existing. The clustered nature of the data provides the opportunity to bring to the forefront the existence of multiple technology hierarchies and examine their impact on the productive performance of the countries operating under each sector. The latter has important policy and regulation implications.

|          | Manufacturing | Transportation |
|----------|---------------|----------------|
| 1999     | .000          | .000           |
| 2003     | .000          | .000           |
| 2006     | .000          | .000           |
| Total    | .000          | .000           |
Following, Table 5.9 presents the results from the testing of the second research hypothesis examined in this chapter, i.e. the two sector technologies are equally distant from the European level of technology or put it another way whether the two sectors equally contribute to the EU level of technology. We test the null for the beginning, the middle and the last year of our sample period. The indication we get is that the sector technologies employing a rather different technology do not trigger to the same extent the technological advancements occurring at the European level. We notice that for 1999 and 2003 the null hypothesis is rejected but this is not the case for 2006 as we fail to reject the null. This finding points towards the direction of technological convergence as time goes by. The technological advancements taking place at the EU level seem to affect the two sectors quite differently. This could be attributed to a large set of parameters such as the level of absorptive capacity, regulation and policy, exploitation of spillover effects and other learning-related processes. It goes without saying this is just an observation and not a stylized fact. However, the null is rejected when the whole period is taken into consideration indicating that the latter is not an established fact but a rather weak indication of how the two sectors affect the each other and the EU level overall.

| Table 15 Results from the testing of Hypothesis 2 (p-values) |
|-------------------------------------------------------------|
| Common contribution of sector technologies                  |
| 1999  .000                                                 |
| 2003  .006                                                 |
| 2006  .695                                                 |
| Total .000                                                 |

In is noticeable from the above discussion that the introduction of multi-dimensional technologies affects the benchmarking by reducing the scale of heterogeneity. Once we adopt a stair-wise heterogeneity reduction framework, the comparisons become smoother since each DMU is compared to close peers participating in a homogeneous –in terms of technology structure- frontier since the terms of comparison make more sense.

The reduction of heterogeneity level offered by the hierarchical technologies homogenizes the structure, by providing a safety net called sector-specific technology which embodies common practices and capabilities – already explored and exploited or not- that flow among the sectors of Manufacturing and Transportation. By that we get a much more accurate measurement of the performance in order to identify the true story about the industry’s achievements.

The progressive increase of the scale of heterogeneity resulting from hierarchical technologies, traces the path to a better understanding of the driving forces regarding the improvement in the performance of each DMU. Using only one aggregated level of
heterogeneity one gets a misleading view regarding the ongoing process but as we move to a reduced but more solid and compact –in technological terms- level of analysis i.e. sector-specific technologies, we get a more representative picture of the capabilities of the DUMs under examination. The existence of the multiple levels of technological structure, namely the sector and the EU technology level, could identify the technological drivers of EU (in terms of best practices of superior technology of a particular sector).

The importance of the above is obvious after the previous discussion. It could provide an indication about the multidimensional nature of technology, or in other words about the decomposition of technology heterogeneity by introducing more technology levels that share a common characteristic e.g. technology of transportation industries. This could be proved to be a useful analytical tool to the formation of a homogeneous production frontier, to the most possible extent, under which operate several distinct technological groups exploiting the spillover effects which flow/circulate within the respective structure.

All in all, the disentangling of heterogeneity stemming from hierarchical technologies lead to a situation where there are appropriate conditions for a performance-based comparison among DMUs. In this line of argument, the reduction of heterogeneity seems to give rise to the identification of particular groups that exhibit similar performance under their sector technology. Catching-up or falling behind phenomena might take place either by exploitation of complementarities among the similar DMUs or by adopting practices originating or generated by a higher level of aggregation such as the EU technology.

5.4.2 Performance heterogeneity across technology hierarchies

Up until now it has become evident that the partitioning of the overall technology gives rise to distinct, yet interconnected, technologies at a lower level, i.e. at the sector level. Despite the fact that the emerging technologies differ substantially, those can identify the drivers of the overall technology as already mentioned. Apparently, under the sector technology, whether it is the manufacturing or the transportation one, industries exhibit different, on average, productive performance levels, throughout the period of study. Fig. 5.7 below demonstrates that fact. It is obvious that there is severe heterogeneity in the performance of the industries which operate under different technological structures but under the same structure as well, indicating that the identity of the industry should not be neglected.

To the figures shown below, we aim at demonstrating the differences arising from the different levels of technology hierarchy that is the (i) industry’s technology, (ii) the sector’s technology and (iii) the overall level of technology along with the year effect from 1999 through 2006. Fig. 5.7 below plots the productive performance levels along with the mean performance
of all the countries operating under each industry from 1999 through 2006. Notably, there is severe performance heterogeneity across industries of the same sector and across sectors as expected. Therefore, the identity of the industry along with the technological structure it operates under should be taken into account.

**Figure 5.7 Heterogeneous performance patterns among the industries**

![Graph showing industries' productive performance heterogeneity](image)

**Note:** Manufacturing Sector: FB: Food & Beverages, TXT: Textiles, WP: Wood Products, PP: Pulp Paper, CHM: Chemicals and Chemical Products, OTHR: Other non-Metallic Minerals, BM: Basic Metals, TEQ: Transport Equipment, CNST: Construction, Transportation Sector: LT: Land Transport, WT: Water Transport, AT: Air Transport, SUP: Supporting and Auxiliary Transport Activities.
Apparently, this is not the case for the industries’ year heterogeneity as shown in Fig. 5.8 below. More precisely, all the countries in all industries do not seem to alter their productive performance on an annual basis which implies that there are other factors rather than the time heterogeneity which affect their productive performance levels.

**Figure 5.8 Year heterogeneity in productive performance**

Fig. 5.9 below depicts the technology gap values associated to the intermediate levels of technology hierarchy i.e. the manufacturing and the transportation sector technology. A quite mixed picture is pinpointed indicating significant differences in the performance of the industries and the ability to be benefited by the sector technological opportunities. In this line, the association between the performance of the industry and that of the sector should come into sharper focus as to put all the pieces together to get the broad picture. Different industries face different technological opportunities and barriers in improving their performance. Groups of industries sharing common technological characteristics emerge giving rise to the importance of the industry’s technology across countries and years.
Figure 5.9 Sector-specific technology gap values

Note: **Manufacturing Sector:** FB: Food & Beverages, TXT: Textiles, WP: Wood Products, PP: Pulp Paper, CHM: Chemicals and Chemical Products, OTHR: Other non-Metallic Minerals, BM: Basic Metals, TEQ: Transport Equipment, CNST: Construction, **Transportation Sector:** LT: Land Transport, WT: Water Transport, AT: Air Transport, SUP: Supporting and Auxiliary Transport Activities.

In spite of the mixed picture presented above regarding the technology gap values of the industries with respect to the sector technology hierarchy, the figure below (Fig. 5.10) presents the year effect on the technology gap values with respect to the sector technologies. It is obvious that the year effect seems to exhibit a turbulence for some years of the study period whilst after that it returns to the initial levels. Since the average technology gap levels appear to be increased for some years, this might be evidence of a technological step-back related to some industries or put it another way, evidence of failure to catch-up with the technological achievements taking place at the sector level.
A similar picture regarding the technology gap values is depicted with respect to the overall technology in Fig. 5.11 below. The average technology gap of each industry with respect to the European level of technology takes the form of a polynomial function indicating the degree of heterogeneity which appears to be clustered to some industries. Compared to the picture we got when the intermediate levels of technology hierarchy (Fig. 5.9), we observe that a different pattern regarding the performance of the industries’ emerges. The same group of industries behaves totally different under alternative technological structures implying that there are different technological opportunities to be exploited when disaggregated technological hierarchies are taken into consideration.
Figure 5.11 Heterogeneous patterns of industries technology gap values with respect to the European-level technology heterogeneity. Likewise the case of the sector technology gap values, seems like the year heterogeneity affects almost identically the alternative hierarchies. This might be an indication that the factors affecting the alternative technology hierarchies are rigid over the years and not related to the technological hierarchy adopted. Extending this argument, at this stage, we could speculate rather safely that the factors affecting the performance of the industries’ are tied up to each industry or in other words, exhibit time persistent behaviour.

Fig. 5.12 below illustrates the technology gap trend with respect to the European level of technology heterogeneity. Likewise the case of the sector technology gap values, seems like the year heterogeneity affects almost identically the alternative hierarchies. This might be an indication that the factors affecting the alternative technology hierarchies are rigid over the years and not related to the technological hierarchy adopted. Extending this argument, at this stage, we could speculate rather safely that the factors affecting the performance of the industries’ are tied up to each industry or in other words, exhibit time persistent behaviour.

**Figure 5.12 European-specific technology gap trend**
The above discussion points towards the direction of some worth exploring issues. It is evident that the disaggregation of the overall technology brings to the fore some groups of industries exhibiting similar performance patterns with respect to the sector technology but when we focus on the broad picture that of the European level of technology, a quite differentiated pattern emerges regarding the performance of the same industries. The existence of technological breakthroughs and step-backs along with the opportunities arising from the technological structure are also evident which brings to the fore the importance spillover effects generated both at the sector and the European level as well.

5.4.3 Technologically heterogeneous regimes, absorptive capacity and spillover effects

Table 5.10 below presents the estimation results for the parameters of the models specified in equations 5.9 through 5.11.

To begin with, let us focus on the industry level estimations that is, the first two columns of Table 5.10 below. The countries operating under the technology of both the industries of manufacturing and transportation, the path dependence exerts a positive and significant impact (Hypothesis 1 is not accepted) on the levels of the current productive performance. This means that past competencies and capabilities are projected on the current period. As expected, attained (high) levels of absorptive capacity affect the performance of the country in a significant and positive way, indicating that policies to promote any of the pillars constituting the global competitiveness index will not be meaningless (Hypothesis 2 is not accepted). Regarding the spillover effects originating from the sector-specific technology, it seems that have a positive and significant influence only on the industries of manufacturing (Hypothesis 3a is partly not accepted). For the case of the industries of transportation, sector-specific spillover effects are not significant for the distinct transportation technologies probably due to the rather differentiated nature of their operating mechanisms and technological capabilities. In the same lines lays the effect of the spillover effects originating from the European technology (Hypothesis 3b is partly not accepted). The combined effect of absorptive capacity and spillover effects capturing the ability and potentiality to absorb and accumulate the incoming knowledge indicate that low levels of absorptive capacity and low accumulation ability lead to reduced performance (Hypothesis 4 is not accepted). Even if the spillover effects originating from the sector-specific technology do manage to penetrate the wall of industry technology, these are constrained by the ability of each country to exploit that knowledge.

Shifting the attention to the next two columns of Table 5.10 that is the case where the sector-technology is considered and the productive performance of each country with respect to the sector technology is evaluated the pattern is similar to the case where the industry level
technology was considered, for both cases. To avoid perpetuation of the same argumentation on
the each specific research question, we will only focus on the moral gained. Despite the fact that
the intermediate heterogeneity regimes exist and are distinct the value added to the analysis
seems to be quite limited. This matches with the previous finding regarding the convergence of
the intermediate levels to the European technology in 2006. Another candidate explanation for
the non-significant effects on the transportation case is that this is might because of the limited
number of the instruments leading to poor identification compared to the case the
manufacturing industries. In any case, the main finding of this level investigation is that there is a
totally different pattern of the factors influencing the performance of a country under an
industry of the manufacturing or transportation sector.

Finally, we focus on the case of the European technology. In this case the productive
performance of each country is evaluated with respect to the best available level of technology in
Europe. Again, path dependence phenomena are in operation (Hypothesis 1 is not accepted)
while countries with low absorptive capacity levels fail to accommodate for the European
achievements (Hypothesis 2 is not accepted). Apparently, spillover effects running at a European
level accompanied by a decent level of absorptive capacity positively and significantly affect the
productive performance of each country (Hypothesis 4 is not accepted). The interaction of the
binary variable, indicating participation at the transportation sector, with the continuous variable
capturing spillover effects attached to that technology, catch and hold the significance of the
sector’s identity and its contribution to the European technology. In this case appears that in
accordance to the analysis presented in previous sections of the present chapter, the
transportation sector technology feeds the European one, implying that the spillovers generated
from the transportation sector are strong enough to dominate at a higher level (Hypothesis 5 is
not accepted.), that is the technology of the industries of the transportation sector might be the
drivers of the overall technology after all.

In the case just presented we notice a change of pattern. In the European context (high
volume of heterogeneity) we can identify the factors attached to the transportation technology
which cannot be identified in levels where heterogeneity is restricted. That is, the significance of
the sector’s identity is revealed along with the technical knowledge and opportunities attached.
Another aspect that arises is the fact that technological heterogeneity is the real kicker in order to
identify the performance mechanisms of a group. Put it another way, within the European
context the technological identity and background production characteristics matter. The wider
and technologically diversified a group is, the easiest to find sub-groups standing out for their
performance prove to be. In other words, the technological heterogeneity in high aggregation
levels provides fruitful ground to unravel the quality of the characteristics (e.g. ability to absorb new knowledge) of the units participating in this heterogeneous group and is only conspicuous when we look at the broader picture and not the other way around. This might also be an explanation about the reason why we failed to reject the null hypotheses for the case of the sector-level technological regime. Moreover, you can be more beneficiated by a heterogeneous group of participants rather than a homogeneous one. When units operate within a diversified group (European case), there are multi-dimensional contributions since there is potential to be lifted by the tile called spillover effects. All in all, heterogeneity is grounded on a low aggregation level (industry level) where it is hard to be disentangled but it only reveals itself as we move to higher aggregation levels (European levels). The intermediate levels appear to the “safety stations” towards the final destination and are there in case the gas is over earlier than expected.

Table 5.10 GMM estimation results

| Dependent Variable: Productive Performance | Industry Level | Sector Level | European Technology |
|------------------------------------------|----------------|--------------|---------------------|
| Path dependence                          | .370***        | .349***      | .679***             | .294***             | .293***             |
|                                          | (.003)         | (.000)       | (.000)              | (.003)              | (.001)              |
| GCI_{i,t-1}                              | .006*          | -.006        | -.015***            | -.008               | -.016**             |
|                                          | (.089)         | (.370)       | (.000)              | (.115)              | (.002)              |
| Tg_{Sector}                              | .213***        | -.134        | .234**              | -.136               | -                   |
|                                          | (.003)         | (.502)       | (.038)              | (.347)              | -                   |
| Tg_{Europe}                              | -.159**        | .281         | -.098               | .035                | -                   |
|                                          | (.036)         | (.154)       | (.122)              | (.789)              | -                   |
| GCI_{i,t-1} * Tg_{Sector}                | -.020*         | -.003        | .035***             | .022                | -                   |
|                                          | (.100)         | (.935)       | (.001)              | (.387)              | -                   |
| GCI_{i,t-1} * Tg_{Europe}                | -              | -            | -                   | -                   | .033**              |
|                                          |                |              |                     |                     | (.012)              |
| Transportation * Tg_{Sector}             | -              | -            | -                   | -                   | .065*               |
|                                          |                |              |                     |                     | (.058)              |
| Constant                                 | .516***        | .492***      | .146                | .461***             | .320***             |
|                                          | (.000)         | (.000)       | (.252)              | (.000)              | (.000)              |
|Obs.                                      | 918            | 408          | 918                 | 408                 | 1,326               |
|No. of Groups                             | 153            | 68           | 153                 | 68                  | 221                 |
|No. of Instruments                       | 94             | 94           | 88                  | 88                  | 73                  |
|Wald test (p-value)                       | .000           | .000         | .000                | .000                | .000                |
5.5 Conclusions

The purpose of this chapter was to decompose the overall technology into sub-sets based on the criterion of the sector's identity in order to reduce the amount of heterogeneity among the units under investigation so as to draw inferences about their performance mechanisms. To do so, we devised a unique dataset consisting of seventeen European Union countries in thirteen industries, nine from the manufacturing and four from the transportation sector from 1999 through 2006. In this chapter we have shown that the partitioning of the overall technology into lower aggregation levels based on the criterion of the identity of the sector is possible but computationally demanding. The intermediate levels of technological disaggregation are indeed distinct but as the results shown, the latter do not contribute to the investigation of the drivers of the productive performance of the units under examination. Therefore, that level of heterogeneity could be suppressed. By any means, the results presented are not conclusive as far as the level of heterogeneity is concerned, and should be taken with caution. We do not neglect that the intermediate levels do explain the variability in the productive performance of the units of interest, instead, we argue that the amount of variability explained is not sufficient to draw credible conclusions.

Absorptive capacity levels, time persistent patterns of productive performance, European spillover effects and the combined effect of the ability and potentiality to accumulate new technical knowledge are the main drivers of the productive performance of each country. Moreover, as we getting closer to the end of the examined period, we find indications of some kind of technological convergence between the sectors’ technologies as the latter are absorbed by the European technology. Manufacturing and transportation industries do exhibit different performance patterns and seem to be influenced diametrically by the same factors. Results indicate that the transportation sector is the main contributor of the European technological advancements. Inarguably, spillover effects are considered as “tile to lift all the boats” especially at the European level where there is interaction and interdependence among the units. Last but not least the main finding is that we are inclined to believe that heterogeneity is clustered in low aggregation levels e.g. industry technology level, where it is difficult to be disentangled but it is revealed in high heterogeneity levels such as the European level.

The rather narrow time window and the number of industries and sectors included are some of the limitations we had to cope with. Restricted access to specialized databases, variables which capture the notions we are using to explain the phenomena taking place in the production environment are also found among the limitations. Future research could be benefitted by the inclusion of more years, industries and specialized indices capturing economic activity.
References

Arelano, M. and Bond, S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*, 277-297.

Britto, G., & McCombie, J. S. L. (2008). Productivity growth and space: a multilevel Verdoorn model (No. 03-08). Working paper CCEPP.

Castellacci, F. (2007). Technological regimes and sectoral differences in productivity growth. *Industrial and Corporate Change, 16*(6), 1105-1145.

Casu, B., Girardone, C., Ferrari, A., & Wilson, J. O. (2014). Integration, productivity and technological spillovers: Evidence for eurozone banking industries. *Productivity and Technological Spillovers: Evidence for Eurozone Banking Industries (February 20, 2014).*

Cohen, W. M., & Levinthal, D. A. (1989) Innovation and learning: the two faces of R & D. *The Economic Journal, 99*(397), 569-596.

Cohen, W. M. and Levinthal, D. A. (1990) Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128-152.

Del Bo, C. F. (2013). FDI spillovers at different levels of industrial and spatial aggregation: Evidence from the electricity sector. *Energy Policy, 61*, 1490-1502.

Dosi, G., Lechevalier, S. and Secchi, A. (2010) Interfirm heterogeneity: nature, sources and consequences for industrial dynamics. An introduction. *Industrial and Corporate Change, 19*(6), 1867-1890.

Enerdata. [http://www.enerdata.net/](http://www.enerdata.net/) (accessed on 25.02.2013).

EU-KLEMS Growth and Productivity Accounts. [http://www.euklems.net/](http://www.euklems.net/) (accessed on 02.03.2013).

European Commission, Financial Programming and Budget Directorate. [http://ec.europa.eu/budget/contracts_grants/info_contracts/inforeuro/inforeuro_en.cfm](http://ec.europa.eu/budget/contracts_grants/info_contracts/inforeuro/inforeuro_en.cfm) (accessed on 12.03.2013).

Hayami, Y. (1969). Sources of agricultural productivity gap among selected countries. *American Journal of Agricultural Economics, 51*(3), 564-575.

Hayami, Y., & Ruttan, V. W. (1970). Agricultural productivity differences among countries. *The American Economic Review, 895*-911.

Holtz-Eakin, D., Newey, W. and Rosen, H.S. (1988) Estimating Vector Autoregressions with Panel Data. *Econometrica, 56*(6), 1371-1395.

Hox, J. J., Moerbeek, M., & van de Schoot, R. (2010). Multilevel analysis: Techniques and applications. Routledge.
Kontolaimou, A. (2014). An efficiency analysis of European banks considering hierarchical technologies. *Applied Economics Letters, 21*(10), 692-696.

Krautzberger, L. and Wetzel, H. (2012) Transport and CO2: Productivity Growth and Carbon Dioxide Emissions in the European Commercial Transport Industry. *Environmental and Resource Economics* 53(3), 435-454.

Luke, D. A. (2004). Multilevel modeling (Vol. 143). Sage.

Nadiri, M.I. (1993) Innovations and technological spillovers. National Bureau of Economic Research, (DOI): 10.3386/w4423

O'Donnell, C. J., Rao, D. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics, 34*(2), 231-255.

Organization for Economic Cooperation and Development, Structural Analysis Database. [http://www.oecd.org/industry/ind/stanstructuralanalysisdatabase.htm](http://www.oecd.org/industry/ind/stanstructuralanalysisdatabase.htm) (accessed on 08.03.2013).

Sala-i-Martin, X., Blanke, J., Drzeniek Hanouz, M. Geiger, T; Mia, I. and Paua, F. (2008) The Global Competitiveness Index: Prioritizing the Economic Policy Agenda. *The Global Competitiveness Report 2008-2009* eds PORTER, M.E. and SCHWAB, K. (Geneva, World Economic Forum).

Sala-i-Martin, X. and Artadi, E. (2004), ‘The Global Competitiveness Index’, in The Global Competitiveness Report: 2004–05, M. Porter et al. (eds), Oxford: Oxford University Press.

Simar, L., and Wilson, P.W. (1998) Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Management Science, 44*, 49-61.

Simar, L., and Wilson, P.W. (1999) Estimating and bootstrapping Malmquist indices. *European Journal of Operational Research,115*, 459-471.

Simar, L., and Wilson, P.W. (2000) A general methodology for bootstrapping in nonparametric frontier models. *Journal of Applied Statistics* 27, 779–802.

Simar, L. and Wilson, P.W. (2007) Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics, 136*(1), 31-64.

Verspagen, B. and De Loo, I. (1999) Technology spillovers between sectors. Technol. Forecast. Soc. 60, 215-235.

Wilson, P. (2008) *FEAR*: A software package for frontier efficiency analysis with R. *Socio-economic Planning Sciences* 42(4), 247-254.

World Economic Forum. [http://www.weforum.org/](http://www.weforum.org/) (accessed on 5.04.2013).
Chapter 6 Energy Efficiency and Productive Performance: A Complicated Relationship

6.1 Introduction

Over the years increasing interest has embrace the energy use as an input to the production process on a global-wide scale and key notions such as competitiveness, productivity and energy efficiency have emerge in every corner of the empirical literature (e.g. Chiu et al., 2012; Zhu et al., 2014). The ways to measure its effect have emerge in an exponential manner according to the primary focus of the study. At the core of its measurement and due to its scarcity, many techniques have been introduced to calculate the optimal use given the level of energy already employed. Researchers, scholars, international agencies and policy makers, have studied the notion from different standpoints which despite the fact that the methodology employed is differentiated, the results do not seem to deviate extremely.

As an input to the production, energy affects the level of the productive performance of a unit but at the same time the calculation of energy efficiency level is defined over the same technology set as the productive performance. At this point becomes clear that the relationship between the two notions is quite tangled and in order to shed light to specific aspects of their linkage further investigation is required while the issues of endogeneity and heterogeneity have been rather neglected by the existing studies. To do so, we employ a balanced panel of seventy eight countries around the globe from 2002 through 2011. Energy efficiency is affected by a plethora of factors such as geographical location, development levels, productivity levels and so on, which have been recognized, acknowledged and investigated by the related literature. Despite the fact that important conclusions and policy suggestions have come to the fore, one cannot neglect the fact only partial consideration of heterogeneity has been incorporated into the study. Such being the case, in this chapter we utilize a composite index, common to all the countries under investigation, the use of which is twofold since (i) it takes into consideration many aspects of the economic environment and other characteristics shaping it and (ii) simultaneously incorporates the variability of all those factors in one single index representing the level of the technological ability, knowledge accumulation and absorptive capacity that is the global competitiveness index. The latter paves the way to study the significance of any spillover effects originating from the complex association between the productive performance and energy efficiency which are moderated by the level of the absorptive capacity.

The above bring us to the doorstep of the inescapable truth that the relationship among the energy efficiency, productive performance and spillover effects captured by the technology
gap values is far from straightforward. Considering the above, this chapter investigates issues such as (i) the identification of any heterogeneous patterns of the energy efficiency and productive performance relationship with respect to the competitiveness level of the country, (ii) the time persistence of energy efficiency, (iii) the role of spillover effects originating from the cluster and the global technology and (iv) the exploration of any non-linear relationship between energy efficiency and productive performance. Moreover, the main goal here is not to identify a topology regarding the energy efficiency levels across the globe, but to shed light to the underlying mechanisms of the mechanisms of the absorptive capacity while the originality of this study lies upon the fact that the partitioning factor is a multifaceted one including many aspects of the productive environment and at the same time is associated with any unobserved factors affecting directly the productive performance and therefore indirectly the energy efficiency. Subsetting the technology set is also twofold since (i) it relaxes the technological isolation assumption allowing for inter-country spillover effects (Tsekouras et al., 2015) and (ii) gives rise to the importance of the technological hierarchy of the heterogeneous competitiveness regimes (Bartlesman et al., 2013, Castellacci, 2007). In this line, we aspire to draw inferences about the role of absorptive capacity to the improvement of the energy efficiency levels through the global competitiveness index which to the best of our knowledge has not been attempted so far.

This chapter is structured as follows: the next section demonstrates the related literature, Section 6.3 presents the methodological strategy and the research questions, Section 6.4 describes the data and variables used, Section 6.5 focuses on the estimation results while Section 6.6 concludes the chapter.

6.2 Literature review

During the last two decades or so, due to the efforts for environmental friendly and energy saving ways of production, increased energy demand and carbon dioxide emissions (e.g. Kyoto Protocol, 2005; Change, 2007; da Graça Carvalho, 2012, International Energy Agency -IEA-, 2007, 2008; Organization for Economic Cooperation and Development -OECD-, 2008; Taylor et al., 2010; Paris Declaration, 2015), has led many researchers, scholars and international agencies to acknowledge and highlight the importance of the energy input in the production process since the latter is under severe scarcity and needs to be used in an efficient manner. It has been common knowledge that energy efficiency improvements remain a top priority for the international community (IEA, 2007a; 2007b; IEA, 2008a; 2008b; 2008c). In this line, Paterson (1996) argues that energy efficiency is a topic-related notion and in order to identify any changes many indicators, diversified in nature and concept, should be taken into consideration. Since
then, energy oriented studies have emerged in an exponential manner, filling the voids of the related literature (Zhang, 2003; Ang, 2006; Hu and Wang 2006; Liao et. al., 2007; Liddle, 2010).

Within the empirical literature, the case of China has inspired a considerable amount of studies analysing a broad spectrum of the Chinese economy focusing either on selected administrative provinces or categorizing them based on geographical location (e.g. Shi et al., 2010, Wang et al., 2014, Du et al., 2014, Lin and Du, 2014) to control for their differences by employing a variety of non-parametric as much as parametric methodologies such as Data Envelopment Analysis to calculate slack-based measures of energy efficiency (Zhou and Poh, 2006; Wang et al., 2013, Du et al., 2014), Stochastic Frontier Analysis (Lin and Du, 2013), Directional Distance Functions and simpler or more sophisticated versions of the Malmquist index to decompose the factors the energy or environmental efficiency index embraces (Chiu et al., 2012, Cui et al., 2014), frequently accompanied by a meta-frontier framework attempting to account for the pertinent technological heterogeneity (e.g. Wang et al., 2014).

Similar studies have been conducted for OECD countries (Zhou and Poh, 2006; Camarero et al., 2008) and countries around the globe as well (Lin et al., 2013; Zhou et al., 2014) adopting in general lines coherent methodologies. Focusing on the latter branch of the literature, the need for taking into account the heterogeneity among the countries, clustering procedures based on specific factors such as income level, developed or developing countries and hierarchical clustering have been employed (Castellacci, 2011; Zhang et al., 2011; Lin et al., 2013; Li and Wang; 2014). Latent class models have also emerged as a method to decide upon the optimum number of clusters, in an endogenous manner, based on information criteria (Kumbhakar and Orea, 2004; Lin and Du, 2014). In spite of the accuracy of the clustering approach one might followed, the moderating factor against which the groups are created is prone to subjectivity since the selection, in most cases, neglects for numerous aspects of the economy even though some attempts to incorporate the impact of competitiveness in the sense of output augmentation do exist (Wagner and Schaltegger, 2004; Chiu et al., 2012). Such being the case, the need for a commonly accepted factor embracing the same quantitative as much as qualitative pillars for each and every economy participating into the study to highlight the heterogeneity among them appears to be necessary. To the very best of our knowledge, the latter still remains a void to be filled.

It is by any means undeniable, that the issues surrounding the notion as much as the context of energy efficiency per se but also in conjunction to its relationship with technical progress and productivity growth in general, have been long ago recognized by the pioneering work of Berndt (1990) who explored the relationship between the aforementioned notions
argued that the technical progress diffusion, learning and adoption of achievements are critical to comprehend the mechanisms of that process. From another standpoint, governments and international agencies have been advocating improving energy efficiency much more directly in recent years. For example, recently the US introduced the ‘Energy Savings and Industrial Competitiveness Act’ (2013), serving as a clear indicator to industry that energy efficiency and the competitiveness of industries are intrinsically connected to each other. This sentiment has also been echoed by the World Bank (2009) and the United Nations (UNIDO working paper by Eichammer & Walz, 2011) who also elaborate on the fact that improving energy efficiency not only can be achieved without negative economic consequences but should in all reality generate improvements in economic performance. In accordance to the aforementioned, Cohen and Levinthal (1989; 1990) argued about the existence and significance of technological opportunities, absorptive capacity, dynamic capabilities of the operating environment which could explain the workings of productivity and competitiveness improvement. Moreover, productive performance can be considered as a learning and dynamic process of accumulated competencies and capabilities (Dutta et al., 2005). Such a relationship has remained tangled and quite complex throughout the years in such a degree that recent specialized reports (e.g. European Council for an Energy Efficient Economy, 2011) have characterized the issue as still being a “hard shell”. Such reports attempt to link competitiveness -in terms of output augmentation- of the European Union’s (EU) countries, to the energy efficiency in a variety of ways (energy use prices, consumers’ rational and irrational beliefs or the industry of interest) or deal with the catching-up phenomena of the EU industries (O’Mahony and Ark, 2003). Moreover, another important aspect of such studies is that those appear to be in favour of the standpoint that the economies “have to deal within dynamic contexts” and consequently, these pave the way for the introduction of path dependence (e.g. David 1985; 1986, Martin and Sunley, 2006) whenever one aims to study an empirical relationship of such kind.

Pulling together the above lines of research and the breakthroughs those have come up with we can cease the opportunity to study the relationship between energy efficiency, technical progress and productivity growth through the standpoint of spillover effects or reverse spillover effects. The literature on spillover effects is quite extended, as are the ways to assess the magnitude of spillover effects, and any attempt to enlist all the related studies will be far from complete. Instead of reviewing the literature on spillover effects, we may mention some recent contributions on different fields of empirical research.

It has become apparent from recent contributions that when productivity growth and spillover effects come into sharper focus, in the empirical studies in firm-level (e.g. Gustafsson
and Segerstrom, 2010) considering heterogeneity among units (e.g. Damijan et al., 2013) as much as in country-level (e.g. Crespo and Fontoura, 2007), much of the attention has been placed either on the moderating role of foreign direct investments (Martin and Bell, 2007; Zhang et al., 2010) and knowledge seeking foreign direct investments in the form of reverse spillover effects (Driffield, and Love, 2003; Chen et al., 2012) highlighting the mechanisms related to absorptive capacity (e.g. Mancusi, 2008) and institutions (e.g. Coe et al., 2009), or on R&D-driven productivity developments (Cameron et al., 2005; Wieser, 2005; Zhu and Leon, 2007; Leahy and Neary, 2007). In addition, there are studies acknowledging the existence of technological inter-linkages and inter-industry flows focusing either on specific types of flows which may arise from R&D activities (Cainelli and Iacobucci, 2012, Del Bo, 2013), or those which are closely attached to factors related to the spatial or cognitive distance distribution of production entities, as the different types of variety (e.g. Frenken et al., 2007; Del Bo, 2013) or breadth and relatedness of technological linkages associated to international trade (Boschma and Iammarino, 2009).

Beyond any doubt the significance of knowledge diffusion, technical progress, absorptive capacity have heretofore been acknowledged (Cohen and Levinthal, 1989;1990; Girma, 2005) as promoting technical progress and productivity improvement, no systematic attempt has been documented as yet to explore improvement through the moderating effect of absorptive capacity as captured by the global competitiveness index (onwards, GCI) so as to control for additional aspects of the production environment combined with institutional aspects, such as human capital and macroeconomic environment among others (Sala-i-Martin et al., 2008; World Economic Forum, 2013) common across countries, to study the relationship between productive efficiency and spillover effects.

It goes without saying that patterns of energy efficiency across studies in most cases present an inter-temporal improvement providing suggestions for economic policy or alternative production possibilities. One of the most interesting aspects of the energy oriented studies is that a U-shaped relationship between the energy (or environmental) efficiency and gross domestic product per capita or industrial structure (Hu and Wang, 2006, Zhang et al., 2011, Zhang and Choi; 2013, Li and Wang, 2014) arises. However, some points of scepticism regarding the aforementioned approaches come to the fore. Existing studies adopting a second stage analysis to determine the effect of a set of explanatory variables (for example Wand and Li, 2014) focus only on the environmental efficiency of the meta-frontier without considering the factors affecting the environmental efficiency for the case of individual frontiers i.e. that of the clusters whilst at the same time suppress possible endogeneity issues dominating such specifications. Moreover, despite the fact that dynamic models have been employed in the literature (Zhang et
al., 2011; Li and Wang, 2014), the role of the past energy (or environmental) performance i.e. the path dependence of energy efficiency, has not been taken into account while there is a considerable stock of studies acknowledging its importance to the evolution of the technological trajectory of a system (David, 1985; 1986, Martin and Sunley, 2006).

Integrating all the above aspects of the literature, the present study aspires to make a step forward by adopting a slack-based total factor productivity measure that of energy efficiency and a second stage Generalized Method of Moments (GMM) estimator so as to investigate the factors affecting the energy efficiency for both the cluster frontiers and the global meta-frontier. At the same time, we acknowledge the endogenous association of the productive performance of each country in each of the cluster frontiers and the technological heterogeneity as captured by the technology gap for the global meta-frontier case as well as the twofold effect of the competitiveness level by studying the combined effect of absorptive capacity and spillover effects, as captured by the technology gap, at the global level. We also consider the role of time persistent pattern of energy efficiency for each category, we identify a U-shaped relationship between the energy efficiency and productive performance and we also explore the impact of potential flows of the universally available technical knowledge to the individual heterogeneous competitiveness regimes highlighting once more the significance of absorptive capacity.

In spite of the important contributions, there is room for fruitful theoretical and empirical considerations as well, among energy efficiency, productive performance and technology gap since those are defined on the same technology set while at the same time there are unexplored aspects associated to the (quasi) moderating role of competitiveness level.

6.3 Methodological strategy and research questions

The analysis developed herein consists of three interconnected pieces. In the first one, we cluster the countries into distinct groups i.e. clusters, based on the GCI those exhibit based on the k-means clustering procedure, we calculate the (relative) productive performance of each country and technology gap for each cluster adopting the metafrontier framework and then we calculate the energy efficiency for the individual clusters and the universal frontier as well while the at the third stage we focus on the (quasi) moderating role of competitiveness to examine for heterogeneous patterns in energy efficiency accommodating for the underlying endogenous relationship of productive performance and energy efficiency. Nevertheless, before we develop the methodological strategy, we need to present some theoretical underpinnings.

6.3.1 Endogeneity, heterogeneity and conceptual assumptions

It has become apparent from the empirical literature that the underlying mechanisms running through the relationship between the energy efficiency and productive performance
 carries a high degree of complexity and in order to disentangle their knot, a study ground has to be established. Such being the case, the analysis should be developed around the endogenous attachment of the two notions, the heterogeneity among the units under investigation and the moderating role of the absorptive capacity proxy by the competitiveness level, all of them framed by some conceptual underpinnings.

In this work, energy efficiency is defined on the context of production rather than cost frontiers which in turn are defined over the basis of the production possibility set given technology or in other words in technology sets. Likewise, productive performance is defined over production frontiers and therefore on technology sets as well. As Hu and Wang (2006) argue, energy efficiency is a derivative measure of performance which occurs after the evaluation of the productive performance of the Decision Making Units (DMUs). Therefore, the two notions occur under the same data generation mechanism. Thus, from a theoretical viewpoint, both energy efficiency and productive performance share common technological characteristics which are deeply rooted to the corresponding production technology which in fact cannot be observed. What we do observe is just the result of an underlying transformation process in the form of an observable performance outcome whether in the form of a performance value with respect to the energy input or any other input of the bundle of inputs pinpointing the omitted variables identification problem. In addition, the presence of time persistence captured by the path dependence phenomenon, raises severe concerns since the lagged value could be correlated with factors not included in the specification and have been added to the disturbance term. More precisely, both productive performance and energy efficiency levels can be correlated with policies implemented, technology adopted and production priorities scheme applied. It goes without saying that the omitted selection criteria and rules regarding the energy efficiency and overall country’s performance are not homogeneous (for instance United States of America, China, Europe).

The latter issue paves the way to the introduction of heterogeneity with respect to the role of competitiveness. When competitiveness comes into play, the economic outputs (e.g. Gross Domestic Product, Gross Value Added) appear to be more representative outputs compared to those measured in physical units per se. Energy efficiency levels are closely related to production processes and technological characteristics which are broadly defined by a large set of factors which include economic, financial, social, institutional, cultural, and knowledge components (Wang et al., 2013). Although the literature provide a thorough categorization of factors related to energy efficiency at a firm level (Kounetas and Tsekouras, 2008; Kounetas et al., 2012), to the best of our knowledge such a taxonomy, at a country level, is not available at the moment. That
said, in this work, we account for country heterogeneity at a global level in an indirect way, employing the GCI (Sala-i-Martin, 2008, World Economic Forum) which ranks market economies dynamism with respect to (i) resource drivers (ii) efficiency mechanism drivers and (iii) innovation activities’ drivers and is meant to be used as a summary of current “market” conditions and potential. The GCI pillars concern institutions, infrastructure, macroeconomic environment, health and primary education, higher education and training, goods market efficiency, labor market efficiency, financial market development, technological readiness, market size, business sophistication and innovation (World Economic Forum, 2013).

The above arguments can be formalized into distinct, yet interconnected, conceptual assumptions in order to facilitate the investigation of the moderating role of competitiveness on the energy efficiency levels. Such being the case, the use the GCI certainly ensures that multiple dimensions, common across countries, have their own merit as far as the level of the competitiveness of a country is concerned. However, the notion of global competitiveness could also be reduced to be twofold indicating from the one hand the grounds upon which country performance differentials are rooted and from the other, could indicate the ability of a country to exploit spillover effects that is, the absorptive capacity. Moreover, it is reasonable to argue that productive performance of a DMU within a cluster and the distance of that DMU against the global level of technology captured by the technology gap can also be thought of as twofold as those indicate both the productive performance, on a benchmarking base, within clusters and the potential of a DMU to catch up, in terms of performance, via “local” and “global” spillovers respectively.

6.3.2 The global competitiveness index (GCI) as a partition criterion

Beyond any doubt most technological advancements take place at the global level of production where the technological isolation assumption has been relaxed (Tsekouras et al., 2015) allowing for inter- and intra-units technological flows as well as spillover effects. In the case examined herein where the units under consideration are countries, the ways to create groups in order to study the heterogeneous patterns of the individual frontiers are simply endless. Since we focus on the moderating role of competitiveness, absorptive capacity and spillover effects, we rely on the GCI to create clusters of countries sharing the same characteristics as an additional attempt to account, in a greater extent, for the heterogeneity among the DMUs under investigation.

Fig. 6.1 below illustrates the distribution of the GCI for the period of study. It is quite obvious by the bimodal distribution of the GCI, that two distinct groups, of different mean GCI,
co-exist in the dataset throughout the period 2002-2011. Therefore, we have the less competitive cluster (onwards LCC) and the competitive cluster (CC).

Figure 6.1 GCI distribution for the period 2002-2011

To identify each group’s units so as to focus on explaining their behaviour in subsequent stages of the analysis, we employ the $k$-means clustering procedure on a yearly basis, to construct the clusters. Moreover, the fact that two clusters co-exist, serves as a first indication that different patterns arise regarding the impact of absorptive capacity and technical knowledge diffusion as captured by the level of competitiveness in the improvement of the energy efficiency level. Table 6.1 below, illustrates the countries participating in the dataset along with the results of the clustering procedure on an annual basis.
### Table 16.1 Classification of countries to clusters based on the GCI for the period 2002-2011

| Cluster 1 | Cluster 2 | Cluster 1 | Cluster 2 | Cluster 1 | Cluster 2 | Cluster 1 | Cluster 2 |
|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Argentina | Egypt     | 1-10      | -         | Lithuania | 1, 4-10   | 2, 3      | Slovenia   | 4-10      | 1-3       |
| Australia | -         | 1-10      | Estonia   | -         | Luxembourg| -         | 1-10      | South Africa| 4-10      | 1-3       |
| Austria   | -         | 1-10      | Ethiopia  | 1-10      | Macedonia | 1-10      | -         | Spain      | 10        | 1-9       |
| Bahrain   | 4-8, 10   | 1-3, 9    | Finland   | -         | Malaysia  | -         | 1-10      | Sri Lanka  | 1-10      | -         |
| Bangladesh| 1-10      | -         | France    | 1-10      | Malta     | 4-10      | 1-3       | Sweden     | -         | 1-10      |
| Belgium   | -         | 1-10      | Georgia   | 1-10      | Mexico    | 1-10      | -         | Switzerland| -         | 1-10      |
| Bolivia   | 1-10      | -         | Germany   | 1-10      | Morocco   | 1-10      | -         | Tanzania   | 1-10      | -         |
| Brazil    | 1-10      | -         | Greece    | 1, 4-10   | Mozambique| 1-10      | -         | Thailand   | 4-8, 10    | 1-3, 9    |
| Bulgaria  | 1-10      | -         | Hungary   | 4-10      | Netherlands| -        | 1-10      | Trinidad & Tobago| 1-10      | -         |
| Canada    | -         | 1-10      | Iceland   | -         | New Zealand| -       | 1-10      | Tunisia    | 6-9       | 1-5, 10   |
| Chile     | -         | 1-10      | India     | 1-10      | Nigeria   | 1-10      | -         | Turkey     | 1-10      | -         |
| China     | 2-6       | 1, 7-10   | Indonesia | 1-10      | Norway    | -         | 1-10      | Ukraine    | 1-10      | -         |
| Colombia  | 1-10      | -         | Ireland   | -         | Pakistan  | 1-10      | -         | United Arab Emirates| 4-6       | -         |
| Costa Rica| 1-10      | -         | Israel    | -         | Peru      | 1-10      | -         | United Kingdom| -         | 1-10      |
| Croatia   | 1-10      | -         | Italy     | 1, 3-10   | Philippines| 1-10     | -         | United States of America | -         | 1-10      |
| Cyprus    | 4-8, 10   | 1-3, 9    | Japan     | -         | Poland    | 1-10      | -         | Uruguay    | 1-10      | -         |
| Czech Rep.| 1, 6, 10  | -         | Jordan    | 1, 4-10   | Portugal  | 4-10      | -         | Venezuela  | 1-10      | -         |
| Denmark   | -         | 1-10      | Kenya     | 1-10      | Romania   | 1-10      | -         | Vietnam    | 1-10      | -         |
| Dominican Rep.| 1-10 | - | Korea Rep.| 1-10 | Singapore | - | 1-10 | |
| Ecuador   | 1-10      | -         | Latvia    | 1, 4-10   | Slovak Rep.| 1-10    | -         | |

**Note:** The numbers 1 to 10 represent participation in each group for the years 2002 to 2011 i.e. 2002=1, 2003=2, 2004=3, 2005=4, 2006=5, 2007=6, 2008=7, 2009=8, 2010=9 and 2011=10.
6.3.3 Productive performance, technology gap energy and efficiency calculation

In order to estimate the productive performance of the countries participating in each cluster, we employ the input orientation on a multi-input single-output Data Envelopment Analysis (DEA) model under variable returns to scale technology which allows the best input mix to vary considering the size of the country (Halkos and Tzeremes, 2009). This model requires no particular parameterization of the production technology capturing technological heterogeneity.

More precisely, in the framework of \( k \) frontiers \((k=LCC, CC)\), every country under each frontier employs a vector of inputs \( x \in \mathbb{R}^n \) to produce a single output \( y \in \mathbb{R}^m \). The production possibility set is given as \( S = \{(x, y) : x \text{ can produce } y \} \in \mathbb{R}^{n+m} \) with the input set defined as \( L(y) = \{x \in \mathbb{R}^n : (x, y) \in S\} \). The input-oriented efficiency associated with \( S \), can be measured with respect to the input set through the direct input distance function \( D_i(x, y) = \sup \{\theta > 0 : x/\theta \in L(y)\} \). Therefore, the productive performance for a given country in each of the examined clusters i.e. frontiers, is given as:

\[
\hat{\eta}_{i,x,y} = \hat{\theta}(x, y) = \min \left\{ \theta > 0, y, \theta \leq \sum_{i=1}^n y_i, \gamma_x \geq \sum_{i=1}^n y_i \right\}
\]

for \( y_i \) such that \( \sum_{i=1}^n y_i = 1, y_i \geq 0, i = 1, 2, \ldots, n \)

In the case where multiple technologies, become available, each country is considered as operating under exactly one of the two frontiers, implicitly adopting the technological isolation assumption supporting further the complete heterogeneity between them. Under the aforementioned circumstances, the individual estimation of the productive performance of the countries under the competitive and less competitive frontier makes no sense.

Relaxing the hypothesis of technological isolation, the notion of metafrontier comes into play. Thus, given the two GCI-based technologies, that is the \( LCC \) and the \( CC \) frontier, the metatechnology set \(^33\), denoted as \( S^M \), can be defined as the convex hull of the jointure of all the \( p \) distinct technology sets represented as \( S^M = \{(x, y) : x \text{ can produce } y \text{ in at least one of } S^1, S^2, \ldots, S^p\} \) (Battese et al., 2004, O’Donnell et al., 2008). The input set \( L^M(y) \) associated with the metatechnology is defined as

\(^33\) Accordingly, the metaproduction input set for \( S^M \) is and the input distance function with respect to \( S^M \) is \( D_i(MF; (x, y)) = \sup \{\theta > 0 : y/\theta \in L^M(y)\} \) where the metafrontier - onwards -MF- associated with \( S^M \) is represented by the set \( MF = \{(x, y) \in S^M : D_i^M(x, y) = 1\} \).
for a single technology, while the corresponding productive efficiency score of each country with respect to homogeneous boundary for all heterogeneous countries can be measured by the input-oriented metatechnical efficiency score \( MTEff(x, y) \) and it is easy to obtain by solving an analogous LP problem as in (6.1).

The introduction of metafrontier analysis (Hayami, 1969, Hayami and Ruttan, 1973) as an approach that allows the comparison of different technologies (Battese and Rao, 2002, Battese et al., 2004) can be used in order to explain differences in production opportunities that can be attributed to available resource endowments, economic infrastructure, and other characteristics of the physical, social and economic environment in which production takes place (O'Donnell et al., 2008, Kontolaimou et al., 2012) considering more aspects of the existing heterogeneity among the DMUs. O'Donnell et al., (2008) extended Battese et al., (2004) using conventional Shepard distance functions to estimate technical efficiency with respect to that metatechnology and several individual technology sets. Each efficiency score obtained from the estimation with respect to the common technology can be used to define the so-called metatechnology ratio \( MTR(x, y) \) which is considered as a measure of proximity of the \( k \)-th group individual frontier to the metafrontier and could be defined as:

\[
MTR_k(x, y) = \frac{MTEff_k(x, y)}{Eff_k(x, y)}
\]

while the distance between the individual clusters-frontiers and the universal frontier can be estimated by the technology gap given by the formula below:

\[
Tg_k(x, y) = 1 - MTR_k(x, y)
\]

In addition, the DEA model produces overall radial adjustments, that is the amount of slack input use and radial adjustment to reach the efficient frontier. More precisely and focusing on the energy efficiency estimation, two strands of energy efficiency indicators on the basis of DEA appear in the literature; the partial factor energy efficiency and total factor energy efficiency. The former are calculated as a ratio in a single input-output framework ignoring input complementarities and substitution effects and consequently may be misleading while the latter as the target optimal to actual energy input ratio in a multiple factors framework, ceteris paribus (Hu and Wang, 2006). Energy efficiency improvement is based upon the total factor productivity improvement (Boyd and Pank, 2000) since energy should be combined with additional inputs to produce output (Hu and Wang, 2006) and is considered as superior to the former (Wang et al., 2014).
In this chapter, we adopt the total factor energy efficiency introduced by Hu and Wang (2006) in order to estimate the energy efficiency score of each country, on a yearly basis, under each frontier by calculating the following formula:

\[
\text{Energy Efficiency}_{i,t,k} = 1 - \frac{(\text{Energy input slack} + \text{Radial Adjustment})_{i,t,k}}{(\text{Actual Energy input})_{i,t,k}}
\]

(6.4)

6.3.4 Time persistence, absorptive capacity and spillover effects

In the third stage of our analysis, we specify different econometric models to investigate alternative research questions. Such being the case, we focus on investigating the behaviour of energy efficiency for each of the clusters and the universal technology as well, by specifying alternative econometric models for the clusters and the universal frontier as shown below by equations 6.5 and 6.6 respectively:

\[
\begin{align*}
\text{EnEff}_{i,t,k} & = a_0 + \beta_1 \text{EnEff}_{i,t-1,k} + \gamma_1 \text{Eff}_{i,t,k} + \gamma_2 \text{CO}_{i,t,k} + \delta \text{GCI}_{i,t,k} + u_{i,t,k} \\
\text{EnEff}_{i,t, \text{Universal}} & = \zeta_0 + \xi_1 \text{EnEff}_{i,t-1, \text{Universal}} + \phi_1 \text{GCI}_{i,t-1} + \phi_2 \left( \text{GCI}_{i,t-1} \cdot \text{Tg}_{i,t-1} \right) + \psi_1 \left( \text{Tg}_{i,t-1} \cdot \text{Eff}_{i,t,k} \right) + \psi_2 \text{Switch}_{i,t-1} + \lambda \text{GCI}_{i,t} + v_{i,t}
\end{align*}
\]

(6.5) (6.6)

Including lagged regressors of the dependent variable in both equations raises autocorrelation concerns in conjunction to possible endogeneity issues between energy efficiency \( \text{EnEff}_{i,t,k} \) and productive performance \( \text{Eff}_{i,t,k} \) since those are defined on the same technology set along with possible correlation with the disturbance terms. Also, the fact that the form of heteroscedasticity is not known \textit{a priori}, points towards the direction of the Generalized Method of Moments estimator or difference estimator of Arellano-Bond (1991) first proposed by Holtz-Eakin et al., (1988). This is the workhorse for examining the main research question of this chapter which can be stated as follows:

\textbf{H}_1: Productive performance and energy efficiency are endogenously associated and the impact of productive performance on energy efficiency is moderated by the regime of competitiveness as captured by the global competitiveness index

More precisely, \( \text{EnEff}_{i,t,k} \) is the energy efficiency of the \( i \)-th country under the \( k \)-th cluster in time \( t \) and \( \text{EnEff}_{i,t-1,k} \) is its lagged value capturing the time persistent pattern of energy efficiency which brings us to the second research hypothesis examined herein:

\textbf{H}_2: Energy efficiency exhibits time persistent patterns under heterogeneous competitiveness regimes.
The present of the quadratic term of productive performance, \( (Eff^2) \), has been included to capture any non-linear effects of the productive performance on the energy efficiency of each cluster taking into consideration that both are defined on the same production possibility set.

The corresponding research hypothesis can be formed as follows:

**H1:** Productive performance levels exhibit a non-linear effect on energy efficiency depending on the competitiveness regime each country operates under. In other words, there is a trade-off between increased levels productive performance and energy efficiency which is moderated by the level of absorptive capacity and knowledge seeking behaviour as captured by the level of the global competitiveness index.

The rest of the regressors, that is the carbon dioxide emissions, \( CO_{i,t} \), have been included to account for the production intensity of each cluster and the global competitiveness index, \( GCI_{i,t} \), which has been treated as predetermined since it is not considered correlated with future errors, is the operative variable to investigate the mechanisms of absorptive capacity.

As far as the model for the universal technology is concerned, that is equation 6.6 above, we followed a rather different specification to examine additional research questions. More precisely, the inclusion of the lagged value of the technology gap, \( Tg_{i,t-1} \), intends to capture the effect of past achievements generated at the universal level to each country’s energy efficiency, the significance of spillover effects. In this line of argument, one should acknowledge the fact that the generation and diffusion of spillover effects is triggered by the level of technical knowledge each country possesses which brings to the fore the role of each country’s competitiveness. The combined effect of absorptive capacity and spillover effects captured by the variable \( GCI_{i,t-1} * Tg_{i,t-1} \) is included to investigate whether past achievements and developments exert a significant impact on current energy efficiency levels which raises the next research hypothesis and can be stated as follows:

**H2:** The exploration of spillover effects generated at the global level depends on the level of the absorptive capacity of each cluster. Framed differently, energy efficiency levels are connected with the ability of each country to absorb new technical knowledge conveyed by spillover effects.

The above variables, that is the \( Tg_{i,t-1} \) and \( GCI_{i,t-1} * Tg_{i,t-1} \), have been treated as endogenous due to the fact that are correlated with the energy efficiency since the technology gap indicates the performance of each country at the universal level and is defined on the same production possibility set as the productive performance is. Considering the fact that we already have been engaged in examining the impact of spillovers in conjunction to the fact that we have been relied
on the absorptive capacity to create the clusters, the next plausible step to make is to examine which competitiveness regime accumulates the technological developments. In this case, the research hypothesis is as follows:

\[ H_5: \text{The new technical knowledge is not being equally accumulated rather it heavily depends, in a moderation fashion, on the competitiveness regime each country operates under. Framed differently, the competitiveness regime and the level of absorptive capacity of each country matters in its future development since a country might desire to move to another production trajectory but the lack of means or other kinds of socio-economic rigidities prevent future achievements.} \]

The above hypothesis is tested by the effect of the variable \( D \times T_g \) which is the interaction effect between a binary variable indicating participation to the less competitive group (LCC) and the spillover effects aiming at capturing the effect of spillovers on the less competitive cluster. We also allow for changes in the socio-economic environment might occur affecting each country’s participation in each cluster every year, by including the binary variable \( Switch \) in lagged form so as to accommodate any adjustments in alternative production technology, capturing any transitions throughout the period of study. The rest of the variables are included for the reasons already mentioned above while the terms \( u_i,t \) and \( v_i,t \) capture additional unobserved factors. The parameters to be estimated are the \( \beta, \gamma, \delta, \xi, \psi, \theta, \lambda \).

6.4 Data and variables

In order to investigate our research questions, we have composed a unique dataset derived from distinct and reliable data sources. Such an undertaking resulted in a balanced panel consisting of seventy eight countries around the globe over a ten years period, i.e. from 2002 to 2011. Therefore, the final dataset consists of 780 observations. This dataset provides the opportunity to study simultaneously any heterogeneous patterns might exist in the productive performance of the individual clusters and the global level of technology as well, examine the role of competitiveness on the energy efficiency and highlight the significance of spillover effects through the standpoint of absorptive capacity.

As far as the estimation of the first stage is concerned, that of the evaluation of the energy efficiency of each country, a single-output and three inputs approach was adopted. The output variable is captured by the Gross Domestic Product (\( Y \)) of each country measured in millions United States (US hereafter) dollars while the inputs are captured by the Capital stock (\( K \)), in millions US dollars, the Labour (\( L \)), in millions of persons engaged, and the Energy use (\( E \)), in

\[ \text{See Table 6.1.} \]
kilo tons of oil equivalent. It should also be noted that all the monetary values are in constant prices 2005.

Regarding the second stage analysis, some additional variables where collected such as the Carbon Dioxide Emissions (CO₂) in country level, measured in kilo tons of oil equivalent, along with the Global Competitiveness Index (onwards GCI) of each country, a composite index embracing twelve pillars\textsuperscript{35} which provide insight into the drivers of the countries’ productivity, prosperity and economic growth (World Economic Forum) which plays the role of moderator of the empirical relationships we aspire to shed light on. As a matter of fact, the novelty and uniqueness of this dataset is found on the grounds of exploring the performance of the countries’ according to their GCI on a yearly basis, since it captures the absorptive capacity potential of each country under heterogeneous competitiveness regimes.

As already mentioned, distinct and specialized databases where employed to construct this dataset. More specifically, data on the Gross Domestic Product, Capital stock and Labour input, where collected through the Groningen Growth and Development Centre (GGDC) database. Data on the Energy use and carbon dioxide emissions (onwards, CO₂) were drawn from the International Energy Agency (IEA) database, while data regarding the GCI were gathered from various editions of the Global Competitiveness Report published by the World Economic Forum.

Tables 6.2, and 6.3 below, illustrate the variables’ description and the descriptive statistics by cluster and in total respectively. It is obvious that the competitive cluster (CC) produces more output using capital intensive and energy consuming techniques in contrast to the less competitive cluster (LCC) which seems to employ labour intensive techniques. Despite the those observations based on descriptive statistics, the underlying relationship between the production process and technological possibilities as well as opportunities of the two clusters is far more complicated and demands for a more spherical appointment. Such an investigation is attempted on the following sections.

\textsuperscript{35} Institutions, Infrastructure, Macroeconomic Environment, Health and Primary Education, Higher Education and Training, Goods Market Efficiency, Labor Market Efficiency, Financial Market Development, Technological Readiness, Market Size, Business Sophistication and Innovation.
Table 6.2 Variables, units of measurement and sources

| Variable                      | Units of measurement      | Source               |
|-------------------------------|---------------------------|----------------------|
| GDP (Y)                       | Millions US dollars       | GGDC                 |
| Capital (K)                   | Millions US dollars       | GGDC                 |
| Labour (L)                    | Millions of persons engaged | GGDC              |
| Energy use (E)                | Kilo tons of oil equivalent | International Energy Agency |
| Carbon dioxide emissions (CO₂) | Kilo tons of oil equivalent | International Energy Agency |
| Global Competitiveness Index (GCI) | Pure number           | World Economic Forum |

All the monetary values are in constant 2005 prices.

Table 6.3 Descriptive statistics for the clusters for the period 2002-2011

| Variables | Less Competitive Cluster | Competitive Cluster | Total |
|-----------|--------------------------|---------------------|-------|
| Y         | 410,164                  | 1,147,236           | 715,388 |
|           | (910,744)                | (2,522,955)         | (1,802,391) |
| K         | 1,241,318                | 3,720,178           | 2,267,820 |
|           | (2,790,085)              | (8,120,601)         | (5,771,277) |
| L         | 35.276                   | 26.536              | 31.657 |
|           | (101.547)                | (97.125)            | (99.769) |
| E         | 79.545                   | 191,379             | 125,856 |
|           | (204,895)                | (470,432)           | (345,095) |
| CO₂        | 202,681                  | 474,775             | 315,356 |
|           | (644,167)                | (1,261,886)         | (958,689) |
| GCI        | 3.954                    | 5.115               | 4.435 |
|           | (.409)                   | (.367)              | (.694) |

Note 1: Numbers indicate the mean value while parentheses correspond to the standard deviation.
Note 2: The GCI (Global Competitiveness Index) refers to each cluster as well as the panel for the years 2002-2011.

6.5 Results and discussion

6.5.1 Initial explorations

In this sub-section we will focus on the three core variables of this chapter that is the energy efficiency, productive performance and technology gap. Moreover, we will study the behavior of those variables combined to other variables of interest which we will also focus on.

To start with, let us focus on the energy efficiency values for the case of the less competitive group (LCC) and that of the competitive group (CC). Fig. 6.2 below, illustrates the distribution of the energy efficiency for the two clusters for selected years, that is the beginning (i.e. 2002), the middle (i.e. 2007) and the last year (i.e. 2011) of the study. Both distributions are bimodal and exhibit a time persistent pattern throughout the period of study indicating distinct groups of countries within each cluster. It is also observable that for the case of the competitive group, the distributions are characterized by a smoother evolution compared to those of the less competitive group.
A similar pattern is depicted in Fig. 6.3 below regarding the distribution of the productive performance of the countries within the clusters since the latter are bimodal as well. From the one hand, this makes perfect sense since energy efficiency and productive performance are defined over the same technology set and this is the main source of endogeneity between the two. On the other hand, one cannot neglect the fact that the productive performance seems to evolve in a non-linear manner for both clusters, with the competitive group to exhibit a turbulence of higher degree but this is just an indication and at this stage, further attempts to justify this finding would be far from robust.
Fig. 6.4 below pulls together the above two variables and highlights the non-linear effect of productive performance on the energy efficiency values of the two distinct heterogeneous competitiveness clusters. For the case of the less competitive group, a non-linear relationship between the productive performance and energy efficiency does not seem to be supported by the evidence but this is not the case for the case of the competitive group which seems to exert a non-linear effect and more precisely of an emerging U-shape.

Figure 6.4 Non-linear effect of productive performance on energy efficiency

Fig. 6.5 below demonstrates the association between the energy efficiency and technology gap for the two clusters by forming four quadrants inserting two lines at the mean of energy efficiency and technology gap. The quadrants allow us to address any polarization phenomena taking place throughout the period of study for all the countries of each cluster. More precisely, the less competitive group (LCC) exhibits a quite mixed picture with inconclusive evidence of some sort of linear relationship between the two variables. The picture is quite different for the case of the competitive group (CC) since as we notice, a polarization scheme is identified. That is, countries with high levels of energy efficiency (up-left quadrant) and those with low energy efficiency levels, located at the down-left quadrant, are characterized by diverse levels or resource utilization and technical knowledge leading to the polarization phenomenon we observe. It becomes apparent that there is a relationship between the energy efficiency and the performance with respect to the universal level of achievements which needs to be amplified so as to reveal the nature of the underlying effect.
Fig. 6.6 below sets under sharper focus the behavior of the switchers i.e. the countries switching between competitiveness clusters throughout the period of study. This variable is a binary response variable which indicates whether a country has shift cluster from year to year and it is included in the analysis to shed light on the dynamics of the transition between different production technologies triggered by knowledge effects, absorptive capacity levels and technical capabilities of each country. Likewise the above case, the lines represent the mean value of the energy efficiency and technology gap respectively and have been inserted to assist us in identifying an underlying pattern. In this case, beyond any doubt we document two different situations. Regarding the non-switchers i.e. countries not shifting to another production technology, a polarized and sticky group-wise behavior is documented around all the quadrants indicating the existence of sticky sub-groups within the non-switchers set while as far as the switchers i.e. countries shifting to another competitiveness regime at least once throughout the period of study are concerned a scattered pattern is noticed. The latter fact enhances the previous argument regarding the sticky behavior of production technology. Moving a step further, Table 6.4 below, provides evidence for the switches have taken place between the two heterogeneous competitiveness regimes throughout the period of study. That is, almost 60% of the non-switchers (i.e. 432 out of 739) belong to the low competitiveness cluster enhancing the finding regarding the group stickiness while only 5% (25 out of 457) of the low competitiveness countries did alter their production technology at least once. As a final step in quantifying the effect of the switching between the clusters we calculated the transition probability matrix as shown in Table 6.5 below. In order to conclude that the transitions occur in a significant manner, the elements in the diagonal must exceed 33.33% which does not appear to be the case.
here. Given that we are inclined to conclude that participation to a cluster based on their competitiveness levels exhibits a sticky behavior and appear to be time persistent for the particular sample and time window.

Figure 6.6 Energy efficiency and technology gap association for the Switch variable for the period 2002-2011

Table 6.4 Cross-tabulation of Switch and Cluster for the period 2002-2011

| Switch | LCC  | CC  | Total |
|--------|------|-----|-------|
| No     | 432  | 307 | 739   |
| Yes    | 25   | 16  | 41    |
| Total  | 457  | 323 | 780   |

Table 6.5 Transitions between the two clusters for the period 2002-2011

| Switch | No   | Yes  |
|--------|------|------|
| No     | 95.06| 4.94 |
| Yes    | 76.47| 23.53|

6.5.2 Focusing on the heterogeneous competitiveness regimes

Before we proceed to the discussion of the individual cluster models, let us focus on the associations between the main variables of each model. Table 6.6 below, depicts a correlation matrix for the case of the LCC for the period of study. It is quite obvious that energy efficiency and productive performance are highly associated since those are defined over the same technology set. This is the main source of endogeneity ruling the individual cluster models. We also notice that the competitiveness level i.e. the absorptive capacity level is mostly attached to the productive performance rather than to the energy efficiency. It could also be argued that
there is an indirect effect i.e. moderating effect of absorptive capacity on energy efficiency running through the level of productive performance. That is, technical knowledge and capabilities are projected on the productive performance level and since it is endogenously related to the level of energy efficiency those are transmitted accordingly. A similar picture is illustrated at Table 6.7 below, for the case of the CC this time. That is, productive performance and energy efficiency are highly correlated but in the case of the competitive cluster we notice that absorptive capacity and productive performance are characterized by a higher association compared to the case of the less competitive cluster implying that technological improvements should be supported by the ability to absorb new advancements. At the moment, this is just an indication and no further conclusions can be drawn. We need to explore more the relationship between productive performance and energy efficiency and this is exactly what follows.

Table 6.6 Correlation matrix with respect to the Less Competitive Cluster for the period 2002-2011

|                  | Productive Performance | Energy Efficiency | GCI     |
|------------------|------------------------|-------------------|---------|
| Productive Performance | 1.000                  |                   |         |
| Energy Efficiency  | 0.911                  | 1.000             |         |
| GCI               | 0.245                  | 0.208             | 1.000   |

Table 6.7 Correlation matrix with respect to the Competitive Cluster for the period 2002-2011

|                  | Productive Performance | Energy Efficiency | GCI     |
|------------------|------------------------|-------------------|---------|
| Productive Performance | 1.000                  |                   |         |
| Energy Efficiency  | 0.828                  | 1.000             |         |
| GCI               | 0.321                  | 0.279             | 1.000   |

Table 6.9 below presents the estimation results for the less competitive cluster (LCC), the competitive cluster (CC) and the universal frontier. We will begin exploring the research hypotheses by looking at the LCC first. Past levels of energy efficiency seem to exert a positive and significant influence on the current levels meaning that there is time persistent pattern (Hypothesis 2 not rejected). Past accumulated knowledge and technical capabilities are projected on the current levels and affect future achievements. It is straightforward that past levels of energy efficiency whether high or low positively affect the current ones meaning that it not easy to escape low performance and dismal technological trajectories. Extending this argument, the absorptive capacity, technical knowledge and technological capabilities as captured by the global competitiveness index, seem to play a crucial role in determining current energy efficiency of a country within the low competitiveness cluster. The positive and statistically significant effect the GCI exerts in the dependent variable in conjunction to the insignificant effect of productive performance on the energy efficiency levels raises doubts as far as the role of absorptive capacity is concerned. Therefore, Hypothesis 1 for the case of the LCC does not seem to be confirmed.
In spite of the moderating role of the competitiveness, the relationship between the productive performance and energy efficiency proves to be inconclusive. More precisely, energy efficiency seems to scratch the surface of the productivity developments even if those are defined over the same technology set. The exact mechanism connecting both of them is vague but we cannot neglect the fact that improvements are attributed to the multifaceted role of competitiveness i.e. the role of absorptive capacity. In other words, the LCC absorbs technical knowledge so as to improve the level of its energy efficiency but the latter is highly determined by the degree of absorptive capacity due to the operating environment, regulations, infrastructure, human capital and production technology achievements since the aforementioned should be aligned to reach higher levels of energy efficiency since those are embodied in the production set of each country.

The notion of the production set along with the aforementioned, brings us to the forefront the role of productive performance to the improvement of the current levels of the energy efficiency. However, such a claim cannot be supported considering that neither the productive performance nor the higher levels of productive performance are significant indicating that for the case of LCC the productive performance neither affects energy efficiency in a systematic way nor a non-linear relationship can be supported so as to assume that for increased levels of productive performance, energy efficiency rises as well, i.e. a U-shape relationship cannot be supported (Hypothesis 2 is not accepted). All in all, the LCC absorbs new technical knowledge but the source and the extent deserve further investigation. Results up to this point seem to be inconclusive.

A considerably differentiated picture is captured by the specification for the case of the CC. Time persistence of energy efficiency appears to be a significant factor of the current levels in this case as well meaning that the path dependence phenomenon is in operation so Hypothesis 2 is not rejected. However, a rather different scheme regarding the GCI occurs. For the CC any technological capabilities, knowledge diffusion captured by the GCI are directly incorporated in the production technology and therefore increase the absorptive capacity of each country. Energy efficiency improvements are deeply rooted to technological achievements taking place due to production possibilities exploited. In this case, the moderating effect of competitiveness, in spite of the fact that it does not exert a significant influence, has entirely been projected on the production possibility set i.e. on productive performance which affects positively and significantly the energy efficiency. Putting aside the insignificant effect of GCI, Hypothesis 1 can partially be accepted. Although the GCI appears to affect indirectly energy efficiency through the productive performance improvements, the relationship between the latter appears to be more clear compared to the case of the LCC. That is, productive performance
appears to be a crucial driver of energy efficiency while a non-linear relationship of a U-shape is documented between the two (Hypothesis 3 is not rejected). CC exploits the already achieved levels of technical knowledge moderated by the high competitiveness levels to increase more their energy efficiency levels. In a nutshell, for the case of CC, improvements in the energy efficiency levels are moderated by the GCI which has been projected on the productive performance improvements.

Fig. 6.7 below illustrates the type of non-linear relationship between the levels of energy efficiency and productive performance has been identified by the empirical models. From the one hand, for the LCC, as already mentioned, no systematic relationship has been identified meaning that there are more aspects of the operating environment and others factors which have not been appointed here affecting the relationship between the two. Indeed, absorptive capacity is among them but its effect needs to be amplified to produce a systematic empirical relationship. On the other hand, a U-shape relationship is identified for the case of the CC. Here, results have been twisted since the effect of absorptive capacity i.e. the heterogeneity of the competitiveness regime has been fully embodied in the production capabilities and consequently, has been projected on the productive performance levels. Increased levels of productive performance are associated with higher levels of energy efficiency while for low levels of productive performance, energy efficiency is dropping. This finding is in the core of this chapter since it helps us visualize a theoretical relationship which is defined upon the actual production possibility set and this is the source of the endogeneity between the energy efficiency and productive performance. Low levels of productive performance lead the levels of energy efficiency to drop down, but after the accumulation of technology advancements and absorption of technical knowledge, productive performance boosts energy efficiency.

Figure 6.7 Non-linear relationship between energy efficiency and productive performance for the period 2002-2011
6.5.3 The case of universal frontier and the spillover effects

The last part of this subsection is dedicated to the conclusions can be drawn from the specification regarding the universal frontier. Before we shift the attention at the mechanisms of the universal technology and how it is diffused, it is not worthless to make some observations regarding the connections among the variables of interest. Table 6.8 below presents the associations between the main variables of the universal frontier specification. As expected, technology gap and the level of competitiveness are negatively associated implying that the greater the degree of the absorptive capacity the lower the gap from the available technology. This means that countries exhibiting high level of technical capabilities and are better equipped with knowledge absorption mechanisms along with developed institutions is less likely to perform poorly on a global level. Moreover, the association between the GCI and the rest of the variables is quite weak to reveal the underlying mechanisms in operation, so in order to draw any conclusions we have to rely on the universal frontier model which studies those relationships under a more formal framework.

Table 6.9 below presents the estimation results for the case of the globally available state of technology. Inarguably, in this case as well, the time persistence of past levels of energy efficiency is documented affecting the current ones in a significant manner (Hypothesis 2 is not rejected). However, in this case the role of absorptive capacity appears to be more complicated than in the individual competitiveness regimes. It is quite obvious that the role of competitiveness level affect the attainable energy efficiency levels of the universal frontier significantly but it works through different channels. Low levels of productive performance with respect to the universal level of technological developments, captured by $\text{Technology Gap}_{it}$, lead to increased levels of technology gap. Such being the case, there are more opportunities to catch-up which affects in its own right the absorptive capacity and technological capabilities (e.g. Cohen and Levinthal, 1989, 1990). Although the opportunities arising from technology spillovers are higher for countries lagging in terms of productive performance or higher technology gap, since there is more room for the inefficient to improve their performance, such an exploitation depends on the overall absorptive capacity of each country i.e. competitiveness level. Put it another way, the generation of spillover effects at the global level may occurs but we do not possess an objective mechanism to identify if the latter are intense or strong enough to penetrate the thick and sticky “wall” of competitiveness regime each country operates under. The latter brings to the forefront the significance of the combined effect of the absorptive capacity and spillover effects, captured by the interaction term $GCI_{it-1} * \text{Technology Gap}_{it-1}$, representing the joint effect of the ability and potentiality to absorb new technical knowledge which appears to be
positive and significant leading to improvements at the levels of energy efficiency (Hypothesis 4 is not rejected). The next plausible question is to ask which cluster is the most beneficiated at the end of the day. The answer is by any means the LCC. The positive and significant effect of the interaction between the binary variable indicating participation to the LCC group and the spillover effects, that is $D^*_{Technology\ Gap_{i,t-1}}$, indicates that new knowledge can be accumulated up to a certain extent (it is significant only at 10% level of significance), compared to the CC (Hypothesis 5 is not rejected). Indeed spillovers do manage to penetrate the competitiveness wall but not entirely meaning that the countries closer to the optimum capacity are more beneficiated. Furthermore, a joint hypothesis test, $\left( H_0 : \psi_1 = \psi_2 = \psi_3 = 0 \right)$, points towards the direction that spillovers, absorptive capacity and regime-specific knowledge and technical capabilities accumulation are jointly significant at 5% level of significance. These findings add value to the existing literature since these dimensions have not been explored yet by the existing studies. The workings of energy efficiency investigation prove to be rather tangled and complex. The introduction of additional aspects such as the competitiveness regime, the exploitation of spillover effects along with the interaction effects appear to be non-redundant. To the contrary, those proved to be quite enlightening in exploring such a bewildering relation. High levels of emissions do not affect significantly the energy efficiency at the global level and it is not surprising the fact that switching between competitiveness regimes does not affect the global performance of the countries.

| Table 6.8 Correlation matrix with respect to the Universal frontier |
|---------------------------------------------------------------|
| **Technology Gap** | **Energy Efficiency** | **GCI** |
| Technology Gap     | 1.000                |         |
| Energy Efficiency  | 0.031                | 1.000   |
| GCI                | -0.381               | 0.044   | 1.000  |
Table 6.9 GMM Estimation Results for the Less Competitive Cluster (LCC), the CC and the Universal Frontier

| Dependent Variable: | LCC | CC | Universal Frontier |
|---------------------|-----|----|-------------------|
| Energy Efficiency   |     |    |                   |
| \( \text{Energy Efficiency}_{i,t-1} \) | .175** | .127** | .474*** |
|                     | (.086) | (.060) | (.127) |
| \( \text{Productive Performance}_{i,t} \) | -.106 | -3.321** | - |
|                     | (1.056) | (1.362) | - |
| \( \text{Productive Performance}_{i,t} \) | .804 | 3.045*** | - |
|                     | (.675) | (9.02) | - |
| \( \text{Technology Gap}_{i,t-1} \) | - | - | -1.346*** |
|                     | - | - | (.522) |
| \( \text{GCI}_{i,t-1} \times \text{Technology Gap}_{i,t-1} \) | - | - | .323** |
|                     | - | - | (.128) |
| \( \text{GCI}_{i,t} \) | .067* | .022 | .037*** |
|                     | (.039) | (.035) | (.018) |
| \( \text{D} \times \text{Technology Gap}_{i,t-1} \) | - | - | .087* |
|                     | - | - | (.047) |
| \( \text{Carbon Dioxide Emissions}_{i,t} \) | .000* | .000*** | .000* |
|                     | (.000) | (.000) | (.000) |
| \( \text{Switch}_{i,t-1} \) | -.077 | 1.146** | .208* |
|                     | (.330) | (.530) | (.113) |
| Model Diagnostics and Sample Size |     |    |                   |
| Wald (p-value)      | .000 | .000 | .000 |
| No of groups        | 55  | 43  | 78 |
| No of instruments   | 112 | 112 | 133 |
| N                   | 380 | 244 | 624 |

Note 1: Numbers in parentheses for the estimated coefficients correspond to the associated standard errors of the estimation.

Note 2: The table illustrates the One-Step Estimation results considering the robust version (asymptotic) variance-covariance matrix.

Note 3: As far as the coefficients of the Carbon Dioxide Emissions are concerned, those are not actually zero but correspond to a very small number, i.e. smaller than .0001. This is captured by the symbol “+”.

Note 4: Stars indicate statistical significance at different significance levels i.e. ***=1%, **=5%, *=10%

6.6 Conclusions

Over the years the very nature of the energy input has attract significant attention as a basic ingredient of the production process. The reasons it has been studied to such a broad respect can only be compared to the diversity of the techniques, methodologies and approaches the scholars, researchers and other advising agents have implemented. From a total factor productivity measurement perspective, energy efficiency is a derivative measure defined on the same production possibility set as the productive performance of the units has been defined as well. To the best of our knowledge, existing studies have overlooked the fact that the two notions are interconnected since at the majority of cases, the investigation of the channel underneath which those are linked remains unexplored. Such being the case, the primary focus of this chapter was to shed light to the mechanisms of the complicated relationship between the productive performance and energy efficiency and how this relationship is moderated by the existence of heterogeneous competitiveness regimes.
The impetus of this study was multifaceted. At the core of the empirical investigation was the tangled connection between the productive performance and the energy efficiency level viewed from the angle of the absorptive capacity levels as captured by the global competitiveness index. Absorptive capacity brings to the forefront the existence of spillover effects. Spillover effects oriented studies are not scarce in the literature and whether those are foreign direct investments or R&D driven, attempting to explain improvements of the total factor productivity outcomes. Rather, in this analysis in spite of the fact that we also explore the impact of spillover effects on the energy efficiency levels, their source and nature is diametrically opposite. We explore spillover effects which originate directly from the productive performance achievements and are projected on the energy efficiency levels through the channel of the absorptive capacity of each country. The latter gives rise and reason to the heterogeneous competitiveness regimes we analyzed in order to explore the moderating role of the absorptive capacity on alternative production technologies. To accomplish such a task, we devised a balanced panel of seventy eight countries around the globe from 2002 to 2011 that is a decade. In order to test our research hypotheses, we clustered the countries according to their competitiveness level creating two clusters of distinct competitiveness levels which later on we studied their units from a universal technology perspective.

Findings wise, we documented the following. Absorptive capacity levels seem to be the golden key to the less competitive countries in order to improve their energy efficiency but productive performance does not appear to affect the former since technological advancements need to be combined with many aspects of the operating environment. Unlike, in the case of the competitive countries cluster, technical knowledge has been embodied to levels of productive performance in the extent that a U-shape relationship between the levels of energy efficiency and productive performance indicating that increasing the productive performance of a country comes at the cost of reducing its energy efficiency level but up to a certain point beyond which the accumulated knowledge and production capabilities change the direction of the this tangled relationship highlighting the fact that the two measures are endogenously related since those are defined over the same technology set. Shifting the attention at the technological achievements at the universal level, the role of inter-countries spillover effects are a crucial factor to their improvement in conjunction to the absorptive capacity level and group identity as well. However, switching between clusters, on a yearly basis, is not likely to occur indicating that technological advancements require a longer term adjustment period. That said, we should also not neglect to mention that the path dependence phenomenon is present at every specification we studied indicating that past achievement whether desirable or less, do influence future
performance or put it another way performance is sticky in nature and is determined by past technological, institutional, regulatory trajectories and decisions from the angle of the policy maker.

All in all, as every study, the present study has some limitations and the conclusions drawn herein are subject to the time window, countries included, analysis and methodologies implemented. The lack of a solid theoretical framework to use as a roadmap, suppress the possibility for deductions based on econometric modeling, the only thing is crystal clear so far is the tangled and complex relationships among key notions such as energy efficiency, competitiveness and technological heterogeneity. To this end, future research may be benefited by considering more countries, spreading the time window and selecting additional moderating factors as robustness checks to the results demonstrated.
References

Ang, B. W. (2006). Monitoring changes in economy-wide energy efficiency: from energy–GDP ratio to composite efficiency index. *Energy Policy, 34*(5), 574-582.

Arelano, M. and Bond, S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*, 277-297.

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

Battese, G. E., & Rao, D. P. (2002). Technology gap, efficiency, and a stochastic metafrontier function. *International Journal of Business and Economics, 1*(2), 87-93.

Battese, G. E., Rao, D. P., & O'Donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis, 21*(1), 91-103.

Berndt, E. R. (1990). Energy use, technical progress and productivity growth: a survey of economic issues. *Journal of Productivity Analysis, 2*(1), 67-83.

Boschma, R., & Iammarino, S. (2009). Related variety, trade linkages, and regional growth in Italy. *Econ. Geogr., 85*(3), 289-311.

Boyd, G. A., & Pang, J. X. (2000). Estimating the linkage between energy efficiency and productivity. *Energy policy, 28*(5), 289-296.

Cainelli, G., & Iacobucci, D. (2012). Agglomeration, related variety, and vertical integration. *Economic Geography, 88*(3), 255-277.

Camarero, M., Picazo-Tadeo, A. J., & Tamarit, C. (2008). Is the environmental performance of industrialized countries converging? A ‘SURE’approach to testing for convergence. *Ecological economics, 66*(4), 653-661.

Cameron, G., Proudman, J., & Redding, S. (2005). Technological convergence, R&D, trade and productivity growth. *European Economic Review, 49*(3), 775-807.

Castellacci, F. (2007). Technological regimes and sectoral differences in productivity growth. *Industrial and Corporate Change, 16*(6), 1105-1145.

Castellacci, F. (2011). Closing the technology gap?. *Review of Development Economics, 15*(1), 180-197.

Cui, Q., Kuang, H. B., Wu, C. Y., & Li, Y. (2014). The changing trend and influencing factors of energy efficiency: The case of nine countries. *Energy, 64*, 1026-1034.

Change, C. (2007). Intergovernmental Panel on Climate Change. *World Meteorological Organization.*

Chen, V. Z., Li, J., & Shapiro, D. M. (2012). International reverse spillover effects on parent firms: Evidences from emerging-market MNEs in developed markets. *European Management Journal, 30*(3), 204-218.
Chiu, C. R., Liou, J. L., Wu, P. I., & Fang, C. L. (2012). Decomposition of the environmental inefficiency of the meta-frontier with undesirable output. *Energy Economics, 34*(5), 1392-1399.

Coe, D. T., Helpman, E., & Hoffmaister, A. W. (2009). International R&D spillovers and institutions. *European Economic Review, 53*(7), 723-741.

Cohen, W. M., & Levinthal, D. A. (1989) Innovation and learning: the two faces of R & D. *The Economic Journal, 99*(397), 569-596.

Cohen, W.M. and Levinthal, D.A. (1990) Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128-152.

Crespo, N., & Fontoura, M. P. (2007). Determinant factors of FDI spillovers–what do we really know?. *World development, 35*(3), 410-425.

da Graça Carvalho, M. (2012). EU energy and climate change strategy. *Energy, 40*(1), 19-22.

Damijan, J. P., Rojec, M., Majcen, B., & Knell, M. (2013). Impact of firm heterogeneity on direct and spillover effects of FDI: Micro-evidence from ten transition countries. *Journal of Comparative Economics, 41*(3), 895-922.

David, P. A. (1985). Clio and the Economics of QWERTY. *The American economic review*, 332-337.

David, P.A. (1986) Understanding the economics of QWERTY: the necessity of history. *Economic History and The Modern Economics* eds W.N. Parker. Oxford, Blackwell.

Del Bo, C. F. (2013). FDI spillovers at different levels of industrial and spatial aggregation: Evidence from the electricity sector. *Energy Policy, 61*, 1490-1502.

Driffield, N., & Love, J. H. (2003). Foreign direct investment, technology sourcing and reverse spillovers. *The Manchester School, 71*(6), 659-672.

Du, K., Lu, H., & Yu, K. (2014). Sources of the potential CO2 emission reduction in China: A nonparametric metafrontier approach. *Applied Energy, 115*, 491-501.

Dutta, S., Narashimhan, O. and Rajiv, S. (2005) Conceptualizing and measuring capabilities: Methodological and empirical application. *Strategic Management Journal 26*(3), 277-285.

Eichhammer, W. & Walz, R. (2011). Industrial energy efficiency and competitiveness, United Nations Industrial Development Organization, Working paper 05/2011.

European Commission, European Council for an Energy Efficient Economy, Energy Efficiency Plan, (2011) accessible at

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Reg. Stud., 41*(5), 685-697.
Girma, S. (2005). Absorptive capacity and productivity spillovers from FDI: A threshold regression analysis*. *Oxford bulletin of Economics and Statistics, 67(3), 281-306.

Groningen Growth and Developing Centre, GGDC Productivity Level Database. http://www.rug.nl/research/ggdc/data/ggdc-productivity-level-database (accessed on 08.03.2013).

Halkos, G. E., & Tzeremes, N. G. (2009). Exploring the existence of Kuznets curve in countries’ environmental efficiency using DEA window analysis. *Ecological Economics, 68*(7), 2168-2176.

Hayami, Y. (1969). Sources of agricultural productivity gap among selected countries. *American Journal of Agricultural Economics, 51*(3), 564-575.

Hayami, Y., & Ruttan, V. W. (1970). Agricultural productivity differences among countries. *The American Economic Review, 895*-911.

Holtz-Eakin, D., Newey, W. and Rosen, H.S. (1988) Estimating Vector Autoregressions with Panel Data. *Econometrica, 56*(6), 1371-1395.

Hu, J. L., & Wang, S. C. (2006). Total-factor energy efficiency of regions in China. *Energy policy, 34*(17), 3206-3217.

International Energy Agency, IEA Statistics. http://www.iea.org/ (accessed on 08.03.2013).

International Energy Agency (2007a). Tracking Industrial Energy Efficiency and CO2 Emissions. OECD/IEA, Paris.

International Energy Agency (2007b). Energy Use in the New Millennium: Trends in IEA Countries. OECD/IEA, Paris.

International Energy Agency (2008a). Worldwide Trends in Energy Use and Efficiency: Key Insights from IEA Indicators Analysis. OECD/IEA, Paris.

International Energy Agency (2008b). Energy Technology Perspectives 2008: Scenarios and Strategies to 2050. OECD/IEA, Paris.

International Energy Agency (2008c). World Energy Outlook 2008. OECD/IEA, Paris.

Kontolaimou, A., Kounetas, K., Mourtos, I., & Tsekouras, K. (2012). Technology gaps in European banking: Put the blame on inputs or outputs?. *Economic Modelling, 29*(5), 1798-1808.

Kounetas, K., Mourtos, I., & Tsekouras, K. (2009). Efficiency decompositions for heterogeneous technologies. *European Journal of Operational Research, 199*(1), 209-218.

Kounetas, K., Mourtos, I., & Tsekouras, K. (2012). Is energy intensity important for the productivity growth of EET adopters?. *Energy Economics, 34*(4), 930-941.

Leahy, D., & Neary, J. P. (2007). Absorptive capacity, R&D spillovers, and public policy. *International Journal of Industrial Organization, 25*(5), 1089-1108.
Li, M., & Wang, Q. (2014). International environmental efficiency differences and their determinants. *Energy, 78*, 411-420.

Liao, H., Fan, Y., & Wei, Y. M. (2007). What induced China’s energy intensity to fluctuate: 1997–2006?. *Energy Policy, 35*(9), 4640-4649.

Lin, E. Y. Y., Chen, P. Y., & Chen, C. C. (2013). Measuring green productivity of country: A generalized metafrontier Malmquist productivity index approach. *Energy, 55*, 340-353.

Lin, B., & Du, K. (2013). Technology gap and China’s regional energy efficiency: A parametric metafrontier approach. *Energy Economics, 40*, 529-536.

Lin, B., & Du, K. (2014). Measuring energy efficiency under heterogeneous technologies using a latent class stochastic frontier approach: An application to Chinese energy economy. *Energy, 76*, 884-890.

Liddle, B. (2010). Revisiting world energy intensity convergence for regional differences. *Applied Energy, 87*(10), 3218-3225.

Mancusi, M. L. (2008). International spillovers and absorptive capacity: A cross-country cross-sector analysis based on patents and citations. *Journal of International Economics, 76*(2), 155-165.

Marin, A., & Bell, M. (2006). Technology spillovers from foreign direct investment (FDI): the active role of MNC subsidiaries in Argentina in the 1990s. *The Journal of Development Studies, 42*(4), 678-697.

Martin, R., & Sunley, P. (2006). Path dependence and regional economic evolution. *Journal of Economic Geography, 6*(4), 395-437.

O’Donnell, C. J., Rao, D. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics, 34*(2), 231-255.

OECD (2008), Promoting Sustainable Consumption: Good Practices in OECD countries. www.oecd.org/dataoecd/1/59/40317373.pdf

O’Mahony, M., & Van Ark, B. (2003). *EU productivity and competitiveness: an industry perspective: can Europe resume the catching-up process*. Luxembourg: Office for Official Publications of the European Communities.

Orea, L., & Kumbhakar, S. C. (2004). Efficiency measurement using a latent class stochastic frontier model. *Empirical Economics, 29*(1), 169-183.

Patterson, M. G. (1996). What is energy efficiency?: Concepts, indicators and methodological issues. *Energy policy, 24*(5), 377-390.

Sala-i-Martin, X., Blanke, J., Drzeniecki Hanouz, M., Geiger, T., Mia, I., Paua, F., 2008. The Global Competitiveness Index: prioritizing the economic policy agenda. In: PORTER, M.E.,
SCHWAB, K. (Eds.), The Global Competitiveness Report 2008–2009. World Economic Forum, Geneva.

Shi, G. M., Bi, J., & Wang, J. N. (2010). Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. *Energy Policy*, 38(10), 6172-6179.

Taylor, P. G., d'Ortigue, O. L., Francoeur, M., & Trudeau, N. (2010). Final energy use in IEA countries: The role of energy efficiency. *Energy Policy*, 38(11), 6463-6474.

Tsekouras, K., Chatzistamoulou, N., Kounetas, K., & Broadstock, D. C. (2016). Spillovers, path dependence and the productive performance of European Transportation sectors in the presence of technology heterogeneity. *Technological Forecasting and Social Change*, 102, 261-274.

United Nations, Framework Convention on Climate Change, The Kyoto Protocol (2005) [http://unfccc.int/kyoto_protocol/items/2830.php](http://unfccc.int/kyoto_protocol/items/2830.php)

United Nations, Framework Convention on Climate Change, Paris Declaration (2015), [http://newsroom.unfccc.int/media/121166/paris_declaration_r20-summit.pdf](http://newsroom.unfccc.int/media/121166/paris_declaration_r20-summit.pdf)

Wagner, M., & Schaltegger, S. (2004). The effect of corporate environmental strategy choice and environmental performance on competitiveness and economic performance: an empirical study of EU manufacturing. *European Management Journal*, 22(5), 557-572.

Wang, Q., Zhao, Z., Zhou, P., & Zhou, D. (2013). Energy efficiency and production technology heterogeneity in China: a meta-frontier DEA approach. *Economic Modelling*, 35, 283-289.

Wang, Z., Feng, C., & Zhang, B. (2014). An empirical analysis of China's energy efficiency from both static and dynamic perspectives. *Energy*, 74, 322-330.

Wieser, R. (2005). Research and development productivity and spillovers: empirical evidence at the firm level. *Journal of Economic Surveys*, 19(4), 587-621.

World Bank (2009), Tapping a hidden resource: Energy efficiency in the Middle East and North Africa, Report No. 48329-MNA—the Energy Sector Management Assistance Programme.

World Economic Forum, Official web-site available at [http://www.weforum.org/](http://www.weforum.org/).

(last accessed on 10/10/2014).

Zhang, Z. (2003). Why did the energy intensity fall in China's industrial sector in the 1990s? The relative importance of structural change and intensity change. *Energy Economics*, 25(6), 625-638.

Zhang, Y., Li, H., Li, Y., & Zhou, L. A. (2010). FDI spillovers in an emerging market: the role of foreign firms' country origin diversity and domestic firms' absorptive capacity. *Strategic Management Journal*, 31(9), 969-989.

Zhang, X. P., Cheng, X. M., Yuan, J. H., & Gao, X. J. (2011). Total-factor energy efficiency in developing countries. *Energy Policy*, 39(2), 644-650.
Zhang, N., & Choi, Y. (2013). Total-factor carbon emission performance of fossil fuel power plants in China: A metafrontier non-radial Malmquist index analysis. *Energy Economics, 40*, 549-559.

Zhou, P., Ang, B. W., & Poh, K. L. (2006). Slacks-based efficiency measures for modeling environmental performance. *Ecological Economics, 60*(1), 111-118.

Zhu, L., & Jeon, B. N. (2007). International R&D Spillovers: Trade, FDI, and Information Technology as Spillover Channels*. *Review of International Economics, 15*(5), 955-976.

Zhu, Z. S., Liao, H., Cao, H. S., Wang, L., Wei, Y. M., & Yan, J. (2014). The differences of carbon intensity reduction rate across 89 countries in recent three decades. *Applied Energy, 113*, 808-815.
Chapter 7 Conclusions

7.1 Brief Overview

The ample interest of every strand in Efficiency and Productivity Analysis during the last decades has been placed on unravelling the mechanisms and identifying the sources of heterogeneity among the units under consideration so as to guarantee to the most possible extent that the benchmarking process takes places among similar Decision Making Units. Regarding the sources of heterogeneity have been scouted among the ownership scheme of the firm, the managerial ability, the size of the firm, the technology the production entity has access to among others. The latter could be further attributed to resource endowments, productivity differentials, regulations over the production process and past achievements which determine to a significant extent, future developments. All in all, these factors have been explored under the label of “technological heterogeneity”. Efficiency analysis’ empirical literature has been benefited by the introduction of metafrontier, almost a decade ago, which envelops the individual frontiers and accounts for all the possible heterogeneity among the units under examination since the latter are evaluated against the available state of knowledge.

In this thesis, we employ the concept of metafrontier to relax the technological isolation assumption and allow for inter-frontier spillover effects. This is where the technological heterogeneity enters the scene. The introduction of the metafrontier allows for the calculation of technology gap values, which measures the distance of each individual frontier to the best practice that is the metafrontier, used to capture technological heterogeneity and therefore account for spillover effects among the units as the latter embracing productivity differentials and technical knowledge which brings to the forefront the core of the present thesis. In this thesis, we were particularly interested about the distorting role of technological heterogeneity in the benchmarking process. More precisely, we aspired to investigate how technological heterogeneity regimes influence the productive performance of the units of the group under investigation. The latter paves the way to outline the contribution of this thesis.

As mentioned, we investigate the channels via which the technological heterogeneity, captured by the technology gap values, affects productive performance. Considering the fact that productive performance and technology gap values are defined over the same technology set, endogeneity issues arise and we need to study this complicated relationship under a causality framework. Taking into consideration the endogenous relationship between productive performance and technology gaps, considering alternative technological hierarchies to study the odds of exhibiting heterogeneous behaviour, associating the levels of competitiveness to the
absorption of new technical knowledge and exploiting the spillover effects but also disaggregating the overall technology to identify the sources of heterogeneity were among the main contributions of the present thesis.

None of the above would have been possible to study without the unique datasets we devised by combining distinct but complementary databases such as Groningen Growth and Development Centre, Organization for Economic Co-operation and Development Structural Analysis, Enerdata-Odyssey database, EU KLEMS Growth and Productivity Accounts, International Energy Agency, European Commission (DG Budget) and World Economic Forum. The first dataset includes data on seventeen European Union’s countries for thirteen industries –nine of the Manufacturing and four of the Transportation Sector- from 1999 through 2006. The choice of those two sectors is was not random. Since the topic we aim to investigate is that of technological heterogeneity we had to infuse as much as we could so as to unravel the mechanisms underneath. Such being the case we used industries from two distinct yet intrinsically interconnected sectors operating within Europe and are being affected by the same policies and regulations. As far as the second dataset compounded, our aim was to get a broader picture about the effect of technological heterogeneity on productive performance –this time under heterogeneous competitiveness regimes-, so collected data on seventy eight countries around the globe from 2002 through 2011. The diversity of the countries and technology level each one employed was the main reason to such an undertaking in order to get an insight outside Europe or better yet, to study the situation in Europe along with that outside the European borders.

As far as the main findings are concerned, those can be found along the following lines. Throughout the study time persistence of technological heterogeneity, captured by the path dependence phenomenon, appeared to be the major driver of the current performance while there are significant flows, in the form of pure technical spillover effects when the technological isolation assumption is relaxed among the units participating in a technological set, which are triggered be the level of the absorptive capacity of each unit. Technical knowledge, technological opportunities, production capabilities and competencies are enhanced by the combined effect of ability and potentiality to absorb new technical knowledge while any group-specific peculiarities and accumulation capabilities are proved to be of great importance. The technological hierarchy adopted in the benchmarking process found to be significant in terms of the lessons learned and inferences drawn while the disaggregation of the overall technology in order to reduce the heterogeneity among the units to create a more homogeneous environment seems that does not boost performance improvement indicating that technological heterogeneity appears to be
simultaneously the problem and the solution in the benchmarking process. In an attempt to unravel any underlying relationships, a non-linear relationship of a U-shape was brought to the forefront indicating the nested and inherited nature of heterogeneous mechanisms incorporated in the distinct technological regimes.

7.2 Policy Implications and lessons to be learned

The analysis presented in the previous chapters brought to the forefront some useful aspects of the issues examined. These findings could act as guidance, to the most possible extent, for policy purposes.

The most significant finding of this thesis can be argued to be the fact that heterogeneous performance is time persistent, namely the current levels of achievement have been heavily influenced by past ones. The meaning of this argument is found on the idea that production entities, whether those are countries or industries, do not improve any notion of performance from one year to the other since it appears to be hard to escape from regimes of low performance. European agencies and authorities responsible of promoting high performance levels have to take into consideration not only the recent past of each unit but also should consider the importance of the starting point of each unit in terms of technological achievements, and treat each case separately and not collectively since addressing and solving the reason of low performance, is the only way to achieve better performance in the future. That is, the argument that governments’ should target to reach higher performance or competitiveness levels from one year to the other does not appear to be supported by the findings since we document a high dependence of past performance on the current one. Under these circumstances, policies and regulations should be designed and targeted on an individual basis according to the specific characteristics of each entity. Obviously this is a luxury from the standpoint of resources needed, which brings us to the next finding of this thesis.

The analysis revealed that some groups of units exhibit similar behaviour under every specification. This is an indication that those share a robust and persistent set of characteristics which can be used to outline a treatment prescription. The fact that we also identified some technologically heterogeneous units which misfit the benchmarking set provides the opportunity for further analysis on their characteristics. The most prevailing finding is that policies should acknowledge the fact that even though Europe includes a diversified group of countries, not all of them are in the same spot. The so-called transition economics with incomplete market mechanisms cannot be assimilated to the rest the countries and need more time and more structure to achieve so. The regulators have to take that in mind in order to set achievable goals for their league in order to converge to the rest of the European family. In this category fall the
fragmented industries across Europe which are close to be extinct due to the heavy deindustrialization of some countries. Among the “victims” we find the industries of Food and Beverages, Textile products and Air transport. Countries and industries belonging to sensitive groups and exhibit peculiar behaviour, compared to the rest, should be treated differently. Extending the above arguments and in conjunction to the finding that the technological hierarchy matters, regulations should be wisely designed and implemented just because to the different technological regimes. Regulations should be aligned to the needs of these countries and industries instead the other way around, that is each country or industry to struggle to meet requirements cannot be achieved by their resource endowments.

Likewise, the authorities aspiring to reduce the inequality and prosperity differences among the countries around the globe, should acknowledge the fact that an important determinant of the level of competitiveness in conjunction to other country-specific resource endowments. Policies should be targeted to specific groups instead of the totality of the countries due to differences in the accumulation mechanisms in operation within each country. Also, the responsible authorities should have in mind the linkages between the aspects of the economy specific regulations aim at. More precisely, the analysis revealed trade-offs between key notions of the production environment such as the productive performance and the energy efficiency but only for the low competitiveness countries underlying once more the necessity of differentiated treatment among alternative groups.

7.3 Limitations and Weaknesses

By any means, we should not neglect the fact that this thesis is characterised by certain limitations and weaknesses which could potentially undermine and compromise the validity of the conclusions we reached. Those edges are examined below.

The first and foremost limitation of every empirical study is that the researcher has to tackle with data availability issues. Those issues can arise whether due to the fact that the authorities responsible for providing data do not have update the series up to the current period or other circumstances are keeping them away from doing so, such as the burst of the economic recession during 2008. The latter is the reason why we have not included more countries, industries and years to our analysis. Eventually, our choice was to reduce the dimension of our dataset in favour of including data which would have potentially been affected by the onset of the financial depression. The rather limited time window potentially can undermine the generalization of our results since a more extended time horizon could induce much credibility to the conclusions drawn.
The second strand of scepticism regards some aspects of the empirical analysis. More precisely, the fact we have treated each year of production activity separately, that is we have estimated the productive performance scores, the technology gap values and the energy efficiency scores in a cohort-by-cohort basis could be considered as a controversy the second stage analysis where we introduce the time persistent pattern of performance. In particular, this could doubt the resulted of the estimation from the dynamic panel models we have used employed. That is despite the fact that each year has been treated as a different production function, we have used the panel dimension to account for each year’s production heterogeneity. To the defence of the empirical strategy, by treating each year as a different production function, we therefore admit that the quality of the inputs and outputs does not remain constant each year but undeniably has incorporated past information-, and consequently this affects the production technology as it introduces more heterogeneity to the analysis providing the opportunity to account for this extra heterogeneity on an annual basis throughout the period of study which in conjunction to methods used (see Mundlak’s devise) , we capture the individual heterogeneity on a panel dimension. Moreover, it is reasonable to assume that the economic environment does not remain the same year after year so we can also capture latent aspects of the technological heterogeneity in order to study the set persistent heterogeneous behaviour and year heterogeneity.

Another aspect of criticism might be the nature of the technological hierarchies examined herein. This could be attributed to the fact that there are infinite heterogeneity types but we choose to focus on specific ones whether is for the case of the DMU-specific heterogeneity and Hierarchical Structural Heterogeneity or for the case of heterogeneous competitiveness regimes. The rationale behind that choice comes from the work has emerged through the literature which for the time being has dedicated significant resources to explore the structures examined herein. Our approach aspires to move one step ahead the body of evidence by exploring the causal linkages between the two and at the same time exploring the potentials of additional factors of clustering. The latter, brings us to the next point of criticism.

The factor against which we created the competitiveness clusters can be a point of criticism since other factors such as income class, are available from the World Bank and have been used to other empirical studies. The fact that we could decompose the global competitiveness index to its pillars also raises could also be a weakness. Suffice to say that we have chosen to rely on this index as a holistic measure of a country’s competitiveness embarrassing the same factors across countries and due to the fact that it allowed us to proxy the absorptive capacity which is a under-researched issue in the literature.
Concluding, the comment about the alternative hierarchies could be combined to the nature of the data. Despite the fact that the data employed are of nested nature, the hierarchical approach we attempted did not prove to be quite fruitful. Such being the case it could be thought of as insignificant and could be left out of the presentation. Indeed, exploring the effect of the level of technological hierarchy did not appear to produce any worth presenting results. Viewed from another angle, the fact that we aimed at exploring the effect of multiple hierarchical levels through an empirical methodology which is designed to tackle with such structures but it failed to deliver the desired results, is by itself worth-mentioning since it pinpoints towards the fact that even if additional hierarchical structures can be defined and considered, it is not a sufficient condition to reveal the sources of technological heterogeneity. That is, even if the latter exist, the amount of information in order to identify the sources of heterogeneous behaviour is rather limited. The moral from this exercise, although seemingly unnecessary, it led us to the conclusion that technological heterogeneity is nested on low aggregation levels but it only reveals its mechanisms when the maximum level of aggregation is achieved mainly because under complete heterogeneity the odds of making the difference are much higher.

7.4 Further Research

The analysis presented in this thesis could be beneficiated by possible extensions of the issues examined herein along the following lines of research.

Considering the data availability as a necessary condition for further investigation to draw inferences for the role of technological heterogeneity on the productive performance of the units under examination, more industries of the manufacturing sector could be considered so as to examine the impact of technological heterogeneity and their relative position compared to the European level of technology. As more industries are examined, we could get a spherical view about the mechanisms of the manufacturing technology and we could also identify sub-groups sharing similar characteristics and performance. Then, we could examine those industries to extent the results drawn and investigate how the scheme has altered –if it has indeed- namely, how the inclusion of more (heterogeneous) production entities has contributed to our understanding of the underlying mechanisms of technological heterogeneity and its distorting effect on the benchmarking process.

On the condition that the dataset we already have devised remains as it is, there are some more issues that could be possibly examined accompanied with a carefully designed identification strategy. More precisely, we could focus on the set of industries and countries were identified as technologically heterogeneous and try to investigate the characteristics those have in common so as to stress a pattern or better yet a topology of the sources of heterogeneity across Europe and
sectors. Then, the importance of time persistence along with the initial conditions and level of competitiveness might trace a path to better policy intervention designs to benefit those countries and industries to escape of the loop of low performance.

Another worth investigation aspect of the analysis developed in the above chapters, can be found along the lines of the partition criteria to create alternative technological hierarchies so as to examine, compare and contrast the role as well as inter-linkages of the alternative technological hierarchies and their impact on the time persistent heterogeneous behaviour of the units under examination. The validity of the iterative algorithm presented above could be examined simultaneously.

Furthermore, the attention could be placed on the units performing really well under any technological hierarchy and attempt to identify the driver for such a performance along the lines of absorptive capacity and past performance levels. Extending this argument, we could focus on the pattern of productive performance scores in conjunction to the technology gaps by specifying performance thresholds, to identify sub-groups, or in other words technology clubs, of units with similar characteristics so as to control for technological heterogeneity to some extent in order to reveal the real drivers of the performance the latter exhibit.

Another interesting research extension would be to calculate the environmental efficiency scores by employing the technique of directional distance functions, of the industries and units and compare the latter to the energy efficiency scores so as to investigate if the champions of the energy efficiency are champions of the distribution of the environmental efficiency score and investigate whether there is a connection between those two. Once more, endogeneity issues should be taken into consideration since those are also defined on the same technology sets and one might trigger the other. By any means, this is an issue which is under-investigated by the related literature which could be beneficiated by studying the issue under a causality framework in conjunction to possible non-linear effects.