LANCASTER UNIVERSITY MANAGEMENT SCHOOL

"ESSAYS ON THE EFFECTS OF CLUSTERS AND NETWORKS ON INDUSTRIAL GROWTH DURING THE GREAT RECESSION AND OTHER PERIODS OF INDUSTRIAL SHOCKS"

by

JULIO JOSE PRADO LUCIO PAREDES

THESIS SUBMITTED IN FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

DECEMBER 2016

This thesis is entirely dedicated to my family:

Sole, Anto, Sammy and Joaquín.

You have been the inspiration and the motivation behind every single step of this journey.

Les adoro.

ACKOWLEDGEMENTS

I would like to thank first and foremost my supervisors, Dr. Hilary Ingham and Dr. Robert Read, for all the help and guidance provided throughout these years. Your professional and personal counselling surpassed this thesis. The final version of this thesis has benefited from suggestions made by two reviewers, Dr. Allan Webster and Dr. Kwok Tong Soo, to whom I am grateful. I would also like to acknowledge the support from my PhD colleagues, professors and staff from the Management School and the Economics Department at Lancaster University. I am especially thankful for the advice and friendship from Dr. Ricardo Zozimo.

I would also like to acknowledge the financial and professional support given by IDE Business School in Ecuador. This doctoral thesis has been partially funded by a scholarship offered by the Ecuadorian Government through SENESCYT.

ABSTRACT

This thesis sets out to analyse the effects of diverse forms of geographical location and network structures on industrial growth and business cycle co-movement. The initial focus is on the analysis of the effects of clusters on industrial growth to determine whether clusters can cope with industrial shocks. Next, in order to fully understand the complex relationships that characterise modern industries, the concept of industrial network is used to analyse the input-output global trade relationships to determine if the network characteristics of an industry can affect growth and co-movement. In that sense, this thesis offers a comprehensive review of the determinants of growth at industry level by analysing industrial growth in a broad range of settings; from a geographically-tied clusters definition to a broader network approach using novel techniques and datasets.

On one hand, the results suggest that clusters are relatively neutral; they do not promote higher growth in the presence of a positive national shock and neither do they generate a lower probability of being hit adversely by an economic downturn; location alone may not capture the full scale of relationships that constitute a cluster. On the other hand, the empirical study of industrial networks suggests that some network characteristics affect industrial growth. The most important finding is that industries that have greater co-movement are also those that have higher rates of growth during periods of global economic expansion as well as exhibiting more rapid declines in the face of global economic contraction.

If the centrality of an industry is revealed to be an important transmitter of both global economic growth and downturns, as this thesis suggests, then investigating these phenomena more deeply should be high on the global research agenda.

TABLE OF CONTENTS

LIST OF TABLES AND FIGURES

Chapter 1

Introduction

1.1 Motivation and Context

This thesis began to take shape in the years following the global financial crisis that started in the year 2008 and hit almost three out of four OECD economies. The widespread and long lasting effects of the so-called Great Recession, provoked a heated debate among politicians, practitioners and academics, regarding the usefulness of traditional economic tools to provide adequate answers as to how the crisis started and spread so rapidly at the global level. Among the many issues that were being debated when this thesis was being conceptualised were the mechanisms of shock transmission from specific industries to nations (Acemoglu*, et al.*, 2010), inside a specific industry (Gai*, et al.*, 2010 ; Mendoza*, et al.*, 2010), transmission through multinational firms (Burstein*, et al.*, 2008), from industry to industry at the global level (Kali*, et al.*, 2010) and from country to country (Dong, 2012 ; Fidrmuc*, et al.*, 2012). Most of the papers mentioned above focus on the effects of the financial crisis, or try to investigate the effects of a financial shock in other industries.

This small sample of studies mentioned show how the Great Recession influenced the research interests of a large -and rising- number of scholars. Moreover, there has been a noticeable increase in the use of new techniques to understand shock transmissions. Network theory, Graph theory, Agent-based modelling, and complexity tools are among the most used in the aftermath of the recent global crisis. It is argued that some of these new approaches may provide a better framework to analyse the complex interactions that characterise the global economy and may also offer new insights and some answers to the questions that policymakers are asking from scholars (Geyer*, et al.*, 2010 ; Colander*, et al.*, 2014).

This thesis focuses on the effects that different types of industrial structures have on industrial growth and downturn. Specifically, two types of industrial structures are analysed; the industrial agglomeration and the industrial network. The first one represents the traditional way in which the literature has dealt with industrial growth, generally tied to a specific location or region, following the concepts from Von Thünen (1826), Marshall (1920) and Porter (1990). The second one -the industrial network- is a more recent approach that is not necessarily tied to geography and is more interested in the structure of the network created and the interaction between its industries. The industrial network is a concept that combines tools from graph and network theory (Watts (2002, 2004) and Albert*, et al.* (2002)) with the economic concept of input-output linkages to create a visual representation of the industrial relationships, from which specific metrics that describe the structure of the network can be obtained. Recent efforts to analyse industrial networks in such a way include Fagiolo*, et al.* (2007) 'World Trade Web', Kali*, et al.* (2010) 'International Trade Network', and De Benedictis*, et al.* (2011) 'World Trade Network'.

The pressure that the global recession puts on local and national government is forcing them to adopt certain industrial policies that may not produce the expected result. For example, there are an increasing number of regions and cities that are adopting an industrial development strategy based on geographic agglomerations, often called 'cluster policy'. Clusters are one of the most widely used tools in regional policy, such that some authors are talking about a 'cluster momentum' that has regained popularity after in the light of the recent global crisis (Muro*, et al.*, 2010). The positive and negative effects of industrial agglomerations are well known and have been analysed by prominent scholars (e.g. Marshall (1895), Jacobs (1961, 1970b), Porter (1990) and Krugman (1991)). However the specific effects of clusters on industrial growth and downturn have scarcely been analysed even though many policymakers are trying to 'create' clusters motivated by the large success of agglomerations like Silicon Valley, California; Cambridge, UK; Medicon Valley near Copenhagen; Emilia-Romagna in Italy; Bavaria in Germany, centred in Munich; the Sophia Antipolis technology park in France; and Hsinchu Science Park near Taipei (Yusuf, *et al.*, 2008; p.2).

The Great Recession is not only putting pressure on policymakers but also on scholars, especially in the field of economics. The inability of the traditional tools and models to help policymakers and practitioners to make decisions in real time, as the crisis was developing, has been widely criticised. As a result, an increasing number of researchers are trying to look at old and new economic problems using different tools and frameworks, trying to find a –potentially- better way to analyse some economic issues. The research presented in this thesis is in line with these recent efforts reported in the literature.

1.2 Objectives

The general objective of this research is to analyse the effects of diverse forms of geographical location and network structures on industrial growth and business cycle co-movement, specifically during periods of global economic shocks like the one experienced during the Great Recession. In order to operationalize the research, the thesis is divided in three empirical chapters with specific research objectives.

The first empirical chapter explores the effects of clusters on industrial growth and tries to determine whether clusters can help to promote the effects of a positive economic shock and mitigate the effects of a negative one. Clusters are a recurrent topic of analysis and discussion both among academics and practitioners (Martin, *et al.*, 2003), with almost every region in Europe having some kind of cluster policy -either explicitly or implicitly- in place (Ketels, 2003).

Nevertheless, the relationship between economic shocks and clusters has scarcely been analysed in the literature. This empirical chapter will tackle this research gap. Given the popularity of clusters it is expected to find a significant impact of clusters on industrial growth that justifies this 'cluster momentum'. Nevertheless, the literature has no definitive answer. It has been reported that the findings are highly dependent on the type of clusters chosen for the analysis and the lack of a systematic method to define clusters (Spencer*, et al.*, 2009). A recent study by Rodríguez-Pose*, et al.* (2011) that uses a large dataset, similar to the one used in Chapter Three of this thesis, finds that the effects of clusters on growth are highly heterogeneous and are highly dependent upon some regional and industrial characteristics.

The second research chapter tries to analyse whether the network characteristics of an industry can determine its growth. It is increasingly argued that in order to fully understand the complex relationships that characterise modern industries it is necessary to look beyond geographic agglomerations and embrace the concept of industrial networks (see for example Reyes*, et al.* (2010) ; Kali*, et al.* (2013), & Hausmann*, et al.* (2011a)). Thus, the objective of the second empirical chapter is to use tools from network theory to analyse all the complex input-output global trade relationships.

The third, and final, empirical chapter analyses the effects of industrial networks on the business cycle co-movement. The analysis of co-movement is particularly important since industries with higher co-movement may have the ability to drive global growth during periods of prosperity but may also create a contagion effect during periods of downturn. Using data from the industrial network developed in the second empirical chapter, the work in this chapter tries to determine if the network characteristics of an industry; for example, its centrality or its number of connections can determine its co-movement, or if, on the contrary, higher co-movement is characterized by traditional characteristics like industry size, number of employees, trade openness, etc.

In the case of the two chapters that use networks analysis, the expectation is to find that some network characteristics can affect both industrial growth and co-movement. There is no prior expectation as to which of the network variables will be more significant, or have a larger impact on the dependent variables analysed, since there is scarce literature that looks at the role of global trade networks and growth and co-movement.

1.3 Discussion on the Methodology.

This section will cover a broad review of the methodology and the philosophical background that lay foundation of this research. Due to the specific nature of the methods and data used more information is provided in each empirical chapter.

The XVIIIth century is a well known period for the modern economists. It was at that moment, more than 250 years ago, than the scientific foundations of the economic theory as we now know it took place. There is consensus that the birth of modern economy can be exactly placed in 1776, the year in which Adam Smith published his seminal work (Smith, 1776). But, there are two other -almost equidistant- events that took place as Smith was writing his book that would greatly and decidedly change economy (and society) forever: the French revolution and the industrial revolution in Britain (Sharp*, et al.*, 2012).

Given the nature and the type of work that will be conducted for the PhD thesis, the analysis of the events that took place in the XVIIIth century are of major importance, not only for the research itself, but also for to justify the philosophical approach that has been chosen. This will become clear, as we advance further.

One important question that has arisen in the context of the industrial revolution is: why it took place in Britain and not in other countries? And why it took place in some specific places of the northern part of England (Liverpool, Manchester, Lancaster, Sheffield...), rather than in southern

England (which was at the end of the XVIIIth century was a fairly more socially and economically developed region)? It is this later question, that has created a vast amount of research and theories, involving what is now known as the field of economic geography, and although hundreds of papers have being written on the industrial revolution causes and consequences, the specific topic of geographic location is still a matter of modern debates and research (Broadberry*, et al.*, 2008).

It is these same questions, posed in some cases, more than 200 years ago, that inspired this research. The initial struggle of some firms to enhance their productivity during the 1st wave of industrialization from 1760 to 1831, the massive improvement on productivity and the socio-economic conditions of the industrialized regions during the 2nd wave of industrialization from 1831 to 1899, and the decline and post-industrial crisis of the regions during most of the XXth century (Crafts, 1995). These historical issues create a good background to analyse modern issues related to economic geography and industrial growth, specifically, the effects that industrial agglomerations have on growth at regional level and also analyse whether the network characteristics of an industry can determine its growth and its comovement pattern.

Philosophical approach

It is believed by the researcher, that the economic phenomena investigated is part of the reality and can be objectively interpreted, quantified and measured. Causal relationships can successfully be applied to analyse the topic at hand and some robust conclusions, about the nature of the relationship between the variables are expected to emerge as a result of a scientific research process. From an epistemological point of view, the research will have a positivist approach. This approach is also in line with the vast majority of the literature in the field. It might be appropriate at this time, in order to clarify the choice of positivism, to go back to the roots of scientific knowledge in economics.

The first specific and conscious description of the economic method, was done many decades after Smith's *Wealth of nations* and Ricardo's *Principals of political economy,* by two British authors: Senior in 1827 and Stuart Mill in 1836 (Hunt*, et al.*, 2011). *To them, is attributed the separation between positivism and normativism in economics, that still exists today. The work of these two economists, was directly based on the writings of the great Scottish philosopher David Hume, who almost a hundred years ago before them, created a clear distinction between facts and values, also known as a difference between descriptive and prescriptive statements. Much later, this distinction would be called by Black (1964) "Hume's Guillotine".*

While positivism is more concerned about the description of the economic facts, normativism is concerned with the prescriptive side of economics, not what "is" but what is "ought to be" (Blaug, 1992; p.113). The research in this thesis will follow a descriptive methodology, associated with positivism.

A debate on the methods

According to Boumans (2010);p3 a scientific research should not only be concerned with the "why", the methodology, in this case positivism, but also with the "how", the methods.

Most of the classic economists and scientists from the XVIIth up to the XIXth century are generally grouped as empiricists (although this is debatable under a Popperian approach, as we will see). They conducted experiments, observed reality, tried to come up with new explanations for the problems and when possible, they created new laws and theories. This is an inductive scientific method, and this is the one that will be followed throughout this PhD thesis.

The use of the inductive method in this research will be framed in what is known as the "Samuelson method" rather that a "Newtonian method". Let us clarify. Even if *Principia* (Newton, 1687), is considered one of the most influential books in history, it is now believed by some authors that there was no such thing as a scientific method in Newton´s work, certainly not in the terms of the scientific method that Popper and other proponents of the "hypotheticodeductive" described. Newton, as Keynes (1946) described him, *"was not the first of the age of reason. He was the last of the magicians, the last of the Babylonians and Sumerians, the last great mind which looked out on the visible and intellectual world with the same eyes as those who began to build our intellectual inheritance rather less than 10,000 years ago".*

The stream of empiricism that will be used during this research, is influenced by the work of the economist Paul Samuelson, who was a positivist, but was opposed to the deductive method as depicted by Popper (1959) in general terms and by Friedman (1953) in economic terms. By the second half of the XXth century, Friedman implied that a theory doesn´t need to predict reality, it just needs to predict specific economic event with some degree of accuracy. Friedman goes even further into an extreme form of deductive approach, when he says (quoted by Boumans (2010);p44) *"[if a scientist is] unable to fit data into an equation this is more a test on the skill and patience of the analyst, rather than a test of validity [of the theoretical model]".*

As a counterpoint, Samuelson in line with the Vienna Circle's "logical positivism", describes the problems of a purely deductive approach and stresses that (as quoted in Boumans (2010);p54):

> *Scientists never explain any behaviour, by theory or by any other hook. Every description that is superseded by a deeper explanation turns out as a careful examination to have been replaced by still another description, albeit possible a more useful description that covers and illuminates a wider area.*

This very fruitful debate between Friedman and Samuelson, that shifted most of the economic research from the *a priori* methodology to *a posterior*, is summarized by Hausman (1989), as follows:

> *Milton Friedman tells economists that good theories are those that provide correct and useful predictions, while Paul Samuelson tells economists to formulate theories with operational concepts that are, ideally, logically equivalent to their descriptive consequences.*

Returning to the topic at hand, this research will mainly focus on the inductive approach described above and econometrical techniques will be used to analyse industrial data from different countries and regions in the world. . Theoretical assumptions will be made to create an econometrical model that describes the reality of the industrial clusters and networks analysed. As the data will come mainly from reliable secondary sources, the research will be conducted using detached techniques that will allow maintaining the objectivity and validity of the results.

Brief discussion on the data

Given the approach described in the former paragraphs, the research will used data at the industry level to test the hypothesis and research questions.

Two main datasets are used to conduct the quantitative analysis. The specifics of the collection and transformation process are explained on each of the corresponding chapter. For the first chapter, the research needs to put together a dataset that allows to analyse the economic effect of industrial clusters on industrial growth while controlling for a large number of social, demographic and economic variables. Since the cluster phenomema needs to be understood at disaggregated level of geography and not a the national level, all the data collected needs to available at the province level. In the case of Europe that would be NUTS2 level of data. A data set that has been reported in the literature in a similar type of research (see Rodríguez-Pose*, et al.* (2011)) that has all the characteristics mentioned above is the one put together by the European Cluster Observatory (ECO).

Data collected by the ECO is used as the main source at industry level along with data provided by Eurostat. It offers the most comprehensive database for clusters in Europe, it is easily accessible and reliable and their data cover 15 European Countries, with detailed information for 409 regions at NUTS-2 level from 1995 to 2008. Another positive aspect of ECO Database in terms of this research is that ECO creates a definition of industrial cluster that is very simiar to the one used in this research, that is, it reflects the nature of inter-relations between industries and allows to operationalise the cluster concept. Instead of aggregating industries in the hierarchical way, as the European classification system specifies, ECO combines industries from different parts of the classification system.

For the second and third empirical chapters, the objective is to analyse the effect that the characteristics of the global industrial network has on a number of important variables. This poses an interesting challenge in terms of the dataset since in order to analyse the complex interactions in the global industrial network, a very large dataset that contains information a industry level for a large number of countries, possibly the whole world, is difficult to obtain. To capture the complex nature of international trade linkages, a dataset containing the Input-Output (I-O) matrix for each country in the sample is used (a full description of the characteristics of the dataset can be found in Erumban*, et al.* (2011)). The interesting characteristic of this particular dataset is that it includes data on internal use and consumption for each industry at national level as well as trading partners for each country.

Conclusion

A brief historical review of the main philosophical issues that influenced the topic chosen for the PhD thesis and consequently the methodological approach has been carried out in the preceding paragraphs. From an epistemological point of view, this research is placed in the context of the observed reality and specifically the phenomena that contributed to the observed industrial growth and location of industries in specific geographical clusters, thus the choice of positivism based on descriptive capabilities of the hypothesis, the relevance of the data collected and the belief that an objective research can be conducted. Based on the belief that an empirical research is needed in order to correctly validate the hypothesis, and knowing the risk involving an *a priori* deductive method, the inductive method has been pointed out as the more suitable for the PhD research.

1.4 Overview of the statistical methods and data.

This section will present a brief discussion on the data and the methods used in each of the empirical chapters.

First Empirical Chapter

In this chapter, data collected by the European Cluster Observatory (ECO) is used as the main source at industry level, as well as data provided by Eurostat. ECO is a project managed by the Centre for Strategy and Competition at the Stockholm School of Economics, funded by the European Commission Directorate General Enterprise and Industry. At the moment of the data collection, the ECO offered the most comprehensive database of industrial clusters in Europe. Although some critiques have been raised (Crawley, *et al.*, 2012) regarding the methods used by ECO to identify clusters, their data and methods is in line with the cluster definition used in this thesis, and is easily accessible and reliable, covering 15 European Countries with detailed information for 409 regions at NUTS-2 level from 1995 to 2008.

The sectors created by ECO, reflect the nature of inter-relations between industries and operationalize the cluster concept, in this sense, instead of aggregating industries in the hierarchical way, as the European classification system specifies, the ECO combines industries from different parts of the classification system. This characteristic separates this dataset from others and offers a unique opportunity to analyse the concept of cluster as a collection of inter related industries as opposed to traditional method that includes analysing only the geographical location of industrial agglomerations. This is useful to tackle the research questions proposed in this thesis. Some caveats derived from the way this dataset is constructed are discussed in Chapter Three. For this specific analysis, data from the ECO at sector level for France was chosen, which includes 40 sectors in 22 regions from 1996 to 2008. As a robustness analysis a dataset for Germany consisting of 33 regions and the same 40 sectors is used from 2000 to 2007. The model estimated in this chapter follows the work done by Rodríguez-Pose*, et al.* (2011).

The dataset described in the former section consists of a collection of data from sectors and regions with observations available over 12 years. Given the characteristics of the data, a panel technique is chosen to estimate the empirical model. Using the region and the year as a pivot, a total of 40 estimations using the same method were carried, one for each sector. Alternatively, a Linear Probability Model could have been used but as it well known in the econometrical literature, this method has a large number of caveats, thus using a LPM would be problematic. The option of using a Pooled-OLS would imply assuming homoskedasticity and no serial correlation in the data, which is not the case in this particular dataset. Using either a random or fixed effects panel is the best method since the offers increased precision of regression estimates and the repeated observations on individuals allows for the possibility of isolating the effects of unobserved differences between observations.

The initial dataset consists of observations ranging from the year 1996 to 2008, but as stated in the methods section in chapter three, by construction the dependent variable is binary, a probit panel is used for the estimation. Fixed effects models are ineffective when using a probit panel (Wooldridge, 2001), thus the options are a random effects or a population average model. Given the characteristics of the dataset, consisting of non-independent observations for different industries, a population averaged model is used.

Estimating the main equation in this empirical chapter requires a large process of constructing the variables and processing the data; this process is presented in detail in Section 3.3.

Second Empirical Chapter.

The concept of industrial network that is analysed both in the second and third empirical chapter, tries to overcome the location and geographical restriction that is tied to the concept of clusters by looking at industrial linkages as a complex system. More specifically the second chapter tries to analyse the effects of industrial network characteristics on periods of growth and downturn at industry level. In order to address this research project a highly comprehensive database must be used since the objective is to analyse interactions between industries at global level. The main regression specified in this chapter follows the model of economic growth originally presented in Kali*, et al.* (2007) at national level, and the adaptation to analyse growth in the global network at product level Kali*, et al.* (2013).

Due to data constraints the previews empirical literature, has only been able to analyse either one or a couple of industries at a time, limiting the interactions at country level or at industry level inside one particular country. In order to overcome these limitations, this thesis makes use of a recently published dataset, the World Input-Output Database (WIOD) that includes input and output data for a large number of countries and industries in the world. The effort in constructing this particular dataset is tremendous since the authors have managed to create a global matrix of industrial trade that was not been available until now. No other dataset known by the author, at the moment this research was conducted, would allow constructing this global International Industrial Trade Network.

This dataset will be used in the context of this research in order to construct a global trade matrix, which consists on data for 35 sectors and covers the entire global trade (41 countries and one group representing the rest of the world). The result is a directed network in which each node represents an industry and each edge (or link) represents a trade relationship between two industries. Various metrics for the characteristics of the nodes (at industry level) and the network (at country level) are obtained. These metrics are the backbone from the second empirical chapter and will also be used as explanatory variables in the third empirical chapter.

The dataset used has the structure of an unbalanced panel consisting of 1,470 observations *(N)* and 4 years *(T)*. The small time-series component could be considered to be insufficient to use panel method techniques but, according to Wooldridge (2001; p.251), the asymptotic assumption is still valid even in panels with small T, as long as N is sufficiently larger compared to T.

Given the panel structure of the dataset, the existence of correlation between the explanatory variables and the error term is analysed. To do so, a random effects model and a fixed effects model (within estimator) are both fitted. A Hausman test suggests that the Xs in the model are correlated with error term thus rendering a random effects approach biased and inconsistent. Based on this evidence, the main equation in chapter four is estimated using Fixed Effects, which means that the unobservable characteristics are treated as fixed and removed from the equation using a de-meaning process. The estimation is conducted using robust standard errors clustered by industry.

Alternatively, a pooled OLS method could have been used, but that would average all the data sets and create one single constant, this method could be used if the Xs where not correlated with the error term, but this is not the case, otherwise the results could be inconsistent. So a Fixed Effects Panel is still the best choice to consider de individual characteristics of the industries.

Third Empirical Chapter

This chapter investigates the characteristics of global industrial comovement. In order to analyse the complex interactions that characterize industrial linkages, a fifteen-year time series of valued added correlation is combined with trade intensity data into a network analysis. The result is a Global Comovement Network that represents all the significant links between 35 industries both at national and international level for a sample representing a large fraction of world trade. In a sense, this chapter expands the research and findings presented in the previous chapter. As before, this particular dataset offers exceptional information that is not available elsewhere.

This chapter brings together two strands of literature by analysing global business cycles co-movement under a network framework; a combination that is rarely analysed at the country level and remains unexplored at the industry level. To do so, correlation data of value added for each pair of industries in the sample from 1996 to 2009 is combined with trade intensity data to create a representation of the global co-movement network consisting of 1,437 nodes (industries) and 1,030,330 links (pairs of industries weighted by value added correlation). A description of the empirical literature that influenced the model used in this Chapter can be found in Section 5.2, mainly the work done by Kose*, et al.* (2006) and Di Giovanni*, et al.* (2010).

Data of real Value Added (VA) by industry, from the World Input Output Database (WIOD) is used to calculate the comovement of business cycles between pairs of industries in the sample. In order to obtain a measure of the cycles, the VA series is de-trended using a Hoddrick-Prescott (HP) filter. After de-trending the series of VA, the spearman correlation for each pair of the 1437 industries in the sample is obtained using time series of fourteen years, resulting in 1.030.330 pairs of correlations. This measure has been referred in the literature as being an adequate measure of business cycle comovement, in this case obtained at industry level. This will be the dependent variable in the econometric model analysed in chapter five. The process of constructing that are estimated in chapter five is long and involves a number steps that are clearly presented in Section 5.2 and the rest of the variables used to estimate the main equation are explained in Section 5.4.

The model that is used in chapter five, is estimated using ordinary least-squares (OLS) with robust standard errors. As it was reported earlier, the dependant variable, comovement, is time invariant, thus a different estimation method, for example a panel with fixed effects, is not feasible. Estimating the model by using an OLS for each year in the sample instead of pooling the data is more convenient to tackle this research since the objective is to analyse the specific effects of the independent variables on comovement, before and during the great recession, thus having a separate regression for each year will become convenient for interpreting of the results.

1.5 Overview of Principal Findings

The first empirical chapter tries to analyse whether industrial clusters cope better than non-clustered industries with regional and national shocks. Although the research on industrial agglomerations and clusters is vast, the specific interaction of clusters and economic crises has scarcely been tested. Given that cluster policy is being widely adopted as a tool to minimise the effects of economic crises and improve regional economic and employment growth (Muro*, et al.*, 2010), this lack of attention is perhaps surprising. To tackle this gap in the literature, an econometric model is constructed using a regional positive/negative shock as a dependent variable to test the interaction with clusters at the regional level in 40 sectors in France and Germany for the years between 2000 and 2007.

The findings of the empirical analysis show that the positive or negative effects of clustering are highly heterogeneous and depend upon both the type of industry as well as the regional characteristics. For the large majority of industries, the results suggest that clusters are relatively neutral; they do not promote higher growth in the presence of a positive national shock and neither do they generate a lower probability of being hit adversely by an economic downturn. The findings, in accord with the conclusions in the literature by Gardiner et al. (2011), & Rodríguez-Pose*, et al.* (2011), provide evidence in support of the view that the effect of clusters may have been overstated, both in the academic literature and policy strategy. A conclusion resulting from the findings, which is especially interesting from a policy point of view, is that location alone may not capture the full scale of relationships that constitute a cluster and, specifically, the flow of knowledge within the cluster (Pinch*, et al.*, 2003 ; Giuliani, 2007). Thus, policymakers trying to replicate successful cluster experiences in a particular region without considering the regional, historical and institutional context may fail to obtain the desired results from such a policy.

The second empirical chapter tries to analyse whether the network characteristics of an industry can influence its growth rate. As the complexity of international trade connections has increased, the question of industrial growth has ceased to be solely confined to the geographic location. This leads to the question of what determines the growth of an industry that is part of the international trade network? This is an issue that has not been properly analysed in the literature. To tackle this research, the chapter adopts a quantitative analysis to determine the effects of industrial network characteristics in periods of growth and downturn at the industry level. An International Industrial Trade Network matrix is compiled using data that covers the entirety of global trade for 35 sectors between the years 2006 to 2009, the years of the Great Recession. The results from this empirical study suggest that some network characteristics affect industrial growth. The most important finding is that both density and centrality appear to affect it, although in a small magnitude. The findings suggest that the use of network metrics can be useful to understand the impacts of global trade on industrial growth, but in order to fully analyse the interaction between networks, industries and trade a different empirical analysis is needed. This is what the third empirical chapter sets out to achieve.

To further understand the dynamics of industrial growth in a global context, the concept of business cycle co-movement is analysed in the third empirical chapter, using tools from network theory. This is a combination that has been scarcely analysed at country level and remains unexplored at industry level. To do so, correlation data of value added for each pair of industries in the sample from 1996 to 2009 is combined with trade intensity data to create a representation of the global co-movement network that tries to capture, as best as possible, the intricate linkages and interconnections that exist, both inside a country and in the global network.

The most important finding is that industries that have greater co-movement are also those that have higher rates of growth during periods of global economic expansion as well as exhibiting more rapid declines in the face of global economic contraction. Taking these findings together, industries with a greater centrality are more important disseminators of economic growth but are also important transmitters of crisis. This conclusion is important in the context of both future research and policy implications. If the centrality of an industry is revealed to be an important transmitter of both global economic growth and downturns, then investigating these phenomena more deeply should be high on the research agenda.

Chapter 2

General Literature Review

From Industrial Agglomerations to Industrial Networks

There is an abundant literature related to industrial agglomerations that can be traced back to the beginning of the nineteenth century. Since then, agglomerations have gained, lost, and regained momentum depending on a number of factors. The concept of agglomeration has retained most of its core characteristics over time, but in the recent decades there have been important changes in its conceptualization. There are two views that are worth discussing in detail: First, the industrial cluster that was highly popular during the nineties and is still one of the most discussed and analysed topics in industrial economics and industrial policy, and, second, the industrial network which is a recent addition, but also a highly promising area of research. The following review explores and discusses these concepts, all of which have regained relevance in the years following the Great Recession.

2.1 Industrial Agglomeration

There has been a noticeable increase in the volume of the academic and policy literature relating to industrial agglomeration in the last twenty years, but in order to properly understand the issues surrounding this it is necessary to return to the seminal contributions of Heinrich Von Thünen and Alfred Marshall. Although still highly popular, this classic view of industrial agglomeration was contested in the second half of the twentieth century by Jane Jacobs and her disciples. Both types of agglomerations, the Marshallian and the Jacobean, are discussed in the following pages.

2.1.1 Von Thünen: The Grandfather of Location Theory

The foundations of economic location theory have their origin in the first wave of the industrial revolution in Germany during the early years of the XIXth century. Von Thünen, whose work was almost forgotten for more than a century, published a paper describing the economic process behind the agricultural organisation used in a small region of Germany and laid the ground for his seminal book *The Isolated State* (Von Thünen, 1826). He *"(...) not only ... created marginalism and managerial economics, but also elaborated one of the first models of general equilibrium and did so in terms of realistic econometric parameters."* (Samuelson, 1983; p.1468). Although David Ricardo (1971) provides some insights on productivity and the use of land, Von Thünen was the first to explicitly find an explanation for the patterns found in agricultural locations (Dickinson, 1969). His main question is interpreted as being: "*How will the land be allocated if there is free competition among farmers and landowners with each individual acting according to his perceived self-interest?"* (Fujita, 2010).

During Von Thünen's time, agriculture was still the most important sector in the economy, even if in Great Britain the industrial revolution was changing that reality In Germany, it took a longer period to see such results. That is why most of the work done in first volume of *Isolated State* was mainly about agriculture. Nevertheless, he seemed to be ahead of his time in many things. In the second part of the book, Von Thünen ((1826); especially from p271 to 286), makes a very simple but powerful explanation of what he considers to be the main reasons why industrial agglomerations will emerge, and he states both the centrifugal and centripetal forces that -we now know- act on every modern agglomeration. This part of his work would directly inspire Marshall (1895), Porter (1990) and Krugman (1991).

The reason for agglomerations in the city centre (*centripetal forces)* can be summarized in:

1. Natural or strategic resources: Due to the uneven distribution of inputs needed by

industries, the best location will be in the large town where all of these are available at once. So it can be said that access to strategic resources is one driving force behind clusters. Modern scholars have found evidence both that support (Carlton, 1983) and reject (Ellison*, et al.*, 1999) this statement.

2. Institutions: Institutions (government, military, educations, etc.) are naturally located in the main town. A recent study by Martin*, et al.* (2010) confirmed this statement and found that industrial agglomerations are heavily correlated and dependant on culture and institutions.
3. Culture: Social amenities such as museums, clubs, theatres, etc. are located there. Thus, providing intellectual and cultural reasons to locate there. This could be one of the first interpretations of what we now know as *knowledge spillover*, which is a driving force on the creation of the most successful clusters of all times in Silicon Valley (Saxenian (1994) and Steven (2010)) and other agglomerations around the world (Iammarino*, et al.*, 2006).
4. Abundance of workers: To cope with all the different needs and pleasures from the firms and the citizens working in them, a big pool of workers is needed, not only there will be availability of specialized workers but all sort of *"merchants, artists, craftsmen, domestic servants, labourers and so on, and because they are certain to find employment there will be no shortage of such people"* (Von Thünen, 1826; p.286). This is exactly what Marshall (1895) found out years later: one of the benefits of industrial agglomerations is having a large pool of workers both specialised or not specialised.

Continuing with the analysis of the causes for agglomeration, he accounts for other factors that may specifically contribute to the location of industries in large towns:

1. Economies of scale: His notion of efficiency gains associated with a larger plant, that can only be profitable in large towns, will be one of the most important contributions to classic location analysis and it was formally reintroduced by Marshall (1895), as part of

the holy trinity of what is today known as the holy trinity of Marshallian agglomerations (pool of workers, spillovers and cost saving economies of scale). Although some authors have found limits to the economies of scale in the formation of agglomerations (Moulaert*, et al.*, 1993), it is widely accepted that this is one of the key centripetal forces.

2. Demand conditions: "*The scale of the industrial plant depends on the demand for its products"* (Von Thünen, 1826; p.286). Little attention was placed on the importance of local demand in the creation of industrial agglomeration, the literature had to wait almost 150 years until this factor were reintroduced into the spotlight by Porter's (1990) famous diamond of national competitiveness.
3. Economies of scope: This point is a bit more obscure in *Isolated State*, but one interpretation that can be given is that there is interest on locating in big town centres because many of dealers will be located there, in case an industry needs to reach different kinds of consumers, in the form of a middleman for example it can incur in less marginal costs. Von Thünen did not use the concept of marginal cost, it is introduced here to relate it to the modern concept used nowadays.
4. Division of labour: In this point, Von Thünen (1826; p.288) draws explicitly on Adam Smith and applies its conclusions to location: *"The division of labour is closely connected with the scale of an industrial plant. (...) Regardless of economies of machine-production, the labour product per head is far higher in large than in small factories"*. We know from the previous analysis that large factories are only viable in large towns, thus creating another incentive to agglomerate.
5. Increased competition: The next quotation is simple yet very powerful, as it summarizes not only a key element of agglomeration, but a key element of classical economic theory: "*the large town offers buyers and sellers far more guarantee of being able to buy and sell at current prices"*.

According to Von Thünen, the reasons for the concentration of people in the city were too obvious so instead addressing them, he accounted for the reasons against the location of industries in the capital (*centrifugal force*):

1. Costs of inputs: *"Raw materials are more expensive than in the country towns on account of the higher cost of transport"*. Recent studies have analysed this issued in different industries but there is no conclusive evidence. For example, Aguilar (2008) conducted a study in the lumber industry in United States and found that the centrifugal forces outweighed the centripetal, mainly due to the fact that *"clustering of softwood sawmills is perceived as detrimental to this industry segment because it results in higher costs of inputs, congestion, and undesired competition*"; but Aguilar also concluded that when you incorporate the whole value chain of lumber, some centripetal forces of agglomeration start to emerge.
2. Transportation costs: "*Manufactured articles incur the cost of haulage to the provincial towns they are distributed to the rural consumers"*.
3. Other costs: *"All necessities, especially firewood, are much expensive in large towns. So is rent for flat houses for two reasons: (1) construction costs are higher (...), and (2) sites that may be bought for a few [pounds] in a small town are very dear"*. (Von Thünen, 1826; p.288)

It can be seen that Von Thünen was more interested on the centripetal than the centrifugal forces behind agglomerations. His work on the later is not as detailed, thus other authors' work is analysed to understand this important issue properly.

2.1.2 The Marshallian Industrial District

Alfred Marshall is credited for having created the modern science of economics as it is known today (Belussi, *et al.*, 2009). Along with Von Thünen, Marshall is recognised as one of the first to explore the specific issue of economic location but he did so focusing specifically on what he called the industrial districts unlike Von Thünen who was more interested in agriculture.

In his *Principles of Economics* (1895), Marshall makes the first detailed case-study of the economic forces behind industrial agglomeration (the term 'agglomeration' is attributed to Hoover (1937), although it is widely used to refer to Marshall's research). He argues that there are three main reasons for the industrial agglomerations he observed in many industrial cities in the northern part of the UK during the XIXth Century (Marshall, 1895, pp. 268-9):

1. Proximity to physical resources, such as the character of the climate or the soil (for example, the existence of mines).
2. The patronage of the courts, meaning all the benefits that arise from having a specialised demand, that "owed his origins to the presence of the court".
3. The attraction of a large city (this argument can be directly linked to Von Thünen).

To understand the forces behind agglomerations, it is important to distinguish between internal economies and external economies. According to Marshall, the latter (represented by the above trinity) are much more powerful and explain an important part of industrial location. Internal economies that result from agglomeration are mainly related to the firm itself (i.e., cost reduction). According to Marshall, economies (of scale) can fall in two different classes: *'those dependent on the general development of the industry and those dependent on the resources of individual types of business engaged in it and the efficiency of their management; that is external and internal economies'.*

Internal economies are greatly influenced by the size, performance and characteristics of firms: for example, the larger the production, the greater the economies of scale, so creating an advantage over other competitors in terms of the capability to 'lower the prices at which a business can afford to sell its products'. In a competitive environment, this creates a great benefit to the consumer and drags the prices of commodities down. On the other hand, external economies are more complex in nature and do not depend upon the firm but upon the industry, and there are the *'result from the growth of correlated branches of industry which mutually assist one another, perhaps being concentrated in the same locality'* (Marshall, 1895; p.317). Industrial districts are mainly determined by external economies.

According to Marshall, these three qualities are the stepping stone for creating a primitive location settlement but, over time, the self-reinforcing characteristics (to be defined and explained latter) of the industrial location will transform it into an industrial district. Many authors reviewing Marshall's work argue that the reasons for agglomeration can be summarised by a trinity of external economies (e.g., Fujita et al., 2002; Phelps & Ozawa, 2003; Zucchela, 2006; Kukalis, 2010). :

2 Specialised labour-market pooling.
3 Specialised input and output services.
4 Specialised infrastructure.

These have been summarised by most scholars under the Marshallian trinity and are the main determinants of what is formally called agglomeration economies. Which can be defined as follows (Harrison, 1992; p.472): '*When a locality or region constitutes the site for an expansion of the common pool of labour, capital and infrastructure, or when pecuniary externalities can be traced to the new investments made by a firm in some particular place, the lower unit costs of production facing firms in that place are called agglomeration economies'* According to this definition, the producers located in the industrial district would face lower unit costs than those isolated (located outside of the district).

Marshall was especially interested on the role of small and medium (SME's) firms would play in the district, it was a logical follow up on the distinction made between internal and external economies, as the first one is especially important for larger firms and the latter is crucial for SME's survival. To illustrate this argument, Marshall starts by realising that industrial districts are *a peculiar combination of competition and collaboration, firms specialize in particular phases of the productive process: each phase is not isolated from, but rather functional to, the others* (Belussi, *et al.*, 2009; p.338). The only way in which SME's can leverage the power that larger firms derive from internal economies, is to cooperate, and this can be effectively done by locating in an industrial district where the external economies would be advantageous for the SME's. This is what Marshall called *conscious and intentional* cooperation which would characterize the first stages of agglomeration. According to him that would be less efficient than the *unconscious and automatic* cooperation that could be found in more a more mature agglomeration (sadly, as Belussi*, et al.* (2009) argued, Marshall did not provide empirical evidence or examples of this kind of unconscious and automatic cooperation).

The conscious and intentional cooperation can be found in the various associations that where created in England in the late XIXth century and cited by Marshall in various part of *Principles of Economics:* Manchester Cotton Association, British pottery Manufacturers Association, Bradford Dyer Association, Calico Printers' Association, Cable Makers' Association and Sheffield Cutlery Trades' Technical Society (as described by Belussi*, et al.* (2009)). One of the reasons why Marshall was not so enthusiastic about these associations is that they were based on the individual interest of one group and they would usually devote their main energies to restrict competition and maintain higher prices, which is not in line with the common interest. This is an important issue that, sadly, was not explicitly addressed by Marshall, but can be found in more recent studies on agglomeration as a possible reason for industrial districts' failure (see Akoorie (2011), Sunley (1992), Parr (2002)).

There is an important counterpoint to be made here, according to Marshall these kinds of associations are mostly helpful for SME's and will contribute to their survival, but Robertson (1960 [1923]) thinks these associations will be responsible for the disappearance of SME's. He argues that, inside an association the big firms will always have more power, and will eventually erode (by efficiency or by force) the SME's share inside the association. It seems that when Marshall observed the Northern England industries that he used as an empirical basis for his theories on agglomeration, the coexistence of competition and collaboration he praised was not present, so this was something he wished for as an optimal organization rather than an observed feature. This may appear to be a trivial point, but it is worth noting that most of the work conducted on agglomerations in recent years, has praised the cooperation and competition as a distinctive and beneficial feature of agglomerations (a clear example are Porter's Clusters (Porter, 2000), as it will become evident in the next section of this chapter)

Many counterpoints have been raised to Marshallian agglomerations. One of the first to critically evaluate the concept was Marshall's own disciple Chapman, who wrote a detailed book on the Lancashire cotton industry. One of the things he noted was that industries were not only characterized by centralization, but also from dispersion, which was an attribute found in the iron and steel industries as opposed to the textile industry which is centrally located (Belussi*, et al.*, 2009). This argument can be traced back to the early contributions made by Von Thünen (1826) an his centripetal and centrifugal forces (see the previous section on Von Thünen for details). Chapman also augmented the aspects of industrial districts by adding: the presence of an industrial atmosphere, hereditary specialization, the role of knowledge and innovation.

Surprisingly, it is possible to find in Marshall and his early disciples, a common argument that clearly demonstrate they lacked certain insights into some of the feature exhibited by the observed industrial districts. Marshall pointed out that knowledge and information are 'in the air', and that one of the distinctive features of agglomerations was the presence of a special atmosphere; Chapman wrote that in some cases location is due to no particular reason; and Robertson (another direct disciple of Marshall, author of "The control of industry") argued that another very important cause of industry location was based on some obscure reasons of climate or history. This very shallow description of the causes for agglomeration has justified the increasing interest of modern researchers, but despite the myriad of studies, many of the doubts posed 100 years ago are still in place today.

From this debate it may be difficult to summarise the distinctive characteristics of an industrial district according to Marshall, for that purpose it is useful to review the work undertaken by some contemporary authors that tries to summarise and categorise the typologies of industrial districts based on empirical evidence. For example, Markusen (1996; p.298) determined that Marshallian industrial districts are characterised by:

- Business structure dominated by small, locally owned firms.
- Scale economies relatively low.
- Substantial intra-district trade among buyers and suppliers
- Key investment decisions made locally
- Long-Term contracts and commitments between local buyers and suppliers
- Low degree of cooperation or linkage with firms external to the district
- Labour market internal to the district
- Workers committed to the district rather than to firms.
- High rates of labour in-migration, Low rates of out-migration
- Evolution of unique local cultural identity, bonds
- Specialized sources of finance technical expertise, and services available in district
- Existence of "patience capital" within the district
- Turmoil, but good long-term prospects for growth and employment.

To this list Markusen adds the so called Italian version of industrial (ID) districts which, in addition to the above, also features:

- High incidence of exchanges of personnel between customers and suppliers.
- High degree of cooperation among competitor firms to share risk, stabilize market, share innovation.
- Disproportionate share of workers engaged in design and innovation.
- Strong trade associations that provide shared infrastructure: management, training, marketing, technical or financial help.
- Strong local government role in regulating and promoting core industries.

The modern version of the Marshallian ID is the Italian ID; it is also characterised by small firms collaborating and competing in a determined location, with few market interactions outside the ID, but the main differences between the Italian ID and their XIXth century brothers, is that the collaboration is not unconscious but conscious and deliberate, in some cases with strong intervention from the regional government. This type of collaboration might have helped the survival of Italian IDs as opposed to the English IDs that where described by Marshall and no longer exist. Even here, there are discrepancies on which is the more efficient ID typology. Italian IDs seem to be rather resilient to crisis and industry shocks due to the political organization and the market intervention that characterize them, but other types of ID's especially in the United States (for example, Napa Valley, Orange County, Silicon Valley) exhibit high rates of performance and survival, using a more market-oriented approach.

Although nowadays a pure Marshallian ID is difficult to find, the literature has extensive references to examples that have worked in the past, and some explanations of why they disappeared or evolved into other types of IDs. For example, Markusen proposes that both Pittsburgh and Detroit at their early stages of development resembled a Marshallian ID, but 'the evolution of oligopoly and crowding out of the other sectors left both quite vulnerable to the inevitable maturation and decentralization of those industries' (Markusen, 1996; p.301). This is what other authors call the 'lock-in effect of agglomeration', especially the kind of ID proposed by Marshall which depends on specialization in a single factor or industry, as opposed to the agglomerations based on diversification proposed by Jane Jacobs (1970a).

2.1.3 Marshallian versus Jacobean Agglomerations

There is an intense debate regarding the alleged positive benefits of the Marshallian agglomeration and its effects on regional and industrial growth. Although the Marshallian concept of agglomeration is well-established, there is no general consensus in the literature regarding its effects. The debate between specialisation, a key Marshallian characteristic, and diversification, associated with Jacobean agglomeration, has greatly intensified. Hausmann (2014) argues that specialisation at every level (cities, regions and countries) is a 'dangerous idea': *"(…) while some ideas are intuitive or obvious, they can also be wrong and dangerous. As is often the case, it is not what you don't know, but what you mistakenly think you know, that hurts you. And the idea that cities and countries actually do specialize, and that therefore they should specialize, is one of those very wrong and dangerous* *ideas".*

The diversification argument has its origins in the work of Jane Jacobs in *The Death & Life of Great American Cities (1961)* and *The Economy of Cities (1970b).* Jacobs argues that cities (urbanisation) provide a diversified environment that creates the right incentives for growth. Through diversification, urban agglomerations create positive externalities and knowledge spillovers across industries, not only inside the same industry, as is the case in specialised Marshallian agglomerations. This type of knowledge spillover across complementary industries is the key for new business creation and innovation, thus '*cities provide, not only new problems to be solved but also the best environment to solve them*' Jacobs (1970b). She later reinforces the ideas of diversification externalities by understanding cities as a complex system: '*A diversified city will generate much more local expansion from a new business venture than a small town, much like a well developed forest's ecosystem will convert more sunlight into biomass than a desert'* (Jacobs, 2002).

In this Jacobean view, urbanisation becomes the driving force behind industrial, regional and even national growth. In *Cities & the Wealth of Nations* (Jacobs, 1984), Jacobs explains the five mechanisms through which a city creates economic development (cited and compiled by Desrocher & Hospers, 2007):

1) Enlarged markets for new and different import goods that come from rural areas and other cities.
2) Increased number of jobs in the import-replacing city.
3) Increased transplant of city work into non-urban locations as older enterprises are crowded out.
4) New uses of technology that increases rural production and productivity.
5) Growth of the city capital for investment in the city and elsewhere.

The driving forces of city growth will in turn reshape the economies of other regions by creating five types of regions (compiled by Desrocher & Hospers, 2007):

1) Supply regions: those supplying the city with food and raw materials.
2) Abandoned regions: those that lose population to growing cities.
3) Clearance regions: those where city-developed technology is applied but generate few new

jobs for displaced labour.

4) Transplant regions: those import city-developed factories and other activities that no longer require an urban density.
5) Subsistence regions: those bypassed by economic development.

Jacobs has been highly influential, not only in the literature but also among policymakers. Knowledge spillovers across industries are now seen as an intrinsic part of industrial development, creating positive externalities for firms operating in diversified industrial ecosystems. Nevertheless, many studies also suggest that diversity should be treated carefully. For example, Jacobean externalities can become negative if there is a lack of focus on providing a good local environment. The more heterogeneous the industrial mix of a city, the harder it is to offer a tailor-made solution (Neffke*, et al.*, 2011). Too much diversity appears to have a negative effect on firm and industry performance; for example, Combes*, et al.* (2004) find that diversity is beneficial to a region as long as it is not too spread across different industries.

A key difference between the Jacobean and the Marshallian model is that the former asserts that local competition is an incentive to engage in innovation while, in the latter, the local market power of firms in the labour market favours innovation (Van der Panne & Van Beers, 2006). The large number of studies are evenly split in their findings with evidence supporting both diversity and specialisation externalities. These contrasting results could be the outcome of differences in samples, methodology, aggregation method and so on (Beaudry*, et al.*, 2009). Even using the same sample and method, dissimilar results persist (Combes, 2000). Most of these results seem to suffer from a problem of heterogeneity that is not properly accounted for in the models. This problem of arises when comparing firms operating in the same industry over time and not only when comparing different types of industries or firms. Indeed, both the age of the firm and the industry are highly relevant and an important strand of the literature is concerned with analysing how different types of agglomeration externalities affect industry performance during different stages of its life cycle.

It may well be the case that, once the industry life cycle is accounted for, both Marshall and Jacobs are right. It all depends upon the stage of the industry. For example, Neffke*, et al.* (2011) finds evidence that younger industries benefit from the diversity of Jacobean externalities while more mature ones benefit from the Marshallian specialisation externalities. These results are in line with the findings of Duranton*, et al.* (2001) that diversified cities are more suited for the early stages of a product's life cycle, whereas more specialised places are better able to undertake mass production of fully-developed products. Expanding this argument, Neffke*, et al.* (2011) present a detailed analysis of the relationship between each type of agglomeration externality (Urbanisation, Marshallian and Jacobean) and the life cycle of the industry (young or mature) Other studies that look at clusters from a life-cycle perspective are: Henderson*, et al.* (1995) ; Henderson (1997), Duranton*, et al.* (2001), Van Der Panne (2004), Van Der Panne*, et al.* (2006). See Table 2.1 for further details.

The fact that diversity and specialisation can create both positive and negative externalities, depending upon the industry or the product life-cycle, creates a conundrum from a policy point of view. It is difficult enough to create a policy fostering either diversity or specialisation but, if both can happen simultaneously (or in overlapping and non-linear stages), the complexity escalates. The best approach is probably to conceptualise agglomerations (and their externalities) as a complex adaptative system in which the role of policy-makers is to find that policy that best fits the problem at hand rather than the 'best' overall policy, allowing at the same time for enough flexibility so that each agglomeration follows its own non-deterministic path (Geyer*, et al.*, 2010). Under that view, the role of policy-makers is to maintain a diverse ecosystem that supports new business creation but, at the same time, to create specialisation through, for example, a cluster policy approach (as proposed by Porter, 2003). In order to move beyond the dichotomy between specialisation versus diversification, research has started to explore the concept of *diversified specialisation*. For example, in contrast to diversified cities, diversified-specialised cities tend to be smaller and thereby benefit from lower congestion and production costs. Their advantage relative to specialised cities lies in a comparatively diversified sectoral structure which fosters cross-sectoral spillovers and lessens the impact of sector-specific demand shocks on the regional economy (Farhauer*, et al.*, 2012).

Table 2.1: Agglomeration Externalities & Life Cycle Dynamics

Agglomeration externalities and life cycle dynamics

			Life Cycle stage of Industry	
			Young	Mature
Urbanization	Factor costs	High land rents	0	-
		High wages	0	-
		Congestion	0	-
	Knowledge	Highly skilled labour force	+	0
		Knowledge infrastructure	+	+
		Access to large market	0	+
		Access to sophisticated market	+	0
MAR	Factor Costs	Low matching costs labour market	0	+
		Low inventories	0	+
		Low transportation costs within the value chain	0	+
	Knowledge	Large specialized labour force	0	+
		High intra-industry knowledge spillovers	+	+
		Ease joint innovation efforts within the value cl	0	+
	Market conditions	Easy accesss to specialized clients and suppliers	0	+
Jacobs	Factor costs	Large variety of services and goods	+	0
		Lack of focus	0	-
	Knowledge	High Inter-Industry knowledge spillovers	+	0
	Market conditions	Reduced volatility in demand and supply	+	0

Notes: MAR stands for Marshall-Arrow-Romer.
+, The expected effect is positive. 0, no effects expected or effects cancelling out. -, a negative effect is expected.
Source: Neffke et. Al. (2011).

This section offered a complete review of the origins of agglomeration theory, starting from the classic view of Von Thunen and Marshall that is still today the basis of modern thought. Then, an important critique to the Marshallian agglomeration, the Jacobean agglomeration, was analysed and discussed. While Marshall and his followers (among whom we can count Michael Porter) advocate for agglomerations based on specialization, Jacobs and her followers advocate for diversified agglomerations. Even though these two views may seem irreconcilable, the concept of diversified specialisation and the analysis of agglomerations under the lens of the life-cycle theory brings them together.

2.2 Industrial Clusters & Growth

Industrial clusters are considered the modern relatives of agglomerations and are a recurrent topic of analysis and discussion that goes far beyond the academic field, making a rare transition to policy. This popularity is due to the apparent benefits of clusters in terms of industrial growth. In this section, that relationship is analysed and discussed.

At the national level, the literature is dominated by evidence of there being a positive relationship between clusters and economic growth. Crozet & Koening's (2007) work, based on a large study of 15 European countries from 1980 to 2000, finds a positive relation between regional agglomerations and national growth. Brülhart*, et al.* (2009) find similar results investigating the effects of urban agglomerations on both national and industry level growth using a large dataset for 105 countries but, interestingly enough, their results suggest that positive agglomeration effects decrease for countries with a GDP per capita higher than 10,000 dollars. Although Brülhart*, et al.* (2009) use urbanisations measures as proxies for agglomerations, their findings are relevant here because one of the primary variables used is employment concentration, specifically from a sub-sample of European countries. A similar type of employment measure is used here, albeit at a different level of aggregation. Fujita*, et al.* (2003) find that growth and agglomerations go hand-in-hand, creating a 'self-reinforcing' process such that public policy to foster dispersion (to reduce regional inequality and thus lower the agglomerations effects) could have negative effects on national level growth.

Building on the tradition of 'Jacobean agglomeration', Glaeser (2011) finds a clear and positive correlation between strong urban agglomerations and GDP per capita. Using data for 181 countries, a 10 per cent increase in urban agglomeration is associated with a 61 per cent increase in per capita GDP. Moreover, he also finds an increase in productivity is associated with industrial proximity (in urban areas). He concludes that this is due to the existence of agglomeration economies that arise because 'proximity lowers the costs of shipping goods, such as intermediate inputs for manufacturers, or delivering face-to-face services' and that proximity 'also improves the efficiency of labour markets by providing workers with a plethora of employment options' (Glaeser, 2011).

At the regional level, it is widely agreed that the contribution of Krugman (1991), the New Economic Geography (NEG), has been critical in turning attention back to the importance of (industrial) location to regional (and national) growth. Using a variant from neo-classical trade theory, allowing for factor flexibility (e.g., worker mobility) and also introducing transport costs as a variable, NEG produced a theoretical framework for understanding the causes and effects of agglomeration. The analysis of forward and backward linkages introduced by this paradigm creates the conditions for the clustering of intermediate-goods related industries; the greater the proportion of intermediate goods in the production of final goods, the greater are these demand and cost linkages, and the greater the gains from geographical/spatial clustering (Harris, 2011).

The explanation of which are the forces that affect geographical concentration given in Krugman (1998) is specially relevant of this research. According to Krugman they can be summarised in two categories: Centripetal forces and Centrifugal forces. Centripetal are related to: Market-size effects (linkages), thick labour markets, and pure external economies. Centrifugal are related to: Inmmobile factors, Land rents, and pure external diseconomies. The rest of the differences between the new economic geography and the 'old' one, are mainly based on the premise that the new literature insists on models that are general equilibrium, and in which spatial structure emerges from invisible-hand processes. In order to adapt the models to this view, a number of assumptions need to be fulfilled, in what Krugman has called 'technical tricks': The New Economic Geography is a style of economic analysis which tries to explain the spatial structure of the economy using certain technical tricks to produce models in which there are increasing returns and markets are characterized by imperfect competition (Krugman, 1998).

Even if the New Economic Geography has created a renewed theoretical interest in geography, it is generally accepted that the core components of NEG are still extensively based on the industrial agglomeration literature (Harris, 2011). According to Mccann (2013; p.89) it is fair to say that the contribution of the New Economic Geography are greater in terms of theoretical insights than in terms of empirical developments. Accordingly, given that in this research the industrial agglomeration and location literature has already been extensively reviewed, and that the focus of this research is mainly empirical and not theoretical, not addition and specific analysis of the New Economic Geography literature is offered in this chapter.

A large number of studies have conducted empirical work to test if clusters promote regional growth, many building on the work of Porter in analysing the role of clusters at regional level. Porter uses wages, employment and establishment data from 1990 to 2000 covering 172 Economic Areas in the United States, which are smaller than States but larger than Metropolitan Statistical Areas; finding that regional economic performance is strongly influenced by clusters (Porter, 2003). He suggests that it is not only the presence of strong clusters that define regional performance but national performance as well (Porter, 2003; p.571).

While the literature at the national level lean towards a positive relationship between growth and agglomerations, the results tend to be more ambiguous when the level of territorial aggregation decreases e.g. at a regional level. Morgan, using data from metropolitan regions in the United States from 1990 to 2000, in contrast to Porter (2003), finds that the effects of clusters on growth were heterogeneous, depending upon the type of industry and the dependent variable (Morgan, 2007). Small positive correlation effects were only found in traditional services while small negative correlations were found in traditional manufacturing and knowledge-intensive industries. Morgan (2007) methodology, which uses bivariate correlation as the main measure, may not capture the complex relation that exists between regional growth and clusters. Although the author seems to acknowledge these limitations, the results presented in his paper should be viewed with caution. Gardiner, *et al.* (2011) find that there is no significant correlation between European data on regional productivity growth and regional employment density for the period 1980 to 2007. They also find that the results are highly malleable, depending upon the level of geographical aggregation chosen (i.e., NUTS1, NUTS2, NUTS3) and thus conclude that the relationship between regional agglomerations and regional growth is, at best, ambiguous.

These inconclusive results have prompted a large amount of research to disentangle the effects of clusters. Spencer, *et al.* (2009), suggest that the ambiguity in the results is mainly due to the lack of a common and systematic method to define and analyse clusters but also because the methodology has to account for the regional and structural differences. They argue that trying to replicate Porter (2003), without considering specifics, is mistaken and therefore they propose a new method (still extensively based on Porter). Using Canadian industrial and regional data to test the effects of clustering on average annual income for 2001, employment growth from 1998 to 2005, patents from 2000 to 2003 and the unemployment rate for 2001, these authors find that there is a positive and significant relationship between clusters and economic performance for almost every industry and a negative relation with patents. Overall, these results for Canada, using a different methodology, confirm Porter's results (2003) for the United States.

A comprehensive study by Rodríguez-Pose, *et al.* (2011) uses a dataset for 152 regions in 15 European countries, for the period from 1995 to 2006 to determine whether clusters generate innovation and growth. The study uses a cluster index consisting of a Principal Components Analysis (PCA) of specialisation, focus, and size, as well as two other PCA-indices for innovation and social variables with the dependent variable being the variation of regional GDP per capita.

The influence of clusters on economic growth is found to be lower than expected; specifically, even if clusters have a small positive effect on regional growth, this effect is directly constrained, and dependent on, the pre-existence of adequate social variables e.g. the education level. Consequently, clusters alone are not significantly important for growth. Bishop*, et al.* (2009) use industrial specialisation and diversification (based on a Location Quotient) as dependent variables to test the effects of different types of agglomeration on employment growth. Using a UK dataset from 1995 to 2002, they find that a higher location quotient, meaning a more specialised and clustered industry, is negatively correlated with employment growth.

Given the limitations posed by data aggregation at both regional and national levels, a growing number of studies investigate the effects of clusters on individual firms. Using a USA dataset for establishments from 1976 onwards, Delgado et al. (2010) find a highly positive correlation between clusters and new firm birth, with a specifically significant correlation between start-up employment and firm formation in strong clusters. The study also suggests that clusters foster the expansion of recently created firms, which usually extend into other complementary clusters. Similarly Wennberg*, et al.* (2010) find evidence that a high concentration of cluster employment is related to better chances of firm survival, higher employment and higher salaries in a study of the survival rate of new firms in Sweden in six specific industries (telecoms, consumer electronics, financial services, IT, medical equipment and pharmaceuticals) from 1993 to 2002. Nevertheless, as the other papers cited, their results vary according to the cluster measure used (absolute employee count or relative employment location quotient) and the geographical aggregation (labour market area, county or NUTS-2).

When firms are very closely clustered, competition between them increases and survival rates decrease (De Silva*, et al.*, 2011); as dispersion increases, competition remains similar but survival rates increase. This suggests that cluster effects not only depend upon the concentration of firms in a given location but also, possibly, on the size of the relevant market and the demand (inferred from De Silva*, et al.* (2011)).

A number of other studies address the issue of cluster impact on specific firm performance. Using a sample of 194 USA firms in the semi-conductor and pharmaceutical industries, (Kukalis, 2010) finds that the presence of a cluster may not improved financial performance. There is no first-mover advantage for clustered firms, and neither do they perform better than isolated firms during periods of economic contraction and mature firms in clusters perform worse than mature isolated firms. These findings are in direct contradiction to much of the cluster literature and pose some interesting and profound questions on the validity of cluster policy from a firm point of view. The use of a very limited sample consisting of only two industries calls for further research.

Many studies investigate the positive and negative effects of clusters on a number of economic variables but the specific interaction between clusters and economic crises has been scarcely tested. One important conclusion drawn from the review presented in this section is that cluster performance is affected by a large number of variables both at the regional and national level, and the aggregation level used to determine the cluster effect may also affect the results (Gardiner*, et al.*, 2011). Additionally, it is difficult to disentangle the pure effect of clusters on industrial growth and the effect of the regional and national characteristics. The vast majority of studies that look at clusters analyse a small number of industries in a specific region (Wennberg, *et al.* (2010)), or a specific industry in a sample of regions and countries (Glaeser, 2011), accordingly, the results are circumscribed to that specific location and sample, creating opposing and inconclusive results.

To tackle the sample problem Rodríguez-Pose*, et al.* (2011), use a large data set consisting of 152 regions in 15 countries. They find that influence of clusters on economic growth is found to be lower than expected; specifically, even if clusters have a small positive effect on regional growth, this effect is directly constrained and dependent on the pre-existence of adequate social variables e.g. the education level. Consequently, clusters on their own are not significantly important for growth.

Duschl, *et al.* (2011) analyse the risks of using traditional econometric methods when dealing with atypical scenarios, e.g. assuming a normal distribution, and claim that further research and analysis in the context of the current economic crisis is needed *"if stability in regional growth is the aim of policy, a better understanding of the causes of extreme events and the ability of regional economies to cope with them is of high relevance"* (Duschl, *et al.*, 2011; p.26). Given that cluster policy is being widely adopted as a tool to minimise the effects of economic crises and improve regional economic and employment growth, this lack of attention is perhaps surprising. The critical issue is whether clusters are more likely to be hit by regional and/or national crises than non-clustered industries and whether they grow faster as a result of positive shocks. This Chapter tackles that research gap.

This section offered a review of the literature that studies clusters and their relationship with growth at different levels. A large majority of authors find a positive effect of clustering on growth but there is no consensus as to which mechanisms are behind this positive effect. The vast majority of studies use a small sample, or focus on a specific type of industry, which makes it difficult to compare the results. The very few studies that encompass a large number of industries across different regions and countries find evidence that clusters are relevant to growth only when some pre-existing conditions are met.

2.3 The Industrial Network

The concepts of industrial agglomeration and industrial cluster are specifically tied to geography. This creates certain rigidities when analysing industrial growth in a globalized and highly interconnected world. This is where the concept of industrial network, introduced in this section, becomes useful.

2.3.1 Industrial Networks & Growth

The analysis of growth is a central concern in economics. The first formal study of the origins of growth at the industry level comes from Marshall's analysis of industrial districts (Marshall, 1895, 1920). He states that the main driving force behind industrial growth is the existence of agglomeration externalities that arise from the concentration of similar industries in a location. More recently, the literature on industrial agglomeration has taken three distinct paths that can be summarised in three models (Gordon*, et al.*, 2000): Pure agglomeration, Industrial Complex and Social Networks. Pure agglomeration is in the Marshallian tradition and also includes the approaches by Hoover (1937), Arrow (1962), Romer (1987) – Arrow and Romer, together with Marshall are referred to as the M-A-R agglomeration (Belussi*, et al.*, 2009) –, Krugman (1991) and Porter (1990).

All of these approaches propose definitions that depend upon location, space and geography. In the industrial-complex model, relationships between firms and industries are essentially conceived as using trade links, sales and purchase patterns. These may or may not be explicitly related to geography, but often are. The social network model is rooted in the tradition of Granovetter (1983) looking at intra and inter-firm relationships in a similar manner to the cluster and industrial agglomeration literatures but without the geographical component. Instead, they usually focus on knowledge and information exchange rather than physical or monetary exchange.

These three categories no longer appear valid in that many recent studies look at agglomerations using a framework of complexity theory in which the division between agglomerations, geography and networks is hard to distinguish (Lindsay, 2005 ; Carbonara*, et al.*, 2010).

While Marshall's work on industrial growth has remained highly influential, the focus of the research has shifted, during the last century, from industrial growth at the microeconomic level to the analysis of economic growth at national level, long-term cycles and structural transformation. Some examples of the latter include long waves of economic growth Kondratieff (1925), the Solow model of economic growth Solow (1956), and the analysis of the dynamic structure of industrial cycles (Kuznets*, et al.*, 1966 ; Kuznets, 1971). Along the same lines, Chenery (1960) ; Chenery*, et al.* (1968) attempt to understand the determinants of industrial growth, in both developed countries and developing economies. Chenery finds that growth levels at national and industrial level are highly correlated but, although some specific country characteristics influence industrial growth, it is generally driven by universal factors common to all industries. Chenery also analyses industrial growth in a subset of large economies and finds that the transition from primary to secondary sectors is attained by: 1) raising the accumulation of physical capital and the working skills (productivity); 2) shifting to sectors with higher efficiency and higher demand growth; and 3) diversifying the economic structure, which makes countries less vulnerable to trade and demand shocks (Chenery, 1982). The latter is of special relevance to the empirical research here.

A considerable number of studies have followed on from Chenery. For example, Stockman (1989) finds that, contrary to many classic models of growth, industry-specific technology shocks (i.e., productivity) explain only a very small proportion of industrial output growth. The greater proportion seems to be related to national shocks common to all industries, which are usually related to government policies. Costello comes to similar conclusions, finding that, at the industry level, productivity growth is significantly correlated across industries within a country but is less correlated across countries for any individual industry (Costello, 1993). Here again, national shocks of different nature, appear to be an important determinant of industrial growth. These studies suggest that the link between national and sectoral shocks and their relationship with national and industrial growth need to be taken into consideration. Work by Glaeser*, et al.*

(1991), Mody & Wang (1997) analyses the determinants of industrial growth in China. Among other things, they find an important (negative) 'convergence' effect of the initial conditions of industrial GDP on growth as reported in other well known studies (Barro*, et al.*, 1991 ; Barro*, et al.*, 1992 ; Mankiw*, et al.*, 1992), albeit using GDP at the national level. Mody*, et al.* (1997) also report that industrial growth is determined by specialisation and competition, which are measures of geographic agglomeration, as in Marshall. Gao (2004) finds similar results when analysing regional growth in China.

In recent years, an increasing number of scholars argue that traditional growth models need to be revised due, in part, to their inability to predict and analyse the effects of the Great Recession. Ormerod (2010) argues that the failure of macroeconomic models and classic econometric tools have a great degree of responsibility for the crisis. Some policy-makers felt that the available models were of limited help in facing the crisis (Farmer et al., 2012) and felt 'abandoned by conventional tools'[1]. According to recent critiques, some of these failures can be attributed to the use of extreme reductionist approaches that cannot account for the evolving and complex nature of local, regional, national and international interconnections of the global economy (Farmer*, et al.*, 2012).

To tackle these issues, scholars have adopted new approaches to understand the causes and effects of periods of growth and downturn at different levels of aggregation. Much of this research focuses not only on the recent recession but have their origins at least twenty years before the crisis started. There is certainly a renewed interest that is directly related to the Great Recession.

2.3.2 Networks and Trade

[1] Jean-Claude Trichet, Governor of the European Central Bank in November 2010, as quoted by Farmer*, et al.* (2012).

The analysis of industrial location follows a logical evolution in the literature, beginning with industrial agglomeration, moving to industrial clusters and, more recently, into industrial networks. Empirical research on the latter is taking two paths. The first follows the Nelson*, et al.* (1982) tradition. This incorporates elements of evolutionary economics, like co-evolution and self organisation to the analysis of knowledge in clusters (Lindsay, 2005); the analysis of the properties of industrial networks as complex adaptative systems and their unstable nature (Carbonara*, et al.*, 2010); and the network metrics to analyse the effects of proximity on the uneven knowledge diffusion inside clusters (Giuliani, 2007). Other research uses agent-based modelling, combined with network theory, to understand the effects of proximity on the capacity of industries to adapt and evolve (Carbonara*, et al.*, 2011), the evolution of firms, industries and networks in space (Ter Wal*, et al.*, 2009b) and the characteristics of complexity theory applied to economic geography by Martin*, et al.* (2007).

The second distinctive path in the industrial network literature uses network theory as a way to understand complex relations, contagion and cascade effects, following on from Watts (2002, 2004) and Albert*, et al.* (2002). The empirical research in the ensuing chapters follows this path. A series of seminal papers apply network theory to the analysis of growth at industry level and its effects on country development include: Hidalgo*, et al.* (2007b), Hidalgo*, et al.* (2009) and Hausmann*, et al.* (2011a). The recent literature focuses on the mechanisms of transmission of volatility from sector to countries through industrial networks (Acemoglu*, et al.*, 2010 ; Acemoglu*, et al.*, 2012); a theoretical contribution to this emerging field was made by Ter Wal*, et al.* (2009a) by analysing the many potential ways in which social network analysis could be applied to the analysis of economic geography. Other areas of study include the network characteristics of trade globalisation (Kali*, et al.*, 2007); global financial contagion (Kali*, et al.*, 2010); and the effects of industrial network density and proximity on growth accelerations (Kali*, et al.*, 2013). The analysis of cascade and contagion effects of the Great Recession using network theory is also an on-going research topic (Carvalho, 2008 ; Lee*, et al.*, 2011 ; Dasgupta*, et al.*, 2012 ; Farmer*, et al.*, 2012). Most of these studies are based on classic economic theory but use novel techniques (networks, agent-based and, more generally, techniques from complexity theory) to provide a different perspective on old and new economic issues.

The research literature looking at economic phenomena through the lens of network theory has considerably expanded in recent years. A special focus has been on the analysis of what is known as the international trade network – ITN (Kali*, et al.*, 2010), world trade network – WTN (De Benedictis*, et al.*, 2011) or world trade web – WTW (Fagiolo*, et al.*, 2007). The reasons for this increased interest is that networks metrics improve the empirical application of trade models (Fagiolo, 2010); it provides a better way to understand and represent the intricate structure of trade (Dueñas*, et al.*, 2013) and international trade exhibits characteristics of a self-organisation in complex network that should be analysed as a collective phenomena (De Benedictis*, et al.*, 2011). A recurrent topic is the use of trade networks applied in a traditional gravity model – for example, Baskaran et al. (2011), following the work by Rauch (1999), Baskaran*, et al.* (2011)Baskaran*, et al.* (2011)Baskaran*, et al.* (2011)Baskaran*, et al.* (2011)Baskaran*, et al.* (2011)Baskaran*, et al.* (2011)Baskaran*, et al.* (2011)Baskaran*, et al.* (2011)Baskaran*, et al.* (2011)Baskaran*, et al.* (2011)Baskaran*, et al.* (2011) find that the empirical applicability of Heckhsher-Ohlin trade models can be improved by using network metrics. Using data from well-documented traditional gravity models (e.g., Subramanian*, et al.* (2007), De Benedictis*, et al.* (2011), & De Benedictis*, et al.* (2013)) studies find that network metrics can be highly informative in an international trade context.

This section offers new insights to enrich the debate on the determinants of industrial growth and industrial shocks. By introducing the concept of industrial network, the constraints of geography that is present in the concepts of agglomerations and clusters, are removed and the complex interconnections among different types of industries are accounted for without the constraint of a border or a region. This approach is seen in the literature as a more realistic representation of the way modern industries are interconnected, and may shed some light on the mechanisms behind the transmission of growth and downturn from industry to industry.

2.4 Industrial Shocks

This section focuses specifically on transmission of industrial shocks. First, the more traditional literature based on the business cycle is reviewed to determine the mechanisms of transmission of an industrial shock. Second, a more recent view, the network contagion literature, is discussed.

2.4.1 Business Cycle Co-movement

The analysis of business cycle co-movement is seen as an important tool to formulate better policies to spur growth during periods of bonanza and mitigate contagion during periods of downturn. The question related to which are its determinants, has spurred a large amount of research over the last decades but it has only recently regained momentum in the light of the persistency of the recent global crisis (Imf, 2013).

A seminal theoretical contribution analysing the determinants of co-movement is found in Long, *et al.* (1983). They conclude that business cycle type behaviour is the result of well-defined consumption-production plans in which unanticipated wealth increments are spread over different periods (persistency effect) and different sectors (co-movement effect). A potential problem with this study is that the large number of assumptions (no government, closed economy, no money and no adjustment costs, among others) renders their conclusions open to a number of caveats. Horvath (1998) however, empirically tests a model based on that of Long, *et al.* (1983) in order to understand the cyclical and sectorial linkages in the United States. He finds that small shocks to individual sectors could have large effects on aggregate output volatility, especially if industries are large suppliers of primary inputs to other industries. Horvath finds that up to 80 per cent of aggregate volatility can be explained by specific and small sector shocks. In spite of its important contribution, the previous literature gives no specific clue as to the mechanisms of business cycles transmission, since the focus is more on the relationship between granular and aggregated volatility. For a recent and highly informative analysis on granular and aggregated volatility using network analysis, see Acemoglu*, et al.* (2010) ; Acemoglu*, et al.* (2012).

The first paper to offer a well-developed empirical model to investigate the main drivers of business cycle co-movement is by Frankel*, et al.* (1998). They find that countries with larger trade ties have more similar business cycles; a proposition that has now become a well-known stylised fact of co-movement and largely replicated in later studies.

For example, trade has been found to be a significant and important mechanism of co-movement at the country level due to the effects of globalisation by Kose*, et al.* (2003). Baxter*, et al.* (2005) investigate a number of variables that are traditionally suspected of transmitting co-movement: trade intensity between countries, total trade volume, similarity in export and import baskets and sectoral structure, among others, for a sample of more than 100 countries. They find that the only robust variable is trade intensity. The relationship between trade and co-movement is also tested empirically and found to be significant by Kose*, et al.* (2006) and Johnson*, et al.* (2012). These two studies also find that there are, respectively, a 'co-movement puzzle' and an 'input trade and co-movement puzzle', which consist of the inability of empirical models to replicate the correlation between trade and co-movement observed in the data. Both papers argue that, in order to solve the puzzle, it may be necessary to improve the theory and the empirics of shock propagation. One potential source of these puzzles may be found in the aggregated data used to test empirical models. More granular data would potentially remove much of the omitted variables bias (Di Giovanni*, et al.*, 2010), allowing a better understanding of the underlying mechanisms of shock propagation (Garbellini*, et al.*, 2014). Additionally, the use of sectoral data helps to overcome the problem created by 'the law of large numbers' (Horvath, 1998, 2000) that states that, at a global level, business cycle effects cancel each other out because some sectors grow while others decline, rendering the analysis irrelevant (Boileau, 1996).

There appears to be a general consensus that trade is either the most important transmission mechanism of co-movement or, if not, at least highly significant, both at country and sector level. This consensus ceases when determining why trade is such an important determinant of co-movement. Many mechanisms are discussed in the literature. Ng (2010) finds that trade increases co-movement due to the effect of vertical integration (product fragmentation), especially if trade is concentrated in complementary products (e.g., industrial intermediate consumption, usually measured by input-output tables). Forbes (2002) investigates three channels through which trade can trigger co-movement: i) a competitiveness effect; ii) an income effect; and iii) a cheap import effect. All of these are the result of exchange rate depreciation leading to changes in the relative prices of traded goods and the terms of trade, which affects supply in the country of origin and demand in the recipient country.

There is a potential omitted-bias problem here, which arises from the inability to disentangle trade from financial links (Forbes, 2002). Since trade and financial flows are usually highly correlated (Wanisky & Reinhart, 2000; Van Reijckeherm & Weder, 2010), estimating one also includes the other. The omitted-variable problem is less likely to be present if sectoral data is used instead of country data (Forbes, 2002). Further, changes in final demand are responsible for the rapid spread of the crisis at global level; for example, find that, during the great recession, 20 to 30 per cent of the decline in US and EU final demand was borne by foreign countries (Bems*, et al.* (2010). The work of Garbellini*, et al.* (2014) is of special relevance for this research since it uses the same dataset (World Input-Output Database) as the fourth and fifth chapters of this thesis to analyse the spillover effect of the global crisis at sectoral level.

2.4.2 Contagion in the Industrial Network

Traditionally, the literature has analysed the determinants of co-movement by focusing on business cycle correlation data for pairs of countries or industries and then regressing control variables, containing information on either the pairwise characteristics (e.g., trade intensity and gravity variables), and specific industry or country characteristics (e.g., industry structure, industry size, country openness, country GDP, country productivity). The general findings largely support the claims that, once industry- and country-specific controls are introduced, pairwise trade intensity is usually found to be a significant. This is useful if the objective is to understand the drivers of co-movement between industry (or country) A and industry (or country) B, but it focuses only one pair at a time. If the objective is to understand the relationship between industry A and every other in the sample, the pairwise approach may not provide a complete view of all of the potential co-movement linkages. The solution would be to create some type of industry-specific weighted measure of aggregate co-movement.

Such a weighted measure of co-movement could be interesting because, in a highly inter-connected global economy, it is useful to understand how each industry's business cycle is connected to that of all other industries. This would enable a better representation of global co-movement and provide information on the role played by each industry in driving growth and downturn at the global level. The policy implications could, potentially, lead to reinforce or refocus some of the efforts at industrial, national and global levels to improve growth in the wake of the recent global crisis. To the best of the author's knowledge, no such measure of industry-specific aggregate co-movement has been developed in the literature. Recent efforts to use new techniques in trying to analyse global financial and trade linkages and global crisis spread and contagion however, may shed some light as to how such a measure could be constructed using network theory.

As mentioned above, the literature looking at global inter-connections through the lens of network theory has considerably expanded in the years since the crisis. The main justification for the use of network analysis to understand economic phenomena is the failure of some of the traditional, overly reductive approaches, that cannot account for the complex interactions that occur in the global economy (Farmer*, et al.*, 2012). Recent empirical research applies network theory analysis to global trade using trade data with network analysis allows measures -metrics- of both the nodes (the industries or the countries) and the links (the trade relationship) to be obtained. These measures have the appeal that they capture, not only the pairwise trade relationship, but also all type of complex relationship in the trade network. The number (degree), the strength (weighted degree) and the types (eigenvalue) of connections of a given node as well as the position of the node (centrality), are useful metrics to describe global country and industry linkages.

This type of research includes the use of network characteristics to describe trade globalisation (Kali*, et al.*, 2007), global financial contagion at global scale (Kali*, et al.*, 2010) and the effects of global trade networks on growth accelerations (Kali*, et al.*, 2013). Additionally, some studies use network metrics to analyse international contagion from shocks. Caraiani (2013) uses a complex network framework to analyse international contagion emanating from business cycles in a sample of OECD countries. Garas*, et al.* (2010) use a Susceptible-Infected-Recovered (SIR) model combined with network analysis to determine the probability of the crisis spreading at a global level. A similar approach is followed by Lee*, et al.* (2011) to determine the probability of a 'crisis avalanche' in the global macroeconomic network. All of these papers investigate the spread of the crisis between countries; none of them investigates the spread of the shocks, co-movement, at sectoral level, which is the empirical focus of Chapter Five

Many studies on the other hand, focus their attention specifically on the financial sector and the spread of the crisis at the global level. For example, Kali*, et al.* (2010) use network analysis to model international trade and explain stock returns during periods of crisis. Gai*, et al.* (2010) study the contagion effects of financial shocks using a series of financial indicators for interbank linkages under a complex network analysis. Dette*, et al.* (2011) use a network analysis technique of 'error and attack' to determine how a debt default in a given country spreads at the global level.

In stark contrast to the popularity of networks in the financial literature, its use to understand business cycle co-movement is relatively scarce. The sole paper to try directly to characterise international business cycles using networks is by Caraiani (2013). Its main contribution is the use of a Granger causality correlation network for a sample of G7 and OECD countries; finding, unsurprisingly, that the United States is a key player in the network. Lee*, et al.* (2011) use network analysis to look at the spread of the crisis in the global macroeconomic network but does not use co-movement since their crisis 'avalanches' are only transmitted via trade linkages without accounting for GDP correlation.

This section offers a different perspective to analyse industrial growth. The literature that looks at how shocks spread through the industrial network is still in its infancy, but it offers a very interesting way to analyse the complex relationships that characterise global trade.

2.5 Reflections on the Theoretical Literature

There is a clear evolution in the literature on industrial growth. It starts with the rather simple and static but still very applicable view of the role of agglomeration and specialisation on industrial growth, and then moves towards a more dynamic view of agglomerations and diversity with Jacobs and followers. In the 1990s, it shifts to a more refined, policy-oriented view of industrial growth through Porter's clusters and, more recently, the analysis of industrial growth using a network theory framework. As will become clearer in the succeeding chapters, the empirical analysis of industrial growth proposed in this thesis follows a similar evolution to the one presented in the literature insofar as it progresses from industrial agglomerations and clusters, to industrial networks and global industrial co-movement.

The predominant approach in the literature, the MAR (Marshall-Arrow-Romer) agglomeration, concludes that specialisation is one of the greatest positive externalities of agglomeration. Many cluster initiatives world-wide have been propelled with specialisation in mind. Agglomerations and their modern cousin, clusters, have been found to promote regional and industrial growth. The empirical literature however, remains divided as to what are the real mechanisms by which clusters create growth. It has also been argued that clusters can only foster growth if certain pre-conditions are met in a region or city. For example, clusters have no additional growth effects in regions lacking higher level of education and R&D. The full impact of a cluster on a region's economy requires some basic factors to be in place. This has led some studies to question the validity of clusters as a tool for regional growth; if clusters need an industrial ecosystem in place to show their full benefit, are they really creating prosperity for the region or is it the ecosystem itself that is creating prosperity?

More recently, the Marshallian agglomeration has been challenged by the followers of Jacobs, who proposed that industries benefit from diversity rather than specialisation. The outcome of this controversy has been inconclusive since regions, cities and industries actually appear to suffer positive and negative effects from both types of agglomerations externalities. Industries are highly heterogeneous and go through different stages of evolution, thus the effects of agglomeration externalities affect each one differently, as proposed in the life cycle theory of agglomeration externalities. In the early stages of an industry, diversification is the key for growth while, in its more mature stages, specialisation is needed.

Although the concept of clusters is widely popular among policy-makers and researchers, its geographical limitations also limits the analytical methods available. The analysis of industrial growth within the framework of geographical agglomeration cannot account, for example, for inter-connectedness among industries located in different countries. The limitations of traditional analysis of industrial growth focusing, at best, on a handful of industries at a time using non-dynamic linear methods were exposed during the recent global crisis. In order to capture the complex linkages that characterise the global industrial economy, it is necessary to use a different set of tools and even a different mind-set because it is not possible to analyse industrial growth and trade without considering all of the complex linkages involved. For example, even if an industry is located in a specific region, it will be affected by a complex system of trade linkages that go well beyond the region or country. The analysis of this type of systems requires all of an industry's potential linkages to be considered within a network theory framework.

In the aftermath of the Great Recession, there has been renewed interest in the role that industrial agglomerations may have played in the crisis. A typical example of an agglomeration gone bad, is the automotive industry in Detroit; did the high concentration of firms in that cluster created a system higher risk in the event of a crisis? Or is it the case that the agglomeration itself had nothing to do with the crisis that started at the national level and then created a ripple effect in the automotive industry? The specific issues are whether industrial clusters can cope with economic shocks (see, for example, Skålholt*, et al.* (2012)) or whether they promote resilience (see, for example, Treado*, et al.* (2008) ; Öz*, et al.* (2011) ; Østergaard*, et al.* (2013)). In order to analyse this sort of questions that are casting a shadow of doubt and criticism on specialised agglomerations (Hausmann, 2014), this thesis, in Chapter Three, looks at the relationship between industrial agglomerations and economic shocks; specifically trying to analyse whether industrial clusters can cope with an economic shock.

To tackle the empirical research presented in chapter three, based on the extensive literature on industrial clusters, the model used to test whether cluster can cope with economic shocks is based on Rodríguez-Pose*, et al.* (2011). As reported in this literature review, that particular paper uses a dataset for 152 regions in 15 European countries, for the period from 1995 to 2006 to determine whether clusters generate innovation and growth. The study uses a cluster index consisting of a Principal Components Analysis (PCA) of specialisation, focus, and size, as well as two other PCA-indices for innovation and social variables with the dependent variable being the variation of regional GDP per capita. The paper is specially relevant to the empirical research presented in chapter three, since the definition on industrial cluster is based on Porter (2003) and also some of the same data sources and transformation techniques.

As it has become evident from the most recent literature, some of the traditional methods cannot cope with the complex, non-linear, and unpredictable way in which shock affect industries. Specifically, the topic covered by this thesis, in Chapter Three -industrial agglomeration-, is considered a potentially inefficient way of analysing the effects of economic shocks at industry level. Industrial agglomerations, by definition, are constrained to specific geographic location, but the effects of an economic shock are complex in nature, interconnected in ways that go beyond the geographic boundaries of industrial districts, regions and countries. With that limitation in mind, Chapters Four and Five, look at the issue of industrial growth and industrial downturn using a novel approach based on network theory. The analysis of industries using networks opens up a vast set of opportunities to understand their dynamics and inter-connectedness and how the relationships between industries (all of them at the same time) affect issues like growth or contagion in a crisis.

Chapter four uses the model of industrial growth originally presented in Chenery (1982) and later adapted to analyse the architecture of the global growth and industrial growth networks in (Kali*, et al.*, 2007 ; Kali*, et al.*, 2013), respectively. In Chapter five, the empirical model analyses the network determinants of industrial comovement, this approach follows the model and methods used in Giovanni*, et al.* (2009) and then includes industrial network variables that have been obtained specifically for this research using the method described in chapters four and five.

The literature reviewed shows that an increasing number of studies are using industrial networks to have a new look at old and new economic problems. Chapters Four and Five are part of this new effort to investigate industrial growth and industrial co-movement empirically. This approach has the potential to be highly beneficial, not only from a theoretical point of view but it may offer special insights to policy-makers concerned with industrial growth and downturns.

Chapter 3

The Effect of Economic Shocks On Regional Industrial Clusters

3.1. Introduction

In the last twenty years, the concept of industrial clusters has been widely popularised and has transitioned into the field of public policy and firm strategy. Many cluster initiatives have been created in this time, ranging from explicit public intervention to create successful clusters, to private association strategies aimed at enhancing cluster governance. At least 250 specific initiatives to develop or strengthen clusters were launched world-wide up to 2003 (Ketels, 2003) but that number may have been greatly exceeded since there are 1,235 official European cluster associations registered by the European Cluster Observatory (based on a review made in 2011). In addition, cluster initiatives in much of the rest of the world, especially in developing countries, are not included in any official database, so that the number of clusters and cluster initiatives may be much higher than accounted for officially. In the following sections, the term 'cluster' and 'agglomeration' will be used interchangeably to refer to any type of industrial agglomeration, although many authors have acknowledged there are important differences in the industrial agglomeration typology (Hambrick (1983) ; Markusen (1996) ; Paniccia (2006) ; Kerr*, et al.* (2010)).

The allure of clusters for practitioners, policy-makers and the general public is the result of the iconic experiences of high profile clusters around the world. These include: Silicon Valley; Boston, Mass.; Cambridge, UK; Medicon Valley near Copenhagen; Emilia-Romagna in Italy; Bavaria in Germany, centred in Munich; the Sophia Antipolis technology park in France; and Hsinchu Science Park near Taipei (Yusuf*, et al.*, 2008; p.2). Considerable academic research shows how clusters promote regional growth, spur innovation, reduce transaction costs and increase firm co-operation, among other positive benefits. This has contributed to what has recently been called a 'cluster momentum' (Muro*, et al.*, 2010).

In a period in which industries at the national and regional level are suffering from the most severe recession the world has seen since the 1930s, some academics, politicians and practitioners have asserted that clusters might be the light at the end of the tunnel. Further, formal academic papers making similar propositions are starting to emerge. For example, Muro*, et al.* (2010; p.4) state that "*(...) it is appropriate to revisit the cluster paradigm and consider its special relevance at a moment of deep economic uncertainty, fiscal crisis, partisan gridlock, and necessary governance reform.*" They go even further, suggesting that *"(...) It is true that as a matter of policy action, clusters are all about synergies and efficiencies, and don't tend to cost too much."* (Muro*, et al.*, 2010; p.4).

The analysis proceeds as follows. The first section presents a brief discussion of the main and more relevant conclusions from the literature review presented in Chapter Two and its specific implications for this Chapter. Then follows a discussion of the way to operationalize the research questions, the econometric model and the estimation process are described along with the empirical results. The conclusions are then presented from both an academic and a policy perspective point of view.

3.2. **Empirical Strategy**

This Chapter tackles the question of whether clusters can cope better with shocks than non-clustered industries. A dataset for 22 French regions from 1996 to 2008 and 40 sectors is used. The selection of France is based both on theoretical and practical reasons. In the first case, France has a long tradition of using clusters (called *grappes industrielles*) as a recurrent tool for regional development (Duranton, 2010 ; Martin*, et al.*, 2011), and second, the regional dataset for France is one of the most complete and fulfils the needs of the empirical method used in this chapter. To measure the effects of industrial shocks at both regional and national level, a variable is created using an adapted version of the pioneering approach for analysing growth accelerations of Hausmann*, et al.* (2005). Using the number of employees per industry, the difference between the industry growth rate and the expected growth rate is estimated to create two variables: *positive shock* and *negative shock* for both the regional and national level.

Clusters are identified using two different methods: 1) the traditional location quotient approach of Ellison*, et al.* (1994) and 2) a recent approach to identify clusters proposed by Rodríguez-Pose*, et al.* (2011) in which an index is created based upon three variables is also used a robustness check in this chapter, but only reported in *Appendix 3.5*. Informed by the literature review presented in the last section and in Chapter Two, variables for a large number of regional characteristics are introduced as well as sector-specific characteristics, which are fully described in the next section. To compare the results obtained for France, a dataset for German regions is compiled for the same 40 sectors. Germany was selected for the comparator analysis as it is a country that has similar economic, social and geographic characteristics.

Data collected by the European Cluster Observatory (ECO) is used as the main source at industry level along with data provided by Eurostat. The use of the ECO database has several advantages and disadvantages. It offers the most comprehensive database for clusters in Europe, it is easily accessible and reliable and their data cover 15 European Countries, with detailed information for 409 regions at NUTS-2 level from 1995 to 2008. However, it also comes with several caveats (see, Crawley & Pickernell, 2012). The sectors are created by ECO to reflect the nature of inter-relations between industries and to operationalise the cluster concept. Instead of aggregating industries in the hierarchical way, as the European classification system specifies, ECO combines industries from different parts of the classification system. This creates a suitable dataset for the specific research here but poses an issue of incompatibility with other databases.

Thus, at the sector level, only data provided by ECO can be used. A description of the categorization used is given in *Appendix 3.1*. Although the ECO dataset covers a large great number of countries, in practice much of the information is missing for most of them and, when data is not available for a specific year, it is replaced by the most recent year available. Finally, according to Rodríguez-Pose*, et al.* (2011), ECO uses a reference year to calculate some of the industry-related variables which is not in the same for every country, thus creating a potential problem when using a sample consisting of different country datasets in the same estimation.

For this analysis, ECO data at the sector level for France was chosen, which includes 40 sectors based on, but not equivalent to, NACE rev2 for 22 regions (NUTS 2) from 1996 to 2008. For the purposes of comparison, a dataset for Germany consisting of 33 regions and the same 40 sectors is used from 2000 to 2007. To allow for comparability, a new model for France using the same timeframe as that for Germany is also used. For the variables at the regional level, the information is obtained from Eurostat, since there is no problem of compatibility with the ECO database at this level. Data from Input-Output matrices collected by Eurostat is also used.

3.3. **Estimation Method for Industries and Regions in France**

To estimate the model for France, a panel is chosen and using the region and the year as a pivot, a total of 40 estimations using the same method are carried out, one for each sector. The initial dataset consists of observations ranging from 1996 to 2008, but the construction of the *Shock* variable implies the loss of four years of data so that the final estimation consists of data from 2000 to 2008. The descriptive statistics of the variables used in this chapter can be found in *Appendix 3.2*. Since the dependent variable, *Shock*, is binary, a Probit panel is used for the estimation. Fixed effects models are ineffective when using a Probit panel (Wooldridge, 2001), thus the options are a Random Effects or a Population Average Model. Given that the dataset consists of non-independent observations for different industries (a test for Intra-class Correlation is conducted to assess the probability of non-independent variables), a Population Average Model is fitted using Generalised Estimating Methods (GEE).

Table 3.1: Descriptive Statistics for France, 2000-2008. Model I.

Variable	Obs	Mean	Std. Dev.	Min	Max
Regional Shock Negative (RSN)	7920	0.421	0.494	0	1
Regional Shock Positive (RSP)	7920	0.368	0.482	0	1
Cluster	7920	0.338	0.473	0	1
Size	7920	0.591	1.004	0.000	15.890
Focus	7920	0.905	1.222	0.000	8.460
RD	7920	0.000	2.452	-3.854	8.197
Wealth	7920	0.000	1.222	-2.683	5.083
Employ	7920	0.000	2.147	-10.359	3.142
XportReg	7920	0.085	0.279	0	1
EUAID	7920	1.656	1.140	0.075	6.094
National Shock Negative (NSN)	7920	0.375	0.484	0	1
National Shock Positive (NSP)	7920	0.283	0.451	0	1
lag1NSN	7919	0.375	0.484	0	1
lag1NSP	7919	0.283	0.451	0	1

A potential problem of multicollinearity between the variables is detected using auxiliary regressions (Haddad*, et al.*, 1995). To correct this problem, a PCA is used to reduce the number of variables into those that account for the largest variance (Vyas*, et al.*, 2006). From a theoretical review, it is inferred that three groups of variables can be created to test the model (related to research and innovation, employment and wealth). A PCA is used for each group of variables resulting, in three indexes. The two components that account for the greatest amount of the total variance are used to create each index. For the employment variables, the two components selected account for 75.9 per cent of the variance; 73.9 per cent and 97.5 per cent for innovation and wealth respectively. A summary of the variables incorporated in each index, can be found in *Appendix 3.3.* After the construction of the three indices, a new test for multicollinearity is run

(3.6)

and which determines that there are no further issues.

For each model; looking at positive and negative regional industrial shocks individually, a total of 40 regressions are estimated, each one comprising 198 observations out of a complete sample of 7,920. A sample of the results for a selection of industries in France is reported in Tables 3.2 and the full results can be found in *Appendix 3.4*). The measure of the goodness-of-the-fit is not reported since various strands of the literature suggests that there is no relevant measure for a binary panel (Wooldridge, 2001; p.575). To facilitate the interpretation of results, the marginal effects are reported rather than the raw coefficients. Owing to problems with the convergence of the estimation, two sectors are dropped (business services and financial services), resulting in a total of 38 estimations, one for each sector.

Model I: The final econometric model for the French dataset is as follows:

$$RSN_{irt} = \alpha + \beta_1\, Cluster_{irt} + \beta_2\, Size_{irt} + \beta_3\, Focus_{irt} + \beta_4\, RD_{rt} + \beta_5\, Employment_{rt} + \beta_6\, Wealth_{rt} + \beta_7 XportReg_{rt} + \beta_8 EUAID_r + \beta_9\, NSN_{it} + \beta_{10}\, Lag1NSN_{it} + \varepsilon$$

$$RSP_{irt} = \alpha + \beta_1\, Cluster_{irt} + \beta_2\, Size_{irt} + \beta_3\, Focus_{irt} + \beta_4\, RD_{rt} + \beta_5\, Employment_{rt} + \beta_6\, Wealth_{rt} + \beta_7 XportReg_{rt} + \beta_8 EUAID_r + \beta_9\, NSP_{it} + + \beta_{10}\, Lag1NSP_{it} + \varepsilon$$

Model II: The comparison between the French and German datasets:

$$RSN_{irt} = \alpha + \beta_1\, Cluster_{irt} + \beta_2\, Size_{irt} + \beta_3\, Focus_{irt} + \beta_4\, RD_{rt} + \beta_5\, Employment_{rt} + \beta_6\, Wealth_{rt} + \beta_7 XportReg_{irt} + \beta_8 XportNac_t + \beta_9 EUAID_r + \beta_{10}\, NSN_{it} + \beta_{11}\, Lag1NSN_{it} + \varepsilon$$

$$RSP_{irt} = \alpha + \beta_1\, Cluster_{irt} + \beta_2\, Size_{irt} + \beta_3\, Focus_{irt} + \beta_4\, RD_{rt} + \beta_5\, Employment_{rt} + \beta_6\, Wealth_{rt} + \beta_7 XportReg_{irt} + \beta_8 XportNac_t + \beta_9 EUAID_r + \beta_{10}\, NSP_{it} + \beta_{11}\, Lag1NSP_{it} + \varepsilon$$

As a robustness check, the variable *Cluster_Index* (instead of the *Cluster* dummy) is used in the model as well as the variation in employment trend growth *Region_Shock* (instead of using *negative (RSN)* or *positive shock (RSP)* as the dependent variable). Both estimations results can be found in the *Appendix 3.5 and 3.6*, respectively.

3.3.1 Dependent Variables

To operationalize the concept of an economic shock, an adapted version of the pioneer approach of Hausmann et al. (2005) is used to analyse growth accelerations. This methodology is also employed in several papers (e.g., Hill*, et al.* (2010), Eichengreen*, et al.* (2011) Xu (2011)). Using the number of employees per industry for every base year in the sample, at both the national or regional level depending on the aggregation level, a four-year industry growth rate is regressed on a time trend and the last-year industry growth rate is subtracted. If the difference is greater higher than 2% a *positive shock* is inferred; if the difference is less than -2%, a *negative shock* is inferred. As Hausmann*, et al.* (2005) explain, the use of 2% threshold is arbitrary but could be considered to be a value that represents the natural growth of the economy. Although no more explanation for using this value is given in their paper, they also use a 3.5% threshold that they call 'rapid growth', but this is not applicable to this chapter since the objective here is to determine the existence of a shock, not its magnitude.

The four-year industry growth rate is measured by the slope of the regression line from the natural logarithm of employment on a time trend for the previous four years (without including the base year). This approach is originally proposed in Hausmann*, et al.* (2005) using an eight-year growth trend for GDP per capita as a measure of growth. A four-year growth rate only is used here owing to dataset limitations. The data used here data covers 1996 to 2008 but the method implies that only observation from 2000 to 2008 are considered after the four year growth regression, obviously an eight year growth would further restrict the data from 2004 to 2008 causing an unnecessary and very costly loss in the number of observations. Additionally, employment is used instead of GDP per capita, using the same approach as Hill*, et al.* (2010). The choice of employment needs further explanation. Employment, both in France and Germany, is considered less responsive than GDP in the event of an economic shock due to the existence of employment protection laws, in that sense it may be argued that using employment will not capture industrial shocks. But it is precisely because of that characteristic, employment stickiness, that it used here instead of GDP. If after using this method, a shock is found to be present in a given industry, then we can be certain that shock reflects an underlying change in the economic conditions that is strong enough to be observed even under strong employment rigidity.

The following are the resulting dependent variables:

Regional Positive Industry Shock (RSP): a positive difference of more than 2% from the growth trend for every industry at regional level. The variable then is transformed to either 1 (if the shock is present) or 0 (otherwise), to capture the specific effect of the shock.

Regional Negative Industry Shock (RSN): a negative difference greater than -2% from the growth trend for every industry at regional level. Again, it is then transformed into a binary dummy variable.

National Positive Industry Shock (NSP): a positive difference of more than 2% from the growth trend for every industry at national level. Again, it is transformed into a binary dummy variable.

National Negative Industry Shock (NSN): a negative difference greater than -2% from the growth trend for every industry at national level. It is also transformed into a binary dummy variable.

The caveat of transforming the shock variable into a binary dummy variable is that some information is lost in the process such that a ten per cent shock is therefore treated the same as a three per cent shock. This downside is compensated for by calibrating a distinct negative or positive shock effect, which is the objective of this research. Nevertheless, to avoid any further

(3.1)

issues, the shock variable, both at national and regional level, without any transformation (the difference between the four-year growth trend and the annual growth) is also tested. These variables are called: Region_Shock and Nation_Shock. The results are presented in the Appendix 3.6 and the analysis is presented in the 'Robustness' section of this Chapter.

3.3.2 Independent Variables

Identifying Clusters

This Chapter uses Porter's definition of a cluster as *'a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities'* (Porter, 1998, p.199). There is no general agreement as to how to properly define a cluster, but this definition is also consistent with the framework used by the ECO for the categorisation of industries into sectors. To create a cluster variable that can be fitted into the model for estimation purposes, the Location Quotient (LQ) method is used which based on the relative importance of employment (Schaffer*, et al.* (1969) ; Ellison*, et al.* (1994)). Clusters are designated by a LQ higher than 1, as used by Porter (2003). The LQ data used in here is taken directly from the ECO, where it is called *Specialisation Quotient.* It is defined as:

Specialization Quotient:

$$SQirt = (E_{irt}/\, E_{it}) \Big/ (E_{rt}/E_t)$$

Where: SQ_{irt} = the specialisation quotient for region *r* and industry *i*;

E_{irt} = the number of employees for region *r* and industry *i*;

E_{it} = the total number of employees in all regions for industry *i*;

E_{rt} = the total number of employees in all industries for region *r;*

E_t = the total number of employees in all regions and all industries (in Europe).

If SQ_{irt} >1, the sector is considered to be a cluster (dummy value of 1) and non-clustered

(3.2)

otherwise (dummy value of 0); this variable is called *Cluster*. Table 3.1 shows the tabulation for this variable; a total of 2,676 clusters are found, representing 33.79 per cent of the total sample of industries. This method for identifying clusters is used widely in the literature; including: De Silva (2012), Delgado*, et al.* (2010), Kukalis (2010) and Wennberg*, et al.* (2010)

Table 3.1: Cluster Dummy tabulation in France from 2000 to 2007.

Cluster Dummy	Frequency	Percent
0	5244	66.21
1	2676	33.79
Total	7920	100

Other methods for identifying clusters involve using a sector-based LQ together with a mix of different variables, including measures of regional location and the size of the cluster. The ECO definition of a cluster, for example, use a different system called 'the stars' which uses a mix of LQ, Focus (share of regional employment) and Size (number of employees compared to other European sector), for more information see Sölvell*, et al.* (2009). Rodríguez-Pose*, et al.* (2011) test for the effects of clusters on regional growth and innovation by creating a *Cluster Index* using Principal Component Analysis on three variables: LQ (specialization), Focus, and Size. All of these variables are provided by the ECO database. LQ is defined as in Equation (3.1), Focus and Size are defined as follows (Sölvell*, et al.* (2009; p.4)):

Focus:

$$Focus_{irt} = E_{irt} / E_{rt}$$

(3.3)

Where: E_{irt} = the number of employees for region *r* and industry *i*;

E_r = the total number of employees in all industries for region r.

Size:

$$Size_{irt} = E_{irt} / E_t$$

Where:

E_{irt} = the number of employees for region *r* and industry i

E = the total number of employees in all regions and all industries (in Europe)

The resulting index by combining Specialization, Focus and Size using PCA (following (Rodríguez-Pose*, et al.*, 2011), is called *Cluster_Index* here and is used as a robustness test (the results are presented in Appendix 3.5).

An important caveat is mentioned by the ECO regarding their data:

> '*Data limitations restrict us to the use of employment data to identify and evaluate clusters. This creates a certain bias in our measures towards employment-intensive clusters, especially on the metrics for size and focus. Only the measure for specialisation is unaffected by differences of employment intensity across cluster categories. It would have been preferable to use data on wage bill, productivity, or value added, which would have shifted the balance in favour of capital- or knowledge-intensive cluster categories such as biopharmaceuticals, but as such data was not available in all European countries we have resorted to the use of employment data'* (ECO Web Page; www.clusterobservatory.eu; February 2012).

The use of these two different ways of conceptualising the cluster variable will help to minimise, although not completely eliminate, some of the problems mentioned by the ECO. Other quantitative methods, not used in this Chapter, for identifying clusters include: Input-Output measures, Shift-Share analysis, Giniho coefficients of location, Ellison Glaesser index of agglomeration and Maurel-Sédillot index. For further discussion of these methods see (Rosenfeld, 1997 ; Hill*, et al.*, 2000 ; Giuliani, 2010 ; Stejskal, 2010).

Control Variables

In order to control for specific regional and industry effects, a number of variables are introduced.

Research & Development (R&D)

Innovation and knowledge spillovers have an essential role in the location of firms and industries; R&D-intensive industries are more likely to be closely located (Arrow, 1962). To test this specific assumption, Audretsch*, et al.* (1996) use a model in which they incorporate variables to measure the impact of research intensity on industrial agglomerations, private research expenditure, academic research expenditure and numbers of skilled labour. They find strong evidence that the relative importance of innovation and knowledge spillovers in the industry is a key determinant of the extent to which the location of production is geographically concentrated. Iammarino*, et al.* (2006) come to a similar conclusion, finding that knowledge spillovers are more likely to be present in R&D-intensive locations which, in time, are more likely to be found in industrial clusters.

Another important strand of the literature suggests that the impact of geographic location on innovation can also by assessed using the number of patents in a region or an industry. For example, Porter (2003) finds a strong correlation between the number of patents per employee and industrial location quotients. Patents were also evaluated by Bonnet (2010) in urban settlements in Southern France and concludes that they are more likely to happen in agglomerations where knowledge and innovation are developed and, if some conditions are met, this knowledge will then spread to other regions. Based on the literature and following the work done in Rodríguez-Pose*, et al.* (2011), a set of variables related to regional innovation and knowledge creation are introduced. All these variables are obtained from the ECO, which uses information from Eurostat and ProINNO (a European initiative for fostering innovation). For specific information on the methodology used to create the innovation and research variables presented in this section see Hollanders*, et al.* (2008).

A comprehensive analysis of collinearity using auxiliary regressions shows a potential problem in these variables. To avoid this problem and given that all the variables are supported by the literature and thus relevant to the model, an index using Principal Component Analysis is created based on the method proposed by Vyas*, et al.* (2006). The resulting variable is named *RD*, using two components (the results from the PCA are presented in *Appendix 3.3*).

Wealth

A large number of studies find a strongly positive relationship between clusters and regional growth. Porter (2003) uses regional GDP per capita to account for the effects of clusters on regional growth whereas Morgan (2007) uses regional per capita income, applied to a sample from the United States. Glaeser*, et al.* (2009) uses the logarithm of income per capita and wages to assess the long term growth in cities. Spencer*, et al.* (2009) uses regional average income to assess the agglomeration effects on Canadian clusters. Based on the substantial literature that finds a relation between agglomerations and regional growth, a set of regional variables is introduced in this study to capture the effect of wealth. following the work of Rodríguez-Pose*, et al.* (2011). The presence of multicollinearity is detected using auxiliary regressions and a PCA is used to create the variable *Wealth* (see *Appendix 3.3*).

Employment Conditions

Using data for urban agglomerations in the United States, Glaeser*, et al.* (2001) find that, controlling for differences in population density, education, ethnicity, experience and job tenure, urban agglomerations cause higher wages. De Blasio*, et al.* (2005) analyse the effects of industrial clusters on a specific set of social variables to test if workers in clusters are better off than those in non-clustered industries. Their results are interesting since they confirm the theory by stating that industrial agglomeration increases the chances of being employed, the probability of being an entrepreneur and it also facilitates vertical mobility. However, on the other hand, they find no significant improvement in the wage levels and growth of workers in clusters compared to workers in non-clustered industries. They conclude that belonging to an industrial agglomeration may contribute to income growth in firms and regions but not to increases in individual workers' wages. Other recent studies that incorporate social variables as controls in the context of industrial agglomeration analysis include: Wennberg*, et al.* (2010), which uses the log of regional employment and population density; Spencer*, et al.* (2009), which uses the unemployment rates; Hill*, et al.* (2010) which uses the contribution of regional employment per category; and Rodríguez-Pose*, et al.* (2011), which uses a large number of employment variables combined in an index.

Recent research by Marelli*, et al.* (2011) focuses on assessing the impact of the current global recession on employment at the national and regional level in Europe. Using employment and the change in unemployment before and after the crisis, they find that the effects of the 2007–2008 financial crisis have been particularly severe in the European context and significant 'between country' differences also emerged in the labour market responses. The conclusions of Marelli et al. are particularly relevant to this study:' *"[these] results confirm the need to appropriately investigate the complexity and heterogeneity of regional labour market dynamics and to take into account spatial linkages"* (Marelli et al., 2011, p. 26).

A set of regional employment variables from Eurostat database that are consistent with the literature is included here. As before, the variable *Employment* is created using PCA (see *Appendix 3.3*).

Export Intensity

Exports have long been recognised as affecting regional growth. Schaffer*, et al.* (1969) are the first to provide a solid quantitative method to transform national input-output accounts into a regional framework, including an estimation of export patterns. Since then, many attempts have been made to find the best way to estimate regional output and regional multipliers (e.g. Ullman, 1968 ; Stilwell*, et al.*, 1971 ; Round, 1978 ; Arcelus, 1984). The most widely used non-survey method is the Location Quotient (LQ) which can have a large number of variations (Kronenberg, 2009). A LQ greater than 1 means that the area economy has more than enough employment in industry *i* to supply the region with its product and a LQ less than one suggests that the area is deficient in industry *i* and must import its product if the area is to maintain normal consumption patterns (Schaffer, 1999). This method, also called Simple Location Quotient (SLQ), is a relatively easy way to estimate the export intensity of a region (Flegg*, et al.*, 2011).

The SLQ has its own shortcomings in that it rules out the cross-hauling (Kronenberg, 2009), that is, the possibility that two regions could be export and import partners of the same product at the same time (Stilwell*, et al.*, 1971). The SLQ has also been shown to be a poor estimator of the real employment associated with exports (Harris*, et al.*, 1998). With these caveats in mind, Flegg, *et al.* (2000) create a transformation of the SLQ, the FLQ, based on employment data and which aims to capture the effect of regional specialisation magnitude of regional input coefficients. The FLQ offers consistent empirical results and greater accuracy than other similar coefficients (Flegg*, et al.* (2011, 2012)). The FLQ is therefore used in this study as a proxy for the export specialisation of a region, using the following formula from Flegg*, et al.* (2011)

$$FLQ_i = SLQ_i \times \lambda \qquad (3.4)$$

where:

$$SLQ_i = \frac{REi/TRE}{NEi/TNE}$$

$$\lambda = [log2(1 + TRE / TNE)]^{\alpha}$$

Where: *FLQi* is the Flegg Location Quotient for industry *i*,; *REi* is regional employment in industry *i*; *TRE* is total regional employment; *NEi* is national employment in industry *i* ; and *TNE* is total national employment. The parameter α in λ take values from 0 to 1 that are arbitrary in order to allow for more or less interregional trade. Flegg*, et al.* (2011) analyse the best value for the parameter α and, based on their own results and other studies, the best fit for α is between 0.25 and 0.30. The closer the parameter α is to 0, the more the FLQ will resemble the SLQ. In this study, a value of 0.25 is used to construct the FLQ. The estimated quotient is then transformed into a binary variable that either takes the value of 1, if the resulting FLQ is greater than or equal to 1 or a value of 0 otherwise. The resulting variable is called in this chapter *XportReg* and aims to capture the trade orientation of a sector in a specific region.

The *XportReg* variable captures the effect of exports at a regional level. In order to capture the effect of exports at the national level, another variable is compiled using information from the national Input-Output matrix for each country. A coefficient for industry *i* is created by dividing total exports by the sum of intermediate consumption and final consumption. If the resulting value is greater than the threshold (0.2), then the industry is considered to be export-oriented and assigned a value of 1 (or 0 otherwise). This variable is called *XportNac* here. It captures the openness to trade of an industry at the national level by using national accounts data for each year in the sample. Naturally, the value of this threshold will affect the final outcome of the variable; a 0.2 threshold is used here since it is close to the simple average of the export coefficient for all the sectors in sample. A bigger threshold would rule out a lot of important export patterns. For example, a 0.2 threshold represents an industry for which the value of exports represents 20% of the total value of domestic consumption. Due to a restriction in the data, the variable *XportNac*, is only used for the comparison between France and Germany between 2004 to 2007.

The original ECO dataset is based on a specific grouping of industries into sectors to reflect industry links inside an industrial agglomeration that is incompatible with the categorisation used in the European Input-Output tables. A successful transformation can be made to adapt the I-O classification to the ECO for 33 industries, leaving only seven industries for which no information is available in the I-O. These seven are analysed on a case-by-case basis, using different trade indicators, to infer the export intensity of each industry. Both of the resulting variables discussed in this section, *XportReg* and *XportNac* capture different effects of trade orientation at the national and regional level.

Finally, a variable is tested to control for the existence of old industrial regions (OIR's), which according to the literature can affect the performance of regions. Two different definitions of OIR's are used; those by Birch, *et al.* (2008) and Rodríguez-Pose (1999). The definition of Birch, *et al.* (2008) is misleading, particularly for Germany, since the proposed OIR's are all located in the Western part of the country and do not capture appropriately the intrinsic division between German regions. That of Rodríguez-Pose (1999) seems to be more appropriate to capture regional differences in both France and Germany but the results of including this variable in the model are insignificant in both countries in every estimation tested. Thus, the OIR variable is removed from the model, since it does not seem to affect the overall significance.

3.4. Findings for Industries and Regions in France

3.4.1. The Impact of Economic Shocks on Clusters: An Empirical Analysis of French Regions

The result from the estimation of the Model I, the case of a negative regional shock, shows that the presence of a cluster is insignificant in 28 out of 38 regressions. For those cases in which the coefficient is significant, three are positively correlated with a negative crisis and seven are negatively correlated. Although the majority of results show an insignificant relationship between clusters and a negative regional shock, a case-by-case analysis is needed to determine the individual impact. For the rest of the variables, the most relevant finding is that, as expected, the existence of a national negative shock is highly correlated with the dependent variable; in fact, 33 regressions prove to be significant at either the 1 per cent or 5 per cent level, all of them being positively correlated with a negative regional shock. Only five sectors show no significant relationship: Chemical Products, Construction Materials, Footwear, Heavy Machinery and Stone Quarrying.

The results for the regional control variables that are aggregated in three indices – wealth, employment and R&D – are heterogeneous depending upon the sector but, in the majority of cases, the relationship between these and the regional shock is insignificant (see Figures 3.1 and 3.2).

The results for the *EuAid* variable are interesting. In the event of a negative shock, 21 out 38 coefficients are insignificant and, in the significant ones, the effects are highly ambiguous. In the event of a positive shock however, a large number of coefficients become significant and positively correlated. This suggests that aid from the European Union at regional level may not be effective to cope with a negative shock but it helps to boost growth during a positive shock.

It is also important to investigate the effects of a positive regional industrial shock. This is undertaken for the same 38 sectors as before but with a positive regional shock as the new dependent variable and one of the independent variables is changed to reflect a national shock. For 32 sectors, the relationship between a positive shock and the cluster variable is insignificant. In only two industries is the coefficient significant and positive (Construction and Metal Manufacturing) and it is negative and significant in four industries (Distribution, Furniture, Jewellery and Media & Publishing). With respect to the control variables, the greatest influence on a positive regional shock is again exerted by a national shock; the coefficient has a significant and positive sign in 28 sectors. The regional control variables prove to be very heterogeneous, depending upon the sector, but the results are slightly skewed towards a positive effect of *Wealth* and *R&D* in the positive shock case as well as in the event of a negative shock. The final results need to be analysed on an industry-by-industry basis.

As a robustness check for the dependent variable, the *Regional_Shock* variable is tested. This is the same as the shock variable but not converted to a dummy, so allows different estimation techniques to be used, specifically a traditional panel approach rather than a Probit model. No significant differences are found between the results of this estimations and the previous one. Results are reported in *Appendix 3.6*.

A new set of regressions is then undertaken using a *Cluster Index* instead of the *Cluster Dummy*. The results are highly heterogeneous and, the overall results are consistent with those obtained with the cluster dummy variable – that is, the cluster variable is still largely insignificant for the vast majority of sectors – although there is a change in the magnitude of the coefficients as it is expected given the difference between the two variables used for the comparison. Although the overall results are similar, these two methods for determining the existence of a cluster do not appear to be perfect substitutes. The number of significant sectors does not change considerably but the industries that are significant using the dummy are not the same as when the index is used. Results are presented in *Appendix 3.5*.

Similar unstable results are reported in the cluster literature and constitute a recurrent critique (e.g., Spencer*, et al.* (2009) Wennberg*, et al.* (2010) Gardiner*, et al.* (2011)), because results may well be affected by the chosen cluster variable. So far is this study is concerned, it appears that both cluster variables confirm the largely insignificant relationship between clusters and economic shocks, which lies at the core of this chapter's findings.

Finally, in order to correct a potential problem of heteroskedasticity that could affect the standard errors, a Probit panel is run using a bootstrap estimator. This exercise produces an even greater number of insignificant variables, especially the cluster dummy. This suggests that the large amount of insignificant relationships found and reported here have been correctly estimated and are not the result of the wrongful rejection/confirmation of the null hypothesis due to a biased standard error.

Table 3.2: France, probit panel estimation of Regional Positive Shock (RSP).[2]

	(1)	(2)	(3)	(4)	(5)		(18)	(19)	(20)	(21)	(22)	(23)		(35)	(36)	(37)	(38)
	Aerospace	Agricultural	Apparel	Automotiv	Biotech	...	IT	Jewellery a	Leather pro	Lighting anc	Maritime	Media and ¦	...	Telecom	Textiles	Tobacco	Tourism anc
Cluster	-0.0889	-0.127	-0.202	0.0638	0.0950		0.121	-0.162*	-0.00147	-0.118	0.0772	-0.209***		0.122	-0.00163	-0.0118	-0.0347
	(0.0758)	*(0.132)*	*(0.132)*	*(0.0699)*	*(0.0911)*		*(0.189)*	*(0.0888)*	*(0.0762)*	*(0.118)*	*(0.101)*	*(0.0678)*		*(0.101)*	*(0.101)*	*(0.0962)*	*(0.121)*
Size	-0.00590	0.175	0.00715	0.116**	0.0257		-0.184***	0.0273	-0.110***	-0.0294	-0.0830	-0.0718		0.0926	-0.0369	-0.112	-0.0645
	(0.0309)	*(0.120)*	*(0.0694)*	*(0.0564)*	*(0.0203)*		*(0.0566)*	*(0.0576)*	*(0.0365)*	*(0.0846)*	*(0.161)*	*(0.0688)*		*(0.106)*	*(0.0542)*	*(0.0831)*	*(0.156)*
Focus	0.111*	-0.213	-0.197	-0.105***	-1.203*		0.438	1.027	0.0771	0.306	-0.0737	1.519***		-0.228	0.882	0.00366	0.0740
	(0.0621)	*(0.216)*	*(0.173)*	*(0.0396)*	*(0.726)*		*(1.257)*	*(0.733)*	*(0.100)*	*(0.237)*	*(0.207)*	*(0.315)*		*(0.170)*	*(1.181)*	*(0.0308)*	*(0.0555)*
RD	0.0119	0.0392	-0.0261*	-0.00723	0.0341**		0.0246	-0.0399	0.0139	0.00310	0.00516	-0.000545		-0.0410***	-0.00137	0.0365**	-0.0418
	(0.0176)	*(0.0247)*	*(0.0137)*	*(0.0201)*	*(0.0165)*		*(0.0218)*	*(0.0293)*	*(0.00870)*	*(0.0118)*	*(0.0190)*	*(0.0170)*		*(0.0157)*	*(0.0131)*	*(0.0148)*	*(0.0292)*
Wealth	0.0382	-0.214***	0.0418	-0.0525*	0.0258		0.0754*	-0.0519	0.00453	0.0139	0.000441	-0.00953		0.0504	-0.0495*	-0.00156	-0.110
	(0.0360)	*(0.0563)*	*(0.0293)*	*(0.0310)*	*(0.0356)*	...	*(0.0396)*	*(0.0572)*	*(0.0208)*	*(0.0219)*	*(0.0425)*	*(0.0388)*	...	*(0.0347)*	*(0.0300)*	*(0.0548)*	*(0.0888)*
Employment	-0.00565	0.00699	0.00546	0.00271	-0.0181**		-0.0115	0.00835	-0.00831	0.0121	-0.00657	-0.0306***		0.0119	-0.00759	-0.0353	0.0258
	(0.0128)	*(0.0178)*	*(0.0141)*	*(0.0211)*	*(0.00900)*		*(0.0186)*	*(0.0174)*	*(0.0104)*	*(0.0139)*	*(0.0180)*	*(0.0101)*		*(0.0143)*	*(0.00798)*	*(0.0277)*	*(0.0279)*
XportReg	-0.223***	0.282*	0.0714	0.0708	-0.370***		-0.0932	-0.208**	0.108	-0.168	0.293	-0.252***		-0.0206	-0.188***	-0.177**	
	(0.0781)	*(0.145)*	*(0.182)*	*(0.212)*	*(0.0539)*		*(0.172)*	*(0.0922)*	*(0.0990)*	*(0.131)*	*(0.543)*	*(0.0400)*		*(0.155)*	*(0.0567)*	*(0.0690)*	
EUAID	-0.0151	0.0240	0.00800	0.00996	0.0392**		0.0211	-0.0632**	0.0130	0.0233	0.0249*	-0.0266*		-0.0141	0.00502	-0.0466***	-0.104**
	(0.0137)	*(0.0519)*	*(0.0260)*	*(0.0106)*	*(0.0185)*		*(0.0322)*	*(0.0246)*	*(0.0188)*	*(0.0168)*	*(0.0150)*	*(0.0146)*		*(0.0183)*	*(0.0113)*	*(0.0111)*	*(0.0485)*
NSP	0.249***	0.901***	0.104	0.209	0.613***		0.189**	0.149	0.355***	0.459***	0.484***	0.620***		0.436***	0.431***	0.462***	0.922***
	(0.0932)	*(0.0557)*	*(0.112)*	*(0.136)*	*(0.0818)*		*(0.0934)*	*(0.123)*	*(0.0712)*	*(0.0728)*	*(0.0895)*	*(0.0904)*		*(0.136)*	*(0.127)*	*(0.0590)*	*(0.0248)*
lag1NSP	-0.308***	0.265***	-0.0133	0.285**	-0.0793		0.0271	0.157*	0.00933	-0.0765	0.0475	0.230***		-0.0949	-0.0429	0.0801	0.403***
	(0.0874)	*(0.0847)*	*(0.0630)*	*(0.135)*	*(0.103)*	...	*(0.0602)*	*(0.0948)*	*(0.101)*	*(0.0813)*	*(0.0715)*	*(0.0598)*	...	*(0.0934)*	*(0.172)*	*(0.0724)*	*(0.102)*
N	197	198	198	198	198		198	198	198	198	198	198		198	198	198	198
chi2	87.03	188.2	66.06	45.39	116.1		58.57	40.16	73.82	96.85	78.26	482.1		29.93	153.3	208.4	360.6
p	2.07e-14	4.61e-35	2.54e-10	0.000001	3.06e-20		6.74e-09	0.000015	8.06e-12	2.32e-16	1.10e-12	2.92e-97		0.000881	7.84e-28	2.90e-39	3.47e-72

Notes: Marginal effects are reported; Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01
Only selected industries are reported due to space restrictions. Full table available in the Appendix.
Data for 38 industries. Industries 7 and 14 are omitted due to non convergence

[2] The full transcription of the results for both Positive and Negative Shocks, for all the industries, is available in the *Appendix 3.4*.

Figure 3.1: Number of significant industries and sign of the coefficient found in case of a Negative Regional Shock (RSN). France 2000-2008.

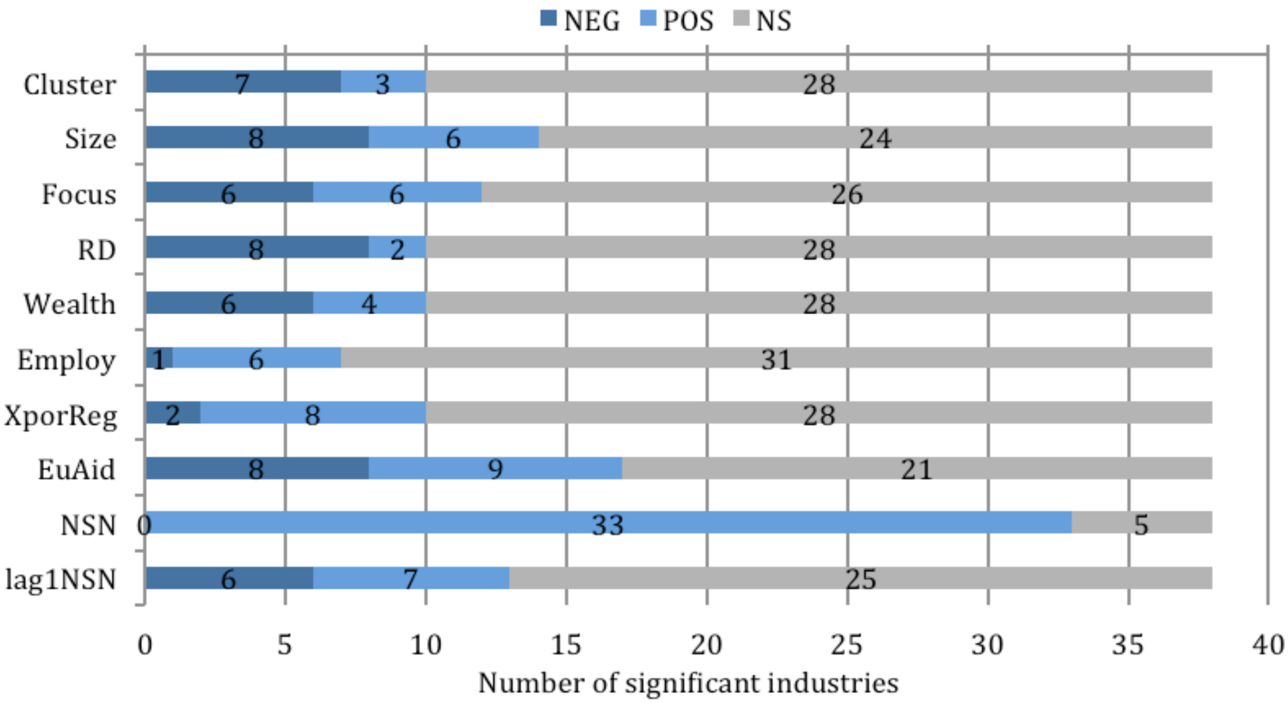
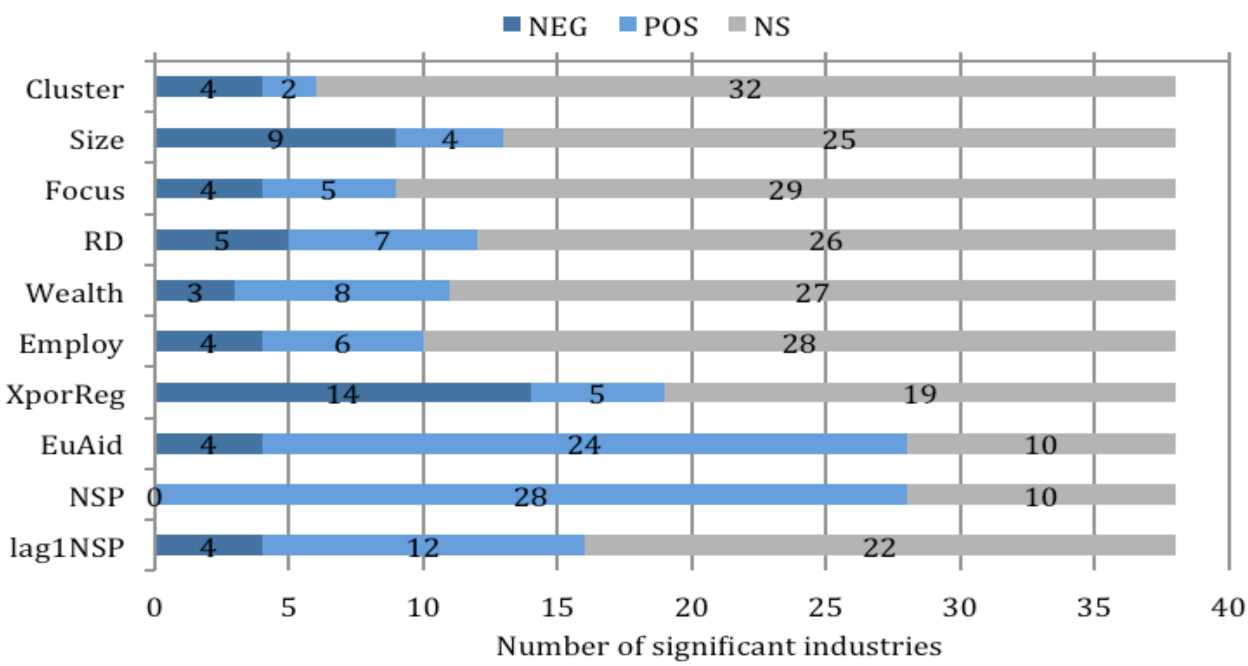


Figure 3.2: Number of significant industries and sign of the coefficient found in case of a Positive Regional Shock (RSN). France 2000-2008.



Notes: Significance measured either at the 10%. Sign of the significant coefficients is reported, as either negative (NEG) or positive (POS). Data as reported in table 3.2 and the *Appendix 3.4* respectively for the results of the estimation.

Source: author's own calculation.

3.4.2 An Analysis of Cluster Findings for France at the Industry Level

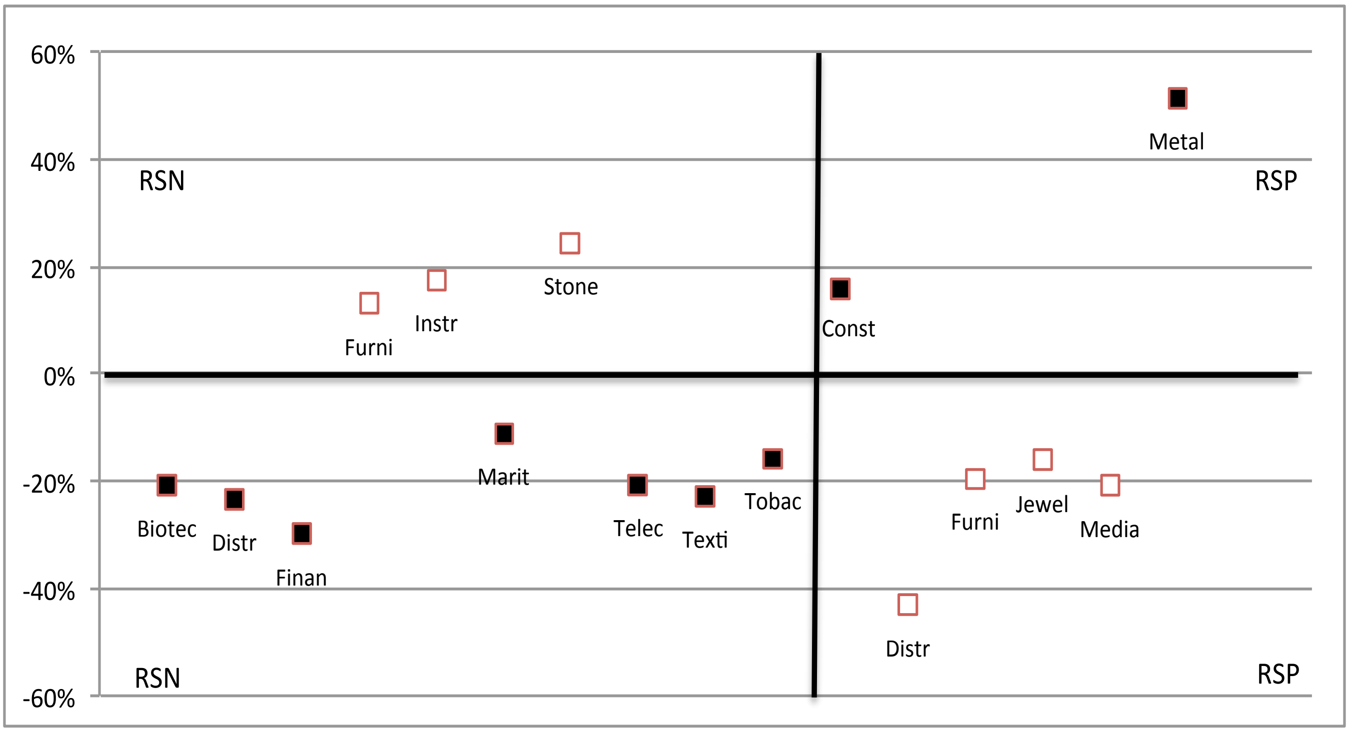
In order to analyse the results obtained more deeply, it is necessary to look at the impact of the key variables on a case-by-case basis. The method used in this paper permits the measurement of the specific impacts of each variable for a large number of sectors. Using the results of the French dataset, the effect of the *cluster* and the *national shock (NSN, NSP)* variables are analysed.

Figure 3.3 shows the impact of a cluster in the presence of both negative and positive regional shocks, for which only the significant results are reported. Seven sectors benefit from being in a cluster in the event of a negative shock; interestingly, many of these are related to high technology or advanced industries (Biotechnology, Distribution, Financial Services, Telecommunications and, to some extent, Maritime). On average, the marginal effect of belonging to a cluster for these sectors in the event of a negative shock is -19 per cent. These results are consistent with previous findings in the literature and may explain why many papers looking at clusters in advanced or high-tech industries tend to find a positive relationship between clusters and a number of regional and firm-level variables (e.g.,. Wennberg*, et al.* (2010)). Only two sectors benefit significantly from clustering in the event of a positive shock: Metal Manufacturing with a marginal effect of 51% per cent and Construction (16%), which are obviously inter-related as supplier-buyer sectors. Interestingly, there are no sectors reporting at the same time a positive effect of clustering during both a negative and positive regional shock.

It is also interesting to analyse those sectors that do not benefit from the presence of a cluster (see Figure 3.3). In the case of a negative shock, Furniture, Instruments and Stone Quarrying have an average marginal effect of 18 per cent. Distribution, Furniture, Jewellery and Media & Publishing are, on average, 25 per cent less likely to feel the positive effects of a positive shock. The only sector that is represented in both effects is Furniture, for which it is reasonable to say that the presence of a cluster is not beneficial in either scenario. If anything, the overall results reinforce the idea presented in the previous section; that the relationship between clusters and economic shocks is highly heterogeneous and dependent upon the sector. These results also suggest that the analysis and the results for any specific cluster do not appear to be generalizable.

The probability of a national shock having an impact on a sector at the regional level is shown in Figure 3.4. A national shock, whether positive or negative, is the most significant variable and has a large regional shock effect. The magnitude of the national shock is shown to be highly dispersed, with some sectors having a probability close to 90 per cent of being affected while others it is close to 15 per cent. It is noteworthy that the dispersion of the probability is higher in the event of a positive shock –with more values concentrated in a band between 35 to 70 per cent, than a negative one –concentrated between 30 and to 50 per cent. This suggests that the effects of a negative shock are more homogeneous across sectors compared to the effects of a positive shock. Nevertheless, a closer look at the effects on each sector reveals the highly heterogeneous impact reported several times in this study and the previous literature.

Figure 3.3: Probability of the Impact of a Cluster in a Negative Regional Shock (RSN) or a Positive Regional Shock (RSP), by sector.



Note: Only results for significant coefficients at the 10% are presented. Based on the results from running Model I (French industries dataset) presented in table 3.2 and the *Appendix 3.4*

Source: author's own calculation.

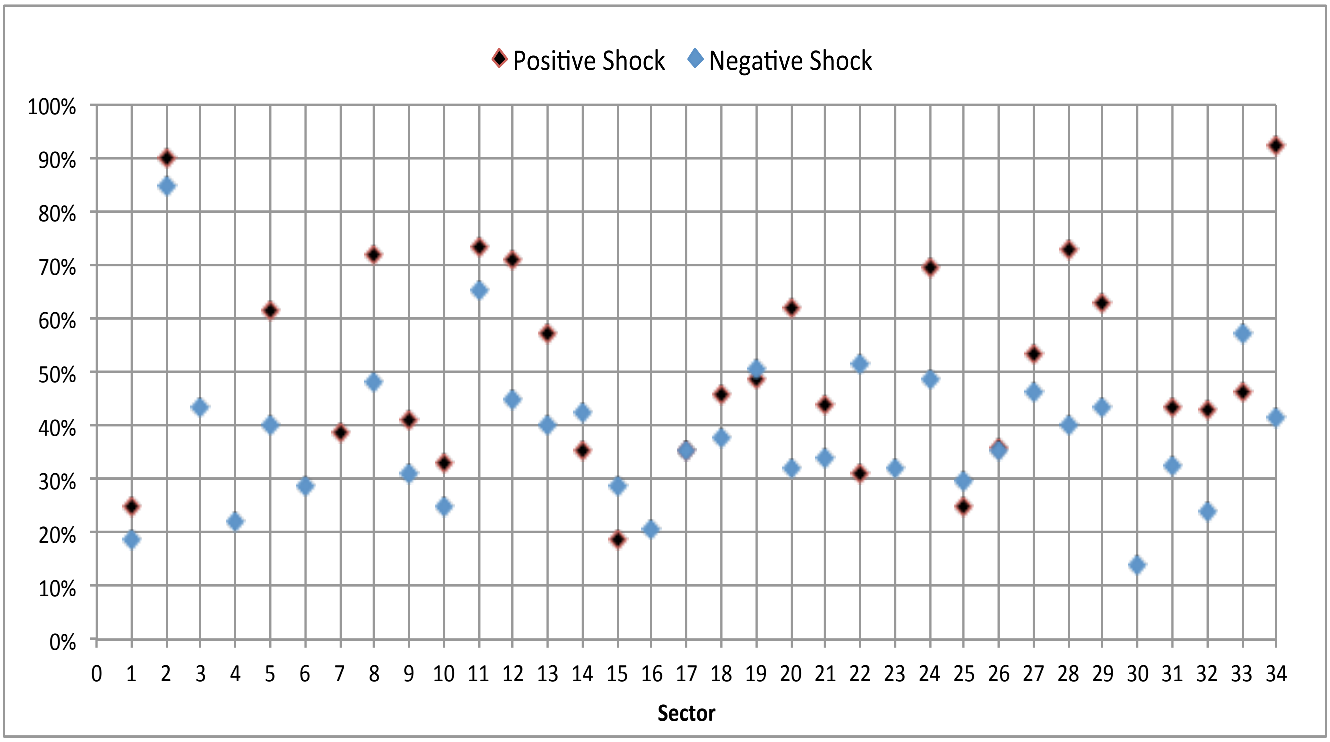
The results reported in Figure 3.4, permits a comparison of the effects of each type of shock for each sector. In Aerospace (coded 1 in the figure) has the lowest impact with both a positive and a negative shock (25 and 19 per cent respectively). The impact Agriculture (coded 2) is completely different; the effect of both positive and negative shocks is very high (90 and 85 per cent). This means that Aerospace is less affected than Agriculture by a crisis but it is also less likely to benefit from a period of growth. Even if these two sectors react very differently to a shock, they could both be said to have low resilience since the impact of both negative and positive shocks have similar magnitudes. Biotech (coded 5) could be said to be highly resilient since the probability of a negative shock (40 per cent) is much lower than that of a positive shock (61 per cent). Other sectors that follow the same pattern of high resilience are: Construction (coded 8), Financial Services (12), Furniture (13), Media & Publishing (20), Metal

Manufacturing (22), Paper Products (24), Processed Food (28), Textiles (32) and Tourism (34). Other sectors that show low resilience are: Distribution (9), Education (10), Entertainment (11), Instruments (14), IT (15), Lighting Equipment (18), Maritime (19), Medical Devices (21), Pharmaceuticals (25), Plastics (26), Power Generation (27), Telecom (31) and Tobacco (33).

A pattern starts to emerge here; it appears that a majority of sectors that are less resilient are related to knowledge and high-tech services, while highly resilient sectors are more related to manufacturing and low-tech services (the major exceptions being Agriculture and Biotech).

Given these interesting results, further questions emerge regarding resilience at regional and national level and also for different type of industries; for example, to what extent is industrial and regional resilience a desirable characteristic? The objective of this study is not to answer such a question but the methodology utilised could be used in future research to tackle, at least partly, this question and other more specific ones. Moreover, the contribution of these results in terms of industrial and regional policy are important in that they shed some light on the distinct effects of regions and sector in the event of different type of shocks.

Figure 3.4: Probability of the Impact of a National Shock at the Regional Level, by sector



1 Aero	10 Educa	19 Maritme	28 Proc Food
2 Agric	11 Entert	20 Media	29 Techn
3 Appar	12 Finan.	21 Medic	30 Sport
4 Autom	13 Furnit	22 Metal	31 Telec
5 Biotec	14 Instrum	23 Oil	32 Text
6 Build	15 IT	24 Paper	33 Tobacc
7 Bus. Serv	16 Jewel	25 Pharma	34 Tourism
8 Constr	17 Leath	26 Plastic	
9 Distrr	18 Electr	27 Power	

Note: Only results for significant coefficients at the 10% are presented. The numbering of each sector is valid only for this figure. Based on the results from running Model I (French industries dataset) presented in table 3.2 and the *Appendix3.4*.

Source: author's own calculation.

3.5. **Robustness Analysis: a Comparison Between France & Germany**

In order to allow for the comparability of the results obtained for France, a dataset for Germany is also compiled. At the time of collection, data was only available for Germany for the years 2000 to 2007. In order to maintain the comparability of the datasets for France and Germany, the two models are re-estimated using this comparable data. The model uses the same formulas for independent, dependent and control variables as before except for the two additional variables described in Equations 3.5 and 3.6. The same 40 sectors are used for each country, with 22 regions in France and 33 in Germany (NUTS 2 Level) using data from ECO and Eurostat.

After constructing the shock variable, the dataset is reduced to the years 2004 to 2007 such that the number of observations for France is reduced from 7,920 to 3,520 observations. Estimation of the model for each of the sectors using a Probit panel would be problematic based on the very limited number of observations per sector which could compromise the accuracy of the model. Instead, a pooled-Probit technique is used to estimate the second model so as to be able to compare the results for French and German regions rather than for each industry. While there is a loss of specificity, since a pooled-Probit does not take into account the specific effects of time in the sample and the results will not provide information for every industry in the sample, comparability of the effects of each variable will be possible at an aggregated level. To control for the specific effects of time and sector, a series of dummy variables are introduced in each of the pooled-Probit estimations.

Heteroskedasticity in a pooled Probit model has important implications, mainly that the estimation will be inconsistent (Wooldridge, 2001; p.600-602). A test for heteroskedasticity is conducted; the Breusch-Pagan, tests the null hypothesis that the error variances are all equal versus the alternative that the error variances are a multiplicative function of one or more variables. In the case of France, columns 1 (Regional Shock Negative) and 2 (Regional Shock Positive) in Table 3.3, the Breusch-Pagan results show, respectively, a low chi2 of 0.56 thus rejecting the presence of heteroskesdasticity, and a high chi2 25.98 thus signaling the presence of this problem in this estimation. Accordingly to these results, the estimation method used in column 1 of table 3.3 is a Pooled Probit, and for column 2 where heteroskedasticity is found, a

Heteroskedastic-Probit is used.

The same approach is used to test for heteroskedasticity in the German dataset. The results show a large chi2 (59.03) for column 3 in table 3.3 and a small chi2 (1.09) for column 4. Thus, a HC-Probit is used to run the regression in column 3, and a Pooled-Probit is used in column 4. An additional test is carried, only for the cases in which the HC-Probit estimation is used, by running a Wald Chi2. In both cases, we are able to reject the null hypothesis, indicating that the coefficients are not simultaneously equal to zero.

The results shown in Table 3.3 offer an interesting view of each variable's effect in the event of regional shocks. It is important to note that the coefficient of the cluster variable is insignificant at both the 1 per cent and 5 per cent levels. This also confirms the results obtained in the panel estimation for France. The only case in which it is found to be significant is at the 10 per cent for a positive shock in Germany. This suggests that industrial agglomeration is neither positively nor negatively related to shocks in either of these two countries. The coefficient of the national shock (*NSN, NSP*) is, as before, highly significant. Furthermore, a closer comparison between the two countries shows that the magnitude of the coefficient is greater in France than in Germany, where the effect of a negative shock is insignificant and the positive shock is significant but has a smaller magnitude. For example, in the event of a negative shock (*NSN*) at the national level, the impact on French regions is more than eight times greater than in German regions (although the coefficient is not significant in the latter). Conversely, in the event of a positive shock (*NSP*), French regions grow faster than German ones. This is an interesting finding since it points towards the resilience of the regions in each country. France appears to be highly resilient (strong crisis, strong recovery), while those in Germany seem to be less volatile, with a less negative impact during a crisis but also lower growth afterwards. Which one is a better characteristic is not within the scope of this study but these results are very useful for understanding and interpreting the rest of the coefficients.

The results of the control variables show that the variables introduced to capture the export intensity at both regional and national levels provide mixed results. In the case of France, exports are insignificant in the case of a negative regional shock. In the event of a positive shock however, the coefficient is significant at the 1 per cent level but, unexpectedly, the magnitude of the coefficient is large and has a negative sign. This suggests that French regions that are export-oriented at the national level can expect to grow less during a positive shock than those regions that are more domestically-oriented.

Table 3.3: Pooled Probit France and Germany from 2004 to 2007.

	FRANCE		GERMANY	
	Regional Shock Negative (RSN)	Regional Shock Positive (RSP)	Regional Shock Negative (RSN)	Regional Shock Positive (RSP)
Cluster	-0.0301	0.00558	0.0242	-0.0624*
	(0.0232)	*(0.0206)*	*(0.0320)*	*(0.0352)*
Size	0.0267**	-0.0390***	-0.00876	-0.00966
	(0.0118)	*(0.0135)*	*(0.0197)*	*(0.0251)*
Focus	-0.0314**	0.0348***	0.0290**	-0.0492***
	(0.0149)	*(0.0122)*	*(0.0142)*	*(0.0169)*
RD	-0.00942***	-0.00309	-0.0141**	0.0131
	(0.00335)	*(0.00406)*	*(0.00703)*	*(0.00824)*
Wealth	-0.00372	0.0165*	-0.00200	0.0182*
	(0.00808)	*(0.00842)*	*(0.00940)*	*(0.0109)*
Employment	-0.00555	0.00349	0.000683	-0.0122
	(0.00606)	*(0.00780)*	*(0.00721)*	*(0.00858)*
XportNac	-0.0901	-0.279***	-0.230**	0.272***
	(0.0857)	*(0.0996)*	*(0.108)*	*(0.101)*
XportReg	0.00259	-0.0239	-0.0302	0.118***
	(0.0316)	*(0.0404)*	*(0.0419)*	*(0.0395)*
EUAID	-0.0105**	0.00805	0.440	-0.350
	(0.00441)	*(0.00607)*	*(0.426)*	*(0.721)*
NSN	0.365***		0.0397	
	(0.0298)		*(0.0279)*	
lag1NSN	0.0713***		-0.00922	
	(0.0275)		*(0.0244)*	
NSP		0.393***		0.144***
		(0.0269)		*(0.0206)*
lag1NSP		0.00911		0.0450**
		(0.0206)		*(0.0208)*
Observations	3519	3519	5171	5171
Year Dummy (3)	Yes	Yes	Yes	Yes
Industry Dummy (39)	Yes	Yes	Yes	Yes
Estim. Method	Probit	Het-Probit	Het-Probit	Probit
Pseudo R2	0.1566	n.a.	n.a.	0.1794
Wald test of lnsigma2=0:				
Chi2	n.a.	50.18	10.51	n.a.
P(Chi2)	n.a.	0.0000	0.0052	n.a.

Notes: Marginal effects are reported; Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01
2004 is the reference dummy year. Tourisms, is the reference for dummy industry
Data for 40 industries.
Source: Author's own calculation

In the case of German regions, the coefficient for *XportNac* has the expected sign and magnitude and is significant, depending upon the case, at the 1% or 5% levels. In the event of a negative shock, regions specialised in export-oriented industries would be 23% less affected while during a positive shock they would grow 27.2% faster (Table 3.3). Interestingly when analysing only export-orientation at the regional level (see *XportReg*), no significance is found for either France or Germany, except for the case of a positive shock in German regions. In this case, the coefficient is significant at the 5% level and both the sign and magnitude are comparable to those for *XportNac*.

Overall, the results appear to suggest that trade openness at the national level is more significant than at the regional level. This result might seem counter-intuitive but it is important to realise what each of these variables is measuring. *XportReg* can be said to be capturing inter-regional exports while *XportNac* is capturing exports out of the country. In this sense, the results for France suggest that its regions are somewhat disconnected from the national export structure. The German regions appear to be more connected to the national export structure, reflected in the results for *XportNac* and *XportReg* during a positive shock. No further explanations for regional exports can be obtained with this model and dataset. The degree of connectedness between regions and the national export structure is topic open for future research.

The remainder of the sector variables, *Size* and *Focus*, produce different results depending upon the country. *Size* is only significant for France, with a positive sign in the case of negative regional shock and a negative sign for a positive shock. This means that, overall, being in a large sector has negative effects. On the other hand, *Focus* is always significant in both countries but with a different sign. In France, a more focused sector appears to cope better with periods of crisis and growth while in Germany it is the exact opposite. These results reflect the very different structure of the French and German regions; the former characterised by a Statist model and the latter by a corporatist one (Birch*, et al.* (2008)) and this is believed to influence both their regional policies and its outcomes.

4.1 Summary & Conclusions

The objective of this Chapter is to analyse the interactions between regional economic shocks and a group of sector-specific and region-specific variables. Particular attention is paid to the role of industrial clusters with respect to both positive and negative regional shocks. The main purpose is to test the view that clusters are a powerful policy tool in the face of the present economic recession and a means to protect industries and regions from future shocks. Do clusters protect industries in the case of a negative economic shock and can clusters promote growth during a period of positive economic shocks?

The results can be summarised in the following terms. First, at an aggregated level and in the event of a negative regional shock, clusters do not seem to protect sectors from the negative effects. When analysing the impacts at industry level however, seven out thirty-eight cases in France report positive effects of belonging to a cluster.

Second, in the event of a positive regional shock, clusters do not contribute to enhancing its positive effects; in this case, the findings hold at both the aggregated and industry-levels. In other words, no evidence is found to support the general claim that clusters either lessen or augment the effects of economic shocks. Instead, clusters are found to do no harm but the additional benefits are highly dependent upon which industry is taken as a reference. In the vast majority of cases, the effects are neutral.

Third, and as expected, national industrial shocks have a large effect on regional industrial shocks and they explain a large proportion of the variation in employment. In general terms therefore, there is little that a region can do to avoid a negative shock when a national shock is present. Fourth, regional variables related to income, employment and innovation appear to have highly heterogeneous effects such that no specific conclusions can be obtained from this analysis.

Finally, the concept of resilience is explored using the difference between positive and negative shocks at the sectoral level. A large number of highly resilient sectors are found to be related to manufacturing and low-tech sectors while low resilience is usually found in knowledge-based and high-tech sectors.

These findings lead to the conclusion that, on average, clusters are ineffective against an economic shock but, in very specific cases, the empirical evidence shows that cluster membership may slightly increase the protection against a negative shock. It is also found that in very few cases, the presence of a cluster might actually increase the effect of an economic shock. The same conclusions apply for a positive shock; the results provide no support for the view that clusters promote the benefits of a growth period. If anything, the empirical analysis in this Chapter reinforces the idea that the relationship between clusters and regional growth is ambiguous (Gardiner*, et al.*, 2011), that the effects may be heterogeneous and even unstable depending upon the type of industry and aggregation level (Morgan, 2007) and that the influence of clusters on economic growth might be lower than is believed (Rodríguez-Pose*, et al.*, 2011).

This study shows that, in the context of global recession, the actions taken both by private and public sector need to go beyond cluster policy. There might be a 'cluster momentum' as some academics have pointed out but clusters alone may not be the answer to minimise the effects of a crisis and/or maximise the effects of a recovery. There are great benefits to be derived from clusters and industrial agglomeration but the long list of benefits may not include protection against negative economic shocks. This raises the issue as to why clusters are claimed to be crisis-resistant and/or growth-promoting. As reported in this Chapter, some variables related to the national economic environment appear to have a strong influence on how hard a region is affected by an economic shock. In the analytical literature however, clusters are largely considered to be region- or location-specific such that, in many cases, little attention is paid to national variables. If this is the case, clusters may be mistakenly considered to be more/less responsible for crisis/recovery than in actual fact. The empirical analysis in this Chapter shows clearly that the regional and national context are both important. Clusters cannot be isolated from the rest of the region and the country. the recurrent debate that separates between regional and national policy needs to be reconsidered.

Some caveats regarding the empirical findings in this study need to be considered. First, the use of changes in employment to determine the existence of a shock, the dependant variable, may introduce a bias to the detriment of those sectors that are capital-intensive. To capture the full effects of an economic shock, changes in sales or GDP at sectoral level for every region should be included. Owing to data constraints, this not possible for this study. Second, the principal variable used to identify clusters is based on employment data and a location quotient, which could also introduce a bias. It would be desirable to see if the empirical results hold up when other techniques to identify clusters are used, such as Input-Output analysis or and agglomeration index.

Finally, there are several ways in which this research could be improved. Only two countries are used in this study; an extended cross-country, comparison, especially including those countries that may have significant differences in their regional structures, would be ideal so as to contrast the results and determine if the patterns of significant and insignificant effects found here are reproduced consistently. In particular, it would be interesting to analyse the interaction between economic shocks and clusters in countries with different levels of development; for example, between those in Europe and Asia or South America. This study also provides an interesting view of the relationship between regional and national trade openness and economic shocks although this is not its main objective and no further exploration of this relationship was undertaken. A key issue is to understand how trade openness contributes to the resilience of regions; the results in this study point to some striking differences between France and Germany that should be further explored. Finally, the concept of resilience is also explored using positive and negative shocks at both regional and national levels. Further research is needed to understand properly the effects of resilience in specific industries, which is still an emerging concept but gaining importance.

Chapter 4

An Empirical Analysis of Industrial Growth in the International Trade Network

4.1 Introduction

The search for the determinants of industrial growth has been a central piece of analysis in the economics literature for more than a century (Marshall, 1895, 1920) and still remains an open question. As the complexity of international trade connections have increased, the question of industrial growth has ceased to be solely confined to geographic location. This leads to the question of what determines the growth of an industry that is part of the international trade network and can the network characteristics of an industry affect its growth? These questions have regained a sense of urgency in the light of the recent period of instability in the world economy in the wake of the recent global crisis.

The persistent and on-going global crisis that started in the late months of 2007, together with the concomitant inability of some standard economic models to predict the crisis and its effects, has been a call-to-action for many researchers. The failure of macroeconomic models and the standard econometric tools have to take a great degree of responsibility for the crisis (Ormerod, 2010). Some policy-makers feel that the available models were of limited help in facing the crisis and were 'abandoned by conventional tools'[3] (Farmer, *et al.*, 2012). According to recent critiques, some of these failures may be attributed to the use of extreme reductionist approaches that cannot account for the evolving and complex nature of local, regional, national and international interconnections of the global economy (Farmer, *et al.*, 2012).

[3] Jean-Claude Trichet, Governor of the European Central Bank in November 2010, as quoted by Farmer, *et al.* (2012).

Recent studies have started to address some of these concerns by merging standard economic theory with new concepts and techniques drawn from other disciplines in order to obtain a different description of the growth and crisis process. At the macroeconomic level, the focus has been on the analysis of the spread of the crisis between countries using network analysis (Lee*, et al.*, 2011), the process of contagion in industrial clusters using complexity theory (Wang*, et al.*, 2010) and financial contagion in international trade networks using graph and network theory (Kali*, et al.*, 2010). The application of these techniques to economics is still in its infancy but they are seen as a means to understand economic issues from a different perspective.

At the industry level, the focus in the recent literature has been on the analysis of industrial agglomerations, clusters and industrial networks using network and complexity theory. For example, Hidalgo*, et al.* (2007b) determine the existence of a complex product space that is highly correlated with economic development. Successive papers by Hidalgo*, et al.* (2009) and Hausmann*, et al.* (2011a) have created an index of economic complexity derived from industrial data that is believed to be a better predictor of economic growth than the ones reported in traditional models. Similarly, Kali*, et al.* (2007), Fagiolo*, et al.* (2007) and Reyes*, et al.* (2010) suggest that using techniques based upon complexity and networks enable researchers to obtain statistics that describe the structure and evolution of trade linkages in a way that existing measures cannot capture. Specifically, it is believed that global trade, which is characterised by a large number of intricate relations, connections and paths, exhibits characteristics of a complex network (Fagiolo*, et al.*, 2007). Thus, techniques drawn from network theory can be highly informative in describing and analysing the whole structure of trade (De Benedictis*, et al.*, 2013).

This chapter adopts a quantitative approach to analysing the effects of industrial network characteristics on periods of growth and downturn at the industry level. A trade network matrix is compiled using the World Input-Output Database (WIOD), which consists of data from 35 sectors covering global trade. For a detailed analysis on the sources and methods used to compile the WIOD, see Erumban*, et al.* (2011). This Chapter focuses on the impact of the Great Recession so this dataset only covers the period 2006 to 2009.

The contribution of this study can be summarised in three ways. First, a large majority of the literature looking at international trade networks uses countries as the unit of analysis and focuses on aggregate international trade rather than trade relations between industries (i.e., intermediate consumption). This study uses industries as the unit of analysis together with a worldwide trade matrix that includes both internal and external input-output connections to capture the full complex structure of industrial trade. For the purposes of this Chapter it is called the International Industrial Trade Network (IITN). Second, the scarce literature looking at the IITN is mainly concerned with the evolution and pattern of trade structures and its effects on integration, volatility or bilateral trade intensity. This study applies the IITN to a traditional industrial growth model in order to determine if the network characteristics of an industry determine its short-term growth. In addition, a measure of industrial downturn is used to obtain more information on growth patterns. Third, this Chapter focuses on the years of the Great Recession, from 2007 to 2009, which remains relatively unchartered territory.

The results of the empirical analysis in this Chapter show that some industrial network characteristics may affect growth and downturns, under certain conditions, while others have no significant effect. Industries that are more centrally located in the network tend to grow faster and have lower probabilities of suffering the effects of a downturn. Additionally, the domestic industrial density of a country has an effect on growth and downturns, but this effect is also dependant on meeting certain conditions. Other important results are that neither the number of trade partners of an industry nor the industries to which it is connected appear to be important determinants of growth or downturns. Being central in the global network appears to be more important than the number of connections or being connected to more 'popular' industries (the word 'popular' is often used in network analysis to describe the concept of eigenvector).

The Chapter is organised as follows. The next section presents an exploratory analysis of the IITN with a description of the main network metrics used and a statement of the principal hypotheses. Section 4.3 uses a conventional industrial growth model in which, a number of network variables obtained from the IITN are included. Section 4.4 analyses the results from different specifications of the regressions and looks for the robustness of the specified model. The last section presents the conclusions.

4.2 Constructing the International Trade Network Graph.

To capture the complex nature of international trade linkages, a dataset containing the Input-Output (I-O) matrix for each country in the sample is used (a full description of the characteristics of the dataset can be found in Erumban*, et al.* (2011)). The interesting characteristic of this particular dataset is that it includes data on internal use and consumption for each industry at national level as well as trading partners for each country. This enables the creation of a 'true' representation of the network of internal and external trade for every industry and every country in the sample.

The first step is to transform the global input-output matrix into a network. There are 35 industries in the sample, classified under ISIC rev2; these are the nodes. The link between each pair of industries is the trade relationship in US Dollars between those industries, based on exports (from industry i to industry j). Since the exports from industry i to industry j are the mirror of the imports to industry j from industry i, only the value of exports is used. Given that the direction of the trade is considered in the network approach, it is therefore possible to identify whether there is an export or import relationship between each pair. This distinction is important when analysing output and input degree. The sample consists of the trade relationships between 35 industries located in 42 countries, resulting in a total of 1,470 nodes and more than two million links for each year. To focus the analysis on the relevant relationships and make the data more manageable, a threshold is imposed. Only those trade links greater than 10 million Dollars are considered. The resulting directed network consists of 34 industries[4] for each year (2006 to 2009), 1,470 nodes and 111,000 edges[5].

It is important to keep in mind that the industrial network data put together for this study, consists of trade data between pair of industries, this means that final household consumption for each industry is not directly accounted for. This is a caveat that needs to be considered both in terms of the sampling process, since a potential bias towards producer goods industries may arise, and in terms of the interpretation of the results. For example it may the case that manufacturing industries may be over represented and financial or education may be underrepresented. There is no specific solution to this caveat since the objective of this study is to specifically analyse intermediate consumption data for each pair of industries. Nevertheless, not taking into account final consumption data might become an issue if the sample chosen would only look at a small number of industries, but the novelty of the dataset constructed for this chapter, is that it includes industrial trade data for every single pair of industries in the global trade network. This means that even if a trade link between industry i and j may only capture the intermediate consumption and not the final consumption, the rest of the link with the 33 other industries in the network, will capture the final consumption. For example, suppose that we look at trade between Agriculture and Processed Food, it is clear that a big part of the total

[4] Data for the industrial grouping 'Private Households with employed persons' contains a large number of zero values (there is no internal or external trade), which may introduce a bias into the analysis, thus it is removed from all of the samples. Removing this particular industry from the sample does not affect the overall results since its weight in total trade is very small.

[5] The exact number of edges and nodes depends upon the chosen year. To obtain the metrics each year of the global industrial network, the specialised software Gephi is used. For details on each of the metrics calculated by Gephi and the algorithms that are implemented by this software, refer to http://wiki.gephi.org/index.php/Category:Measure.

production from Agriculture will be consumed by Processed Food, but there is also a portion of the production that goes directly to the final consumer, which is not captured directly in the simple trade relationship between the two industries. But that information is not lost in the dataset that is implemented in this study, since the trade channel to sell those agricultural products to the final consumer will be accounted for in other industries, for example Wholesale or Retail Trade. As this dataset includes trade data for Agriculture and every other single industry, the total production data from Agriculture industry must be equal to the total intermediate consumption of Agricultural products from all the other industries.

4.3 Description & Analysis of the Network Metrics

To obtain a first glance of the characteristics of the industrial network and follow its short term evolution, a comparison is made between the network metrics from 2006 to 2009. A description of all the industries and countries included in this sample can be found in *Appendix 4.1*

4.3.1 Node Degree

The basic level of network analysis is the node degree, which is a simple count of the number of edges that are connected to a given node. The global industrial network is dominated by what can be called 'hyper-connected' nodes; defined as industries that are connected to 50 per cent or more of global industries. 'Chemicals & Chemical Products' in Germany is the most hyper-connected industry, with a node degree of 1,053, which means that it is connected to 72 per cent of all the potential nodes. Interestingly Germany is the country with the highest number of hyper-connected industries (see Table 4.1).

Table 4.1: Sample of the World's Most Connected Nodes

	Id	Country	Industry	Degree	Percentage of connections
2006					
	DEU9	Germany	Chemicals and Chemical products	1053	0.72
	USA30	USA	Renting of M&Eq and Other Business Activities	951	0.65
	DEU13	Germany	Machinery, Nec	949	0.65
	DEU15	Germany	Transport Equipment	936	0.64
	DEU14	Germany	Electrical and Optical Equipment	929	0.63
	DEU12	Germany	Basic Metals and Fabricated Metal	917	0.62
	CHN14	China	Electrical and Optical Equipment	828	0.56
	RoW8	Rest of World	Coke, Refined Petroleum and Nuclear Fuel	755	0.51
2009					
	DEU9	Germany	Chemicals and Chemical products	1034	0.70
	CHN14	China	Electrical and Optical Equipment	1026	0.70
	USA30	USA	Renting of M&Eq and Other Business Activities	988	0.67
	DEU13	Germany	Machinery, Nec	919	0.63
	DEU14	Germany	Electrical and Optical Equipment	884	0.60
	DEU15	Germany	Transport Equipment	881	0.60
	DEU12	Germany	Basic Metals and Fabricated Metal	879	0.60
	CHN9	China	Chemicals and Chemical products	784	0.53
	RoW8	Rest of World	Coke, Refined Petroleum and Nuclear Fuel	764	0.52
	RoW9	Rest of World	Chemicals and Chemical products	748	0.51

Source: Author's own calculations.

It is worth noting that rapid change can occur in the degree of connectivity; for example, CHN14 'Electrical & Optical Equipment' in China went from 828 to 1,026 links between 2006 and 2009 and CHN9 'Chemical Products' from 567 to 784. For other industries, this change has been negative. The largest losers starts with DEU8 'Coke, Refined Petroleum & Nuclear Fuel' which lost 655 links, followed by DEU11 'Other Non-Metallic Mineral' which lost 574 links and GBR3 'Food, Beverages & Tobacco' which lost 464 links.

The degree measure includes both exports and import links, so it is desirable to decompose linkages into out-degree (export link) and in-degree (import link) to obtain a better perspective of how the trade networks are evolving. A brief analysis of the 'in' and 'out' links shows that RoW2 ('Mining & Quarrying' in the Rest of the World) is the industry that lost the most in-degree links

(427), followed by five German industries DEU11 ('Other Non-Metallic'), DEU8 ('Coke & Refined Oil'), DEU29 ('Real Stated Activities'), DEU2 ('Mining') and DEU14 ('Electrical Equipment') which lost 221, 187, 185, 179 and 138 in-degrees respectively. These values represent a considerable reduction in the import links for these industries during the time-frame being analysed and may potentially have an important effect on the rest of the global industrial network. Additionally, when looking at the list of the ten industries with the largest negative out-degree change, nine out of 10 are located in Germany, with reductions ranging from 468 for DEU8 to 107 for DEU29.

Based on this brief review of hyper-connected industries and their change between 2006 and 2009, it is possible to conclude that node degree (input and output degrees) could have an important effect on the global network and specifically on each industry's growth. It remains to be seen if the relationship between node degree and industrial growth is statistically significant and relevant in terms of its magnitude.

4.3.2 Node Centrality

The relationship between trade and growth is often analysed using either absolute or relative monetary values. The drawback of this approach is that it can only account for direct relationships between two pairs of countries or industries while the global network is characterised by more complex relationships (Kali*, et al.*, 2007). For example, it is interesting to know if the position of a given industry in the global network affects its growth. An industry that is more 'central' might be considered more vital to the network since a large number of industries use it as a bridge to link with other industries, either as supplier or intermediate consumer. On the other hand, a given industry may not be in the 'middle' of the network but may be connected to a significant number of other important industries. In this case, although this industry may not be important in itself, it may nonetheless be critically important because it is connected to other 'popular' industries. In order to operationalise the concepts of how central and popular a given industry is, two network metrics are introduced: betweeness centrality (Betweeness) and eigenvalue centrality (Eigenvalue).

Betweeness measures how often a node appears on the shortest path between nodes in the network. It is often considered a measure of how vital a given node is for the network (Easley*, et al.*, 2010; p.1864). Nodes with high betweeness may have a considerable influence within a network by virtue of their control over information or, in this case, the value of trade value passing between other nodes (Newman, 2010; p.185). A brief analysis of the data reveals that the list of hyper-connected industries is very similar to those that have the highest betweeness. Looking at industries with a lower degree value however, the former relationship does not appear to hold perfectly; that is, nodes that have a low degree may have relatively high betweeness. For a detailed discussion on low degree and high betweeness networks see Newman (2010; p.188). The fact that some industries rank differently in terms of degree and betweeness is interesting since it may suggest that industrial growth is not only dependent upon the number of connections a given industry has but also on the position of that industry in the global network. This is something that needs to be tested.

The literature on the effects of centrality on industrial shocks is still very sparse and usually focuses on one specific sector. The vast majority of cases analyse some sort of centrality metrics in the financial sector (e.g. Kali*, et al.* (2010); Lee*, et al.* (2011) Battiston*, et al.* (2012)). These studies find that centrality may be a good predictor of the spread of a crisis and contagion but provide no specific analysis of the relationship between centrality and industrial downturn. A similar approach to the one presented in this Chapter is found in Blöchl*, et al.* (2010) and Blöchl*, et al.* (2011). Using input-output trade data, they analyse the probability of a shock in a number of world industries given by a centrality measure. The evidence in the network literature is insufficient to make a priori claims regarding the expected sign and magnitude of the centrality variable but most related papers suggest that greater centrality exposes industries to shocks.

Another observation of interest is that the biggest nodes, in terms of trade value, do not appear to be the biggest in terms of betweeness. In this case, each node is calculated in terms of the number of connections and also the trade value of those connections. The metric used is the 'weighted degree', shown together with node betweeness in Figure 4.1. This graphical representation is useful as a first glance at the patterns that exist in the global industrial network. In the figure, the sizes of the nodes represent the weighted degree and a darker colour represents greater node betweeness. A visual inspection suggests that many dark-coloured nodes are not always the largest ones in terms of trade weight. This observation is important because one of the most widely spread beliefs about the Great Recession is that larger industries in terms of trade are more likely to be affected by an economic shock. Since these are usually the most connected industries in the world as well, the argument is therefore that very large industries pose a greater risk to the global economy. The issue is then if what determines the growth and downturn of a given industry is not only its size but also (or predominantly) its centrality.

Eigenvalue is used as an additional metric to analyse node centrality in the global network; in a social networks context, it measures the 'popularity' of a node. In many circumstances a node's importance in a network is increased by having connections to other nodes that are themselves important. Instead of awarding nodes one point for each neighbour, eigenvalue centrality gives each node a score that is proportional to the sum of the scores of its neighbours (Newman, 2010; p.169). The eigenvalue, along with betweeness, is used to test if the position of an industry and the types of connections are important determinants of industrial growth and downturn.

4.3.3 Network Density

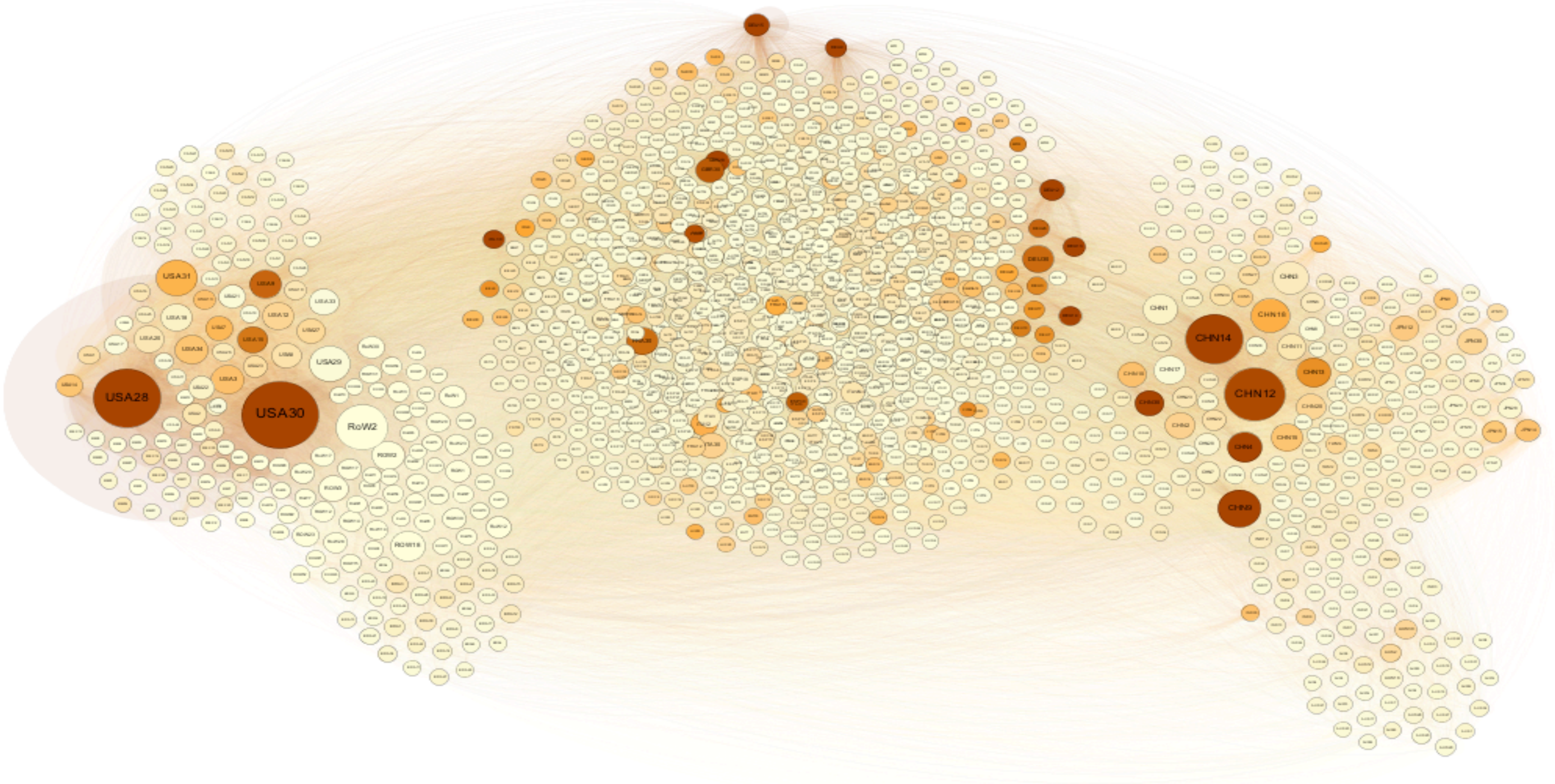
Network density measures the connections an industry has within a single country. This provides a better understanding of how growth in a given industry is influenced by the national network. Network density captures the completeness of a network by analysing the relative fraction of links that are present compared to all possible connections (Jackson, 2010; p.Location 779). The first use of density in an international trade context is by Kali*, et al.* (2007) to describe what they call the architecture of globalisation. In a more recent paper, Kali*, et al.* (2013) reintroduce this concept in a more specific approach to analyse the density of its product space (Hidalgo*, et al.*, 2007a ; Hausmann*, et al.*, 2011b) and effects on the probability of growth accelerations (Hausmann*, et al.*, 2005). These are first attempts to use global trade data at the sectoral level and use the characteristics of the network to analyse the effects on growth. A similar conceptual approach is being used in the present paper, but using a different dataset, a different aggregation of the industries, a different econometric model and focusing not only in growth but also in crisis during the Great Recession. They find that density has a non-linear (convex) effect on growth; a higher density increases the probability of industrial growth up to a certain point, after which further increases in density stop contributing to growth.

The metric of network density in this paper is calculated for each country in the sample individually without considering the international trade, just the domestic trade links between industries. The resulting density metric is used in a quadratic form to capture the effects reported in Kali et al. (2013).

4.4. Empirical Strategy to Analyse Industrial growth using Networks

The primary interest of this investigation is to analyse the effects of network characteristics on industrial growth. The literature on industrial growth is used to select the best econometric model. The dataset used has the structure of an unbalanced panel consisting of 1,470 observations *(N)* and four years *(T)*. The small time-series component could be considered to be insufficient to use panel method techniques but, according to Wooldridge (2001; p.251), the asymptotic assumption is still valid even in panels with small *T*, as long as *N* is sufficiently larger compared to *T*.

Figure 4.1: Weight and centrality in the global industrial network



Notes: Each node represent an industry, the edges connecting each node represent trade value. Size of the nodes represents the weighted degree. Dark colour represents a higher node betweeness (a measure of centrality). Notice that many dark coloured nodes are not always the biggest ones in terms of trade weight. Data for year 2006.

Source: Author's own calculations

Before proceeding with the estimation process, the presence of outliers is analysed. The dependent variable, *Growth*, is restricted to values between two and minus two percent, thus eliminating four industries in Slovakia and one in Malta. Additionally, all of the observations for Luxembourg, Malta and the Rest of the World are removed; this is due to the large number of zero values that are present in those countries after obtaining the network metrics. The industry 'Private Households with Employed Persons' is also removed for the estimation process for the same reasons. Finally, five observations are removed from the sample due to having very large and unusual values of industrial openness, which could be attributed to a mistake in the sample, due to the small number of the removed data points they will not affect the results.

The complete sample is used to obtain the network metrics described in the last section without removing the outliers, although they are not used in the estimation of industrial growth. Although some industries and countries are removed for the econometric estimation, the network metrics still hold information from the full sample. The final dataset consists of 1,269 observations for each year. No evidence of significant collinearity is found in the explanatory variables used in Equation 4.1, a correlation matrix is presented in *Appendix (4.2).*

The main regression specified in this chapter follows the model of economic growth originally presented in (Kali, *et al.*, 2007) at national level, and the adaptation to analyse growth in the global network at product level (Kali, *et al.*, 2013). The specification in these papers, and the one presented here is considers a long-run growth model where a industry GDP is a function of initial GDP conditions, physical capital, human capital, and a vector of control variables that represent country-specific and industry characteristics (degree of openness, geographical conditions, a measure of productivity, etc). These models of industrial growth build upon the models originally presented in (Chenery, 1982).

$$(4.1)$$

The industrial growth regression is specified as follows:

$$\begin{aligned}\text{Growth}_{ict} = {} & \propto_0 + \beta_1 OutDeg_{ict} + \beta_2 Eigen_{ict} + \beta_3 Betw_{ict} + \beta_4 Density_{ct} \\ & + \beta_5\, GDP_{ict} + \beta_6 IndOpen_{ict} + \beta_7 Downturn_{ict} + \beta_8 Lab_{ict} + \beta_9 LabH_{ict} \\ & + \beta_{10} CountOpen_{ct} + \beta_{11} Gov_{ct} + \beta_{12} Inf_{ct} + \boldsymbol{Year} + \varepsilon_{ict}\end{aligned}$$

Where: $Growth_{ict}$ is the logarithmic year on year change of industry GDP for industry *i*, in country *c*, and year *t*. On the right hand side of the model, the network variables enter the model. $OutDeg_{ict}$ is a simple count of the number of outward links an industry has. The input degree, which measures only incoming trade relations, (imports) was also used in *Eq(4.1)* instead of *OutDeg*, without affecting the results. $Between_{ict}$ is a metric of centrality that measures how many times an industry is in the shortest path between two pair of industries. $Eigen_{ict}$, measures how important (in terms of trade connections) are the nodes to which an industry is connected to. It assigns a higher weight if the node in question is connected to important nodes. $Density_{ct}$, is a measure of how close to complete is a country's domestic network, in terms of all the potential links available. GDP_{ict} is the industrial value added obtained from the input-output matrix. The literature on industrial growth reports the use of 'initial conditions' of GDP to capture the convergence effect (Mody*, et al.*, 1997) that has been reported in the national growth literature (Barro*, et al.*, 1992). The $GDP97_{ic}$ is the logarithmic value (in current Dollars) of GDP per industry in the year 1997. It was originally used in the *Eq(4.1),* but due to the estimation method used, which is a Fixed effects within estimator, this variable is dropped from the model, thus the GDP_{ict} variable is introduced as a proxy. $IndOpen_{ict}$ is the result of dividing the sum of exports and imports (in dollars) for each industry, by the value added of that industry; the variable is presented in its logarithm form. The resulting coefficient is a common measure of an industry's trade openness. $CountOpen_{ct}$ is the result of dividing the sum of exports and imports by the GDP at country level; the variable is presented in its logarithmic shape. $Downturn_{ict}$ is a binary variable that captures the presence of an industrial downturn in a given industry. To construct this variable, a similar approach to Hausmann*, et al.* (2005) is used. The annual logarithmic growth rate for the last eight years is regressed on a time trend; if the difference between the estimation and the observed annual growth rate of that year is below -2%, then a downturn exists in that industry. The 2% threshold is used to select only downturns that are of a significant magnitude. A similar procedure is used by Hausmann*, et al.* (2005) to determine the existence of growth accelerations. The variable is used in this binary form since the objective is to account for the existence or not of downturn in each industry, not the magnitude.

Lab_{ict} is the labour productivity per employee in terms of hours worked and $LabH_{ict}$ is the proportion of high skilled labour in an industry. To control for the effects of country-level specific variables on industrial growth, a number of other variables are included. Gov_{ct} is the percentage of government spending over total GDP in a given country. Inf_{ct} is the year average of inflation in a given country. The possibility of a non-linear relation for Government and Inflation with growth is reported in the literature, hence a quadratic term for each variable is also included in the model; the quadratic terms are calculated after standardising the variables to avoid issues of collinearity. The variable *Year*, in *Eq(4.1),* is a dummy variable that controls for year effects in the sample; it is renamed *Recession* and takes the value of one for the years 2008 and 2009 in the full sample. When the sample is split in two, the variable takes only a one year effect (either 2006 or 2009). The descriptive statistics for these variables is presented in Table (4.2).

Since there is an evident break in the observations given by the beginning of the recession in 2008, a 2006-2007 sample and a 2008-2009 sample are also used with the same specifications in addition to the full sample to estimate Equation (4.1). The estimation is conducted using robust standard errors clustered by industry.

Given the panel structure of the dataset, the existence of correlation between the explanatory variables and the error term is analysed. To do so, a random effects model and a fixed effects model (within estimator) are both fitted using the specification in Equation (4.1). A Hausman test suggests that the *X*s in the model are correlated with error term thus rendering a random effects approach biased and inconsistent. Based on this evidence, Equation (4.1) is estimated using Fixed Effects, which means that the unobservable characteristics are treated as fixed and removed from the equation using a de-meaning process. A correlation matrix for all the variables used in Eq(4.1) is available in *Appendix (4.2)*

Table 4.2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Growth	5067	0.059	0.178	-1.321	1.415
Downturn	5064	0.293	0.455	0	1
Output Degree	5067	0.776	0.921	0	7.630
Eigenvalue	5067	0.142	0.148	0	0.878
Betweeness	5067	0.011	1.026	-0.357	17.654
Network density	5067	0.119	0.975	-1.173	1.489
GDPi	5067	8.878	1.930	0.985	14.494
Industry openness	5067	0.449	0.891	-2.606	3.383
Country openness	5067	4.341	0.505	3.105	5.156
GDPc	5067	6.131	1.554	2.823	9.567
Inf	5067	-0.015	1.019	-1.765	3.686
Lab Product	5056	3.935	1.088	-0.460	9.464
Lab Hskills	5067	0.299	0.177	0.000	0.943

Table 4.3: Variable Definitions

Name	Definition	Source
Growth	LogGDPt - LogGDPt-1, for industry i, country c, and time t (based on constant values)	WIOD
Downturn	Dummy variable that takes value of 1 if the industry is in shock (shock is defined as a deviation of -2% from the last 8 years growth rate).	Own calculations based on WIOD
GDPi	Log of the industry's i GDP, in country c, at time t (in current millions of dollars)	WIOD
GDPc	Log of country c GDP, at time t (in current dollars)	WIOD
GDP97	Log of the industry's i GDP, in country c, in 1997 (in current millions of dollars)	WIOD
Industry openness	Exports plus imports divided by value added at industry level in time t (in millions of dollars)	Own calculations based on WIOD
Country openness	Exports plus imports divided by value added at country level in time t (in millions of dollars)	OECD database
Labour Prod	Labour productivity at industry i, country c and time t. (Total hours worked / GDPi)	WIOD
HighS Lab	Proportion of high skilled labour as percentage of the total labour in industry industry i, country c and time t.	WIOD
Inflation	Rate of inflation in country c, in time t (annual average)	World Economic Outlook Database
Government	Percentage of Government spending over GDP for country c, in time t	World Economic Outlook Database
Outdegree	Is a simple count of the number of outward connections an industry i, country c and time t has	Own calculations based on WIOD
Degree	Is a simple count of the total number of inward and outwards connection an industry i, country c and time t has.	Own calculations based on WIOD
Eigenvalue	A measure of the "popularity" of an industry in terms of the importance of the industries to which it is connected to. Takes values from 0 to 1.	Own calculations based on WIOD
Betweeness	A measure of the centrality of each industry in the network, how often an industry is in the shortest path between other industries. Takes values from 0 to 1.	Own calculations based on WIOD
Net Density	A measure of how complete is the internal network of a country in terms of all the possible available connections between its industries. Takes values from 0 to 1	Own calculations based on WIOD

4.5 Empirical Findings for Industrial Growth Using a Network Analysis

The results can be summarised as follows. First, the network characteristics and the position an industry occupies in the international trade network appear to determine its growth. Second, national network density affects industrial growth in a non-linear relationship. Third, being more centrally-located in the international trade network, As measured by betweeness, has a dual effect; it is positive for industrial growth during non-recession years but is negative during a recession. Fourth, being connected with more 'popular' industries, measured by eigenvalue, and having a larger number of output industrial connections appears to have a small and insignificant effect on growth. The results for the growth regression are presented in Table (4.4).

The first step in the empirical strategy presented in the last section, is to estimate Equation (4.1) in its the basic form, without including the network variables. The results are shown in Table (4.4), column 1. In general, the coefficients have the expected results suggested by the literature. *GDP,* both at the industry and country levels, has a positive and significant effect on industrial growth. The *GDPc* coefficient is unexpectedly negative but this could be explained by the time period selected; industries that were located in countries with a higher GDP were growing more slowly than others. The coefficient for *Downturn* has the expected negative sign and is highly significant. *Country Openness* has the expected positive sign as reported in the literature. The negative coefficient for *Industry Openness* might be surprising since the opposite effect on growth might be expected, although the coefficient is statistically insignificant. A similar result is also reported by Giovanni*, et al.* (2009), where trade openness at sector level increases growth volatility, thus leading to periods of slower (or negative) growth. The data sample analysed here may coincide with one of these periods. The quadratic terms of Government spending (*Gov)* and Inflation (*Inf)* are positive, which suggests a concave relationship with the dependent variable; this result is consistent with classic economic theory that states that higher spending and a positive, although not too high, rate of inflation leads to higher growth.

Table 4.4: Regression for Industrial Growth Using Eq(4.1)

		1	2	3	4
		BASE MODEL	NETWORK VAR.		
		Full Sample	Full Sample	2006-2007 Sample	2008-2009 Sample
Network	Out Degree		0.020	-0.020	-0.038
	Eigenvalue		-0.231 *	-0.156	0.055
	Betweeness		-0.005	0.022 **	-0.016
	Net density		-0.103 ***	-0.028	-0.109 ***
	Net density2		-0.109 ***	-0.035	-0.227 ***
Industry	GDPi	0.481 ***	0.487 ***	0.710 ***	0.692 ***
	Indust Open	-0.038	-0.029	-0.050	-0.040
	Downturn	-0.171 ***	-0.173 ***	-0.127 ***	-0.131 ***
	Lab Product	0.099 ***	0.099 ***	0.129 **	0.254 ***
	Lab Hskill	-0.131	-0.141 *	0.096	-0.339
Country	Count Open	0.238 ***	0.235 ***	0.242 ***	-0.010
	GDPc	-0.309 ***	-0.284 ***	-0.271 ***	-0.474 ***
	Gov	-0.135 ***	-0.147 ***	-0.090 ***	-0.152 ***
	Gov2	0.026 ***	0.022 ***	0.015	0.020 ***
	Infl	-0.012 ***	-0.015 ***	-0.017 **	-0.021 ***
	Infl2	0.012 ***	0.012 ***	0.018 ***	0.018 ***
	Recession	-0.062 ***	-0.060 ***		
	Year 2006			0.041 ***	
	Year 2009				-0.061 ***
	Constant	-3.645 ***	-3.699 ***	-5.997 ***	-3.759 ***
	N	5053	5053	2589	2592
	R-sq	0.766	0.768	0.676	0.860
	Method	Fixed Eff.	Fixed Eff.	Fixed Eff.	Fixed Eff.

Significance level: * p<0.1 ** p<0.05 *** p<0.01

Having found that the base model in Table (4.4) column 1 has a high explanatory power and that the results for most of the variables are as expected, the next step is to include the network variables. The results for the three samples are presented in Table (4.4), columns 2, 3, and 4. *Out-degree* has an insignificant coefficient throughout the specifications presented; thus, having a greater number of industrial links appears to have little impact on industrial growth.

The coefficient for *betweeness* is significant and positive for the 2006/2007 sample but the sign of the coefficient changes in the other two samples. This suggests that the position of an industry in the global network is relevant to determine growth, although the effects will depend upon the period of analysis. More centrally-located industries grow faster during periods of global growth but may also be affected by a global downturn. The coefficient for *eigenvalue* has a negative sign for the first two samples, but is only significant at the 10% level for the full sample. This result suggests that being connected to 'popular' or highly connected industries could have a negative, although statistically insignificant, effect on industrial growth.

Network density in its quadratic form has a consistently negative sign throughout the samples and is highly significant for the full sample and the 2008/2009 sample. This means that density has a convex shape; lower levels of density are related to higher industrial growth and higher density is associated with lower growth. The same type of result is reported in the only other study that uses density in a similar context to this research. Kali*, et al.* (2013) find a negative and significant sign for the quadratic coefficient of their density variable. They find a convex relationship between the probability of growth accelerations and industrial density but do not provide any specific explanation of the implications of this result in terms of industrial growth. The results shown in Table (4.4) suggest that industrial density could influence industrial growth but, as in the case of Kali*, et al.* (2013), no specific implications can be derived.

4.6 Robustness Analysis of Industrial Growth

The results from estimating Equation (4.1) so far suggest that most of the network variables included in the base model have an effect on the dependent variable. Nevertheless, the estimation presented in Table (4.4), columns 1 to 4 may be subject to endogeneity issues. Potential problems may relate to the endogeneity of trade at the country level (Frankel*, et al.* (1999) ; Saborowski*, et al.* (2010)) and according to the literature, the industry openness variable is also suspected to be endogenous. To test for the presence of endogeneity, a common method involves estimating a model containing a set of valid instrumental variables, to fit a model assuming endogeneity and then test that assumption (Baun, 2006; p.211-215). The usual problem is finding an instrument that is positively correlated with the endogenous variables but not correlated with the error term. The choice of a suitable instrumental variable is not straightforward and is usually subject to critiques and debate. In order to produce a set of valid instruments, two variables are proposed, the first one based on the traditional way in which a correlated instrument is calculated by obtaining the lagged value of the suspected endogenous variable, in this case, the first lag of *Industry Openness,* which is, by definition, highly correlated with the endogenous variable.

The second variable that is proposed as an instrument is Degree, this variable is a simple count of the number of industries to which an industry is connected and is based on a measure of international trade. The degree does not differentiate between exporting and importing links, it just produces an aggregate measure of the number of industrial trade partners. Since trade openness is the sum of the value of exports and imports in a given industry divided by that industry's GDP, it is reasonable to believe that the trade connections of an industry could be correlated with its openness to trade.

The two proposed instruments are used simultaneously to test for endogeneity in a two-stage least squares (2SLS) estimation; according to Wooldridge (2001; p.301) lagging a variable does not always remove the endogeneity problem, thus two instrument are used and tested.

The second lags of Industry Openness and Degree in its logarithmic form are used as instruments[6]. The results for the first stage of the regression, pass the tests for weak identification and rejects the null of underidentification. The summary results of the first stage regression are presented in the following table:

Summary Results for First-Stage Regression (Based on Eq 4.1)

	Significance		Underindentification		Weak Indentification
Variable	F	P-val	Chi-sq	P-val	F
Indust Open	28.62	0	57.55	0	28.62

The Hansen 'C' test for orthogonality of the instruments shows that there is no correlation with the error term, making these valid instruments to control for endogeneity, nevertheless, the use of instruments to remove endogeneity can bias the results if the suspected endogenous variable turns out to be exogenous. Accordingly, the next step is to test for that possibility. The C test applied to Industry Openness strongly fails to reject the null hypothesis of exogeneity, suggesting that this variable cannot be treated as endogenous. These results are presented in the following table:

Testing the validity of the instruments (Based on Eq 4.1)
Intrumented: Indust Open

Hansen J Statistic	Chi-sq	0.3530
	P-val	0.5525
Endogeneity Test	Chi-sq	0.0770
	P-val	0.7816

[6] Other specifications in which the first lag of industry openness was used as an instrument alone or in combination with degree, tested positive for over identification or for weak specification.

Other exogenous variables in Equation (4.1) are also tested for endogeneity with the same results; thus concluding that the coefficients presented in Table (4.4) are free from endogeneity issues.

Industry Openness in Table (4.4) is not significant in any of the samples. In order to analyse the sensitivity of the model, a new specification omitting this variable is fitted for Equation (4.1). The results presented in Table (4.5) suggest that the model is robust. All of the variables maintain their previous magnitude and sign. Only a negligible change in the significance of the *OutDeg* variable in one of the samples is found.

Table 4.5: Robustness Analysis for Industrial Growth

Results for Industrial Growth Regression (removing industry openness)

		5	6	7	8
		BASE MODEL	NETWORK VAR.		
		Full Sample	Full Sample	2006-2007 Sample	2008-2009 Sample
Network	Out Degree		0.016	-0.029	-0.046 *
	Eigenvalue		-0.273 **	-0.269	0.009
	Betweeness		-0.004	0.022 **	-0.017
	Net density		-0.105 ***	-0.026	-0.110 ***
	Net density2		-0.109 ***	-0.034	-0.229 ***
Industry	GDPi	0.495 ***	0.500 ***	0.734 ***	0.708 ***
	Indust Open				
	Downturn	-0.171 ***	-0.173 ***	-0.128 ***	-0.132 ***
	Lab Product	0.105 ***	0.103 ***	0.133 ***	0.263 ***
	Lab Hskill	-0.128	-0.139	0.091	-0.333
Country	Count Open	0.232 ***	0.230 ***	0.237 ***	-0.030
	GDPc	-0.327 ***	-0.297 ***	-0.288 ***	-0.513 ***
	Gov	-0.134 ***	-0.147 ***	-0.095 ***	-0.153 ***
	Gov2	0.026 ***	0.022 ***	0.017	0.020 ***
	Infl	-0.012 ***	-0.015 ***	-0.018 **	-0.021 ***
	Infl2	0.012 ***	0.012 ***	0.018 ***	0.019 ***
	Recession	-0.063 ***	-0.060 ***		
	Year 2006			0.042 ***	
	Year 2009				-0.065 ***
	Constant	-3.675 ***	-3.736 ***	-6.108 ***	-3.613 ***
	N	5053	5053	2593	2596
	R-sq	0.765	0.768	0.676	0.860
	Method	Fixed Eff.	Fixed Eff.	Fixed Eff.	Fixed Eff.

Significance level: * p<0.1 ** p<0.05 *** p<0.01

(4.2)

In addition to the industrial growth dependent variable used in Equation (4.1), this study uses the *Downturn* to estimate a second model in Equation (4.2). This is done as a supplementary test of robustness but also to obtain additional information on how the network variables interact under different specifications. Downturn is used as an explanatory variable in Equation (4.1) but it now enters the model as the dependent variable with the specification presented in Equation (4.2). Although the presence of this variable is justified theoretically in both equations, some concerns of causality may arise. But the issue may not be relevant due to the following reasons: First, in the correlation matrix (see *Appendix 4.2*), there is no indication of a correlation issue between the variables issued in both Eq(4.1) and Eq(4.2). Second, the Growth variable which is highly correlated with Downturn is used only in Eq(4.1) but not in Eq(4.2). Downturn is used in this latter equation as a proxy to test the robustness of the specification, the expectations are that the independent variables show the opposite effects as the ones showed in Eq(4.1).

$$\begin{aligned}\text{Downturn} = {} & \propto_0 + \beta_1 OutDeg_{ict} + \beta_2 Eigen_{ict} + \beta_3 Betw_{ict} + \beta_4 Density_{ct} \\ & + \beta_5\, GDP_{ict} + \beta_6 IndOpen_{ict} + \beta_7 Lab_{ict} + \beta_8 LabH_{ict} \\ & + \beta_9 CountOpen_{ct} + \beta_{10} Gov_{ct} + \beta_{11} Inf_{ct} + \delta \boldsymbol{Year} + \boldsymbol{\delta Ind} + \varepsilon_{ict}\end{aligned}$$

All of the variables are defined as in Equation (4.1) with the exception of *Year* and *Ind* which are dummy variables to control for the effects of time and heterogeneity at the industry level. Since the dependent variable is a binary variable, the chosen method is a Random Effects Probit. This method is better than a simple pooled-probit since it controls for the effects of unobservable variables and heterogeneity in the observations. The downside of using this estimation technique is that the marginal effects of the coefficients cannot be measured; only their signs and significance level can be analysed, but not their magnitude. Since the objective of estimation Equation (4.2) is to validate the results obtained in Equation (4.1), interpreting the signs and significances of the variables should be sufficient. To control for heterogeneity at the industry level, dummy variables are included. Year dummies are also included in all the samples. Both sets of dummies are jointly significant. To control under the same conditions as in Equation (4.1), the quadratic term for *Gov* and *Inf* are introduced.

Table 4.6: Regression for Industrial Downturn Using Eq (4.2)

		1	2	3	4
		BASE MODEL	NETWORK VAR.		
		Full Sample	Full Sample	2006-2007 Sample	2008-2009 Sample
Network	Out Degree		-0.041	0.110	-0.064
	Eigenvalue		0.131	1.318 **	1.018 **
	Betweeness		-0.007	-0.313	-0.015
	Net density		-0.191 ***	-0.156 **	-0.228 ***
	Net density2		-0.211 ***	-0.552 ***	0.095
Industry	GDPi	-0.230 ***	-0.198 ***	-0.370 ***	-0.217 ***
	Indust Open	0.295 ***	0.323 ***	0.310 **	0.375 ***
	Lab Product	0.105 **	0.065	0.086	0.086
	Lab Hskill	1.349 ***	1.464 ***	-1.107 **	2.489 ***
Country	Count Open	0.100	0.135	-0.672 ***	0.498 ***
	GDPc	0.249 ***	0.324 ***	0.182 *	0.336 ***
	Gov	0.014	0.054	-0.176 **	0.137 ***
	Gov2	-0.034	-0.046 *	0.000	-0.048
	Infl	0.036	0.073	-0.665 ***	0.382 ***
	Infl2	-0.060 ***	-0.084 ***	0.072	-0.171 ***
	Year Dummy	YES	YES	YES	YES
	Industry Dummy	YES	YES	YES	YES
	N	5053	5053	2589	2592
	Method	RE, Probit	RE, Probit	RE, Probit	RE, Probit

Significance level: * p<0.1 ** p<0.05 *** p<0.01

The overall results from the estimation of Equation (4.2), presented in Table (4.6), confirm the previous findings. Network *Density* is highly significant throughout the samples, reinforcing (and amplifying) the previous findings. That is, lower levels of density are associated with weaker effects of an industrial downturn and higher levels of density increase the strength of its effects. The rest of the network variables have the expected sign; that is, the opposite of those found in Equation (4.2) and are not statistically significant. A specific point should be made regarding the *Eigen* variable, which has a positive sign and is significant at the 5 per cent level for the 2006/2007 and the 2008/2009 samples. This result suggests that being connected to well-connected industries increases the probability of an industrial downturn.

4.7 Summary & Conclusions

This study investigates whether the network characteristics of an industry influence its growth. A large number of studies focus on the relationship between trade and growth at the sectoral level but few analyse the role that global industrial networks play in industrial growth and downturns. Traditional approaches cannot fully capture the complex nature of the global trade network and the mechanisms that drive growth in a highly interconnected world. Previous research focuses on using network metrics to analyse the patterns of global trade, growth accelerations at sector level and economic development but little attention has been paid to the analysis of industrial growth at the global level. This chapter tackles this gap in the literature by analysing a highly representative percentage of global industrial trade as a complex network to determine if the network characteristics of a given industry (size and number of connections, position and density) determine its growth and the likelihood of its experiencing a downturn. The study focuses on two years before and two years during the Great Recession as an attempt to look inside the black box of the crisis.

The results suggest that some network characteristics obtained from international trade data can determine industrial growth or downturn but only up to a certain level. An initial finding is that the position of an industry in the global network, given by a measure of centrality (betweeness), may play an important role in industrial growth but is highly dependent on the period of analysis. The effect of centrality is found to be statistically significant and positive in the 2006-2007 sample, while the opposite is true for the 2008-2009 sample where a negative although insignificant coefficient is reported. These results suggest that, during non-recession years, having greater centrality increases industrial growth while during years of economic turbulence, being more central could hurt growth. When looking at industrial downturns, the relationship is the inverse; greater centrality decreases the probability of crisis during non-recession years although the coefficients are not significant. Previous studies, albeit using different models and datasets, also find that betweeness is a good predictor of trade relations.

Neither the number of trade partners of an industry, measured by the output degree, nor the size of the industries to which it is connected, measured by the eigenvalue, appears to be important determinants of growth. When attempting to explain a downturn however, the coefficient for eigenvalue becomes significant and positive, suggesting a higher probability of experiencing an industrial downturn. These results contradict the general belief among policy-makers and business leaders, that the more trade connections an industry has, the better, especially if these connections are with large and important industrial hubs around the world. This variable has a dual role that needs to be further analysed in future research, potentially using larger time series data. A shortcoming of the dataset and method used is that they cannot account for the dynamics between the dependent and the independent variables, since they are all measured at the same time period. Potentially, some of the changes in the variables may take some years to fully impact the dependant variable. A bigger dataset may allow using a dynamic panel to test for these effects.

A country's national network density measuring how complete internal trade links are is found to have a convex non-linear relationship with industrial growth. At low levels of density, an increase in density increases growth; beyond a certain threshold, it has a negative relationship with growth. As expected, the opposite happens in the case of an industrial downturn, with a concave non-linear relation with density. The non-linear results for this variable are consistent with those reported in previous studies (Kali*, et al.*, 2013). The issue is therefore whether a higher industrial density is a desirable feature. To address this issue, a different type of research design and objective is needed, which could be a future topic of research. In the context of the current study it can only be said that density influences industrial growth although not with a large magnitude.

The empirical findings in this Chapter reinforce those in the recent literature that suggest that network theory helps to understand and explain industrial growth, albeit the empirical results of the estimation suggest the impact on the dependent variable may be of small magnitude. Even with these results, it is believed that there are a number of ways in which traditional industrial economics can apply some of the tools used in this study to expand the knowledge and potentially offer a new perspective to old economic issues.

A logical extension of this study would be the analysis of the contagion of the recession in the global industrial network to establish whether network characteristics determine the patterns and probability of contagion. During the years of turbulence that followed the beginning of the Great Recession, a mantra was that some industries are 'too big to fail'. In short, the argument is that, if an industry is too big in terms of GDP or employment, governments should take every possible action to avoid its collapse and a consequent systemic risk for the rest of the economy. In the light of the results in this study, the concept of 'too-big-to-fail' needs to be revised and expanded to incorporate those that are 'too-connected-to-fail' (Chan-Lau, 2010) and 'too-central-to-fail' (Blöchl*, et al.*, 2010 ; Battiston*, et al.*, 2012). This study highlights the importance of centrality and connectedness but further research could potentially have important theoretical and policy implications.

Chapter 5

Empirical Analysis of Business Cycle Co-movement in the Industrial Network

5.1 Introduction

After almost two decades of increased growth and reduced GDP volatility in the global business cycles, often referred to as the Great Moderation, the world started to experience in 2007 a surge in volatility that eventually resulted in the worst global crisis, the Great Recession, in more than eighty years. By the end of 2008, 90 per cent of the OECD countries exhibited a simultaneous decline in trade dubbed as the Great Synchronisation (Araújo*, et al.*, 2011). This period is not only striking in terms of the large number of countries that experienced a trade decline, but also because this recession appears to be the only one in the last fifty years to produce such a sudden, severe and globally synchronised collapse of international trade (Antonakakis, 2012). In the aftermath of the global crisis, there has been a renewed interest in analysing the global synchronisation of business cycles and understanding the channels through which specific shocks spread.

The literature analysing the determinants of business cycles, a deviation from the long-term growth trend, is extensive. Business cycle theory can be traced back to the work of Kondratieff (1925) and empirical work of Kuznets (1966). The most influential empirical contributions to understanding the determinants of business cycle co-movement came in the mid-1990s. Boileau (1996) uses a macroeconomic model, Horvath (1998) presents the first sectoral level empirical analysis of business cycles, based upon previous theoretical work by Long*, et al.* (1983) and the seminal empirical contribution of Frankel*, et al.* (1998), who established the now well-known stylised fact that countries with closer trade links tend to have more tightly correlated business cycles. Many studies have since corroborated the evidence that the main mechanism of business cycle diffusion is trade intensity at the country level (Kose*, et al.*, 2003 ; Imbs, 2004 ; Baxter*, et al.*, 2005 ; Kose*, et al.*, 2006 ; Calderon*, et al.*, 2007) and at sectoral level (Di Giovanni*, et al.*, 2010). These findings have spurred a new wave of research to attempt to understand if the characteristics of bilateral trade affect business cycle movements: similarity in industry structure (Imbs, 2004), intra-firm trade between multinationals (Burstein*, et al.*, 2008), input linkages between cross-border firms (Bergin*, et al.*, 2009), production fragmentation and trade in substitute versus complement products (Ng, 2010) and the effect of vertical integration on co-movement (Di Giovanni*, et al.*, 2010).

In direct response to the global crisis, the recent literature focuses on the contagion and spread of the business cycle rather than its determinants. For example, Caraiani (2013) uses a complex network framework to analyse the international contagion of business cycles. Lee*, et al.* (2011) analyse the probability of a 'crisis avalanche' in the global macroeconomic network. Kali*, et al.* (2010) use network analysis to model international trade and explain stock returns during periods of crisis. Gai*, et al.* (2010) study the contagion of financial shocks using a series of financial indicators for interbank linkages under a complex network analysis. By using networks, Dette*, et al.* (2011) determine how a debt default in a given country spreads at the global level. By analysing the complex nature of linkages that characterise the global economy, network analysis can offer a different perspective in a way that traditional methods cannot (Farmer*, et al.*, 2012).

This chapter brings together two strands of literature by analysing global business cycles co-movement under a network framework; a combination that is rarely analysed at the country level and remains unexplored at the industry level. To do so, correlation data of value added for each pair of industries in the sample from 1996 to 2009 is combined with trade intensity data to create a representation of the global co-movement network consisting of 1,437 nodes (industries) and 1,030,330 links (pairs of industries weighted by value added correlation). Given the lack of attention given in the existing literature to the industry level analysis of business cycles at the global level (the exception being Di Giovanni*, et al.* (2010)), this study uses industry level data from a global input-output database (35 industries located in 41 countries plus a grouping for the rest of the world)[7] to capture, as best as possible, the intricate linkages and interconnections that exist both within a country and in the global network.

The traditional approach when analysing business cycle co-movement is to look at each pair of countries or industries, focusing on the co-movement relationship between country (industry) A and country (industry) B. Even if this type of analysis is highly informative, it focuses on the relationship between A and B, not on A and B themselves. This Chapter is concerned with identifying which industries exhibit greater co-movement at the global level and analysing their characteristics. This requires an aggregate measure of co-movement for each pair of industries (1,030,330 potential links) but to report the data focusing on each of the 1,437 industries. In order to do so, this study proposes a new measure based on a weighted degree 'Co-movement', which is an aggregated measure of business cycle co-movement from 1996 to 2009 for each industry obtained using network analysis. To analyse the characteristics of industrial co-movement during a specific period, the *Weighted Degree* variable is regressed on a number of explanatory variables, focusing specifically on the period from 2006 to 2009; i.e. two years before the Great Recession and two years during it.

The main results are summarised as follows. This study finds that those industries that exhibit a larger co-movement are neither the largest in terms of GDP, nor in terms of number of employees. This is contrary to the general belief that the size of an industry implies a greater risk of shock contagion – the 'too-big-to-fail' mantra. This means that the largest global industries in terms of GDP, located in the United States, and the largest in terms of employment, located in China, are not the ones driving global co-movement at the industry level. On the contrary, some smaller industries may deserve more attention from policy-makers. Additionally, the study finds

7 The same international trade database used in Chapter Four.

that, during years of global growth like 2006 and 2007, the industries that are growing fastest are those that have greater co-movement. During global recession years like 2009, the opposite is true; industries that decline are those that exhibit greater co-movement. This finding suggests that industries with greater co-movement have a dual effect on the global network: expanding growth during periods of global expansion and creating a negative cascade during periods of contraction. The findings also suggest that industries with greater co-movement are also those that have a large number of connections in the global trade network. This, together with the aforementioned findings, suggests that policy-makers should focus on the concept of 'too-connected-to-fail' and 'too-central-to-fail' rather than thinking about industrial co-movement in terms of too-big-to-fail.

The Chapter is organised as follows. Section 5.2 presents a detailed explanation of the empirical strategy and a descriptive analysis of the data obtained from the Global Co-movement Network. Section 5.3 contains the results of the empirical exercise to obtain the characteristics of industrial co-movement during the Great Recession. This is followed by a sensitivity analysis of the results. The final section offers a discussion of the results in terms of their potential policy implications and draws some conclusions.

5.2 Empirical Strategy

The empirical analysis in this Chapter has several stages, summarised as follows. Using a novel dataset, a measure of Industrial Co-movement and a measure of Industrial Trade Intensity are derived. These measures are used to create a Global Co-movement Matrix and network analysis is used to obtain metrics that aid the understanding of the complex interactions. An econometric model is then constructed and executed to provide a better understanding of the characteristics of the Global Industrial Co-movement.

5.2.1 Components of the Global Co-movement Matrix

Data for real Value Added (VA), by industry, from the World Input Output Database (WIOD) is used to calculate the co-movement of business cycles between pairs of industries in the sample. To obtain a measure of the cycles, the VA series is de-trended. In this regard, there is a lack of consensus on which is the best de-trending method; for a discussion on the different methods, critiques and empirical applications see Bjørnland (2000). Nevertheless, in a very similar context to the one used in this paper – co-movement and trade - the results has been proven to be robust to changes in the de-trending method (for specific examples, see Frankel*, et al.* (1998) and Di Giovanni*, et al.* (2010)), thus, in this study, the VA series is de-trended using a Hodrick-Prescott (HP) filter. After de-trending the VA series, the Spearman correlation for each pair of the 1,437 industries in the sample is calculated for the time-series of fourteen years (from 1996 to 2009), resulting in 1,030,330 pairs of correlations. The Spearman is used instead of the Pearson´s correlation, since it is considered in the recent literature as an adequate measure of business cycle co-movement in periods of global crisis (Sandoval*, et al.*, 2012).

The problem with this type of measure is that it can only capture the business cycle co-movement between two pairs of countries or industries. This may be sufficient when analysing a small sample of countries or a region. However, if the objective is to analyse a large number of countries or industries that are globally inter-connected, then a simple co-movement measure cannot capture all of the complex linkages that exist. This study proposes a new measure of business cycle co-movement that treats the global industrial input-output data as a complex system using network analysis. The industrial VA correlation data is transformed into a square matrix consisting of 1,437 rows and columns, containing both positive and negative correlation values. Only those pairs of industries that have positive correlations are relevant to the construction of the proposed new co-movement measure. Negative correlation suggests a lack of existence of a common trend between two time-series. Given that the objective of this study is to obtain a measure of co-movement, negative correlation values are therefore excluded from the global co-movement matrix.

The existence of a positive correlation between two pairs of industries does not necessarily imply there is a direct and significant relationship between them. Two industries could have a similar business cycle pattern even if they have no direct relationship; for example, if they belong to the same industry or are located in the same country such that the correlation is spurious. In the literature, this is dealt with only using correlation values that are higher than a given threshold. For example, Caraiani (2013) uses a threshold of 0.3; meaning that pairwise correlations that are lower than 0.3 given a value of zero. This solution reduces the risk of spurious correlations being included in the analysis but it is difficult to create a compelling argument for the choice of the threshold.

In this study, a different approach is proposed in order to remove potentially spurious correlations and obtain a better representation of the global co-movement network. There is a general agreement in the literature that the main driver of business cycle co-movement is the intensity of bilateral trade[8], either at the country level (Kose*, et al.*, 2003 ; Imbs, 2004 ; Baxter*, et al.*, 2005 ; Kose*, et al.*, 2006 ; Calderon*, et al.*, 2007) or at the sectoral level (Di Giovanni*, et al.*, 2010). It is a well-known stylised fact that greater trade intensity increases business cycle co-movement. This study's empirical strategy draws heavily on this stylised fact.

In order to retain just the most significant pairs of links between industries in the global co-movement matrix, only those pairs that have greater-than-average trade intensity are left in the sample, where the average value is 0.0016. The result is a matrix of industrial VA correlation for high levels of trade. The logic behind this procedure can be explained as follows: if two pairs of industries are linked by a positive correlation and, at the same time, by a highly intense trade relationship, then these two industries are not only moving together but also a shock from one industry will be transmitted to the other through trade, which is the most relevant transmission

8 A critique of the trade intensity explanation can be found in Imbs (2004).

mechanism according to the literature. Note that nothing can be said about the direction of the shock, it could either go from ***i*** to ***j*,** or from ***j*** to ***i*.**

The approach used by Di Giovanni*, et al.* (2010) at sectoral level and Frankel*, et al.* (1998) at the country level, is used here to calculate trade intensity (TI). They calculate four measures that have the same numerator, the sum of bilateral exports from country ***c*** to ***d*** for every pair of industries ***i*** and ***j*,** normalised (divided) by: 1) total bilateral GDP; 2) total bilateral sectoral GDP; 3) total bilateral trade; and 4) total bilateral sectoral trade. There is no specific reason to prefer one measure to the other. Moreover, both Frankel*, et al.* (1998) and Di Giovanni*, et al.* (2010) clearly state that their findings are not affected by their choice of measure. Accordingly, the choice of measure in this study based on data availability as well as the need to find an efficient means of working with a large amount of data. The selected measure is total trade normalised by total bilateral sectoral GDP:

$$Trade_{ij}^{cd} = \log\left(\frac{1}{T}\sum_{t}\frac{X_{i,t}^{cd} + X_{j,t}^{dc}}{Y_{i,t}^{c} + Y_{i,t}^{d}}\right) \quad \textbf{(5.1)}$$

Where X_{it}^{cd} represents the value of exports in sector ***i*** from country *c* to country (and vice versa X_{jt}^{dc}); Y_{it}^{c} is the GDP of country ***c*** ; Y_{it}^{d} and is the output of sector ***i*** in country ***c*** in period ***t*.**

The matrix of value added correlation is transformed into an undirected network, where each industry in the sample is considered a node and the correlation between any two industries is the link. This network is termed here the *Global Co-movement Network*.

All of the self-loops, same node links, are removed which, in practice means, that all the values of correlation equal to 1 are removed. This leaves only those links that range between 0 and 0.999 in the network. Additionally, the procedure of creating a network removes all of the links equal to zero and treats these links as non-existent. The resulting Global Co-movement Network has 1,167 nodes and 149,347 links that contain averaged correlation data from 1996 to 2009.

The objective of this Chapter is to analyse the role that each industry plays in the global co-movement network and its characteristics. In order to obtain an industry-specific measure of co-movement, the weighted degree is calculated *(*simply called *Co-movement* here). This is a metric that counts the number of nodes that are directly connected to each given node, weighted by the value of each link's correlation.

5.3 Descriptive Analysis of the Global Co-movement Network

The graphical representation of the Global Co-Movement network (GCN) is presented in Figure 5.1. The colour of each node is the degree, which represents for each node *i,* the number of industries that at the same time are positively correlated to *i* and have a high trade intensity. Links with a low trade intensity have already been filtered out. The size of the nodes is the weighted degree, which is simply the degree of each industry multiplied by the intensity of the correlation.

From the GCN, the industries can be ranked in terms of their co-movement (measured by the weighted degree), shown in Table 5.1; the degree measure is also presented in the table. The values of weighted degree and degree are obtained from the GCN using the filter of trade intensity greater than 0.0016 and ranked in column 1 of the table. This procedure provides the most relevant co-movement links based upon trade intensity as well as correlation values. The analysis that follows is based on the results presented in Table 5.1, column 1.

The industry that tops the list is DEU12 ('Basic & Fabricated Metal' in Germany), which exhibits a weighted degree of 49.5 and a degree of 845. The next two industries are DEU9 ('Chemical Products') and DEU14 ('Electric Equipment'), which have slightly lower weighted degrees but a higher degree. In order to interpret these values, although both measures are informative and complement each other, the weighted degree is the preferred choice for this study because it does not only count the number of connections it also weights them by their strength. This results in a more exact representation of industrial co-movement. If only the degree is analysed, this could result in a large number of connections with small correlations being captured. For example, in the cases of DEU9 and DEU14 they both have a significantly larger degree than DEU12, meaning that they are more connected. Once the intensity of these connections is accounted for, their weighted degree value means that they rank slightly lower. This explanation also applies to the rest of the values and is the reason why *weighted degree* is chosen as the main dependent variable in the model to determine the characteristics of co-movement.

Intuitively, the industries in Table 5.1 are those that exhibit greater co-movement; i.e., when their business cycles move, a large number of industries around the world also move in the same direction. It is important to note that this measure refers only to large values of trade intensity, or at least the values reported in column 1 of the table. In theory, an industry that has a large co-movement will spread its cycle to all the other industries with which it has a trade relationship or, similarly, will be the recipient of the cycle from any of its connected industries. A critical issue is whether the dissipation effect is greater than the vulnerability effect. Looking at the raw data of weighted degree alone is not sufficient since the global co-movement network is undirected, that is no causality can be implied. Moreover, this issue goes beyond the scope of this thesis and constitutes an interesting topic for future research. Nevertheless, an approximation can be given by analysing econometrically the role of those industries with large co-movement in years of global prosperity or downturn.

Table 5.1: Sample of Industrial Co-movement Data: Top 50 Industries Ranked by their Co-movement, using different filters

Industry Id	Degree	Weighted Degree	Industry Position				Industry	Country
			(1)	(2)	(3)	(4)		
			Filter: TI > 0.0016 & Corr >0.0	Filter: TI > 0.0016 & Corr >0.3	Filter: TI > 0.00 & Corr >0.0	Filter: TI > 0.00 & Corr >0.3		
DEU12	781	49.547	1	1	9	12	Basic Metals and Fabricated Metal	DEU
DEU9	845	44.181	2	4	4	4	Chemicals and Chemical Products	DEU
DEU14	865	44.048	3	2	1	1	Electrical and Optical Equipment	DEU
SWE12	671	43.025	4	3	10	10	Basic Metals and Fabricated Metal	SWE
DEU10	758	39.983	5	5	12	21	Rubber and Plastics	DEU
BEL12	633	36.349	6	16	66	96	Basic Metals and Fabricated Metal	BEL
NLD12	607	36.254	7	7	61	76	Basic Metals and Fabricated Metal	NLD
ITA12	797	35.135	8	6	3	3	Basic Metals and Fabricated Metal	ITA
DEU13	793	34.339	9	12	6	7	Machinery, Nec	DEU
ITA13	817	33.392	10	10	2	2	Machinery, Nec	ITA
ESP15	610	33.102	11	8	26	27	Transport Equipment	ESP
GBR12	600	33.071	12	9	48	28	Basic Metals and Fabricated Metal	GBR
ESP12	576	32.452	13	11	27	22	Basic Metals and Fabricated Metal	ESP
ITA14	760	32.371	14	13	5	5	Electrical and Optical Equipment	ITA
FIN12	566	31.780	15	14	57	54	Basic Metals and Fabricated Metal	FIN
GBR15	683	30.825	16	15	30	38	Transport Equipment	GBR
SWE15	643	30.638	17	20	38	46	Transport Equipment	SWE
SWE13	665	30.591	18	17	11	9	Machinery, Nec	SWE
NLD13	637	29.623	19	22	28	26	Machinery, Nec	NLD
GBR14	682	29.055	20	25	51	67	Electrical and Optical Equipment	GBR
DEU15	718	28.994	21	48	47	94	Transport Equipment	DEU
AUT12	630	28.988	22	18	25	32	Basic Metals and Fabricated Metal	AUT
FRA12	656	28.893	23	23	44	58	Basic Metals and Fabricated Metal	FRA
ITA15	706	28.784	24	21	8	8	Transport Equipment	ITA
MEX14	465	28.710	25	19	94	69	Electrical and Optical Equipment	MEX
RUS12	597	28.560	26	24	63	70	Basic Metals and Fabricated Metal	RUS
FRA9	632	28.088	27	36	97	127	Chemicals and Chemical Products	FRA
FRA14	705	27.316	28	28	29	39	Electrical and Optical Equipment	FRA
USA14	722	26.087	29	26	13	19	Electrical and Optical Equipment	USA
HUN12	452	26.040	30	29	92	79	Basic Metals and Fabricated Metal	HUN
CZE13	549	25.903	31	27	58	45	Machinery, Nec	CZE
GBR9	554	25.209	32	35	42	41	Chemicals and Chemical Products	GBR
SVK12	440	25.182	33	38	144	150	Basic Metals and Fabricated Metal	SVK
FIN14	648	25.176	34	31	36	43	Electrical and Optical Equipment	FIN
NLD14	594	24.984	35	42	93	119	Electrical and Optical Equipment	NLD
HUN15	480	24.783	36	41	139	146	Transport Equipment	HUN
NLD10	554	24.692	37	32	71	63	Rubber and Plastics	NLD
NLD15	525	24.684	38	33	103	90	Transport Equipment	NLD
GBR13	646	24.362	39	37	41	55	Machinery, Nec	GBR
AUT13	657	24.359	40	30	20	20	Machinery, Nec	AUT
CZE12	530	24.343	41	43	108	115	Basic Metals and Fabricated Metal	CZE
BEL10	577	24.336	42	51	52	59	Rubber and Plastics	BEL
DNK13	607	23.533	43	34	49	53	Machinery, Nec	DNK
ESP14	529	23.529	44	40	74	72	Electrical and Optical Equipment	ESP
DEU6	574	23.013	45	53	64	56	Wood and Products of Wood and C	DEU
USA12	584	22.971	46	39	53	48	Basic Metals and Fabricated Metal	USA
DEU16	608	22.852	47	47	43	51	Manufacturing, Nec; Recycling	DEU
BEL13	550	22.371	48	46	60	52	Machinery, Nec	BEL
DEU4	575	21.928	49	55	50	49	Textiles and Textile Products	DEU
CZE15	566	21.762	50	63	82	93	Transport Equipment	CZE

Definitions: TI is Trade Intensity; Corr is Correlation as defined in this paper. Degree is the sum of nodes to which an industry is directly connected. Weighted Degree is the sum of the degree multiplied by the correlation of each pair. Columns (2), (3) and (4) show the position of each industry in terms of weighted degree using different filters. The values of weighted degree using a TI filter of 0.0016 are presented in this table and ranked in column (1). The values for the rest of the filters are not reported, only their position.

Two interesting patterns emerge from Table 5.1. Germany is the country that has the largest number of industries in the top fifty co-movement ranking (nine), followed by the UK and the Netherlands, with five each. It is interesting to note that there are no industries from China and only two industries from the United States present in this ranking, probably due the very large domestic markets that exists in these two countries, which are not captured by the international trade data. This is in spite of some of the industries from these countries being among the biggest in the world in terms of GDP, trade volume or employment. They appear however, to be much less important in terms of global co-movement.

Looking at the types of industry that appear in the ranking, 'Basic Metals & Fabricated Metal' appears fifteen times while 'Machinery' and 'Electrical & Optical Equipment' both appear eight times in the top fifty. In terms of GDP and trade volume, these are not the biggest global sectors; the ranking is dominated by industries from the secondary sector. These patterns are further analysed in the next section.

The remaining columns in Table 5.1 provide summary information concerning the top fifty industries in terms of weighted co-movement after changing the filter parameters. The data in column 1 is filtered by trade intensity. Using only those pairs of industries that exhibit high trade intensity and using them to construct the Global Co-movement Network, this Chapter attempts to focus only on those links that actually transmit co-movement, given that the main transmission mechanism is trade. The only other option is to select the most relevant pairs of links is to define a threshold that defines (arbitrarily) which are the relevant nodes as in Caraiani (2013). His study imposes a threshold for values of correlation above 0.3 but no justification for this threshold is given. This study tests to see if the use of a correlation threshold affects the results. Columns 2, 3 and 4 in Table 5.1 attempt to check for this in a simple manner. These filters are tested econometrically in Section 5.5. The intention in presenting the industries in terms of the weighted degree results is to check whether there are observable changes in the ranking positions of the industries. If there are no significant changes in position, then a priori the choice of filter does not affect the results.

The rank position of an industry in Table 5.1 column 1 is used as the base scenario. In column 2, the Trade Intensity (TI) filter of 0.0016 is used in combination with a correlation filter (Corr) of 0.3. The results of this exercise, shown in column 2, are very similar to those in column 1; most of the industries stay in the same position or move only a few places. In Table 5.7 column 3, no filter is applied; in this case, there are noticeable variations in the ranking position of industries with respect to column 1. In column 4, a correlation filter of 0.3 is used but without a TI filter and the results are noticeably different to the base scenario.

Using only a correlation filter does not produce consistent results as can be seen in comparing columns 2 and 4. The results are much more stable when a trade intensity filter is used, as can be seen by comparing columns 1 and 2. This analysis also suggests that caution should be used when interpreting the results shown in Table 5.1. It is tempting to state that industry *A* has a greater co-movement than industry *B,* but this interpretation may simply depend upon the filtering method used and the relationship may be reversed when using another filter. For example, the first three industries in the table swap places when the filter is changed. The objective of this Chapter however, is not to develop a methodology to provide a perfectly stable ranking of industrial co-movement but to understand its main drivers. The different co-movement filters therefore need to be tested to determine the robustness of these results for the different filters and this is done in section in sections 5.4 and 5.5. First, the base scenario, (TI>0.0016 and Corr>0.00) is analysed. Then, as a test for robustness, the other three filters are used.

A summary of the main Descriptive statistics is presented in Table 5.2. From a simple observation of the statistics it can be seen that some of the variables may be subject to outliers. This is the case of GDP and Population, for which the median and the mean are considerably different. This issue needs to be considered before the estimation process.

The presence of three outlier observations with large and unusual GDP growth rates are detected and removed. The three outliers removed are industry 24 and 25 in Slovakia and industry 15 in Malta. Potential outliers are detected when analysing the variables for *Population* and *Gdp;* respectively, all the industries located in India and China and several industries located in the United States. Removing, or dealing with, these observations however, would greatly affect the outcome of the regression so that they are left in the sample but all the series is transformed in to its logarithmic form. Equation 5.2 is first estimated with the dependent variable at its level values but a test for misspecification, linktest, is found to be significant. To resolve this issue, the log values of *Co-movement* are used as a dependent variable in the equation; no further misspecification problems are found. The results of the misspecification test for each year are also presented in Table 5.4. Finally, to avoid a violation of the OLS assumptions, the normality of the estimation residuals is tested and no significant skewness problems are found.

Table 5.2: Descriptive Statistics Chapter Five

Variable	Observations	Mean	St. Dev.	Min	Median	Max
Comovement (Weighted Degree)	4668	1.84	0.85	-4.24	1.94	3.9
Growth	4684	0.06	0.22	-3.33	0.08	5.78
GDP	4684	25.53	87.98	-0.4	5.16	1970.26
Employment	4684	0.83	4.64	0	0.1	104.21
Open (Country Openess)	4684	95.03	49.93	22.31	85.77	280.62
Connectivity (Outdegree)	4684	76.34	93.4	0	42	763
Centrality (Betweeness)	4684	0.41	0.11	0	0.42	1
Population	4684	101.97	261.54	0.41	16.38	1334.5
Secondary	4684	0.46	0.5	0	0	1
Terciary	4684	0.48	0.5	0	0	1
HHpart (Household demand)	4684	0.01	0.02	0	0.01	0.22

5.4 The Empirical Model of the Determinants of Co-movement

The focus of this empirical exercise is on the most recent global crisis period, specifically selecting two years before the crisis (2006 and 2007) and two years during the crisis (2008 and 2009). The model is concerned with providing a deeper understanding of the characteristics of industrial co-movement using data from the Global Co-movement Network as a primary source (the data is averaged between 1996 and 2009 and control variables for the period 2006 to 2009).

$$(5.2)$$

By construction the Comovement data is time invariant, thus restricting the estimation method choices.

$$Comovement_{ic} = \beta_0 + \beta_1 GDP_{ict} + \beta_2 Growth_{ict} + \beta_3 Employment_{ict} + \beta_4 HHpart_{ict} + \beta_5 Open_{ct} + \beta_6 Population_{ct} + \beta_7 OutDeg_{ict} + \beta_8 Between_{ict} + \delta Sector + \delta Industry + \delta Country + \varepsilon_{ic}$$

Where $Co\text{-}movement_{ic}$ is the measure of Weighted Degree obtained from the Global Co-movement Network for each industry ***i*** in country ***c***. GDP_{ict} is the value added in current US Dollars during time *t*. $Growth_{ict}$ is the annual change in real value added for each industry *i*. $Employment_{ict}$ is the number of employees (millions) for each industry *i*. $HHpart_{ict}$ is the participation of final household consumption in each industry *i* over value added for industry *i*. $Open_{ct}$ is a widely-used measure of country openness calculated by summing total exports and imports and dividing by the current value of GDP for country *c*, in time *t*. $Population_{ct}$ is the number of inhabitants in a country (millions). A word of caution might be necessary regarding the Population variable since population does not change a lot year over year and in that case the identification of the variance would be problematic, specially in the presence of country fixed effects; nevertheless it is important to keep this variable in the model to capture the effect of larger population and small year on year changes that do exist in the dataset.

Chapter Four finds that some of the network characteristics of industries affect industrial growth; for example, the position they occupy in the global network and the national industrial density. In order to test some of these network characteristics in the context of the Global Co-movement Network, two variables are introduced to the model $OutDeg_{ict}$ and $Between_{ict}$:

As reported in Chapter 4, to capture the complex nature of international trade linkages, a dataset containing the Input-Output (I-O) matrix for each country in the sample is used (a full description of the characteristics of the dataset can be found in Erumban, *et al.* (2011)). The interesting characteristic of this particular dataset is that it includes data on internal use and consumption for each industry at national level as well as trading partners for each country. This enables the creation of a 'true' representation of the network of internal and external trade for every industry and every country in the sample.

The first step is to transform the global input-output matrix into a network. There are 35 industries in the sample, classified under ISIC rev2; these are the nodes. The link between each pair of industries is the trade relationship in US Dollars between those industries, based on exports (from industry *i* to industry *j*). Since the exports from industry *i* to industry *j* are the mirror of the imports to industry *j* from industry *i*, only the value of exports is used. Given that the direction of the trade is considered in the network approach, it is therefore possible to identify whether there is an export or import relationship between each pair. This distinction is important when analysing output and input degree. The sample consists of the trade relationships between 35 industries located in 42 countries, resulting in a total of 1,470 nodes and more than two million links for each year. A full description of the data used in this section can found in Chapter Four, Section 4.2. A description of the industries and countries considered in the dataset is found in *Appendix (4.1)*.

$OutDeg_{ict}$ represents the number of outward links each node has; a simple count of the number of outward nodes to which each industry is connected in the IITN. Since this measure is obtained from an input-output matrix, it shows how many industries in the world are using the product that is being exported from *i* as an input for producing *j*. $Between_{ict}$ is a measure of centrality of each industry in the network; it provides a measure of the average distance from a given node to all the rest of the nodes in the network. Intuitively, it measures how central an industry is in the network. For a detailed description of these and other network metrics, refer to Newman (2010; p.169-177).

Finally, *Sector, Industry* and *Country* are dummy variables included to control for fixed effects. In the case of Sector, the industries are grouped into Primary, Secondary and Tertiary to control for the sector structure effect on the dependent variable; the omitted category is Primary. The controls for sector grouping (primary, secondary and terciary) are different than the controls for specific industry (a dummy is included for each of the industries in the sample), this clarification is necessary to understand how each of the industry controls are identified. A table describing these statistics of these variables is available in Table (5.2*)*. A Table containing the variable definitions is available in Table (5.3).

Table 5.3: Variables definition Chapter Five

Name	Definition	Source
Co-movement (Corr. Degree).	A measure of industrial business cycle co-movement for industry *i,* obtained from the Global Co-Movement Network. It measures how many industries *j* have similar business cycles to the ones observed in *i*	Own calculations based on WIOD
Growth	LogGDPt - LogGDPt-1, for industry i, country c, and tim	Own calculations based on WIOD
GDP	Log of the industry's i Value Added, in country c, at time t (in millions of dollars)	WIOD
Employment	Number of employees (in millions) at industry level for each country in time t	World Economic Outlook Database
Connectivity (Outdegree)	Is a measure of the number of industries to which an industry is connected to.	Own calculations based on WIOD
Popularity (Eigenvalue)	A measure of the "popularity" of an industry in terms of the importance of the industries to which it is connected to. Takes values from 0 to 1.	Own calculations based on WIOD
Centrality (Betweeness)	A measure of the centrality of each industry in the network, how often an industry is in the shortest path between other industries. Takes values from 0 to 1.	Own calculations based on WIOD
Country Openness	Exports plus imports divided by value added at country level in time t	Own calculations based on WIOD
Population	Is the value of population for every country in time t (in millions)	World Economic Outlook Database

The model represented by Equation (5.2) is estimated using ordinary least-squares (OLS) with robust standard errors. As it was reported earlier, the dependant variable, comovement, is time invariant, thus estimation Equation (5.2) with, for example, a panel with fixed effects, is not feasible. Estimating the model by using an OLS for each year in he sample instead of pooling the data, is more convenient to tackle the objectives of this research since we want to analyse the specific effects of the independent variables on comovement before and during the great recession, thus having a separate regression for each year will become convenient for interpretation of the results. The presence of collinearity in the right-hand side variables is not detected (correlation matrix available in *Appendix (5.1)*. The results are presented in Table 5.4.

Table 5.4: Estimation Results of the Determinants of Co-movement.

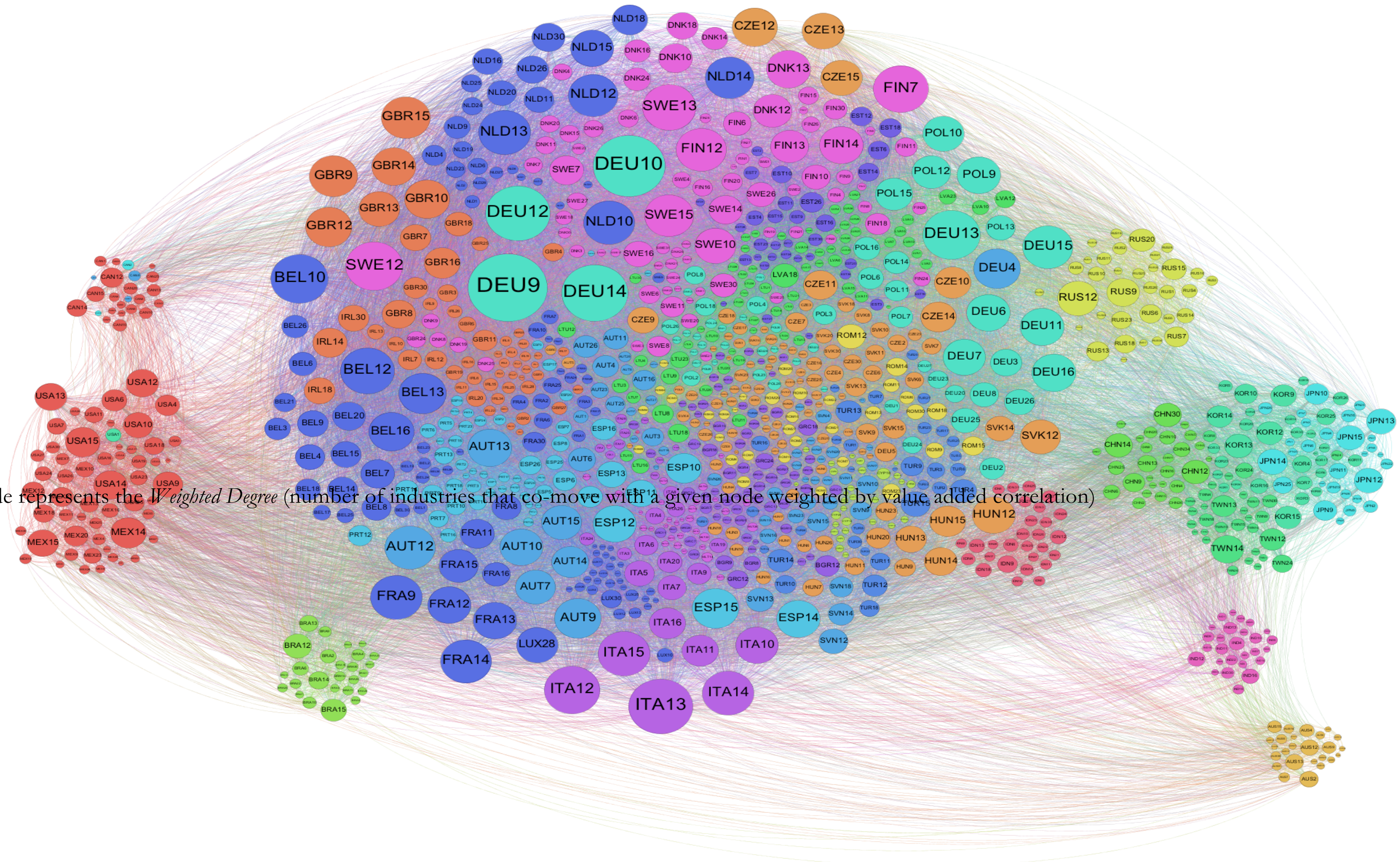
Main characteristics of industrial comovement

LHS: Comovement (log)		(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2006	(6) 2007	(7) 2008	(8) 2009
Industry	GDP	-0.0011 *	-0.0010 *	-0.0009 *	-0.0010 *	-0.0016 ***	-0.0015 ***	-0.0014 ***	-0.0014 ***
	Growth	0.6033 ***	0.7145 ***	-0.2792	-0.3250 **	0.7268 ***	0.7614 ***	-0.1596	-0.3852 ***
	Employment	-0.0031	-0.0026	-0.0035	-0.0031	-0.0019	-0.0004	-0.0011	-0.0009
	HHpart	4.3948 ***	5.7172 ***	6.1816 ***	4.8503 ***	3.6076 **	3.7618 **	4.0379 **	3.5569 **
Country	Open	0.0080 ***	0.0073 ***	0.0058 ***	0.0079 ***	0.0078 ***	0.0073 ***	0.0062 ***	0.0082 ***
	Population	0.0039 ***	0.0044 ***	0.0040 ***	0.0039 ***	0.0034 ***	0.0037 ***	0.0033 ***	0.0034 ***
Network	OutDeg (Connectivity)					0.0030 ***	0.0029 ***	0.0026 ***	0.0027 ***
	Between (Centrality)	2.4467 ***	1.5677 ***	0.9346 ***	1.7981 ***				
	Secondary	0.7233 ***	0.8058 ***	0.7981 ***	0.8101 ***	0.7007 ***	0.7754 ***	0.7590 ***	0.7694 ***
	Tertiary	0.2111	0.2313	0.2800	0.2776	0.1931	0.2192	0.2569	0.2839
	Country F.E.	YES	YES	YES	YES	YES	YES	YES	YES
	Industry F.E.	YES	YES	YES	YES	YES	YES	YES	YES
	N	1158	1158	1158	1158	1158	1158	1158	1158
	R-sq	0.590	0.571	0.559	0.573	0.587	0.589	0.579	0.576
	Link Test	0.632	0.112	0.062	0.572	0.909	0.992	0.491	0.413

Gdp coefficient has been multiplied by 1000 to facilitate interpretation. The dependent variable is the logged Comovement (Weighted Degree). Comovement is calculated using a filter of TI >0.0016 and Correlation>0.00. The variables OutDeg and Between are calculated at industry level, but appears separated in the table for clarity. The ommitted category to avoid perfect collinearity is Primary. The Link Test, tests the null hypothesis that the model is correctly specified by adding a squared variables in the model; p-values for the included variable are presented in this table

Significance level *p<0.1, ** p<0.05, *** p<0.01

Figure 5.1: Global Co-movement Network (average correlation and trade data from 1996 to 2009).



The size of each node represents the *Weighted Degree* (number of industries that co-move with a given node weighted by value added correlation)

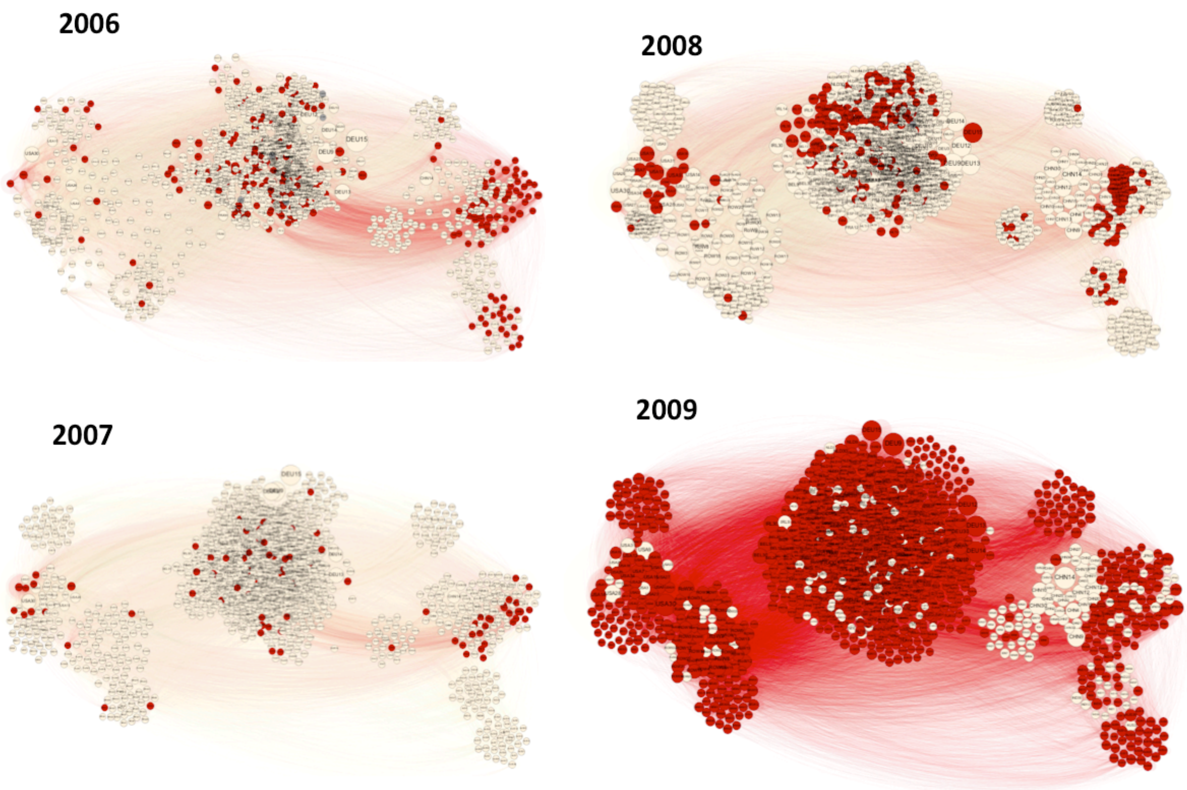
5.5 Empirical Analysis and Findings of the Determinants of Co-movement

The results of estimating Equation (5.2) are presented in Table 5.4. The objective of the estimation is to determine the main characteristics of the new measure of industrial co-movement discussed in the previous section, with specific reference to the most recent global crisis.

The overall explanatory power of the variables included is high (the R-squared ranges from 0.56 to 0.59). The data presented in Table 5.1 in the previous section show that some of the nodes that have a greater co-movement are not always those that are the largest in terms of GDP. The *Gdp* variable tests this preliminary observation; its negative and significant coefficient confirms the hypothesis that industries with a larger GDP have lower co-movement. This result is contrary to the general view in the literature that larger industries are more likely to generate positive or negative shocks. This finding could potentially have important implications in terms of re-thinking global industrial policy. If the largest industries are not the ones driving global business cycles then, with respect to the recent global crisis, the widespread mantra of 'too big to fail' needs to be revisited. The same applies to the result for *Employment,* which is another standard measure of industry size. The coefficients of this variable are negative and statistically insignificant throughout the samples; suggesting that there is no significant relationship between the number of persons working in a given industry and co-movement.

One of the drawbacks of the measure of co-movement presented here is that causality cannot be inferred, given that it is based on value added correlation data. The issue is therefore whether having a greater co-movement increases the exposure of industries in the event of negative shock (i.e., a vulnerability effect). Further, in the event of a positive shock, whether industries with a greater co-movement grow faster and therefore transmit the shock to other industries. A comprehensive answer to these questions lies beyond the scope of this thesis but a preliminary answer can be derived by including the *Growth* variable in Equation (5.2). The coefficients of the variable are positive and highly significant for 2006 and 2007 and negative and significant for 2009. These results need to be explained in some detail.

Figure 5.2: A Network Representation of the Industries in Crisis.



Note: Each node in red represents an industrial shock to a specific industry. The size of the node represents the size of the industries in terms of GDP. The connections between nodes represent the trade relationships, as have been described in this chapter.

As has been acknowledged, the sample period for the analysis is highly volatile in that it is characterised by rapid changes in the growth trends – precisely why it is so interesting for this analysis. From the graphical representation of the global scope of the crisis (Figure 5.2), the years 2006 and 2007 are the ones that more exactly reflect the conditions of a global economic expansion, with the large majority of countries experiencing positive growth rates. However, the year 2009 more exactly reflects the conditions of a global downturn, with the large majority of countries reporting negative growth rates. The year 2008 could therefore be considered to be a 'transition' year between global expansion and global recession; a grey area in which some countries expand and others decline without a clear dominant global trend. This is precisely what appears to be being suggested by the results. The coefficient of the *Growth* variable is positive and significant for 2006 and 2007, the global expansion years, while it is negative and significant in 2009, a clearly identified global recession year. No statistically significant relationship is found in 2008. These results suggest that higher industrial growth is associated with greater co-movement. This finding holds during a period of global expansion. However, if there is a global downturn, then slower industrial growth is associated with greater co-movement. It is important to remember that co-movement is a measure of how many industries ***j*** have a similar business cycle to the ones observed in ***i***. When ***i*** is growing, the co-movement indicates how many industries will grow, and the opposite when ***i*** is declining. In the light of the regression results, industries with a greater co-movement will create a positive contagion in the global network during periods of global growth. During periods of global downturn however, the industries with greater co-movement will be severely affected and might therefore start a negative cascading effect in the global network.

Continuing with the analysis of the industry level explanatory variables in Table 5.4, the variable *HHpart,* the participation of household consumption on each industry's value added, has a significant and positive coefficient. This suggests that greater co-movement is driven by final consumption. The dummy variables *Secondary* and *Tertiary* capture the effect of industry structure on co-movement, as suggested in the literature. The variable *Primary,* is the omitted category to avoid perfect collinearity and is not considered in the estimation of Equation (5.2). The *Secondary* variable is found to be positive and significant, a result that is consistent with the a priori expectations that a manufacturing industry will have higher openness and global trade connections than the omitted category and thus be exposed to higher co-movement. The *Terciary* is not significant, which is consistent with the dataset that is being used, which emphasises trade of products of services.

Two metrics, the number of outward connections (*Out-Deg*) and the average distance from each industry to all the rest (*Between*), are included in the model to investigate whether the network characteristics of an industry affect co-movement. Owing to potential issues of multiple correlation between the network variables, only one at any time is included in the model. The results for *Out-Deg* are shown in columns 1 to 4 of Table 5.4 and those for *Between* are shown in columns 5 to 8. The results show that the coefficient for *Out-Deg* is positive and highly significant, such that the number of outward connections an industry has determines its level of co-movement. This suggests that what matters when analysing the global co-movement network is not the size of the industry, as shown by the *Gdp* and *Employment* variables, but the number of connections. The *Between* network variable is also found to be positive and significant. This leads to the conclusion that the number of connections and the position an industry occupies given by its centrality in the Global Co-movement Network appears to matter.

Finally, the country level variables *Population* and *Openness* are found to be positive and highly significant throughout the samples. Industries that are located in countries with larger population and are more open to trade therefore have a larger co-movement.

The results presented in Table 5.4 enable a much better understanding of the mechanisms that drive industrial co-movement. Some of the results may have important policy implications and are a call to action for further investigation of the use of network analysis to improve understanding of complex phenomena such as the Great Recession.

5.6 Sensitivity Analysis of the Regressions

This section determines whether the econometric model proposed is sensitive to changes in its specification. The first step is to analyse whether the filtering method used to construct the co-movement variable affects the results. The analysis so far has been based on a filter for large trade intensity (TI > 0.0016) with no correlation filter (Corr > 0.00). The next step involves testing three the three filters presented in columns 2 to 4 in Table 5.1.

Table 5.5: Robustness Analysis Results Using Filters

Robustness of Industrial Co-movement to Selected Filters (year 2006)

LHS: Co-movement (log)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Filter: TI > 0.0016 & Corr >0.0	Filter: TI > 0.0016 & Corr >0.3	Filter: TI > 0.00 & Corr >0.0	Filter: TI > 0.00 & Corr >0.3	Filter: TI > 0.0016 & Corr >0.0	Filter: TI > 0.0016 & Corr >0.3	Filter: TI > 0.00 & Corr >0.0	Filter: TI > 0.00 & Corr >0.3
Industry	GDP	-0.0011 *	-0.0006	-0.0005	-0.0004	-0.0016 ***	-0.0011 ***	-0.0007 **	-0.0007 *
	Growth	0.6033 ***	0.7504 ***	1.0044 ***	0.9299 ***	0.7268 ***	0.8046 ***	1.1262 ***	1.0106 ***
	Employment	-0.0031	-0.0047	-0.0041	-0.0038	-0.0019	-0.0033	-0.0044	-0.0037
	HHpart	4.3948 ***	6.9950 ***	8.5844 ***	9.2988 ***	3.6076 **	5.6144 ***	9.6595 ***	9.7340 ***
Country	Open	0.0080 ***	0.0042 **	0.0001	-0.0012	0.0078 ***	0.0041 **	-0.0002	-0.0014
	Population	0.0039 ***	0.0033 ***	0.0039 ***	0.0040 ***	0.0034 ***	0.0028 ***	0.0040 ***	0.0040 ***
Network	OutDeg (Connectivity)					0.0030 ***	0.0027 ***	0.0014 ***	0.0015 ***
	Between (Centrality)	2.4467 ***	1.7613 ***	2.5721 ***	2.1317 ***				
	Secondary	0.7233 ***	1.0237 ***	0.6203 ***	0.7878 ***	0.7007 ***	0.9951 ***	0.6243 ***	0.7866 ***
	Tertiary	0.2111	0.4850 **	0.2045	0.3827 **	0.1931	0.4570 **	0.2062	0.3804 **
	Country F.E.	YES	YES	YES	YES	YES	YES	YES	YES
	Industry F.E.	YES	YES	YES	YES	YES	YES	YES	YES
	N	1158	1139	1162	1159	1158	1139	1162	1159
	R-sq	0.590	0.541	0.718	0.686	0.587	0.548	0.692	0.672

Gdp coefficient has been multiplied by 1000 to facilitate interpretation. The dependent variable is the logged Co-movement (Weighted Degree). Co-movement is calculated using different filters as specified in each column. For clarity and comparison purposes, only results for the year 2006 are presented in this table.

Significance level *p<0.1, ** p<0.05, *** p<0.01

The results of running Equation (5.2) with four different filters are presented in Table 5.5. For comparability purposes, only the results for 2006 are shown (those for the other years are presented in *Appendix 5.3*). The overall results are found to be robust to the change in the filtering method. The analysis focuses on those filters that take into account trade intensity (columns 1, 2, 5 and 6) because trade is the main mechanism of co-movement transmission. The significance, sign and magnitude of these coefficients are highly stable. Even in the case of the filters that do not control for trade intensity (columns 3, 4, 7 and 8), the results are robust in terms of the sign and significance of the variables although some changes in the significance of *GDP* and *Open* are noticed. It is also evident that not controlling for trade intensity inflates the coefficients of most of the variables.

The robustness of the results to the inclusion of country and industry fixed effects is then tested (see Table 5.6). As expected, the explanatory power of the model is considerably reduced when the country and industry effects are removed, with the R-squareds dropping from values near 0.59 to 0.33, or lower. Nevertheless, most variables (GDP, Growth, Employment, Out-Deg and Between) are consistent in terms of significance, sign and magnitude even without controlling for these effects. This finding is important since these variables are the cornerstone of this study. The two variables that completely change when fixed effects are not controlled for are HHpart and Open. The former interacts with the industry effects and the latter with the country fixed effects. There is no theoretical or intuitive reason why these variables should have negative coefficients as shown in Table 5.6. The most likely explanation for these results is that the model needs the fixed effects control in order to provide an adequate estimation of household demand and country openness.

Table 5.6: Robustness Analysis Results Removing Fixed Effects.

Main Characteristics of Industrial Co-movement Without Controlling for Industry and Country Characteristics

LHS: Co-movement (log)		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		2006	2007	2008	2009	2006	2007	2008	2009
Industry	GDP	-0.0007 *	-0.0006	-0.0006	-0.0007 *	-0.0016 ***	-0.0015 ***	-0.0015 ***	-0.0015 ***
	Growth	1.3214 ***	1.0489 ***	-0.2238	-0.8678 ***	1.4365 ***	1.1367 ***	-0.0730	-0.9251 ***
	Employment	0.0036	0.0049	0.0046	0.0039	0.0044	0.0064	0.0058	0.0048
	HHpart	-0.7973	-0.4309	-0.3637	-0.1882	-0.2443	-0.2541	-0.2795	0.2820
Country	Open	-0.0014 **	-0.0020 ***	-0.0017 ***	-0.0019 ***	-0.0017 ***	-0.0022 ***	-0.0020 ***	-0.0024 ***
	Population	-0.0006 ***	-0.0006 ***	-0.0004 ***	-0.0003 ***	-0.0006 ***	-0.0006 ***	-0.0005 ***	-0.0004 ***
Network	OutDeg (Connectivity)					0.0039 ***	0.0037 ***	0.0033 ***	0.0035 ***
	Between (Centrality)	3.2984 ***	2.8022 ***	2.0295 ***	2.7776 ***				
	Secondary	0.7807 ***	0.7942 ***	0.7691 ***	0.7640 ***	0.6618 ***	0.6629 ***	0.6586 ***	0.6614 ***
	Tertiary	0.2815 ***	0.2629 ***	0.2760 ***	0.3375 ***	0.2192 ***	0.2194 ***	0.2459 ***	0.2845 ***
	Country F.E.	NO	NO	NO	NO	NO	NO	NO	NO
	Industry F.E.	NO	NO	NO	NO	NO	NO	NO	NO
	N	1158	1158	1158	1158	1158	1158	1158	1158
	R-sq	0.330	0.285	0.243	0.313	0.330	0.318	0.280	0.307

Gdp coefficient has been multiplied by 1000 to facilitate interpretation. The dependent variable is the logged Co-movement (Weighted Degree). Co-movement is calculated using a filter of TI >0.0016 and Correlation>0.00. The variables Connectivity and Centrality are calculated at industry level, but appears separated in the table for clarity.

Significance level *p<0.1, ** p<0.05, *** p<0.01

To test for the presence of endogeneity, a common method involves estimating a model containing a set of valid instrumental variables, to fit a model assuming endogeneity and then test that assumption (Baun, 2006; p.211-215). The usual problem is finding an instrument that is positively correlated with the endogenous variables but not correlated with the error term. The instrumental variables proposed are well known in the literature to be correlated with industrial growth: investment and government spending as a percentage of GDP at country level. For a comprehensive exercise on the determinants of growth refer to Sala-I-Martin*, et al.* (2004). The presence of endogeneity is tested using a two-stage least-squares model to estimate Equation 5.2 which includes the fixed effects controls for industry and country.

The results for the first stage regression show that the instruments used are not underindentified, since we reject the null of underindentification at the 5%. Further tests, suggest that the instrumental variables are correlated with the suspected endogenous variable *Growth* and exogenous to the error term according to the test of orthogonality test.

Summary Results for First-Stage Regression (Based on Eq 5.2)

	Significance		Underindentification		Weak Indentification
Variable	F	P-val	Chi-sq	P-val	F
Growth	3.13	0.0442	6.32	0.0425	3.13

The test for endogeneity fails to be rejected; this means that growth should be treated as an exogenous variable in this model. The conclusion from the procedure described above, is that the results of the OLS presented previously, the results from estimating Equation (5.2) are robust and no endogeneity is found to be present.

Testing the validity of the instruments (Based on Eq 5.2)
Intrumented: Government

Hansen J Statistic	Chi-sq	1.2260
	P-val	0.2682
Endogeneity Test	Chi-sq	1.2260
"C statistic"	P-val	0.2682

Testing the validity of the instruments (Based on Eq 5.2)
Intrumented: Investment

Hansen J Statistic	Chi-sq	1.2260
	P-val	0.2682
Endogeneity Test	Chi-sq	1.2260
"C statistic"	P-val	0.2682

5.7 Summary & Conclusions

The analysis of business cycle co-movement and the global linkages of either countries or industries is gaining momentum. This Chapter integrates the business cycle co-movement literature with tools from network analysis to provide a different way of analysing and understanding complex and highly inter-connected global industries. It therefore tackles a research gap that has not been previously addressed to identify the main characteristics of industrial co-movement.

The principal results are as follows. First, contrary to general belief, it is not the largest industries, whether in terms of GDP or number of employees, that determine co-movement. Second, industries that exhibit greater co-movement are found to be those that grow the most during a period of global economic expansion, as in the years 2006 and 2007. These are the same ones that decline the most during periods of global economic contraction, as in 2009. This gives rise to the conclusion that industries with greater co-movement have the potential to expand global growth but may also create a potential negative cascade effect when they are hit by a crisis. Third, industries with greater co-movement are characterised by having a larger part of their value added determined by final household consumption. Finally, the number of connections that an industry has in the global trade network, as well as how central it is to the network, positively determines its co-movement.

The results presented here suggest that the type of policy that focuses only on the Too-Big-Too-Fail industries, may not be appropriate in that it doesn't necessarily delivers the desired results. If those industries that exhibit greater co-movement are not the largest in terms of GDP or employment, then efforts to avoid a 'systemic risk' by bailing out and targeting major industries may actually be ineffective. Moreover, the results show that those industries with greater co-movement are not usually the ones that represent an important part of a country's GDP. Policy makers looking to control systemic risk only in terms of size may therefore completely ignore those industries that are actually the source of the systemic risk.

The results in this Chapter also show that industrial connectedness and centrality may be major determinants of industrial co-movement. These are the concepts of 'too-connected-to-fail' and 'too-central-to-fail'. These may prove to be important tools to identify the most critical industries where efforts to create growth expansion. during periods of global prosperity, and reduced the risk of negative cascade effects, during periods of global downturn, need to be focused. Previous studies state the role of industrial connectedness and centrality in the financial sector but this chapter presents results for multiple inter-connected industries, focusing on the role that each industry plays in the Global Co-movement Network.

The results presented here also shed some light on the principal mechanisms underlying greater industrial co-movement at the global level. This should enable the design of more effective policies to promote growth expansion and mitigate crisis contagion. According to Bems*, et al.* (2012), international contagion during the Great Recession was primarily the result of demand failures that can be ascribed to trade links. In a similar way, the results of this Chapter suggest that final consumption (household demand) is an important determinant of industrial co-movement. If this is the case, then policies aimed at increasing final demand may therefore be conductive to the expansion of industrial growth, if the target is specific high-co-movement industries.

One caveat regarding the use of value added correlation data to construct the Global Co-movement Network is that causality cannot be inferred. This study would have benefited greatly from the creation of a directed network in which the origin of co-movement could be clearly identified. A viable method is found in Garas*, et al.* (2010), which uses the trade weight to impose directions to the links, and Caraiani (2013), which uses a Granger causality correlation. Some caveats still apply in both cases however, due to the need to impose thresholds to establish the direction of any causality.

An alternative way in which the original dataset could be transformed is to examine the evolution of co-movement over time. This chapter follows the traditional approach of calculating the average Spearman correlation for value added over a long time to obtain a robust estimation. In theory however, it is possible to disaggregate co-movement on a year-by-year basis, as proposed by Yetman (2011).

Chapter 6

Summary & Conclusions

This study has been undertaken in the aftermath of the Great Recession, the largest crisis since the 1930s. The objective of this study is specifically focused on industrial growth and economic downturn. Incorporating data covering the Great Recession represents a good fit and an ideal opportunity to investigate this relationship.

This thesis sets out to analyse the effects of diverse forms of geographical location and network structures on industrial growth and business cycle co-movement.

6.1 Principal Findings of the Thesis

The principal findings of the thesis are chapter specific and are summarised successively below. A synthesis that analyses the overall implications of the findings is also presented in this section.

The Relationship Between Economic Shocks & Clusters

Can industrial clusters cope better than non-clustered industries with regional and national shocks and what do we really know about clusters and economic shocks? There is a large amount of research that analyses the positive and negative effects of clusters on a number of economic variables, but the specific interaction of clusters and economic crises has been scarcely tested. Given that cluster policy is being widely adopted as a tool to minimise the effects of economic crises and improve regional economic and employment growth, this lack of attention is perhaps surprising. To tackle this gap in the literature, an econometric model is constructed using a regional positive/negative shock as a dependent variable to test the interaction with clusters at the regional level for each of the 40 sectors, and a set of control variables both at the regional and national level, including a variable that represents a national sector-specific shock.

The findings of the empirical analysis suggest there is not a one-size-fits-all answer. The positive or negative effects of clustering are highly heterogeneous and depend upon both the type of industry, as well as the regional characteristics. For the large majority of industries, the results suggest that clusters are relatively neutral; they do not promote higher growth in the presence of a positive national shock and neither do they generate a lower probability of being hit adversely by an economic downturn.

The findings in this study of the effects of economic shocks on clusters provide evidence in support of the view that the effect of clusters may have been overstated, both in the academic literature and policy strategy. These findings are in accord with the conclusions from some previous studies.

Given the great popularity of clusters among practitioners and policy-makers, these results may therefore come as a surprise. If the geographical agglomeration of industries is, on average, not creating a specific advantage during periods of growth and downturn, clustering must have other effects that explain the large number of agglomerations that are found in any typical region. As shown in the literature, location alone may not capture the full scale of relationships that constitute a cluster and, specifically, the flow of knowledge within the cluster. For example, it may be the case that industrial agglomerations benefit from knowledge spillovers which are not captured by the model used in Chapter Three. Additionally, some clustering may also be explained by the existence of specific cluster policies; industries may choose to locate in a particular region if they benefit directly from an industrial/regional policy (e.g., tax rebates, special infrastructure, etc.). These examples show why clustering may occur even if the findings in the study presented in Chapter Three do not show an increased effect on growth.

The Effect of Network Characteristics On Industrial Growth

Can the network characteristics of an industry influence its growth rate? As the complexity of international trade connections increased, the question of industrial growth ceased to be solely confined to the geographic location. This leads to the question of what determines the growth of an industry that is part of the international trade network. Can the complex characteristics of the network affect industrial growth? These questions have regained a sense of urgency in the light of the recent period of instability in the world economy. In this Chapter, the focus is on the location of a given industry in the global network; this is a broader concept than the geographic location of industries used in the empirical chapter. It adopts a quantitative analysis to determine the effects of industrial network characteristics on periods of growth and downturn at the industry level.

The results from this second empirical study suggest that some network characteristics affect industrial growth. The most important finding is that both density and centrality appear to affect industrial growth, albeit by a small magnitude. This study constitutes the first attempt to analyse the complex international linkages that exist in global trade using network theory and sheds light on the characteristics of the global industrial network. A number of research questions related to the characteristics of global linkages and their effects on growth remained unanswered however, owing to the restrictions of the sample used. For example, it is not possible to establish whether the characteristics of a given industry increase co-movement and, specifically, whether some industries are more likely to stimulate economic growth in others within their network and vice versa and to transmit a crisis by creating a negative effect in their network.

Industrial Networks & Business Cycle Co-Movement

To further understand the dynamic of industrial growth in a global context, the concept of business cycle co-movement is then analysed using tools from network theory. This is a combination that has been scarcely analysed at country level and remains unexplored at industry level. The current research uses industry level data from a global input-output database, to try to capture, as better as possible, the intricate linkages and interconnections that exist both inside a country and in the global network. The most important finding is that industries that exhibit greater co-movement are not the largest in terms of GDP or employment. Instead, they are those that have a larger number of trade connections and, in particular, those that are more centrally located in the network. The characteristics of the network itself therefore appear to be important determinants of co-movement. In addition, the findings also suggest that industries that have greater co-movement are also those that have a higher rate of growth during periods of global economic expansion as well as exhibiting more rapid declines in the face of global economic contraction. Taking these findings together, industries with a greater centrality are both more important disseminators of economic growth and also important transmitters of crisis.

This conclusion is important in the context of both future research and policy implications. If the centrality of an industry is revealed to be an important transmitter of both global economic growth and downturns, then investigating these phenomena more deeply should be high on the research agenda. The findings in this Chapter suggest that focusing solely on the big industries may be misleading when analysing the global industrial network.

Synthesis of the Empirical Findings of the Thesis

The three empirical chapters in this thesis have a common thread of analysis. The findings suggest that both levels of analysis –regional agglomerations, tied to geography and the global networks, more interested in the interaction between industries– are informative and need to be considered, both separately and jointly, in order to provide a fuller understanding of the complex economic forces that interact at different levels of aggregation.

One of the findings in this work shows that industries located in a specific region can suffer large positive and negative impacts that originate at the national level (Chapter Three). Where do these shocks come from? We know, based on the rich literature, that one of the main mechanisms of shock transmission between industries is trade. The larger the degree of industry openness is, and the larger its dependence on other industries' inputs, the more exposed that industry is to an external shock. The findings in this thesis suggest that the effect of trade on industrial growth is even deeper than previously thought. Industries that have a larger co-movement may be responsible for sending both positive and negative shocks throughout the global network, regardless of their size in terms of GDP and employment. Thus, even if the focus of the analysis is the region, one must understand the role each local industry plays in both the national and international context. Chapters Four and Five represent an attempt to analyse these other dimensions. Although in this thesis there is no specific chapter that includes both the network dimension and the regional dimension in the same analysis, the findings of each chapter point towards the strong interaction that exists.

'Think global, act local' could summarise another interesting finding from the thesis. One of the recurrent critiques to industrial clusters is that the characteristics of location no longer determine the capacity an industry has to growth and compete. The findings in Chapter Three seem to reinforce that statement; in the large majority of cases the presence of clusters turned out to be unrelated with industrial growth, while the findings in Chapters Four and Five showed the importance of global connectedness and centrality for industrial growth. But this is not the whole picture; the findings also suggest that, industry performance is not only dependant on national and external shocks, but also on local characteristics, e.g. R&D, Wealth and Employment conditions in the region. Industrial growth is affected by the regional, national and internal context. As it turns out, 'global' and 'local', are both important determinant of industrial growth, this thesis has made an effort of bringing this two concepts together.

The findings are also relevant from a policy point of view and some of the implications are explained in the next section.

6.2 Policy Implications

The research presented in this thesis begins with a more traditional look at the determinants of industrial growth in regions and clusters and then moves on to apply a more modern approach in which industrial growth is analysed using networks. In spite of the importance of networks to economic activity, until recently they have not been a central concern for economists (Beinhocker (2007; p.141). The motivation of this study has been specifically to use tools from network theory to offer a fresh view of a traditional economic problem – industrial growth. Specific policy implications are outlined in each of the empirical chapters; this section discusses some general implications of the most relevant findings.

By analysing the effects of economic shocks on regional industrial clusters, this study finds that there is no evidence to support the general claims that clusters either lessen, or augment, the effects of economic shocks. In the vast majority of cases, the effects are found to be neutral. From a policy point of view, this means that policy-makers should beware of considering clusters as a panacea. When dealing with industrial shocks at the national level, there is very little difference a cluster appears to make. Of course, this does not mean that clusters are ill-conceived, but rather that there are numerous reasons why policy-makers might wish to follow a specific industrial agglomeration policy. Protecting against negative shocks is not generally one of these reasons. In the event of an economic shock, other policy measures may also be needed to protect clusters against a downturn since the effects of regional industrial clustering is probably not enough. In fact, such groupings may not help, or may even have a negative effect, depending upon the industry. An important word of caution for policy-makers arises from this finding. There is an increasing interest in trying to replicate iconic clusters, like Silicon Valley, in many parts of the World. These initiatives have been dubbed 'wannabe clusters' and most of these imitators will be unsuccessful (Ffowcs-Williams (2012; p.26)). The problem with most of these initiates is that they account only for the geographic agglomeration characteristics of clusters and forget their evolutionary and complex nature which is the one that defines, for example, the knowledge flow. The findings in these research reinforce the idea that clusters, just measured and identified by it agglomeration (location quotient), will not necessarily increase industrial growth. Policy-makers should avoid the temptation of 'building' industrial agglomerations in politically predetermined locations. The process of industrial growth is much more complex, and evolutionary, that some care to admit and may not be controlled by a system of centralised planning.

The findings also suggest that the effects of economic shocks – both positive and negative – are highly heterogeneous, depending upon industrial, regional and national characteristics. This means that policy-makers should avoid the 'one-size-fits-all' policy approach. Instead, efforts need to be made to understand the specific nature and effects of shocks on each type of cluster and prepare specific policy actions on a case-by-case basis. In such a heterogeneous context, centralised and generic policies may therefore cause more harm than good.

The overall findings of this thesis suggest that the complexity framework may have important applications for policy-makers. Specifically, the use of network theory in the context of global trade has the potential to highlight patterns that have not previously been accounted for. A significant majority of policy decisions are the outcome of analysing only a small part of the economic system. This however, may prevent decision-makers from having a complete perspective of the problem at hand. '*In analyzing a complex system you have to consider the interconnectedness of the parts together with the parts themselves, which implies that in a complex system, the whole* *is not necessarily equal to the sum of the parts'* Colander*, et al.* (2014; p.13). When looking specifically at trade networks, focusing only on bilateral trade using a reductionist approach can only explain a small amount of the shocks and intricate relationships. This is because these trade links are not only direct but also indirect; only a complexity framework therefore can capture these relationships (Fagiolo (2010)).

An increasing number of studies have generated interesting policy advice derived from the use of network theory to analyse trade networks. For example, to '*create an environment where a greater diversity of productive activities can thrive and, in particular, activities that are relatively more complex*' (Hausmann*, et al.* (2011a)). Further, it is suggested that policy-makers '*can benefit from understanding the actual structure of the interdependent global trade network to model what would happen to the system if different parts of the network collapsed owing to economic crises or speculative financial attacks*' (Kali*, et al.* (2010)). It is also suggested that policy-makers should note that '*not only the degree of openness that matters for the economic performance of countries, but also (and above all) their positioning within the network of international trade flows*' (Reyes*, et al.* (2010)).

Policy-makers should focus more on the network structure of trade and not just limit their attention to traditional measures. For example, the findings show that neither the size, nor the number of trade connections, are major determinants of industrial growth and co-movement. This means that focusing on traditional large industries could be misleading and therefore ineffective, or even counter-productive. Policy-makers relying only upon partial models and datasets may therefore miss these important issues. Previous studies also highlight similar policy implications and what is called the 'too-central-to-fail' or 'too-connected-to-fail' effects.

Another clear policy implication that arises from the findings is the need to understand the inter-connectedness of the global economy, in the case of this study specifically global trade. Even the smaller and more isolated nodes in the trade network suffer the effects of shocks in a distant part of the network. Policy-makers who restrict their attention to their national context alone or who believe that the implications of a given policy are confined to a specific geographic location should therefor reconsider their policy approach. In a similar sense, the complexity of interactions described in this study is an indication that more co-ordinated policies at a global level need to be considered.

There is an increasing interest in the academic literature to understand how the existence of complex adaptative systems, changes the way in which policy is done (Geyer*, et al.*, 2010 ; Colander*, et al.*, 2014). For example, policy makers need to be more flexible in their approach, and accept that complex systems cannot be controlled using a top-down policy approach, in which cause and effect follows an ordered, pre-known path. Some of the techniques presented in this thesis, specifically in Chapters Four and Five, may allow policy-makers to understand the complex dynamic of trade and industrial growth and act accordingly to start creating a new set of policies that tackle this issue under a different framework. Although policy making under complex adaptative systems is still in its infancy, the topics covered in this thesis are an important contribution to further and deepen that discussion.

6.3 Shortcomings and Limitations of the Research

The research presented in the former chapters starts by analysing the effects of clusters on industrial growth. To operationalize the research, Porter´s cluster concept is used, a choice that not only defines the theoretical framework used in the research but also affects the way clusters are identified. The most common method to identify clusters, the Location Quotient (LQ) is used to determine its existence at regional level, this method oversimplifies the cluster concept and may be problematic, since it only accounts for the geographic nature of clusters, its agglomeration characteristics, but it cannot account for the institutional characteristics of a cluster and most specifically the strength from the informal knowledge network, which according to the literature may be one of the key advantages of belonging to a cluster. To partially overcome this limitation, the research presented in Chapter Three uses an additional definition of clusters, that identifies clusters based on three variables: location, specialisation and focus. Nevertheless, this definition is still tied to geography and cannot account for all the institutional characteristics of clusters. Accordingly, the findings and their interpretation need to consider this caveat and avoid generalisations. Clusters, many have on average a small effect on growth, as the findings in this research show, nevertheless nothing can be said about the success of cluster initiatives that may be defined using a broader definition that the one used here.

The analysis of clusters presented in Chapter Three has two additional limitations, the dataset and the choice of countries. The dataset, obtained from the European Cluster Observatory, puts together different categories of industries to a create new groupings that are more proximate to the cluster definition in Porter (2003). As mentioned in the respective chapter, this re-categorization is highly useful for this research but create a comparability issue. The findings can only be circumscribed to those specific categories, and any comparison with other datasets needs to consider this caveat. Regarding the choice of countries used in the analysis, it would have been desirable to use a large cross-section, however, at the time of collection, the data for all the European countries was not up to date and some countries had a significant number of missing values. This is why only France was chosen for the analysis and Germany used as a comparison. Other specific shortcomings regarding the dataset and the method used are presented in the summary and conclusions section from Chapter Three.

To avoid some of the shortcomings described above, Chapters Four and Five, try to circumvent the geographic constraints of the cluster concept by introducing the concept of industrial network. However, the analysis of industries under a network framework has its own shortcomings. The findings from that analysis suggest that some of the network characteristics of industries may influence industrial growth and industrial co-movement. For example, the network density and the centrality of an industry seem to affect growth. These are interesting results that fulfil the research objectives, but lead to other noteworthy questions. For example, does this mean that industries need a more dense national industrial network in order to grow faster? The average findings suggest that the answer to that question is affirmative. However, an industry-by-industry and country-by-country analysis shows that the results are highly heterogeneous, implying that more research regarding the specific effect of density on growth, for example, at different stages of the industry life-cycle or considering different levels of development, is needed.

By exploring the concept of 'co-movement' in the global trade network, this research shows that the use of network theory may shed some light on the reasons for the rapid spread of the global crisis from one industry to another -seemingly unrelated- one. But the specific role each industry plays in creating positive and negative contagion is difficult to assess. For example, is an industry that exhibits a high co-movement more likely to be hit by a crisis and expand its contagion? The dataset used in this research as well as the method used, could not answer that question since the causality of the co-movement (from industry A to B, or from B to A) is not accounted for in the undirected network that is put together for the study.

6.4 Avenues for Future Research

The combination of network theory and econometric analysis used in this thesis has proven to be very useful. Network theory provides an appropriate framework to analyse the complexity of industrial growth and global trade using specific metrics. Further, the use of an econometric model makes it possible to evaluate the effect of each metric on the dependent variables quantitatively. Using this method, this thesis analyses the effects of some network characteristics on industrial growth and industrial co-movement. The results are interesting from both a theoretical and political point of view and open a number of relevant pathways that can be analysed in future research.

This study determines that centrality exerts an important effect on industrial growth and co-movement. Nothing however, can be stated regarding the role of industries in the so-called potential cascade effect (Acemoglu*, et al.* (2010) ; Hurd*, et al.* (2011)) or avalanche effect (Delli Gatti*, et al.* (2009)). This type of research has the potential to be highly informative since it could determine the patterns of contagion, identify those nodes that are more prone to contagion and potentially provide new insights as to the design of better policies that reduce the systemic risk of cascading and avalanches in the global industrial network.

Another avenue of future research is the analysis of resilience using some of the techniques presented in this thesis. For example, Hill*, et al.* (2010) undertake an interesting analysis of industrial resilience to shocks but the focus is set at the regional level and the study does not account for all the complex interactions and linkages accounted for in this thesis. A combination of their method of analysing resilience together with network analysis, as used in this study, is something that could potentially offer a new perspective on how industries react to shocks and how those shocks are transmitted through the network. For example, some industries may themselves be very resilient but, because they are more central in the network, they may pass the effects of a shock to other industries. There may also be other industries that have very low resilience but, depending upon their position in the network, may not transmit shocks to others. In general, the analysis of industry resilience within a network is one of the most promising avenues for future research as the recent popularity of this issue demonstrates (Christopherson*, et al.*, 2010 ; Hervas-Oliver*, et al.*, 2011 ; Martin, 2011 ; Xu*, et al.*, 2011).

This thesis also analyses the regional context of an industry is located, by looking specifically at the concept of industrial clusters. The findings suggest that clusters effects are neutral in the vast majority of industries, however this result may be linked to the definition of cluster that is chosen in this thesis. Nothing is said in this research about the institutional organization of the clusters. What is the effect on growth of an explicit cluster initiative? Does a local government sponsored initiative perform better than a private one? This type of research more, focused on institutional design and the way industries organise themselves to compete, may shed some light on why cluster policy is so popular and omnipresent in regional policy.

References

Acemoglu, D.; A. Ozdaglar and A. Tahbaz-Salehi. 2010. "Cascades in Networks and Aggregate Volatility," National Bureau of Economic Research,

Acemoglu, Daron; Vasco M. Carvalho; Asuman Ozdaglar and Alireza Tahbaz-Salehi. 2012. "The Network Origins of Aggregate Fluctuations." *Econometrica*, 80(5), 1977-2016.

Aguilar, Francisco X. 2008. "Effect of Centrifugal Forces on Cluster Patterns in the Softwood Lumber Industry of the United States." *Forest Science*, 54(2), 242-249.

Akoorie, Michèle E.M. 2011. "A Challenge to Marshallian Orthodoxy on Industrial Clustering." *Journal of Management History*, 17(4), 451-470.

Albert, Réka and Albert-László Barabási. 2002. "Statistical Mechanics of Complex Networks." *Reviews of Modern Physics*, 74(1), 47-97.

Antonakakis, Nikolaos. 2012. "The Great Synchronization of International Trade Collapse." *Economics Letters*, 117(3), 608-614.

Araújo, Sónia and Joaquim Oliveira Martins. 2011. "The Great Synchronisation : Tracking the Trade Collapse with High-Frequency Data," R. Baldwin, *The Great Trade Collapse : Causes, Consequences and Prospects.* London: Center for Economic Policy Research,

Arcelus, Francisco J. 1984. "An Extension of Shift-Share Analysis." *Growth & Change*, 15(1), 3.

Arrow, Kenneth. 1962. "Economic Welfare and the Allocation of Resources for Invention," Universities-National Bureau, p. 609 - 626.

Audretsch, David B. and Maryann P. Feldman. 1996. "R&D Spillovers and the Geography of Innovation and Production." *The American Economic Review*, 86(3), 630-640.

Barro, Robert J and Xavier Sala-i-Martin. 1992. "Convergence." *Journal of Political Economy*, 223-251.

Barro, Robert J; Xavier Sala-i-Martin; Olivier Jean Blanchard and Robert E Hall. 1991. "Convergence across States and Regions." *Brookings Papers on Economic Activity*, 107-182.

Baskaran, Thushyanthan; Florian Blöchl; Tilman Brück and Fabian J. Theis. 2011. "The Heckscher–Ohlin Model and the Network Structure of International Trade." *International Review of Economics & Finance*, 20(2), 135-145.

Battiston, Stefano; Michelangelo Puliga; Rahul Kaushik; Paolo Tasca and Guido Caldarelli. 2012. "Debtrank: Too Central to Fail? Financial Networks, the Fed and Systemic Risk." *Sci. Rep.*, 2.

Baun, Christopher. 2006. *An Introduction to Modern Econometrics Using Stata*. Stata Press.

Baxter, Marianne and Michael A. Kouparitsas. 2005. "Determinants of Business Cycle Comovement: A Robust Analysis." *Journal of Monetary Economics*, 52(1), 113-157.

Beaudry, Catherine and Andrea Schiffauerova. 2009. "Who's Right, Marshall or Jacobs? The Localization Versus Urbanization Debate." *Research Policy*, 38(2), 318-337.

Beinhocker, Eric D. 2007. *The Origin of Wealth: The Radical Remaking of Economics and What It Means for Business and Society*. Harvard business school Press.

Belussi, Fiorenza and Katia Caldari. 2009. "At the Origin of the Industrial District: Alfred Marshall and the Cambridge School." *Cambridge Journal of Economics*, 33(2), 335-355.

Bems, Rudolfs; Robert C Johnson and Kei-Mu Yi. 2010. "Demand Spillovers and the Collapse of Trade in the Global Recession." *IMF Economic Review*, 58(2), 295-326.

Bems, Rudolfs; Robert C Johnson and Kei-Mu Yi. 2012. "The Great Trade Collapse," National Bureau of Economic Research,

Bergin, Paul R.; Robert C. Feenstra and Gordon H. Hanson. 2009. "Offshoring and Volatility: Evidence from Mexico's Maquiladora Industry." *The American Economic Review*, 99(4), 1664-1671.

Birch, Kean; Danny MacKinnon and Andrew Cumbers. 2008. "Old Industrial Regions in Europe: A Comparative Assessment of Economic Performance." *Regional Studies*, 44(1), 35-53.

Bishop, Paul and Peter Gripaios. 2009. "Spatial Externalities, Relatedness and Sector Employment Growth in Great Britain." *Regional Studies*, 44(4), 443-454.

Bjørnland, Hilde Christiane. 2000. "Detrending Methods and Stylized Facts of Business Cycles in Norway – an International Comparison." *Empirical Economics*, 25(3), 369-392.

Black, Max. 1964. "The Gap between "Is" and "Should"." *The Philosophical Review*, 73(2), 165-181.
Blaug, Mark. 1992. *The Methodology of Economics, or, How Economists Explain*. Cambridge ; New York, NY: Cambridge ; New York, NY : Cambridge University Press.
Blöchl, F.; H.Z. Munich; E.O.N. Fisher and F. Theis. 2010. "Which Sectors of a Modern Economy Are Most Central?".
Blöchl, Florian; Fabian J. Theis; Fernando Vega-Redondo and Eric O'N Fisher. 2011. "Vertex Centralities in Input-Output Networks Reveal the Structure of Modern Economies." *Physical Review E*, 83(4), 046127.
Boileau, Martin. 1996. "Growth and the International Transmission of Business Cycles." *International Economic Review*, 37(4), 737-756.
Bonnet, Nicolas. 2010. "The Functional Resilience of an Innovative Cluster in the Montpellier Urban Area (South of France)." *European Planning Studies*, 18(9), 1345-1363.
Boumans, Marcel. 2010. *Economic Methodology : Understanding Economics as a Science*. Basingstoke : Palgrave Macmillan.
Broadberry, Stephen; Rainer Fremdling and Peter M. Solar. 2008. "European Industry 1700-1870." *Jahrbuch für Wirtschaftsgeschichte / Economic History Yearbook*, 49(2), 141-171.
Brülhart, Marius and Federica Sbergami. 2009. "Agglomeration and Growth: Cross-Country Evidence." *Journal of Urban Economics*, 65(1), 48-63.
Burstein, Ariel; Christopher Kurz and Linda Tesar. 2008. "Trade, Production Sharing, and the International Transmission of Business Cycles." *Journal of Monetary Economics*, 55(4), 775-795.
Calderon, Cesar; Alberto Chong and Ernesto Stein. 2007. "Trade Intensity and Business Cycle Synchronization: Are Developing Countries Any Different?" *Journal of International Economics*, 71(1), 2-21.
Caraiani, Petre. 2013. "Using Complex Networks to Characterize International Business Cycles." *PLoS ONE*, 8(3), e58109.
Carbonara, Nunzia and Ilaria Giannoccaro. 2011. "Interpreting the Role of Proximity on Industrial District Competitiveness Using a Complexity Science-Based View and Systems Dynamics Simulation." *Journal of Geographical Systems*, 13(4), 415-436.
Carbonara, Nunzia; Ilaria Giannoccaro and Bill McKelvey. 2010. "Making Geographical Clusters More Successful: Complexity-Based Policies." *Emergence : Complexity and Organization*, 12(3), 21-45.
Carlton, Dennis W. 1983. "The Location and Employment Choices of New Firms: An Econometric Model with Discrete and Continuous Endogenous Variables." *The Review of Economics and Statistics*, 65(3), 440-449.
Carvalho, V.M. 2008. *Aggregate Fluctuations and the Network Structure of Intersectoral Trade*. ProQuest.
Chan-Lau, Jorge A. 2010. "Regulatory Capital Charges for Too-Connected-to-Fail Institutions: A Practical Proposal." *Financial Markets, Institutions & Instruments*, 19(5), 355-379.
Chenery, Hollis. 1982. "Industrialization and Growth: The Experience of Large Countries." *World Bank staff working papers*, (539).
Chenery, Hollis B. 1960. "Patterns of Industrial Growth." *The American Economic Review*, 50(4), 624-654.
Chenery, Hollis B. and Lance Taylor. 1968. "Development Patterns: Among Countries and over Time." *Review of Economics & Statistics*, 50(4), 391-416.
Christopherson, Susan; Jonathan Michie and Peter Tyler. 2010. "Regional Resilience: Theoretical and Empirical Perspectives." *Cambridge Journal of Regions, Economy and Society*, 3(1), 3-10.
Colander, David and Roland Kupers. 2014. *Complexity and the Art of Public Policy: Solving Society's Problems from the Bottom Up*. Princeton University Press.
Combes, Pierre-Philippe; Thierry Magnac and Jean-Marc Robin. 2004. "The Dynamics of Local Employment in France." *Journal of Urban Economics*, 56(2), 217-243.
Crafts, N. F. R. 1995. "Exogenous or Endogenous Growth? The Industrial Revolution Reconsidered." *The Journal of Economic History*, 55(04), 745-772.
Crawley, Andrew and David Pickernell. 2012. "An Appraisal of the European Cluster Observatory." *European Urban and Regional Studies*, 19(2), 207-211.
DasGupta, B. and L. Kaligounder. 2012. "Global Stability of Financial Networks against Contagion: Measure, Evaluation and Implications." *Working Paper. Version arXiv:1208.3789*.
De Benedictis, Luca; Silvia Nenci; Gianluca Santoni; Lucia Tajoli and Claudio Vicarelli. 2013. "Network Analysis of World Trade Using the Baci-Cepii Dataset."
De Benedictis, Luca and Lucia Tajoli. 2011. "The World Trade Network." *The World Economy*, 34(8), 1417-1454.

De Blasio, Guido and Sabrina Di Addario. 2005. "Do Workers Benefit from Industrial Agglomeration?*." *Journal of Regional Science*, 45(4), 797-827.
De Silva, Dakshina G. 2012. "Firm Concentration and Growth in the Software Publishing Industry." *Working Paper.*
De Silva, Dakshina G. and Robert P. McComb. 2011. "Geographic Concentration and Firm Survival." *SSRN eLibrary.*
Delgado, Mercedes; Michael E. Porter and Scott Stern. 2010. "Clusters and Entrepreneurship." *Journal of Economic Geography*, 10(4), 495-518.
Delli Gatti, Domenico; Mauro Gallegati; BruceC Greenwald; Alberto Russo and JosephE Stiglitz. 2009. "Business Fluctuations and Bankruptcy Avalanches in an Evolving Network Economy." *Journal of Economic Interaction and Coordination*, 4(2), 195-212.
Dette, Tilman; Scott Pauls and Daniel N Rockmore. 2011. "Robustness and Contagion in the International Financial Network." *arXiv preprint arXiv:1104.4249*.
Di Giovanni, Julian and Andrei A Levchenko. 2010. "Putting the Parts Together: Trade, Vertical Linkages, and Business Cycle Comovement." *American Economic Journal: Macroeconomics*, 2(2), 95-124.
Dickinson, H. D. 1969. "Von Thünen's Economics." *The Economic Journal*, 79(316), 894-902.
Dong, X. 2012. "Network Contagion in Financial Crisis." *Available at SSRN 2073219*.
Dueñas, Marco and Giorgio Fagiolo. 2013. "Modeling the International-Trade Network: A Gravity Approach." *Journal of Economic Interaction and Coordination*, 8(1), 155-178.
Duranton, Gilles. 2010. *The Economics of Clusters : Lessons from the French Experience.* Oxford: Oxford : Oxford University Press.
Duranton, Gilles and Diego Puga. 2001. "Nursery Cities: Urban Diversity, Process Innovation, and the Life Cycle of Products." *The American Economic Review*, 91(5), 1454-1477.
Duschl, Matthias and Thomas Brenner. 2011. "Characteristics of Regional Industry-Specific Employment Growth–Empirical Evidence for Germany." *Working Paper - Philipps-Universität Marburg.*
Easley, David and Jon Kleinberg. 2010. *Networks, Crowds, and Markets.* Cambridge Univ Press.
Eichengreen, B.; D. Park and K. Shin. 2011. "When Fast Growing Economies Slow Down: International Evidence and Implications for China," National Bureau of Economic Research,
Ellison, Glenn and Edward L. Glaeser. 1999. "The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration?" *The American Economic Review*, 89(2), 311-316.
Ellison, Glenn par and Edward L. par Glaeser. 1994. "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach\Par." *National Bureau of Economic Research Working Paper Series\par*, No. 4840\par.
Erumban, A.A.; R. Gouma; B. Los; R. Stehrer; U. Temurshoev, et al. 2011. "World Input-Output Database (Wiod): Construction, Challenges and Applications," *Paper presented at the DIME Final Conference.* 8.
Fagiolo, Giorgio. 2010. "The International-Trade Network: Gravity Equations and Topological Properties." *Journal of Economic Interaction and Coordination*, 5(1), 1-25.
Fagiolo, Giorgio; Javier Reyes and Stefano Schiavo. 2007. "The Evolution of the World Trade Web."
Farhauer, Oliver and Alexandra Kröll. 2012. "Diversified Specialisation—Going One Step Beyond Regional Economics' Specialisation-Diversification Concept." *Jahrbuch für Regionalwissenschaft*, 32(1), 63-84.
Farmer, J.D.; M. Gallegati; C. Hommes; A. Kirman; P. Ormerod, et al. 2012. "A Complex Systems Approach to Constructing Better Models for Managing Financial Markets and the Economy." *European Physics Journal.*
Ffowcs-Williams, Ifor. 2012. *Cluster Develpment: The Go-to Handbook.* Cluster Navigators Limited, New Zealand. .
Fidrmuc, Jarko; Taro Ikeda and Kentaro Iwatsubo. 2012. "International Transmission of Business Cycles: Evidence from Dynamic Correlations." *Economics Letters*, 114(3), 252-255.
Flegg, A. T. and C. D. Webber. 2000. "Regional Size, Regional Specialization and the Flq Formula." *Regional Studies*, 34(6), 563-569.
Flegg, Anthony T. and Timo Tohmo. 2012. "A Comment on Tobias Kronenberg's "Construction of Regional Input-Output Tables Using Nonsurvey Methods: The Role of Cross-Hauling"." *International Regional Science Review.*
Flegg, Anthony T. and Timo Tohmo. 2011. "Regional Input–Output Tables and the Flq Formula: A Case Study of Finland." *Regional Studies*, 1-19.
Forbes, Kristin J. 2002. "Are Trade Linkages Important Determinants of Country Vulnerability to

Crises?," *Preventing Currency Crises in Emerging Markets*. University of Chicago Press, 77-132.
Frankel, Jeffrey A. and David Romer. 1999. "Does Trade Cause Growth?" *The American Economic Review*, 89(3), 379-399.
Frankel, Jeffrey A. and Andrew K. Rose. 1998. "The Endogeneity of the Optimum Currency Area Criteria." *The Economic Journal*, 108(449), 1009-1025.
Friedman, Milton. 1953. *Essays in Positive Economics*. Chicago]: Chicago : University of Chicago Press.
Fujita, Masahisa. 2010. "The Evolution of Spatial Economics: From Thünen to the New Economic Geography." *Japanese Economic Review*, 61(1), 1-32.
Fujita, Masahisa and Jacques-François Thisse. 2003. "Does Geographical Agglomeration Foster Economic Growth? And Who Gains and Loses from It?" *Japanese Economic Review*, 54(2), 121-145.
Gai, Prasanna and Sujit Kapadia. 2010. "Contagion in Financial Networks." *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Science*, 466(2120), 2401-2423.
Gao, Ting. 2004. "Regional Industrial Growth: Evidence from Chinese Industries." *Regional Science and Urban Economics*, 34(1), 101-124.
Garas, Antonios; Panos Argyrakis; Céline Rozenblat; Marco Tomassini and Shlomo Havlin. 2010. "Worldwide Spreading of Economic Crisis." *New Journal of Physics*, 12(11), 113043.
Garbellini, Nadia; Enrico Marelli and Ariel Luis Wirkierman. 2014. "Domestic Demand and Global Production in the Eurozone: A Multi-Regional Input-Output Assessment of the Global Crisis." *International Review of Applied Economics*, 1-29.
Gardiner, Ben; Ron Martin and Peter Tyler. 2011. "Does Spatial Agglomeration Increase National Growth? Some Evidence from Europe." *Journal of Economic Geography*, 11(6), 979-1006.
Geyer, Robert and Samir Rihani. 2010. *Complexity and Public Policy: A New Approach to Twenty-First Century Politics, Policy and Society*. Routledge.
Giovanni, Julian di and Andrei A. Levchenko. 2009. "Trade Openness and Volatility." *Review of Economics and Statistics*, 91(3), 558-585.
Giuliani, Diego 2010. "Methods for Detecting Spatial Clustering of Economic Activities Using Micro-Geographic Data." *Università degli Studi di Roma "La Sapienza"*.
Giuliani, Elisa. 2007. "The Selective Nature of Knowledge Networks in Clusters: Evidence from the Wine Industry." *Journal of Economic Geography*, 7(2), 139-168.
Glaeser, Edward. 2011. "Cities, Productivity, and Quality of Life." *Science*, 333(6042), 592-594.
Glaeser, Edward L; Hedi D Kallal; Jose A Scheinkman and Andrei Shleifer. 1991. "Growth in Cities," National Bureau of Economic Research,
Glaeser, Edward L. and Joshua D. Gottlieb. 2009. "The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States." *Journal of Economic Literature*, 47(4), 983-1028.
Glaeser, Edward L. and David C. Mare. 2001. "Cities and Skills." *Journal of Labor Economics*, 19(2), 316-342.
Gordon, Ian R. and Philip McCann. 2000. "Industrial Clusters: Complexes, Agglomeration and/or Social Networks?" *Urban Studies*, 37(3), 513-532.
Granovetter, Mark. 1983. "The Strength of Weak Ties: A Network Theory Revisited." *Sociological theory*, 1(1), 201-233.
Haddad, L.J.; E. Payongayong; J. Rozen and M. Weeks. 1995. *Strengthening Policy Analysis: Econometric Tests Using Microcomputer Software*. International Food Policy Research Inst.
Hambrick, Donald C. 1983. "An Empirical Typology of Mature Industrial-Product Environments." *The Academy of Management Journal*, 26(2), 213-230.
Harris, Richard. 2011. "Models of Regional Growth: Past, Present and Future." *Journal of Economic Surveys*, 25(5), 913-951.
Harris, Richard I. D. and Aying Liu. 1998. "Input-Output Modelling of the Urban and Regional Economy: The Importance of External Trade." *Regional Studies*, 32(9), 851-862.
Harrison, Bennett. 1992. "Industrial Districts: Old Wine in New Bottles?" *Regional Studies*, 26(5), 469-483.
Hausman, Daniel M. 1989. "Economic Methodology in a Nutshell." *The Journal of Economic Perspectives*, 3(2), 115-127.
Hausmann, Ricardo. 2014. "The Specialization Myth," *Project Syndicate*.
Hausmann, Ricardo; Cesar Hidalgo; Sebastian Bustos; Michele Coscia; Sarah Chung, et al. 2011a. "The Atlas of Economic Complexity," HKS Center for International Development and MIT Media Lab,

Hausmann, Ricardo; Cesar Hidalgo; Sebastian Bustos; Michele Coscia; Sarah Chung, et al. 2011b. *The Atlas of Economic Complexity*. HKS Center for International Development and MIT Media Lab.
Hausmann, Ricardo; Lant Pritchett and Dani Rodrik. 2005. "Growth Accelerations." *Journal of Economic Growth*, 10(4), 303-329.
Henderson, Vernon. 1997. "Externalities and Industrial Development." *Journal of Urban Economics*, 42(3), 449-470.
Henderson, Vernon; Ari Kuncoro and Matt Turner. 1995. "Industrial Development in Cities." *Journal of Political Economy*, 103(5), 1067-1090.
Hervas-Oliver, Jose-Luis; Ian Jackson and Philip R. Tomlinson. 2011. "'May the Ovens Never Grow Cold': Regional Resilience and Industrial Policy in the North Staffordshire Ceramics Industrial District – with Lessons from Sassoulo and Castellon." *Policy Studies*, 32(4), 377-395.
Hidalgo, C. A.; B. Klinger; A. L. Barabási and R. Hausmann. 2007a. "The Product Space Conditions the Development of Nations." *Science*, 317(5837), 482-487.
Hidalgo, C.; B. Klinger; A.L. Barabási and R. Hausmann. 2007b. "The Product Space Conditions the Development of Nations." *Science*, 317(5837), 482-487.
Hidalgo, César A. and Ricardo Hausmann. 2009. "The Building Blocks of Economic Complexity." *Proceedings of the National Academy of Sciences*, 106(26), 10570-10575.
Hill, E.; T. Clair; H. Wial; H. Wolman; P. Atkins, et al. 2010. "Economic Shocks and Regional Economic Resilience," 20-21.
Hill, Edward W. and John F. Brennan. 2000. "A Methodology for Identifying the Drivers of Industrial Clusters: The Foundation of Regional Competitive Advantage." *Economic Development Quarterly*, 14(1), 65-96.
Hollanders, H. and A. van Cruysen. 2008. "Rethinking the European Innovation Scoreboard: A New Methodology for 2008-2010." *Inno-Metrics Publication. Brüssel.*
Hoover, Edgar M. 1937. *Location Theory and the Shoe and Leather Industries*. Harvard U.P.
Horvath, Michael. 1998. "Cyclicality and Sectoral Linkages: Aggregate Fluctuations from Independent Sectoral Shocks." *Review of Economic Dynamics*, 1(4), 781-808.
Horvath, Michael. 2000. "Sectoral Shocks and Aggregate Fluctuations." *Journal of Monetary Economics*, 45(1), 69-106.
Hunt, E. K. and Mark Lautzenheiser. 2011. *History of Economic Thought : A Critical Perspective*. Armonk, N.Y.: Armonk, N.Y. : M.E. Sharpe ;.
Hurd, T. and J. Gleeson. 2011. "A Framework for Analyzing Contagion in Banking Networks." *Available at SSRN 1945748*.
Iammarino, Simona and Philip McCann. 2006. "The Structure and Evolution of Industrial Clusters: Transactions, Technology and Knowledge Spillovers." *Research Policy*, 35(7), 1018-1036.
Imbs, Jean. 2004. "Trade, Finance, Specialization, and Synchronization." *Review of Economics and Statistics*, 86(3), 723-734.
IMF. 2013. "2013 Spillover Report." *IMF Policy paper*, (IMF Multilateral Policy Issues Report).
Jackson, Matthew O. 2010. *Social and Economic Networks*. Princeton University Press.
Jacobs, Jane. 1984. "Cities and the Wealth of Nations: Principles of Economic Life," New York: Random House,
Jacobs, Jane. 1961. *The Death and Life of Great American Cities*. Random House LLC.
Jacobs, Jane. 1970a. *The Economy of Cities*. London: London : J. Cape.
Jacobs, Jane. 1970b. *The Economy of Cities*. Vintage.
Jacobs, Jane. 2002. *The Nature of Economies*. Random House LLC.
Johnson, Robert C and Guillermo Noguera. 2012. "Accounting for Intermediates: Production Sharing and Trade in Value Added." *Journal of International Economics*, 86(2), 224-236.
Kali, Raja and Javier Reyes. 2007. "The Architecture of Globalization: A Network Approach to International Economic Integration." *Journal of International Business Studies*, 38(4), 595-620.
Kali, Raja and Javier Reyes. 2010. "Financial Contagion on the International Trade Network." *Economic Inquiry*, 48(4), 1072-1101.
Kali, Raja; Javier Reyes; Joshua McGee and Stuart Shirrell. 2013. "Growth Networks." *Journal of Development Economics*, 101(0), 216-227.
Kerr, W.R. and S.D. Kominers. 2010. "Agglomerative Forces and Cluster Shapes," National Bureau of Economic Research,
Ketels, Christian. 2003. "The Development of the Cluster Concept–Present Experiences and Further

Developments." *Prepared for NRW conference on clusters, Duisburg, Germany,.*
Keynes, John Maynard. 1946. "Newton, the Man." *Lecture presented at The Royal Society of London.*
Kondratieff, N. D. 1925. "The Static and the Dynamic View of Economics." *The Quarterly Journal of Economics*, 39(4), 575-583.
Kose, M Ayhan; Eswar S Prasad and Marco E Terrones. 2003. "How Does Globalization Affect the Synchronization of Business Cycles?".
Kose, M. Ayhan and Kei-Mu Yi. 2006. "Can the Standard International Business Cycle Model Explain the Relation between Trade and Comovement?" *Journal of International Economics*, 68(2), 267-295.
Kronenberg, Tobias. 2009. "Construction of Regional Input-Output Tables Using Nonsurvey Methods." *International Regional Science Review*, 32(1), 40-64.
Krugman, Paul. 1998. "What's New About the New Economic Geography?" *Oxford review of economic policy*, 14(2), 7-17.
Krugman, Paul R. 1991. *Geography and Trade*. Leuven, Belgium : Cambridge, Mass.: Leuven, Belgium : Leuven University Press ; Cambridge, Mass. : MIT Press.
Kukalis, Sal. 2010. "Agglomeration Economies and Firm Performance: The Case of Industry Clusters." *Journal of Management*, 36(2), 453-481.
Kuznets, Simon. 1966. *Modern Economic Growth : Rate, Structure, and Spread*. New Haven [etc.]: Yale University Press.
Kuznets, Simon and John Thomas Murphy. 1966. *Modern Economic Growth: Rate, Structure, and Spread*. Yale University Press New Haven.
Kuznets, Simon Smith. 1971. *Economic Growth of Nations: Total Output and Production Structure*. Belknap Press of Harvard University Press Cambridge, Mass.
Lee, Kyu-Min; Jae-Suk Yang; Gunn Kim; Jaesung Lee; Kwang-Il Goh, et al. 2011. "Impact of the Topology of Global Macroeconomic Network on the Spreading of Economic Crises." *PLoS ONE*, 6(3), e18443.
Lindsay, Valerie J. 2005. "The Development of International Industry Clusters: A Complexity Theory Approach." *Journal of International Entrepreneurship*, 3(1), 71-97.
Long, John B., Jr. and Charles I. Plosser. 1983. "Real Business Cycles." *Journal of Political Economy*, 91(1), 39-69.
Mankiw, N Gregory; David Romer and David N Weil. 1992. "A Contribution to the Empirics of Economic Growth." *The Quarterly Journal of Economics*, 107(2), 407-437.
Marelli, Enrico P.; Roberto Patuelli and Marcello Signorelli. 2011. "Regional Unemployment in the Eu before and after the Global Crisis." *SSRN eLibrary.*
Markusen, Ann. 1996. "Sticky Places in Slippery Space: A Typology of Industrial Districts." *Economic Geography*, 72(3), 293-313.
Marshall, Alfred. 1920. *Industry and Trade : A Study of Industrial Technique and Business Organization, and of Their Influences on the Conditions of Various Classes and Nations*. London: Macmillian.
Marshall, Alfred. 1895. *Principles of Economics*. London ; New York: London ; New York : Macmillan.
Martin, Philippe; Thierry Mayer and Florian Mayneris. 2011. "Public Support to Clusters: A Firm Level Study of French "Local Productive Systems"." *Regional Science and Urban Economics*, 41(2), 108-123.
Martin, Ron. 2011. "Regional Economic Resilience, Hysteresis and Recessionary Shocks." *Journal of Economic Geography.*
Martin, Ron and Peter Sunley. 2007. "Complexity Thinking and Evolutionary Economic Geography." *Journal of Economic Geography*, 7(5), 573-601.
Martin, Ron and Peter Sunley. 2003. "Deconstructing Clusters: Chaotic Concept or Policy Panacea?" *Journal of Economic Geography*, 3(1), 5-35.
Martin, Xavier; Robert M. Salomon and Zheying Wu. 2010. "The Institutional Determinants of Agglomeration: A Study in the Global Semiconductor Industry." *Industrial and Corporate Change*, 19(6), 1769-1800.
McCann, Philip. 2013. *Modern Urban and Regional Economics*. Oxford University Press.
Mendoza, Enrique G. and Vincenzo Quadrini. 2010. "Financial Globalization, Financial Crises and Contagion." *Journal of Monetary Economics*, 57(1), 24-39.
Mody, Ashoka and Fang-Yi Wang. 1997. "Explaining Industrial Growth in Coastal China: Economic Reforms… and What Else?" *The World Bank Economic Review*, 11(2), 293-325.
Morgan, Jonathan Q. 2007. "Industry Clusters and Metropolitan Economic Growth and Equality." *International Journal of Economic Development*, 9(4), 307-307-330,333-339,341-342,344-347,349-351,353-375.

Moulaert, Frank and Camal Gallouj. 1993. "The Locational Geography of Advanced Producer Service Firms: The Limits of Economies of Agglomeration." *The Service Industries Journal*, 13(2), 91-106.
Muro, M. and B. Katz. 2010. "The New 'Cluster Moment': How Regional Innovation Clusters Can Foster the Next Economy." *Chapter in Advances in the Study of Entrepreneurship, Innovation & Economic Growth*, 22 Editor(s): Gary D. Libecap, Sherry Hoskinson ISBN: 978-1-78052-394-1.
Neffke, Frank; Martin Henning; Ron Boschma; Karl-Johan Lundquist and Lars-Olof Olander. 2011. "The Dynamics of Agglomeration Externalities Along the Life Cycle of Industries." *Regional Studies*, 45(1), 49-65.
Nelson, Richard R. and Sidney G. Winter. 1982. *An Evolutionary Theory of Economic Change*. Cambridge, Mass.: Belknap Press of Harvard University Press.
Newman, Mark. 2010. *Networks: An Introduction*. Oxford University Press, Inc.
Newton, Isaac Sir. 1687. *Philosophiae Naturalis Principia Mathematica*. Londini : [London: Londini : J. Societatis Regiae ac Typis J. Streater, London : Reproduced in facsimile by W. Dawson.
Ng, Eric CY. 2010. "Production Fragmentation and Business-Cycle Comovement." *Journal of International Economics*, 82(1), 1-14.
Ormerod, Paul. 2010. "The Current Crisis and the Culpability of Macroeconomic Theory." *Twenty-First Century Society*, 5(1), 5-18.
Østergaard, C. and E.K. Park. 2013. "Cluster Decline and Resilience-the Case of the Wireless Communication Cluster in North Jutland, Denmark." *Denmark (January 4, 2013)*.
Öz, Özlem and Kaya Özkaracalar. 2011. "What Accounts for the Resilience and Vulnerability of Clusters? The Case of Istanbul's Film Industry." *European Planning Studies*, 19(3), 361-378.
Paniccia, I. 2006. "Towards a New Typology of Industrial Districts and Clusters." *Clusters and Regional Development: Critical reflections and Explorations*, 90.
Parr, John B. 2002. "Missing Elements in the Analysis of Agglomeration Economies." *International Regional Science Review*, 25(2), 151-168.
Pinch, Steven; Nick Henry; Mark Jenkins and Stephen Tallman. 2003. "From 'Industrial Districts' to 'Knowledge Clusters': A Model of Knowledge Dissemination and Competitive Advantage in Industrial Agglomerations." *Journal of Economic Geography*, 3(4), 373-388.
Popper, Karl R. 1959. *The Logic of Scientific Discovery*. New York: Basic Books.
Porter, Michael. 2003. "The Economic Performance of Regions." *Regional Studies*, 37(6-7), 545-546.
Porter, Michael E. 1990. *The Competitive Advantage of Nations*. Macmillan.
Porter, Michael E. 2000. "Location, Competition, and Economic Development: Local Clusters in a Global Economy." *Economic Development Quarterly*, 14(1), 15-34.
Rauch, James E. 1999. "Networks Versus Markets in International Trade." *Journal of International Economics*, 48(1), 7-35.
Reyes, Javier; Stefano Schiavo and Giorgio Fagiolo. 2010. "Using Complex Networks Analysis to Assess the Evolution of International Economic Integration: The Cases of East Asia and Latin America." *The Journal of International Trade & Economic Development*, 19(2), 215-239.
Ricardo, David and Ronald Max Hartwell. 1971. *On the Principles of Political Economy, and Taxation*. Penguin Books Middlesex.
Robertson, Dennis Holme Sir. 1960 [1923]. *The Control of Industry*. Welwyn, England] : Cambridge: Welwyn, England : J. Nisbet ; Cambridge : University Press.
Rodríguez-Pose, Andrés. 1999. "Convergence or Divergence? Types of Regional Responses to Socio-Economic Change in Western Europe." *Tijdschrift voor economische en sociale geografie*, 90(4), 365-378.
Rodríguez-Pose, Andrés and Fabrice Comptour. 2011. "Do Clusters Generate Greater Innovation and Growth? An Analysis of European Regions." *The Professional Geographer*.
Romer, Paul M. 1987. "Growth Based on Increasing Returns Due to Specialization." *The American Economic Review*, 77(2), 56-62.
Rosenfeld, Stuart A. 1997. "Bringing Business Clusters into the Mainstream of Economic Development." *European Planning Studies*, 5(1), 3-23.
Round, J. I. 1978. "On Estimating Trade Flows in Interregional Input Output Models." *Regional Science and Urban Economics*, 8(3), 289-302.
Saborowski, Christian; Mona E. Haddad and Jamus Jerome Lim. 2010. "Trade Openness Reduces Growth Volatility When Countries Are Well Diversified." *Research Working papers*, 1(1), 1-38.
Sala-i-Martin, Xavier; Gernot Doppelhofer and Ronald I. Miller. 2004. "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (Bace) Approach." *The American Economic*

Review, 94(4), 813-835.
Samuelson, Paul A. 1983. "Thünen at Two Hundred." *Journal of Economic Literature*, 21(4), 1468-1488.
Sandoval, Junior Leonidas and Franca Italo De Paula. 2012. "Correlation of Financial Markets in Times of Crisis." *Physica A: Statistical Mechanics and its Applications*, 391(1–2), 187-208.
Saxenian, Annalee. 1994. *Regional Advantage : Culture and Competition in Silicon Valley and Route 128*. Cambridge, Mass.: Cambridge, Mass. : Harvard University Press.
Schaffer, William A. 1999. *Regional Impact Models*. Regional Research Institute, West Virginia University.
Schaffer, William A. and Kong Chu. 1969. "Nonsurvey Techniques for Constructing Regional Interindustry Models." *Papers in Regional Science*, 23(1), 83-101.
Sharp, Paul and Jacob Weisdorf. 2012. "French Revolution or Industrial Revolution? A Note on the Contrasting Experiences of England and France up to 1800." *Cliometrica*, 6(1), 79-88.
Skålholt, Asgeir; Taran Thune and Olav Spilling. 2012. "Coping with Economic Crises – the Role of Clusters."
Smith, Adam. 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations*. London: London.
Solow, Robert M. 1956. "A Contribution to the Theory of Economic Growth." *The Quarterly Journal of Economics*, 70(1), 65-94.
Sölvell, Ö. and C. Ketels. 2009. "The European Cluster Observatory Eu Cluster Mapping and Strengthening Clusters in Europe." *Center for Strategy and Competitiveness.*
Spencer, Gregory M.; Tara Vinodrai; Meric S. Gertler and David A. Wolfe. 2009. "Do Clusters Make a Difference? Defining and Assessing Their Economic Performance." *Regional Studies*, 44(6), 697-715.
Stejskal, Jan. 2010. "Comparison of Often Applied Methods for Industrial Cluster Identification," 282-286.
Steven, Klepper. 2010. "The Origin and Growth of Industry Clusters: The Making of Silicon Valley and Detroit." *Journal of Urban Economics*, 67(1), 15-32.
Stilwell, F. J. B. and B. D. Boatwright. 1971. "A Method of Estimating Interregional Trade Flows." *Regional and Urban Economics*, 1(1), 77-87.
Stockman, Alan C. 1989. "Sectoral and National Aggregate Disturbances to Industrial Output in Seven European Countries," National Bureau of Economic Research Cambridge, Mass., USA,
Subramanian, Arvind and Shang-Jin Wei. 2007. "The Wto Promotes Trade, Strongly but Unevenly." *Journal of International Economics*, 72(1), 151-175.
Sunley, Peter. 1992. "Marshallian Industrial Districts: The Case of the Lancashire Cotton Industry in the Inter-War Years." *Transactions of the Institute of British Geographers*, 17(3), 306-320.
Ter Wal, Anne and Ron Boschma. 2009a. "Applying Social Network Analysis in Economic Geography: Framing Some Key Analytic Issues." *The Annals of Regional Science*, 43(3), 739-756.
Ter Wal, Anne L. J. and Ron Boschma. 2009b. "Co-Evolution of Firms, Industries and Networks in Space." *Regional Studies*, 45(7), 919-933.
Treado, Carey Durkin and Frank Giarratani. 2008. "Intermediate Steel-Industry Suppliers in the Pittsburgh Region: A Cluster-Based Analysis of Regional Economic Resilience." *Economic Development Quarterly*, 22(1), 63-75.
Ullman, Edward L. 1968. "Minimum Requirements after a Decade: A Critique and an Appraisal." *Economic Geography*, 44(4), 364-369.
van der Panne, Gerben. 2004. "Agglomeration Externalities: Marshall Versus Jacobs." *Journal of Evolutionary Economics*, 14(5), 593-604.
van der Panne, Gerben and Cees van Beers. 2006. "On the Marshall–Jacobs Controversy: It Takes Two to Tango." *Industrial and Corporate Change*, 15(5), 877-890.
Von Thünen, Johann. 1826. *Isolated State (English Translation from German, 1966).* Oxford: Pergamon Press.
Vyas, Seema and Lilani Kumaranayake. 2006. "Constructing Socio-Economic Status Indices: How to Use Principal Components Analysis." *Health Policy and Planning*, 21(6), 459-468.
Wang, Guo-hong; Rui Xing; Li-yan Tang and S. Kittisarawanno. 2010. "The Risk of Cascading Breakdown in Industrial Cluster Innovation Networks: A Complex Networks Perspective," *Management Science and Engineering (ICMSE), 2010 International Conference on.* 1445-1455.
Watts, Duncan J. 2004. "The "New" Science of Networks." *Annual review of sociology*, 30(ArticleType: research-article / Full publication date: 2004 / Copyright © 2004 Annual Reviews), 243-270.
Watts, Duncan J. 2002. "A Simple Model of Global Cascades on Random Networks." *Proceedings of the*

National Academy of Sciences, 99(9), 5766-5771.
Wennberg, Karl and Göran Lindqvist. 2010. "The Effect of Clusters on the Survival and Performance of New Firms." *Small Business Economics*, 34(3), 221-241.
Wooldridge, Jeffrey M. 2001. *Econometric Analysis of Cross Section and Panel Data*. MIT press.
Xu, G. 2011. "Growth Accelerations Revisited." *Econ Journal Watch*, 8(1), 39-56.
XU, MING; BRAD R. ALLENBY and JOHN C. CRITTENDEN. 2011. "Interconnectedness and Resilience of the U.S. Economy." *Advances in Complex Systems*, 14(05), 649-672.
Yetman, James. 2011. "Exporting Recessions: International Links and the Business Cycle." *Economics Letters*, 110(1), 12-14.
Yusuf, S. and K. Nabeshima. 2008. *Growing Industrial Clusters in Asia: Serendipity and Science*. World Bank Publications.

APPENDIX

Appendix Chapter Three

Appendix 3.1: Example of the categorization of Industries by the European Cluster Observatory

This information is directly taken from the ECO web page (access: Dec 2011)

The European Cluster Observatory defines clusters by combining related industries into groups, or "sectors". Many of these "sectors" include both manufacturing and service industries related to a particular area.

The basis for these groups is the NACE Rev. 2 classification system, for wich the Observatory uses the 4-digit level. A complete description of the NACE Rev. 2 classification is provided here by Eurostat. However, instead of aggregating industries in the hierarchical way that the classification system specifies, the Observatory combines industries from different parts of the classification system.

Aerospace

30.30 Manufacture of air and spacecraft and related machinery

Agricultural Products

01.61 Support activities for crop production
01.62 Support activities for animal production
01.63 Post-harvest crop activities
01.64 Seed processing for propagation
10.41 Manufacture of oils and fats
10.81 Manufacture of sugar
11.01 Distilling, rectifying and blending of spirits
11.02 Manufacture of wine from grape
11.03 Manufacture of cider and other fruit wines
11.04 Manufacture of other non-distilled fermented beverages
81.30 Landscape service activities

Apparel

13.30 Finishing of textiles
13.91 Manufacture of knitted and crocheted fabrics
14.12 Manufacture of workwear
14.13 Manufacture of other outerwear
14.19 Manufacture of other wearing apparel and accessories
14.31 Manufacture of knitted and crocheted hosiery
14.39 Manufacture of other knitted and crocheted apparel

Automotive

22.19 Manufacture of other rubber products
23.11 Manufacture of flat glass
23.12 Shaping and processing of flat glass
29.10 Manufacture of motor vehicles
29.20 Manufacture of bodies (coachwork) for motor vehicles manufacture of trailers and semi-trailers
29.32 Manufacture of other parts and accessories for motor vehicles
30.40 Manufacture of military fighting vehicles

Construction

08.12 Operation of gravel and sand pits mining of clays and kaolin
20.51 Manufacture of explosives
23.32 Manufacture of bricks, tiles and construction products
23.51 Manufacture of cement
25.11 Manufacture of metal structures and parts of structures
28.14 Manufacture of other taps and valves
41.20 Construction of residential and non-residential buildings
42.11 Construction of roads and motorways
42.12 Construction of railways and underground railways
42.13 Construction of bridges and tunnels
42.91 Construction of water projects
43.11 Demolition
43.12 Site preparation
43.31 Plastering
77.32 Renting and leasing of construction and civil engineering machinery and equipment

Distribution

46.16 Agents involved in the sale of textiles, clothing, fur, footwear and leather goods
46.31 Wholesale of fruit and vegetables
46.32 Wholesale of meat and meat products
46.34 Wholesale of beverages
46.35 Wholesale of tobacco products
46.37 Wholesale of coffee, tea, cocoa and spices
46.38 Wholesale of other food, including fish, crustaceans
46.41 Wholesale of textiles
46.42 Wholesale of clothing and footwear
46.45 Wholesale of perfume and cosmetics
46.46 Wholesale of pharmaceutical goods
46.48 Wholesale of watches and jewellery
47.91 Retail sale via mail order houses or via Internet

Appendix 3.2: Descriptive statistics of the control variables used in PCA.

Variable	Obs	Mean	Std. Dev.	Min	Max
pop	7920	139.6869	187.6857	30.8	968.6
lt_unemployt	7920	3.345051	1.417797	1.23	10.15
employment	7920	62.82929	4.493921	37.8	68.4
fem_employ	7920	56.82727	5.545132	29.6	64.5
mal_employ	7920	68.98232	3.797918	47.3	75.2
hight_employ	7920	6.531465	3.118771	0	17.43
know_employ	7920	33.40934	4.059573	22.19	46.92
manuf_employ	7920	36.42909	5.434246	11.72	45.9
lab_product	7920	56.48944	10.47656	43.92	115.76
patent	7920	86.25263	57.26706	2.34	292.93
hight_patent	7920	16.0452	19.95432	.75	79.12
bio_patent	7920	3.531919	3.83344	0	18.07
it_patent	7920	21.27753	24.24162	.94	103.57
priv_rd_sh~e	7920	.9989899	.5992789	0	2.6
rd_employ	7920	.5920707	.337207	.03	1.67
buss_inves~t	7920	13.76455	3.873766	-6.74	37.26
academic	7920	33.98141	7.670553	19.78	54.54
pub_rd_share	7920	.1929293	.2436215	0	1
reg_innov_~x	7920	.4509091	.1068162	.26	.75
reggdppc	7920	23915.15	4651.434	17700	49000
reggdp	7920	74716.09	95470.67	4729	573081
income	7920	15149.92	1657.202	11112.9	21072.4

Appendix 3.3: Principal Components Analysis results

PCA for variables related to Employment

```
Principal components/correlation                  Number of obs    =      7920
                                                  Number of comp.  =         2
                                                  Trace            =         9
    Rotation: orthogonal varimax (Kaiser off)     Rho              =    0.7594
```

Component	Variance	Difference	Proportion	Cumulative
Comp1	4.60962	2.38427	0.5122	0.5122
Comp2	2.22535	.	0.2473	0.7594

Rotated components

Variable	Comp1	Comp2	Unexplained
pop	0.1006	0.6139	.1653
lt_unemployt	-0.4001	0.0392	.2458
employment	0.4482	0.0546	.08762
fem_employ	0.4225	0.1182	.1869
mal_employ	0.4309	-0.0360	.1286
hight_employ	0.3291	-0.1127	.442
know_employ	-0.0012	0.6015	.1942
manuf_employ	0.3552	0.0441	.4269
lab_product	-0.1739	0.4763	.2878

PCA for variables related to innovation

```
Principal components/correlation                  Number of obs    =      7920
                                                  Number of comp.  =         2
                                                  Trace            =        10
    Rotation: orthogonal varimax (Kaiser off)     Rho              =    0.7325
```

Component	Variance	Difference	Proportion	Cumulative
Comp1	6.01225	4.69998	0.6012	0.6012
Comp2	1.31227	.	0.1312	0.7325

Rotated components

Variable	Comp1	Comp2	Unexplained
patent	0.3853	-0.1978	.1768
hight_patent	0.3327	0.1369	.2378
bio_patent	0.2981	0.0985	.4067
it_patent	0.3426	0.0754	.2459
priv_rd_sh~e	0.3519	-0.1596	.3107
rd_employ	0.3684	-0.1123	.2327
buss_inves~t	-0.0800	0.7452	.3271
academic	0.2862	0.2940	.2611
pub_rd_share	0.1708	0.4891	.3786
reg_innov_~x	0.3969	-0.0883	.09814

PCA for variables related to Wealth

```
Principal components/correlation                  Number of obs    =      7920
                                                  Number of comp.  =         2
                                                  Trace            =         3
    Rotation: orthogonal varimax (Kaiser off)     Rho              =    0.9753
```

Component	Variance	Difference	Proportion	Cumulative
Comp1	1.49384	.061739	0.4979	0.4979
Comp2	1.4321	.	0.4774	0.9753

Rotated components

Variable	Comp1	Comp2	Unexplained
reggdppc	0.4574	0.4276	.04503
reggdp	-0.1035	0.8965	.01375
income	0.8832	-0.1163	.01528

Appendix 3.4: Results for France (full table)

France, probit panel estimation of Regional Negative Shock (RSN) - As presented in Chapter 3.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
	Aerospace	Agricultural products	Apparel	Automotive	Biotech	Building fixtures, equipment and services	Chemical products	Construction	Construction materials	Distribution	Education and knowledge creation	Entertainme nt	Financial services	Footwear	Furniture	Heavy Machinery	Instruments	IT	Jewellery and precious metals
Cluster	0.0645	0.0120	0.152	-0.0434	-0.208**	0.142		-0.0105	0.156	-0.234***	0.0340	-0.212	-0.299***	0.107	0.130*	-0.118	0.175*	0.0118	0.166
	(0.0668)	(0.182)	(0.157)	(0.0731)	(0.0840)	(0.153)		(0.0884)	(0.121)	(0.0541)	(0.135)	(0.143)	(0.0810)	(0.123)	(0.0780)	(0.126)	(0.0930)	(0.118)	(0.107)
Size	-0.000259	-0.0316	0.0611	0.0160	-0.0593***	0.0682	0.0644	-0.0203	-0.104**	0.0435	-0.108	0.272	-0.0304	0.276**	0.0640	-0.204**	0.0289	0.0576*	-0.0830**
	(0.0356)	(0.135)	(0.0952)	(0.0503)	(0.0199)	(0.101)	(0.0825)	(0.0885)	(0.0529)	(0.0571)	(0.0867)	(0.210)	(0.0967)	(0.118)	(0.0934)	(0.0866)	(0.0887)	(0.0323)	(0.0382)
Focus	-0.230*	0.258	-0.168	0.00139	2.501***	-0.335**	-0.226*	0.248	-0.0490	0.225**	0.909**	-0.125	1.378	-0.569*	-0.537**	1.033*	-0.175	0.0782	-1.098
	(0.122)	(0.260)	(0.279)	(0.0428)	(0.755)	(0.159)	(0.134)	(0.444)	(0.160)	(0.0971)	(0.372)	(0.158)	(1.240)	(0.325)	(0.237)	(0.572)	(0.151)	(0.721)	(0.903)
RD	-0.00161	-0.0587**	0.00791	0.0116	-0.0241	-0.0238*	-0.00467	0.0123	0.00323	-0.0325*	0.00440	-0.0516***	-0.0135	-0.0143	-0.0263**	-0.0154	-0.0273	-0.00795	0.0235**
	(0.0168)	(0.0258)	(0.0192)	(0.0151)	(0.0165)	(0.0135)	(0.0217)	(0.0175)	(0.0173)	(0.0171)	(0.0175)	(0.0161)	(0.0144)	(0.0157)	(0.0122)	(0.0137)	(0.0218)	(0.0174)	(0.00984)
Wealth	0.0152	0.163***	-0.0145	-0.0140	0.0523**	-0.0381*	-0.0634*	0.0121	0.00444	0.0278	-0.0367	-0.0267	0.00287	-0.107***	0.0787***	0.0341	-0.132**	-0.0476*	0.00551
	(0.0585)	(0.0424)	(0.0367)	(0.0336)	(0.0261)	(0.0224)	(0.0334)	(0.0350)	(0.0354)	(0.0418)	(0.0544)	(0.0348)	(0.0327)	(0.0352)	(0.0292)	(0.0302)	(0.0565)	(0.0286)	(0.0329)
Employment	0.00655	-0.00638	-0.00868	-0.0292	0.0113	0.0552***	-0.00474	-0.0119	-0.00447	0.00791	0.0514*	0.00250	-0.00513	0.0710**	0.0130	-0.0325***	0.0287**	-0.00300	-0.00808
	(0.0123)	(0.0162)	(0.0180)	(0.0190)	(0.00786)	(0.0186)	(0.00978)	(0.0167)	(0.0147)	(0.0138)	(0.0292)	(0.0143)	(0.0197)	(0.0341)	(0.0159)	(0.0126)	(0.0142)	(0.0104)	(0.00979)
XportReg	0.356***	-0.171	0.0684	-0.0936	0.268**			0.438***		0.0654	-0.154	-0.0935	-0.170	-0.189	0.0237	0.604***	0.553***	-0.0619	0.158
	(0.107)	(0.116)	(0.188)	(0.201)	(0.114)			(0.101)		(0.0957)	(0.414)	(0.122)	(0.176)	(0.125)	(0.138)	(0.0603)	(0.132)	(0.0651)	(0.180)
EUAID	-0.00518	-0.113*	-0.00262	0.0283***	-0.0207*	-0.00656	0.0408***	-0.0331*	0.00408	-0.0194	0.00707	-0.0523***	-0.00888	0.0539***	0.0175*	0.0469***	-0.0815***	-0.0303	0.0554***
	(0.0142)	(0.0674)	(0.0340)	(0.0108)	(0.0111)	(0.0145)	(0.0136)	(0.0183)	(0.0316)	(0.0157)	(0.0174)	(0.0153)	(0.0173)	(0.0187)	(0.0106)	(0.0148)	(0.0237)	(0.0316)	(0.0145)
NSN	0.189*	0.849***	0.434***	0.222***	0.400***	0.285**	0.151	0.483***	0.186	0.311**	0.250**	0.651***	0.446***	0.174	0.401***	0.158	0.422***	0.286***	0.207***
	(0.101)	(0.0506)	(0.111)	(0.0801)	(0.0861)	(0.114)	(0.109)	(0.105)	(0.130)	(0.122)	(0.112)	(0.0583)	(0.0647)	(0.122)	(0.0776)	(0.111)	(0.0954)	(0.0670)	(0.0676)
lag1NSN	-0.172*	0.264***	-0.0374	-0.148	-0.107	0.203***	-0.213***	-0.194**	0.0186	0.0386	0.255*		0.148*	0.0640	0.0435	0.153	-0.172	0.0711	0.124
	(0.0917)	(0.0849)	(0.0652)	(0.114)	(0.0686)	(0.0743)	(0.0739)	(0.0947)	(0.0820)	(0.165)	(0.135)		(0.0858)	(0.0861)	(0.131)	(0.0945)	(0.113)	(0.0770)	(0.0963)
N	197	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198
chi2	82.29	222.5	74.92	71.00	39.13	56.64	27.55	554.4	63.40	1013.7	144.8	106.3	79.92	38.17	187.9	277.7	55.14	62.10	128.1
p	1.78e-13	3.20e-42	4.93e-12	2.84e-11	0.0000241	5.91e-09	0.000567	1.00e-112	2.95e-10	2.12e-211	4.33e-26	8.48e-19	5.21e-13	0.0000354	5.44e-35	8.15e-54	2.97e-08	1.45e-09	1.17e-22

Notes: Marginal effects are reported; Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Only selected industries are reported due to space restrictions.

Data for 38 industries. Industries 7 and 14 are omitted due to non convergence

France, probit panel estimation of Regional Negative Shock (RSN) - As presented in Chapter 3.

	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)
	Leather products	Lighting and electrical equipment	Maritime	Media and publishing	Medical devices	Metal manufacturing	Oil and gas	Paper products	Pharmaceuticals	Plastics	Power generation and transmission	Processed food	Production technology	Sporting, recreational and childrenâ€™s goods	Stone quarries	Telecom	Textiles	Tobacco	Tourism and hospitality
Cluster	-0.0496	-0.0669	-0.111**	-0.00452	0.174	-0.0416	0.00851	-0.0571	0.0330	0.0780	-0.0903	-0.00372	-0.0684	-0.104	0.244**	-0.207**	-0.228**	-0.157**	-0.111
	(0.0925)	(0.127)	(0.0446)	(0.0524)	(0.167)	(0.198)	(0.174)	(0.0919)	(0.104)	(0.104)	(0.0744)	(0.0996)	(0.0725)	(0.0865)	(0.0964)	(0.0843)	(0.0957)	(0.0732)	(0.159)
Size	-0.0186	0.118	0.214*	0.0309	-0.110	0.154	-0.0388	0.0250	-0.151***	-0.0438	0.190***	.0000455	-0.0858**	-0.181	-0.139	-0.234**	0.119*	0.227***	0.127***
	(0.0476)	(0.0800)	(0.120)	(0.0592)	(0.130)	(0.121)	(0.122)	(0.0267)	(0.0401)	(0.101)	(0.0582)	(0.0830)	(0.0336)	(0.163)	(0.0988)	(0.0913)	(0.0662)	(0.0794)	(0.0493)
Focus	-0.162	0.0528	0.266***	-0.0731	-0.0152	-0.295	-0.0116	-0.0292	-0.0823	0.362	0.0986***	-0.0641	0.109	0.0482	-0.208**	0.324	-1.856	0.0203	0.0183
	(0.125)	(0.244)	(0.101)	(0.199)	(0.0826)	(0.257)	(0.128)	(0.108)	(0.149)	(0.436)	(0.0362)	(0.193)	(0.438)	(1.635)	(0.0922)	(0.198)	(1.144)	(0.0407)	(0.0632)
RD	-0.0187	-0.0241*	-0.0133	-0.0107	0.0169	-0.0568***	-0.0231	-0.00369	-0.0199**	-0.00594	0.00889	-0.0173	-0.00494	0.00857	-0.0216	0.00985	-0.0265**	-0.00708	-0.00771
	(0.0154)	(0.0144)	(0.0208)	(0.0145)	(0.0241)	(0.0155)	(0.0323)	(0.0175)	(0.00856)	(0.0157)	(0.0141)	(0.0149)	(0.0174)	(0.0192)	(0.0237)	(0.0213)	(0.0114)	(0.0149)	(0.0234)
Wealth	-0.0453	-0.0128	-0.0194	-0.0435	-0.0329	0.0486	0.0523	0.0600	0.0515**	-0.0210	0.0140	0.0143	-0.0268	0.00153	-0.0465	-0.0181	-0.0230	0.00605	-0.118**
	(0.0315)	(0.0288)	(0.0357)	(0.0284)	(0.0447)	(0.0393)	(0.0402)	(0.0384)	(0.0238)	(0.0272)	(0.0414)	(0.0253)	(0.0356)	(0.0357)	(0.0534)	(0.0376)	(0.0340)	(0.0318)	(0.0481)
Employment	-0.00808	0.0167	-0.0149	0.000901	0.00339	-0.00192	0.0189	-0.0303***	0.00839	-0.0128	-0.0143	0.00597	0.0259**	0.00714	0.0147	-0.00501	0.000572	-0.00632	0.0155
	(0.0108)	(0.0152)	(0.0123)	(0.00883)	(0.0286)	(0.0133)	(0.0210)	(0.0106)	(0.0124)	(0.0129)	(0.0253)	(0.0192)	(0.0106)	(0.0136)	(0.0137)	(0.0134)	(0.0118)	(0.0177)	(0.0230)
XportReg	0.145	-0.183	-0.468***	-0.121	0.0512	-0.0531	-0.135	-0.179	0.215	-0.162	-0.472***	0.0621	0.113	0.144	0.695***	0.384***	0.208**	0.0295	
	(0.122)	(0.142)	(0.0282)	(0.0834)	(0.198)	(0.140)	(0.180)	(0.119)	(0.184)	(0.126)	(0.0280)	(0.174)	(0.163)	(0.152)	(0.0306)	(0.0795)	(0.106)	(0.105)	
EUAID	-0.0408***	-0.0222	-0.00126	0.0262	-0.0382	-0.0497**	-0.00246	-0.0248	-0.00197	0.00636	-0.0553***	-0.00222	0.0104	-0.0378	0.0215*	-0.0316	0.0375**	-0.0138	-0.00902
	(0.0138)	(0.0216)	(0.00916)	(0.0181)	(0.0449)	(0.0198)	(0.0202)	(0.0272)	(0.0150)	(0.0128)	(0.0176)	(0.0175)	(0.0150)	(0.0301)	(0.0126)	(0.0223)	(0.0153)	(0.00976)	(0.0217)
NSN	0.352***	0.375***	0.503***	0.318***	0.339***	0.513***	0.319***	0.488***	0.294***	0.351***	0.461***	0.399***	0.436***	0.141**	0.184	0.324***	0.238***	0.571***	0.415***
	(0.114)	(0.0807)	(0.0960)	(0.0851)	(0.0679)	(0.109)	(0.114)	(0.178)	(0.109)	(0.0807)	(0.0719)	(0.0842)	(0.0607)	(0.0626)	(0.146)	(0.0676)	(0.0816)	(0.0509)	(0.0630)
lag1NSN	-0.163*	-0.00302	-0.0364	0.332***	0.0594	-0.193***	-0.0547	-0.202*	0.487***	0.00637	-0.00107	0.0855	-0.0381	-0.0317	-0.0554	0.138	0.0335	0.0725	0.346***
	(0.0865)	(0.107)	(0.0708)	(0.0740)	(0.0817)	(0.0651)	(0.102)	(0.119)	(0.0856)	(0.0863)	(0.0813)	(0.0887)	(0.0936)	(0.0957)	(0.0865)	(0.127)	(0.116)	(0.0688)	(0.0586)
N	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198
chi2	56.34	94.69	709.7	282.8	37.58	74.07	24.12	54.88	55.99	52.48	182.7	51.27	213.5	29.07	268.7	44.93	50.64	180.1	85.92
p	1.77e-08	6.26e-16	5.09e-146	6.72e-55	.0000449	7.22e-12	0.00729	3.33e-08	2.06e-08	9.31e-08	6.52e-34	00000155	2.48e-40	0.00121	6.35e-52	00000224	00000203	2.28e-33	1.07e-14

Notes: Marginal effects are reported; Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Only selected industries are reported due to space restrictions.

Data for 38 industries. Industries 7 and 14 are omitted due to non convergence

Appendix 3.5: Results for France using Cluster Index (full table)

France, probit panel estimation of Regional Negative Shock (RSN) - Using CLUSTER INDEX.																			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
	Aerospace	Agricultural products	Apparel	Automotive	Biotech	Building fixtures, equipment and services	Chemical products	Constructio n	Constructio n materials	Distribution	Education and knowledge creation	Entertainm ent	Financial services	Footwear	Furniture	Heavy Machinery	Instruments	IT	Jewellery and precious metals
Cluster Index	0.197**	0.0174	1.249	0.384	0.857*	0.0584	-1.388	0.0465	2.946	9.665***	1.270	0.0660	-0.423**	2.652*	0.703	0.000732	1.647*	0.274	0.120
	(0.0891)	*(0.409)*	*(0.879)*	*(0.514)*	*(0.472)*	*(1.591)*	*(1.097)*	*(0.189)*	*(3.015)*	*(3.026)*	*(1.283)*	*(0.574)*	*(0.173)*	*(1.354)*	*(1.609)*	*(0.401)*	*(0.889)*	*(0.169)*	*(0.155)*
Size	-0.0999**	-0.0460	-0.732	-0.207	-0.514**	0.0639	0.940	-0.0557	-1.880	-5.568***	-0.855	0.135	0.426*	-1.321*	-0.337	-0.214	-0.827	-0.119	-0.129
	(0.0426)	*(0.319)*	*(0.519)*	*(0.280)*	*(0.262)*	*(0.916)*	*(0.678)*	*(0.179)*	*(1.802)*	*(1.737)*	*(0.789)*	*(0.590)*	*(0.218)*	*(0.749)*	*(0.964)*	*(0.177)*	*(0.533)*	*(0.113)*	*(0.105)*
Focus	-0.954**	0.244	-1.730	-0.365	-6.383	-0.239	0.549	0.0155	-2.802	-8.056***	-0.988	-0.279	1.865**	-4.493**	-1.627	0.677	-2.058**	-2.479	-1.474
	(0.427)	*(0.659)*	*(1.247)*	*(0.485)*	*(4.311)*	*(1.527)*	*(0.630)*	*(0.823)*	*(2.985)*	*(2.595)*	*(1.896)*	*(0.636)*	*(0.818)*	*(2.192)*	*(3.217)*	*(1.276)*	*(1.024)*	*(1.638)*	*(1.579)*
RD	-0.00900	-0.0582**	0.00790	0.0135	-0.0239	-0.0252*	-0.00437	0.0120	0.00435	-0.0197	0.00157	-0.0508***	-0.0196	-0.00518	-0.0214	-0.0103	-0.0243	-0.00654	0.0148
	(0.0134)	*(0.0250)*	*(0.0188)*	*(0.0150)*	*(0.0204)*	*(0.0149)*	*(0.0218)*	*(0.0172)*	*(0.0177)*	*(0.0199)*	*(0.0157)*	*(0.0161)*	*(0.0140)*	*(0.0158)*	*(0.0133)*	*(0.0143)*	*(0.0218)*	*(0.0167)*	*(0.00902)*
Wealth	0.00985	0.162***	0.00923	-0.0203	0.00323	-0.0280**	-0.105**	0.0161	0.0514	-0.0562	-0.0355	-0.0204	0.00170	-0.0978***	0.0789**	0.0277	-0.159***	-0.0326	0.00170
	(0.0589)	*(0.0442)*	*(0.0363)*	*(0.0354)*	*(0.0319)*	*(0.0135)*	*(0.0500)*	*(0.0351)*	*(0.0407)*	*(0.0473)*	*(0.0524)*	*(0.0386)*	*(0.0317)*	*(0.0295)*	*(0.0325)*	*(0.0305)*	*(0.0563)*	*(0.0306)*	*(0.0328)*
Employment	0.00931	-0.00698	-0.0133	-0.0283	0.0146**	0.0463***	-0.000270	-0.0124	-0.0161	0.0150	0.0581**	0.000428	-0.00400	0.0535	0.00467	-0.0298**	0.0318***	-0.00492	-0.00210
	(0.0128)	*(0.0155)*	*(0.0162)*	*(0.0194)*	*(0.00717)*	*(0.0152)*	*(0.00968)*	*(0.0168)*	*(0.0115)*	*(0.0151)*	*(0.0253)*	*(0.0162)*	*(0.0178)*	*(0.0332)*	*(0.0178)*	*(0.0126)*	*(0.0114)*	*(0.00905)*	*(0.00973)*
XportReg	0.299**	-0.173	0.0959	-0.0492	0.117			0.448***		-0.143	-0.271	-0.125	-0.143	-0.274***	-0.0438	0.611***	0.365	-0.0352	0.0521
	(0.117)	*(0.140)*	*(0.187)*	*(0.165)*	*(0.240)*			*(0.0908)*		*(0.140)*	*(0.282)*	*(0.104)*	*(0.161)*	*(0.0993)*	*(0.126)*	*(0.0634)*	*(0.278)*	*(0.0630)*	*(0.147)*
EUAID	-0.0115	-0.116**	-0.00686	0.0265***	-0.0208*	-0.00161	0.0434***	-0.0332*	0.00546	-0.0170	0.0111	-0.0514***	-0.0103	0.0533***	0.0213**	0.0417***	-0.0772***	-0.0287	0.0578***
	(0.0118)	*(0.0583)*	*(0.0317)*	*(0.0100)*	*(0.0117)*	*(0.0127)*	*(0.0129)*	*(0.0183)*	*(0.0326)*	*(0.0144)*	*(0.0186)*	*(0.0180)*	*(0.0157)*	*(0.0196)*	*(0.0102)*	*(0.0107)*	*(0.0222)*	*(0.0317)*	*(0.0170)*
NSN	0.183*	0.849***	0.299	0.195**	0.376***	0.284**	0.181	0.483***	0.323*	0.152	0.277**	0.654***	0.433***	0.0923	0.402***	0.162	0.388***	0.261***	0.169**
	(0.101)	*(0.0501)*	*(0.202)*	*(0.0786)*	*(0.0889)*	*(0.114)*	*(0.111)*	*(0.106)*	*(0.179)*	*(0.127)*	*(0.113)*	*(0.0541)*	*(0.0681)*	*(0.127)*	*(0.0860)*	*(0.116)*	*(0.0990)*	*(0.0671)*	*(0.0806)*
lag1NSN	-0.211**	0.262***	-0.0181	-0.134	-0.152*	0.203**	-0.181**	-0.193**	0.0398	-0.0143	0.224		0.152*	0.158	0.0260	0.157*	-0.146	0.0682	0.107
	(0.0913)	*(0.0836)*	*(0.0643)*	*(0.118)*	*(0.0803)*	*(0.0879)*	*(0.0786)*	*(0.0956)*	*(0.0781)*	*(0.157)*	*(0.138)*		*(0.0854)*	*(0.104)*	*(0.136)*	*(0.0925)*	*(0.117)*	*(0.0773)*	*(0.0936)*
N	197	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198
chi2	31.57	221.3	73.16	80.26	41.35	55.85	31.29	534.3	42.46	61.81	160.5	113.8	66.02	33.72	166.8	307.1	87.60	55.23	75.86

Notes: Marginal effects are reported; Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Data for 38 industries. Industries 7 and 14 are omitted due to non convergence

France, probit panel estimation of Regional Negative Shock (RSN) - Using CLUSTER INDEX.

	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)
	Leather products	Lighting and electrical equipment	Maritime	Media and publishing	Medical devices	Metal manufacturing	Oil and gas	Paper products	Pharmaceuticals	Plastics	Power generation and transmission	Processed food	Production technology	Sporting, recreational and children goods	Stone quarries	Telecom	Textiles	Tobacco	Tourism and hospitality
Cluster Index	-0.325	1.279***	3.658***	0.600	1.503	0.294	-0.436	1.405**	-0.235	-0.0630	-0.262	1.249	-0.298	-0.454	-0.278	-0.319	-0.465***	-9.270***	35.98***
	(0.267)	*(0.381)*	*(1.029)*	*(1.187)*	*(1.122)*	*(0.406)*	*(1.797)*	*(0.713)*	*(1.449)*	*(0.214)*	*(0.832)*	*(1.063)*	*(0.299)*	*(0.625)*	*(0.680)*	*(0.679)*	*(0.126)*	*(2.663)*	*(10.51)*
Size	0.156	-0.782***	-1.858***	-0.309	-0.889	-0.0980	0.223	-0.777*	0.000254	0.00223	0.352	-0.715	0.0947	0.113	0.0364	0.0157	0.467***	5.606***	-21.12***
	(0.161)	*(0.281)*	*(0.638)*	*(0.657)*	*(0.620)*	*(0.298)*	*(1.081)*	*(0.400)*	*(0.842)*	*(0.0930)*	*(0.478)*	*(0.605)*	*(0.194)*	*(0.413)*	*(0.382)*	*(0.467)*	*(0.107)*	*(1.573)*	*(6.209)*
Focus	0.587	-4.100***	-3.425***	-1.814	-1.021	-1.427	0.527	-3.045**	0.372	0.718	0.262	-1.430	2.379	5.473	0.217	0.530	1.351	7.778***	-23.34***
	(0.628)	*(1.295)*	*(0.996)*	*(3.497)*	*(0.814)*	*(1.652)*	*(2.204)*	*(1.486)*	*(2.584)*	*(0.956)*	*(0.577)*	*(1.194)*	*(2.530)*	*(8.926)*	*(0.653)*	*(1.019)*	*(1.473)*	*(2.236)*	*(6.810)*
RD	-0.0205	-0.0214	-0.00972	-0.0110	0.0155	-0.0523***	-0.0266	-0.00456	-0.0226*	-0.00993	0.0117	-0.0133	-0.000431	0.00188	-0.00882	0.00346	-0.0319**	-0.00354	-0.0151
	(0.0154)	*(0.0149)*	*(0.0234)*	*(0.0140)*	*(0.0189)*	*(0.0158)*	*(0.0243)*	*(0.0170)*	*(0.0120)*	*(0.0138)*	*(0.0132)*	*(0.0145)*	*(0.0168)*	*(0.0191)*	*(0.0202)*	*(0.0208)*	*(0.0130)*	*(0.0191)*	*(0.0230)*
Wealth	-0.0299	0.0303	-0.0977**	-0.0532	-0.0549	0.0625	0.0593*	0.0131	0.0560**	-0.0101	0.0267	-0.00362	-0.0398	0.0127	-0.00795	-0.0293	-0.0291	0.0597*	0.000753
	(0.0294)	*(0.0314)*	*(0.0488)*	*(0.0395)*	*(0.0455)*	*(0.0384)*	*(0.0342)*	*(0.0454)*	*(0.0226)*	*(0.0277)*	*(0.0510)*	*(0.0357)*	*(0.0350)*	*(0.0358)*	*(0.0599)*	*(0.0367)*	*(0.0348)*	*(0.0318)*	*(0.0490)*
Employment	-0.00963	0.0126	-0.00167	0.000276	-0.00534	-0.00638	0.0203	-0.0248**	0.00846	-0.0145	-0.0276	0.00624	0.0250**	0.0110	0.00549	0.00134	-0.00852	-0.0296	-0.00409
	(0.0108)	*(0.0159)*	*(0.0105)*	*(0.00963)*	*(0.0259)*	*(0.0135)*	*(0.0193)*	*(0.0118)*	*(0.0126)*	*(0.0130)*	*(0.0242)*	*(0.0191)*	*(0.0109)*	*(0.0145)*	*(0.0135)*	*(0.0150)*	*(0.0101)*	*(0.0235)*	*(0.0251)*
XportReg	0.184*	-0.250***	-0.485***	-0.142*	-0.101	-0.0850	-0.109	-0.190	0.186	-0.146	-0.469***	0.0301	0.0203	0.136	0.672***	0.374***	0.172	-0.00216	
	(0.103)	*(0.0868)*	*(0.0250)*	*(0.0842)*	*(0.131)*	*(0.0810)*	*(0.233)*	*(0.122)*	*(0.136)*	*(0.115)*	*(0.0317)*	*(0.170)*	*(0.197)*	*(0.149)*	*(0.0539)*	*(0.0987)*	*(0.108)*	*(0.0836)*	
EUAID	-0.0404***	-0.0149	0.00201	0.0250	-0.0466	-0.0483**	-0.00267	-0.0293	-0.000466	0.00108	-0.0619***	0.0000171	0.00275	-0.0362	0.0218*	-0.0253	0.0290*	-0.0258**	-0.0222
	(0.0143)	*(0.0181)*	*(0.0135)*	*(0.0177)*	*(0.0455)*	*(0.0196)*	*(0.0197)*	*(0.0260)*	*(0.0125)*	*(0.0142)*	*(0.0187)*	*(0.0155)*	*(0.0144)*	*(0.0316)*	*(0.0124)*	*(0.0250)*	*(0.0175)*	*(0.0126)*	*(0.0194)*
NSN	0.345***	0.393***	0.479***	0.321***	0.345***	0.517***	0.325***	0.554***	0.297***	0.354***	0.463***	0.390***	0.449***	0.142**	0.214	0.321***	0.279***	0.622***	0.140
	(0.113)	*(0.0850)*	*(0.0989)*	*(0.0837)*	*(0.0660)*	*(0.108)*	*(0.112)*	*(0.192)*	*(0.114)*	*(0.0802)*	*(0.0738)*	*(0.0857)*	*(0.0582)*	*(0.0599)*	*(0.146)*	*(0.0712)*	*(0.0832)*	*(0.0503)*	*(0.119)*
lag1NSN	-0.184**	-0.0181	0.0113	0.323***	0.0498	-0.202***	-0.0629	-0.293**	0.477***	0.00470	0.00692	0.103	-0.0664	-0.0276	-0.0549	0.134	0.0102	0.310***	0.398***
	(0.0811)	*(0.101)*	*(0.0671)*	*(0.0801)*	*(0.0839)*	*(0.0653)*	*(0.118)*	*(0.139)*	*(0.0862)*	*(0.0867)*	*(0.0910)*	*(0.0885)*	*(0.0987)*	*(0.0943)*	*(0.0843)*	*(0.125)*	*(0.121)*	*(0.0727)*	*(0.0628)*
N	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198
chi2	56.97	90.73	199.5	136.4	53.96	63.53	25.18	43.53	62.91	49.49	127.6	47.15	254.3	31.04	124.5	49.60	58.24	437.9	79.59

Notes: Marginal effects are reported; Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Data for 38 industries. Industries 7 and 14 are omitted due to non convergence

Appendix 3.6: Robustness estimation using *Region_Shock* as dependant variable.

France, panel estimation of REGION_SHOCK - As presented in Chapter 3.

	(1) Aerospace	(2) Agricultural products	(3) Apparel	(4) Automotive	(5) Biotech	(6) Building fixtures, equipment and services	(7) Business Services	(8) Chemical products	(9) Construction	(10) Construction materials	(11) Distribution	(12) Education and knowledge creation	(13) Entertainme nt	(14) Farming and Animals	(15) Financial services	(16) Footwear	(17) Furniture	(18) Heavy Machinery	(19) Instruments	(20) IT
Cluster	-0.0197	0.376	-0.0272	-0.0115	0.0422	-0.00969	-0.184*		0.00841	-0.00727	-0.0168***	0.0356	-0.00712	-4.985	-0.00548	0.0439	-0.0195	0.0385	0.0664	0.0653**
	(0.0793)	(0.271)	(0.0246)	(0.00857)	(0.0826)	(0.0143)	(0.105)		(0.00595)	(0.0166)	(0.00557)	(0.0433)	(0.0273)	(9.786)	(0.0112)	(0.0706)	(0.0308)	(0.0268)	(0.126)	(0.0266)
Size	-0.00987	0.107	0.00185	-0.00513	-0.000367	-0.00351	-0.0294	-0.111*	-0.00248	0.00189	-0.00210	0.00627	0.0168	24.36	0.0000900	-0.0778	0.00545	0.00887	0.0182	-0.0104
	(0.0267)	(0.166)	(0.0120)	(0.00980)	(0.00799)	(0.00859)	(0.0237)	(0.0676)	(0.00517)	(0.00874)	(0.00429)	(0.0103)	(0.0227)	(19.01)	(0.00334)	(0.0543)	(0.0151)	(0.0210)	(0.0554)	(0.00872)
Focus	0.0522	-0.134	-0.0124	-0.00212	0.0207	0.0367**	0.0687**	-0.145	-0.0553	0.0344*	0.00488	-0.297***	-0.00320	-3.837	0.00685	-0.103	-0.0774	-0.281*	-0.233	-0.252*
	(0.0692)	(0.164)	(0.0567)	(0.00579)	(0.413)	(0.0161)	(0.0330)	(0.116)	(0.0467)	(0.0200)	(0.00851)	(0.108)	(0.0232)	(5.649)	(0.0689)	(0.171)	(0.0921)	(0.151)	(0.152)	(0.145)
RD	-0.0123	0.0553	-0.00297	-0.00326*	-0.00699	0.00258	-0.0193*	0.00682	-0.000918	-0.00207	-0.000287	0.000566	-0.000328	-0.109	0.00171	-0.00275	-0.00307	-0.000848	-0.00411	-0.00345
	(0.0176)	(0.0359)	(0.00319)	(0.00180)	(0.0113)	(0.00165)	(0.0115)	(0.00487)	(0.00107)	(0.00273)	(0.00144)	(0.00287)	(0.00169)	(2.755)	(0.00146)	(0.00882)	(0.00358)	(0.00403)	(0.0193)	(0.00279)
Wealth	0.0335*	-0.101*	-0.000565	0.00997	0.0117	0.00401	0.00167	-0.0192	-0.000443	0.00186	0.00379	0.0300***	0.000613	1.867	-0.00722	-0.00601	-0.00631	-0.00611	-0.0413	0.00664
	(0.0202)	(0.0529)	(0.00438)	(0.00809)	(0.00927)	(0.00388)	(0.0183)	(0.0166)	(0.00279)	(0.00500)	(0.00341)	(0.0103)	(0.00384)	(3.597)	(0.00532)	(0.0154)	(0.00532)	(0.00918)	(0.0453)	(0.00696)
Employment	0.0112	0.00703	0.00195	0.00446	0.00379	-0.00553**	0.0211**	0.0107	0.000496	0.0119***	-0.000717	-0.0145**	0.00540**	2.306*	0.000506	0.0109	0.00878*	0.0107**	-0.00525	0.00443
	(0.0127)	(0.0219)	(0.00471)	(0.00499)	(0.00538)	(0.00214)	(0.00862)	(0.0105)	(0.00100)	(0.00414)	(0.00132)	(0.00674)	(0.00149)	(1.334)	(0.00133)	(0.0105)	(0.00480)	(0.00455)	(0.0159)	(0.00366)
Export_Reg	-0.0563	-0.355	0.0143	0.00149	-0.0361		0.0546		-0.0115		0.00146	0.0452	0.000689	-52.51	-0.00255	0.0236	0.0363	0.0147	0.205	-0.0166
	(0.112)	(0.233)	(0.0193)	(0.0239)	(0.0385)		(0.0644)		(0.00970)		(0.00639)	(0.0892)	(0.0215)	(97.53)	(0.0169)	(0.0439)	(0.0233)	(0.0814)	(0.321)	(0.0253)
EUAID	-0.0116	-0.0109	0.000170	-0.00360	0.00557	0.000369	0.0176**	0.00369	0.000740	-0.00134	0.000302	-0.0105**	0.00352	0.482	-0.000987	-0.00643	0.00253	-0.00869**	-0.0167	0.00572
	(0.0189)	(0.0416)	(0.00468)	(0.00313)	(0.00579)	(0.00182)	(0.00746)	(0.00488)	(0.00158)	(0.00457)	(0.000805)	(0.00433)	(0.00333)	(1.821)	(0.00113)	(0.0127)	(0.00290)	(0.00389)	(0.0192)	(0.00533)
Nation_Shock	2.200**	1.276***	0.720**	1.225***	0.652***	1.052***	1.421***	1.790***	1.025***	1.231**	0.896***	1.032***	1.251***	1.792***	1.070***	1.030**	1.051***	1.354*	2.042*	0.963***
	(1.053)	(0.243)	(0.307)	(0.254)	(0.154)	(0.119)	(0.109)	(0.478)	(0.112)	(0.516)	(0.180)	(0.265)	(0.107)	(0.471)	(0.115)	(0.406)	(0.217)	(0.790)	(1.111)	(0.210)
Constant	0.0317	0.0340	0.0114	0.0217	-0.0114	-0.0352**	-0.0783	0.421	0.00965	-0.0368*	0.00231	0.144***	-0.0124	1.043	0.00382	0.111*	0.0440	0.0635*	0.191*	0.0168
	(0.0425)	(0.0587)	(0.0131)	(0.0152)	(0.0193)	(0.0169)	(0.0488)	(0.323)	(0.00807)	(0.0218)	(0.00607)	(0.0522)	(0.0111)	(16.01)	(0.00332)	(0.0647)	(0.0296)	(0.0333)	(0.0989)	(0.0111)
N	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198

Standard errors in parentheses
="* p<0.10 ** p<0.05 *** p<0.01"

France, panel estimation of REGION_SHOCK - As presented in Chapter 3.

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
	Jewellery and precious metals	Leather products	Lighting and electrical equipment	Maritime	Media and publishing	Medical devices	Metal manufacturi ng	Oil and gas	Paper products	Pharmaceuti cals	Plastics	Power generation and transmission	Processed food	Production technology	Sporting, recreational and children goods	Stone quarries	Telecom	Textiles	Tobacco	Tourism and hospitality
Cluster	-0.0463	-0.0165	-0.0830	0.0610*	-0.0112*	0.00464	0.0204	-0.266	0.00800	-0.0366	0.00834	-0.00332	-0.000800	0.00850	-0.00549	-0.0218	0.0442	0.0295*	1.091	0.0321
	(0.0370)	(0.0327)	(0.0581)	(0.0365)	(0.00631)	(0.0181)	(0.0162)	(0.407)	(0.00682)	(0.0483)	(0.0102)	(0.0372)	(0.00469)	(0.00733)	(0.0388)	(0.0289)	(0.0348)	(0.0161)	(0.852)	(0.0417)
Size	0.0152*	-0.00490	-0.0245	-0.0265	-0.00121	-0.00124	-0.00114	-0.864*	-0.00292	0.00517	0.00549	0.00618	0.00412	-0.00636	0.00762	0.0137	0.0631	-0.00785	-1.121*	-0.0138
	(0.00905)	(0.0124)	(0.0239)	(0.0203)	(0.00576)	(0.0145)	(0.00976)	(0.476)	(0.00236)	(0.0259)	(0.0147)	(0.0126)	(0.00709)	(0.00621)	(0.0761)	(0.0195)	(0.0535)	(0.00993)	(0.611)	(0.00986)
Focus	0.342	0.0839	0.133	-0.00932	0.0656***	-0.00218	-0.0268	-0.376	-0.00978	-0.0127	-0.0973	-0.0268***	-0.00941	-0.0274	-0.467	0.0574*	-0.0345	0.378	-0.113	-0.00920
	(0.369)	(0.0626)	(0.127)	(0.0752)	(0.0253)	(0.00877)	(0.0230)	(0.353)	(0.0101)	(0.0745)	(0.126)	(0.00946)	(0.0103)	(0.0526)	(0.752)	(0.0296)	(0.0638)	(0.308)	(0.283)	(0.0216)
RD	-0.00200	0.00652	-0.0122	0.00326	0.00163	-0.000838	-0.000108	0.147	0.000302	-0.0197	-0.00169	-0.00596	-0.000647	0.00364	-0.0178*	-0.00564	-0.0127*	0.00133	0.290	0.00511
	(0.00403)	(0.00692)	(0.0106)	(0.00312)	(0.00139)	(0.00283)	(0.00135)	(0.115)	(0.00144)	(0.0217)	(0.00256)	(0.00516)	(0.00130)	(0.00253)	(0.00986)	(0.00558)	(0.00711)	(0.00357)	(0.232)	(0.00573)
Wealth	-0.0182	-0.00374	0.0137*	-0.0145	-0.00585**	-0.000180	-0.0000100	-0.417**	0.000128	0.0267	-0.00131	-0.0198	-0.00156	-0.00557	0.0277*	0.00958	0.0305**	-0.00557	0.315*	0.00200
	(0.0133)	(0.00828)	(0.00709)	(0.0130)	(0.00236)	(0.00672)	(0.00262)	(0.183)	(0.00265)	(0.0268)	(0.00479)	(0.0139)	(0.00147)	(0.00491)	(0.0144)	(0.00891)	(0.0150)	(0.00836)	(0.174)	(0.00673)
Employment	0.000622	0.00000264	-0.0186**	0.00589	0.000959	-0.00153	0.00340*	0.0739	-0.00172	-0.0159**	0.00477**	0.0131	0.00304*	0.000661	-0.00762	-0.000383	-0.00178	0.00157	-0.930	0.00469
	(0.00363)	(0.00902)	(0.00781)	(0.00766)	(0.000848)	(0.00457)	(0.00202)	(0.129)	(0.00198)	(0.00624)	(0.00177)	(0.00969)	(0.00162)	(0.00117)	(0.00628)	(0.00337)	(0.00383)	(0.00114)	(0.666)	(0.00585)
Export_Reg	-0.0702	-0.0681*	-0.0169	0.0822	-0.0189***	0.0238	-0.00295	0.262	0.0256	0.0850	0.0158	0.123***	-0.00135	0.0343*	0.00000149	-0.123	-0.153	-0.0803**	-4.921	
	(0.0663)	(0.0349)	(0.0401)	(0.135)	(0.00675)	(0.0190)	(0.0108)	(0.382)	(0.0175)	(0.0724)	(0.0517)	(0.0457)	(0.00845)	(0.0207)	(0.0547)	(0.113)	(0.109)	(0.0396)	(3.933)	
EUAID	-0.00448	0.00129	-0.0165	0.0164***	0.000748	0.00132	0.000754	-0.00668	0.000380	-0.00925	0.00238	0.000155	0.00122**	0.00538**	-0.0136	0.00515	-0.00449	-0.00240	-0.324	0.00946*
	(0.00405)	(0.00553)	(0.0102)	(0.00392)	(0.000808)	(0.00410)	(0.00114)	(0.0621)	(0.00107)	(0.00971)	(0.00289)	(0.00390)	(0.000549)	(0.00193)	(0.0137)	(0.00901)	(0.00436)	(0.00412)	(0.296)	(0.00572)
Nation_Shock	1.649**	1.134***	1.145***	1.025***	1.337***	0.892***	1.180***	3.267	1.359***	1.032	1.255***	1.802***	0.932***	1.175***	1.145*	0.980**	0.539**	0.930***	4.202	1.037***
	(0.778)	(0.285)	(0.248)	(0.190)	(0.211)	(0.163)	(0.190)	(2.067)	(0.468)	(0.752)	(0.303)	(0.337)	(0.163)	(0.180)	(0.639)	(0.424)	(0.249)	(0.356)	(2.851)	(0.0651)
Constant	0.000255	-0.0116	0.0660*	0.0116	-0.00755	-0.00401	-0.00112	1.587**	0.00609	0.0549	0.0126	0.115**	0.00307	-0.0113*	0.0774	-0.0681	0.0000742	0.00878	1.926*	0.0109
	(0.0117)	(0.0186)	(0.0353)	(0.0629)	(0.00609)	(0.0158)	(0.00412)	(0.663)	(0.00582)	(0.0703)	(0.0126)	(0.0552)	(0.00454)	(0.00582)	(0.0472)	(0.0442)	(0.00831)	(0.00663)	(1.056)	(0.0567)
N	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198	198

Standard errors in parentheses
="* p<0.10 ** p<0.05 *** p<0.01"

Appendix Chapter Four

Appendix 4.1: Industries and Countries included in the dataset.

Industry classification

Code	Industry aggregation
1	Agriculture, Hunting, Forestry and Fishing
2	Mining and Quarrying
3	Food, Beverages and Tobacco
4	Textiles and Textile Products
5	Leather, Leather and Footwear
6	Wood and Products of Wood and Cork
7	Pulp, Paper, Paper , Printing and Publishing
8	Coke, Refined Petroleum and Nuclear Fuel
9	Chemicals and Chemical Products
10	Rubber and Plastics
11	Other Non-Metallic Mineral
12	Basic Metals and Fabricated Metal
13	Machinery, Nec
14	Electrical and Optical Equipment
15	Transport Equipment
16	Manufacturing, Nec; Recycling
17	Electricity, Gas and Water Supply
18	Construction
19	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
20	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
21	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
22	Hotels and Restaurants
23	Inland Transport
24	Water Transport
25	Air Transport
26	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
27	Post and Telecommunications
28	Financial Intermediation
29	Real Estate Activities
30	Renting of M&Eq and Other Business Activities
31	Public Admin and Defence; Compulsory Social Security
32	Education
33	Health and Social Work
34	Other Community, Social and Personal Services
35	Private Households with Employed Persons

Source: World Input-Outpit Database. Enrumban et al. 2011

Countries included in the sample

Code	Country	Code	Country
AUS	Australia	ITA	Italy
AUT	Austria	JPN	Japan
BEL	Belgium	KOR	South-Korea
BGR	Bulgaria	LTU	Lithuania
BRA	Brasil	LUX	Luxembourg
CAN	Canada	LVA	Latvia
CHN	China	MEX	Mexico
CYP	Cyprus	MLT	Malta
CZE	Czeck Republic	NLD	Netherlands
DEU	Germany	POL	Poland
DNK	Denmark	PRT	Portugal
ESP	Spain	ROM	Romania
EST	Estonia	RoW	Rest of the World
FIN	Finland	RUS	Russia
FRA	France	SVK	Slovakia
GBR	Great Britain	SVN	Slovenia
GRC	Greece	SWE	Sweden
HUN	Hungary	TUR	Turkie
IDN	Indonesia	TWN	Taiwan
IND	India	USA	United States
IRL	Ireland		

Source: World Input-Outpit Database. Enrumban et al. 2011

Appendix 4.2: Correlation between the variables used to estimate Equation 4.1.

Correlation Matrix

	Gwt	Outdeg	Eigen	Betw	Net_dens	GDPi	Ind_Open	Count_Op	Downturn	GDPc	Gov	Inf	Lab Prod	Lab Hskill
Gwt	1													
Outdeg	-0.040	1												
Eigen	-0.015	0.591	1											
Betw	-0.008	0.718	0.503	1										
Net_dens	0.003	0.261	0.509	0.160	1									
GDPi	0.037	0.465	0.567	0.255	0.353	1								
Ind_Open	-0.110	0.267	0.075	0.136	-0.001	-0.399	1							
Count_Open	0.039	-0.209	-0.213	-0.067	-0.278	-0.543	0.167	1						
Downturn	-0.750	-0.019	-0.047	-0.018	-0.044	-0.090	0.115	-0.031	1					
GDPc	-0.067	0.480	0.526	0.198	0.451	0.786	-0.076	-0.689	0.000	1				
Gov	-0.245	0.037	0.131	0.028	0.103	-0.101	0.047	0.157	0.193	-0.097	1			
Inf	0.315	-0.181	-0.239	-0.083	-0.136	-0.175	-0.031	-0.008	-0.248	-0.226	-0.351	1		
Lab Prod	-0.096	0.204	0.188	0.088	0.135	0.237	-0.060	0.003	0.049	0.204	0.436	-0.410	1	
Lab Hskill	-0.022	-0.005	0.035	0.055	0.008	0.170	-0.434	0.047	-0.005	-0.027	0.025	-0.071	0.216	1

Appendix Chapter Five

Appendix 5.1: Correlation Matrix

	Comovement	Growth	GDP	Employment	Open	Population	Secondary	Terciary	HHpart	Connectivity	Centrality
Comovement	1										
Growth	-0.03	1									
GDP	-0.04	0.00	1								
Employment	-0.04	0.05	0.29	1							
Open	-0.15	0.03	-0.25	-0.14	1						
Population	-0.04	0.10	0.22	0.47	-0.32	1					
Secondary	0.37	-0.09	-0.12	-0.07	-0.05	0.03	1				
Terciary	-0.29	0.09	0.12	0.04	0.05	-0.02	-0.88	1			
HHpart	-0.06	0.05	0.11	0.13	0.04	-0.01	-0.17	0.18	1		
Connectivity	0.38	-0.03	0.40	0.14	-0.26	0.24	0.22	-0.18	-0.01	1	
Centrality	0.38	0.01	0.21	0.09	-0.27	0.19	0.15	-0.14	0.00	0.59	1

Appendix 5.2: Collinearity Diagnostics.

Variable	SQRT VIF	R- VIF	Tolerance	Squared
Comovement	1.46	1.21	0.69	0.31
Growth	1.03	1.01	0.97	0.03
GDP	1.41	1.19	0.71	0.29
Employment	1.39	1.18	0.72	0.28
Open	1.23	1.11	0.82	0.18
Population	1.5	1.22	0.67	0.33
Secondary	4.77	2.18	0.21	0.79
Terciary	4.5	2.12	0.22	0.78
HHpart	1.07	1.03	0.94	0.06
OutDegree	1.96	1.4	0.51	0.49
Betweeness	1.64	1.28	0.61	0.39
Mean VIF		1.99		

Appendix 5.3: Sensitivity to changes in the filters
(compare to results in Tables 5.2 and 5.3).

Robustness of Industrial Co-movement to Selected Filters - Filter: TI > 0.00 & Corr >0.0

LHS: Co-movement (log)

		(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2006	(6) 2007	(7) 2008	(8) 2009
Industry	GDP	-0.0005	-0.0005	-0.0004	-0.0005	-0.0007 **	-0.0007 **	-0.0006 **	-0.0006 **
	Growth	1.0044 ***	1.1539 ***	-0.0023	-0.5159 ***	1.1262 ***	1.2170 ***	0.0788	-0.5836 ***
	Employment	-0.0041	-0.0030	-0.0048	-0.0045	-0.0044	-0.0025	-0.0041	-0.0039
	HHpart	8.5844 ***	9.8913 ***	10.7376 ***	9.3430 ***	9.6595 ***	9.8873 ***	10.5374 ***	9.8943 ***
Country	Open	0.0001	0.0011	-0.0007	-0.0006	-0.0002	0.0010	-0.0004	-0.0005
	Population	0.0039 ***	0.0047 ***	0.0041 ***	0.0038 ***	0.0040 ***	0.0047 ***	0.0040 ***	0.0040 ***
Network	OutDeg (Connectivity)					0.0014 ***	0.0013 ***	0.0012 ***	0.0012 ***
	Between (Centrality)	2.5721 ***	1.8090 ***	1.1409 ***	2.1452 ***				
	Secondary	0.6203 ***	0.7453 ***	0.7311 ***	0.7491 ***	0.6243 ***	0.7440 ***	0.7261 ***	0.7232 ***
	Tertiary	0.2045	0.2313 *	0.2816 **	0.3024 **	0.2062	0.2312 *	0.2642 *	0.3155 **
	Country F.E.	YES	YES	YES	YES	YES	YES	YES	YES
	Industry F.E.	YES	YES	YES	YES	YES	YES	YES	YES
	N	1162	1162	1162	1162	1162	1162	1162	1162
	R-sq	0.718	0.705	0.686	0.705	0.692	0.693	0.679	0.681

Gdp coefficient has been multiplied by 1000 to facilitate interpretation. The dependent variable is the logged Co-movement (Weighted Degree). Co-movement is calculated using different filters as specified in each column. .
Significance level *p<0.1, ** p<0.05, *** p<0.01

Robustness of Industrial Co-movement to Selected Filters - Filter: TI > 0.00 & Corr >0.3

LHS: Co-movement (log)

		(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2006	(6) 2007	(7) 2008	(8) 2009
Industry	GDP	-0.0004	-0.0004	-0.0003	-0.0004	-0.0007 *	-0.0006 *	-0.0006 *	-0.0006 *
	Growth	0.9299 ***	1.3377 ***	-0.0096	-0.7344 ***	1.0106 ***	1.3739 ***	0.0751	-0.7956 ***
	Employment	-0.0038	-0.0026	-0.0045	-0.0041	-0.0037	-0.0017	-0.0035	-0.0033
	HHpart	9.2988 ***	10.8252 ***	11.4688 ***	10.0740 ***	9.7340 ***	10.1836 ***	10.8492 ***	10.1888 ***
Country	Open	-0.0012	0.0002	-0.0017	-0.0019	-0.0014	0.0002	-0.0015	-0.0018
	Population	0.0040 ***	0.0050 ***	0.0042 ***	0.0038 ***	0.0040 ***	0.0047 ***	0.0040 ***	0.0039 ***
Network	OutDeg (Connectivity)					0.0015 ***	0.0015 ***	0.0014 ***	0.0013 ***
	Between (Centrality)	2.1317 ***	1.2559 **	0.9544 ***	1.8746 ***				
	Secondary	0.7878 ***	0.9146 ***	0.8946 ***	0.9072 ***	0.7866 ***	0.9042 ***	0.8826 ***	0.8808 ***
	Tertiary	0.3827 **	0.3948 ***	0.4460 ***	0.4900 ***	0.3804 **	0.3906 ***	0.4290 ***	0.5001 ***
	Country F.E.	YES	YES	YES	YES	YES	YES	YES	YES
	Industry F.E.	YES	YES	YES	YES	YES	YES	YES	YES
	N	1159	1159	1159	1159	1159	1159	1159	1159
	R-sq	0.686	0.682	0.666	0.686	0.672	0.681	0.664	0.671

Gdp coefficient has been multiplied by 1000 to facilitate interpretation. The dependent variable is the logged Co-movement (Weighted Degree). Co-movement is calculated using different filters as specified in each column. .
Significance level *p<0.1, ** p<0.05, *** p<0.01

Robustness of industrial Co-movement to selected filters - Filter: TI > 0.0016 & Corr >0.3

LHS: Co-movement (log)		(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
		2006		2007		2008		2009		2006		2007		2008		2009	
Industry	GDP	-0.0006		-0.0005		-0.0005		-0.0005		-0.0011	***	-0.0011	***	-0.0010	**	-0.0010	***
	Growth	0.7504	***	0.7329	**	-0.2311		-0.2884	*	0.8046	***	0.7675	***	-0.0900		-0.3136	*
	Employment	-0.0047		-0.0036		-0.0043		-0.0043		-0.0033		-0.0018		-0.0023		-0.0022	
	HHpart	6.9950	***	7.6628	***	8.0233	***	7.0908	***	5.6144	***	5.8346	***	5.9560	***	5.3064	***
Count	Open	0.0042	**	0.0042	**	0.0027		0.0040	*	0.0041	**	0.0042	**	0.0032	*	0.0043	*
	Population	0.0033	***	0.0037	***	0.0033	***	0.0033	***	0.0028	***	0.0030	***	0.0027	***	0.0028	***
Netw	OutDeg (Connectivity)									0.0027	***	0.0027	***	0.0025	***	0.0025	***
	Between (Centrality)	1.7613	***	1.6104	***	0.9834	***	1.1578	***								
	Secondary	1.0237	***	1.1114	***	1.0920	***	1.0941	***	0.9951	***	1.0762	***	1.0592	***	1.0652	***
	Tertiary	0.4850	**	0.5068	**	0.5525	***	0.5479	***	0.4570	**	0.4841	**	0.5151	**	0.5383	***
	Country F.E.	YES		YES		YES		YES		YES		YES		YES		YES	
	Industry F.E.	YES		YES		YES		YES		YES		YES		YES		YES	
	N	1139		1139		1139		1139		1139		1139		1139		1139	
	R-sq	0.541		0.538		0.529		0.528		0.548		0.550		0.542		0.539	

Gdp coefficient has been multiplied by 1000 to facilitate interpretation. The dependent variable is the logged Co-movement (Weighted Degree). Co-movement is calculated using different filters as specified in each column. .

Significance level *p<0.1, ** p<0.05, *** p<0.01