Applications of Network Analyses to Systemic Risk in Financial Systems and to Macroeconomic Growth and Volatility

A thesis submitted for the degree of Doctor of Philosophy

By

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Abstract

This thesis contributes to the applications of network analysis to the areas of macro-prudential policy and granular macroeconomics for GDP growth and volatility. Following the main introduction of the thesis, Chapter 2 investigates the properties of the global banking system flows, as a cross-border banking system, given by the BIS consolidated banking statistics. It contributes to the literature in two ways. First, by extending the systemic risk analysis in Markose et al (2017) to quantify the implied loss in case of failure of the systemically most important banking system. For this, I use the Eigen-pair method of Markose-Giansante with the maximum eigen-value yielding the systemic risk index and the right and left eigenvector centralities providing measures, respectively, for systemic importance and systemic vulnerability of banking systems. Second, by filling in major data gaps in the within country sectoral flow of funds in the BIS data, and analysing the sectoral cross-border flows (non-financial sectors across and within countries). In Chapter 3, a new and innovative approach based on the Ghosh inverse is used to quantify the falling in GDP growth given an increase in the financial sector share of gross operating profits to the detriment of other sectors of the economy. The final chapter builds on the Carvalho-Gabaix-Acemoglu approach of granular macroeconomics. It innovates by analysing the impact of sectoral final demand shocks on GDP volatility given the centrality of the sectors. This is compared with the Carvalho-Gabaix-Acemoglu approach of supply side productivity shocks. Both approaches show the growth of the financial sector centrality as a major contributor to GDP volatility.

Chapter 1

1.1 Introduction

Financial and trade liberalization are two of the most profound transformations of policy strategies in recent decades, whose impact has become the subject of the recent macroeconomic debate and research. One of the impacts of financial liberalization, along with the repeal of the US 1933 Glass–Steagall Act in 1999, is the Global Financial Crisis (GFC) (Arestis and Singh (2010)). The GFC originated with the US subprime mortgage market and was magnified by financial innovations such as credit default swaps and collateralized debt obligations (Arestis and Karakitsos (2009)). The problems of solvency of financial institutions with toxic assets spread to the rest of the financial system and to the real sector within the US, and to the rest of the world. This caused the Great Recession that cost taxpayers an unprecedented US$14 trillion (Alessandri and Haldane (2009)). Furthermore, the GFC has exposed shortcomings of mainstream macroeconomic models and their use for policy analysis (Markose (2013), Wieland (2010) and Blanchard (2018)). In fact, using this class of models both economists and financial market practitioners failed to predict the crisis (Lawson (2009)). Many critics argue that macroeconomists failed to foresee the crisis because of heavy reliance on a particular class of macroeconomic models that have abstracted away institutional details and financial interconnections in the provision of liquidity, capital adequacy and solvency (Wieland (2010), Colander (2008) and Markose (2013)). This led to the rethinking of the macroeconomic modelling, particularly with regard to the financial system. Haldane (2009) has renewed interest in the study of the economy as a complex network, emphasizing the need to model the interconnectedness of the financial system for systemic risk and contagion analysis for macro-prudential policy design. An approach to systemic risk at best should allow for (i) the definition of a metric that can identify if financial intermediation is becoming more or less unstable, (ii) the identification of systemically important institutions, (iii) the quantification of the domino effects in case of its failure and (iv) simulations for effective policy measures to mitigate the negative externalities of financial institutions (Markose (2012, 2013)).

In regard to the effects of the trade liberalization, the process of globalization of supply chains has led to the international integration of markets for goods, factors and technology (Slaughter and Swagel (1997)). This has led to the reorganization of production activities which can be modelled as a network at a global level. Phenomena such as offshoring has experienced non-trivial upward trend over the years in search of exploring low factor cost differentials (Bramucci (2016)). Defined as the reallocation of production processes abroad, either to a foreign affiliate or to an external supplier (Olsen (2006)), offshoring is reported to have increased in many OECD countries by 30% between 1970 and 1994 (Hummels et al (2001)); and in the UK it increased by 33% in 1984 and by 40% in 1995 (Hijzen et al. (2005)), while in the EU(27) it rose from 26% of value added in 1995 to 42% in 2008(Parteka and Derlacz (2013)).

Due to associated lower input prices, up to 2008, offshoring resulted in a cost saving in the range of 20% to 60% and higher profit margins and profits (Milberg and Winkler (2009)). However, evidence shows that the rise in profits fails to translate into capital investment in national economies that conducted the offshoring. This is because, since the 1980s, non-financial corporations have shifted in their investment strategies toward investing in financial instruments of various sorts, including shares buyback (Tomaskovic-Devey at al., (2015)), and toward maximising shareholder value (retaining net gains to shareholders and paying higher dividends) out of capital accumulation and long-term growth.

This event led to an impressive expansion of the financial sector and the arrogation of a very large percentage of corporate surpluses (over 60% in the US), underscoring the paucity of real investment in these economies and also the growing income inequality (Stockhammer, 2004). In fact, Johnson (2009) as cited in Moosa (2010) reports that from 1973 to 1985, the financial sector in the US earned less than 16 per cent of domestic corporate profit. However, in 1986, that figure reached 19 per cent, and then it fluctuated around 21 per cent during the 1990s. In the first decade of the 21st century it reached 41 per cent.

All this has instigated an extensive research on theoretical models and empirical examination on the effect of offshoring on macroeconomic variables, and on the re-assessment of the effects of financialisation on economic growth (Cecchetti and Kharroubi (2012, 2015)).

It is in this context that we develop this thesis with the three chapters dedicated to the major challenges faced by macroeconomics in dealing with the significance of the interconnectedness of the national economies within a global framework in which there are cross-border and within economy imbalances, mostly arising from the excessive growth of the financial sector in advanced economies like the US and UK. Each chapter contains an abstract and all the necessary literature, data analysis, results and conclusions. In Chapter 2 we model the global banking system network for 21 countries using BIS consolidated bilateral bank statistics and within country sectoral flow of funds data to investigate the systemically important banking system and quantify its contagion effect. We also investigate the early warning signal for the financial crisis using the Eigen-pair method of Markose-Giansante with the maximum eigenvalue approach yielding the systemic risk index for the global banking system measured as a percentage of loss of capital of the banking system. The right and left eigenvectors give the systemic risk and vulnerability indices for the individual banking systems, respectively. We find that financial interconnectedness in international financial markets increased over time, especially in the run up to the 2007 financial crisis. We show that the United States is systemically most important banking system in the cross-border setting. However, with the inclusion of the within country sectoral flow, we find that the US Non-Banking and the Public Sectors are the systemically important sectors. A failure of the US banking system would result in massive loss in terms of the aggregated 21 countries' total capital losses of their banking systems. Further, we find that the systemic risk index based on the network maximum eigenvalue provides useful information to foresee crisis.

In Chapter 3 we use ICIO and STAN input-output data for the US to yield a new approach based on the Ghosh inverse to quantify the falling wages in the most offshored sectors and increased financial sector share of gross operating profits to the detriment of other sectors of the economy. Our results suggest that a falling trend in wages over the period is associated with the sectors that have suffered offshoring. We also show that declining wage share has negative effect on total output growth. Further, we argue that increase in financial sector profits share relative to the rest of sectors of the economy has negative effect on total output.

In Chapter 4, we propose a demand driven GDP volatility measure and compare its performance with actual GDP volatility, and estimate the role of the financial sectors on GDP volatility given its centrality in the production network. We find that demand-driven GDP volatility explains about 60 per cent of actual GDP volatility measures, and it is able to replicate the most important swings in macroeconomic volatility, such as the Great Moderation and the relatively increased volatility from the mid-1990s up to 2007. More importantly we find that the surge in the centrality of the financial sector, particularly in the 1990s, was the main factor that determined the increased volatility up to 2007. In general, these results conform with the granular macroeconomic hypothesis on the relevance of idiosyncratic sectoral productivity shocks on aggregate volatility such as Gabaix (2011).

2 Chapter 2

A Macro Network of Financial Imbalances: A Cross-Border and Multi-Sector Analysis

Abstract

This study explores the properties and stability of cross-border bank exposures for 21 countries using bilateral data spanning 2005Q4 – 2013Q4, and within country sectoral flows of fund data between 2010 and 2013. The objective is to identify the systemically most important and vulnerable countries and sectors, and conduct a contagion analysis. Furthermore, the study also investigates whether the information contained in maximum eigenvalue systemic risk index provides an early warning signal for financial crisis. The main findings suggest that financial interconnectedness in international financial markets increased in the run up to the 2007 financial crisis and declined after the crisis. The United States banking system was the systemically most important one. A failure of the US banking system would result in massive loss amounting on average about 93% of the aggregated 21 countries' total capital of their banking systems. The sectoral data analysis including within country sectoral flows shows the US Non-Banking and the Public sector as the most systemically important. We also argue that maximum Eigenvalue systemic risk index provides useful information to foresee crisis.

Keywords: Networks, financial stability, contagion, cross-border analysis

2.1 Introduction

The 2007 Global Financial Crisis (GFC) started in the US sub-prime mortgage market and propagated rapidly to the entire global financial system and to the real sector within the US and to the rest of the world, causing the Global Great Recession. The GFC exposed the shortcomings of microprudential policies focusing on individual financial institutions, and underscored the importance of interconnections between financial institutions for contagion and system failure (Caruana (2010)) and Markose (2013)). This led to the area of macro-prudential policy which focuses on the stability and resilience of the macroeconomy and the financial system as whole, through an effective monitoring not just of the individual institution’s soundness, but also of national and a cross-border financial surveillance of the risk and vulnerabilities implied by direct and indirect financial linkages (Espinosa-Vega and Solé (2010)).

The financial network analysis has been recommended by Allen and Babus (2009) and Haldane (2009) as a powerful tool for macroprudential policy analysis and design, to yield a holistic picture that characterizes the financial markets and their interconnectedness and impact on the real economy. The financial network approach to systemic risk at best should allow for (i) the definition of a metric that can identify if financial intermediation is becoming more or less unstable, (ii) the identification of systemically important institutions, (iii) the quantification of the domino effect in case of its failure and (iv) simulation for effective policy measures to mitigate the negative externalities of financial institutions (Markose (2012) and BoE (2010)).

The operationalization of the financial network for systemic risk analysis requires the identification of the adequate network metrics to determine the stability of the financial network and what financial institution is contributing to instability, and to provide an early warning signal in the run up to crisis. Of the numerous financial networks-based methods that have been developed for systemic risk analysis, we adapt the Eigen-pain method proposed by Markose (2012, 2013) in a cross-border macro-net framework that was first proposed by Castrén and Rancan (2014). Markose (2012, 2013) shows that this measure are superior to the market data-based methods for systemic risk modeling[1] which are found to run into the so called paradox of instability (Borio and Drehmann (2009), Minsky (1982)) that underscores the need to focus on a network model of direct financial exposures and obligations.

However, empirical research analysing whether the proposed systemic risk and vulnerability indexes can give early warning signal of financial crisis is still limited. Also limited is the research on the cross-border financial transactions, and the analysis of cross-country multi-sectoral financial transactions, combining the cross-border banking system exposures with flows of funds between sectors within countries. The lack of cross-border bilateral data has been pointed out as one of the most important constraints.

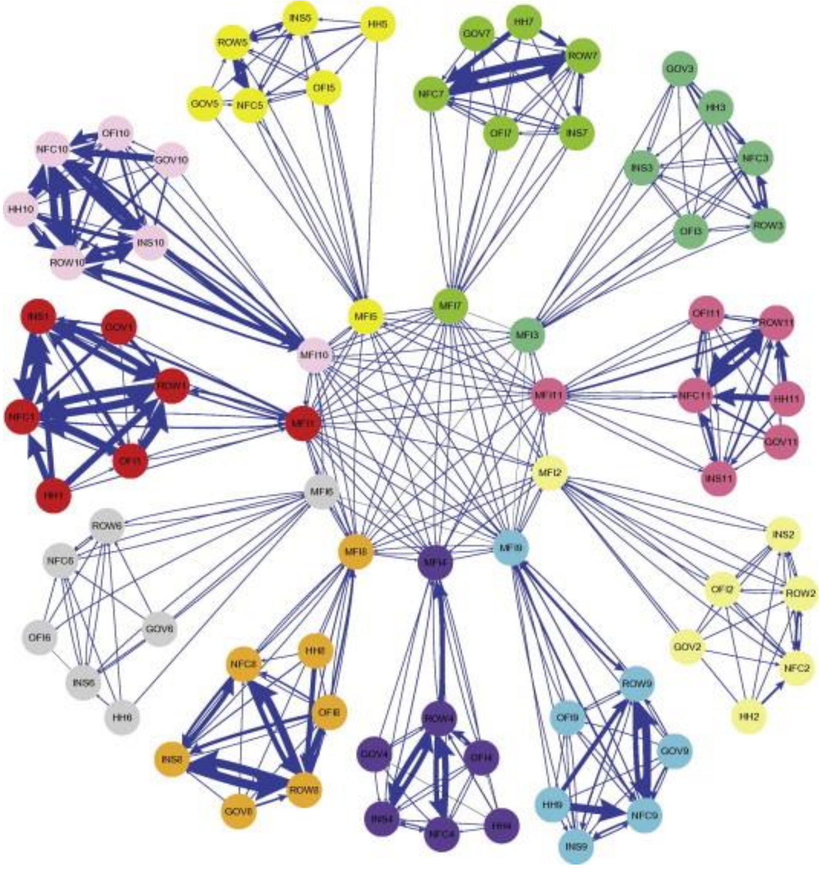
Against this background, the objective of the study is to re-examine the properties and stability of cross-border bank exposures for 21 countries using bilateral data spanning 2005Q4 – 2013Q4, as in Markose et al (2017) and within countries sectoral flows of funds between 2010

[1] The main market-based systemic risk measures that have been proposed are Conditional VaR (CoVaR) by Adrian and Brunnermeier (2009), System Expected Shortfall (SES) by Acharya et al. (2010), Co-risk by Chau-Lan (2010), DIP (Distress Insurance Premium) by Huang et al. (2010), POD (Probability that at least one bank becomes distressed) by Segoviano and Goodhart (2009), Shapley-Value by Tarashev et. al. (2010) and Macro-prudential capital by Gauthier et. al (2009) as cited by Markose (2012, 2013).

and 2013 as Castrén and Rancan (2014). This study identifies both the systemic risk most important and most vulnerable countries and sectors, and conducts a contagion analysis. Furthermore, it investigates the information content in the maximum eigenvalue based systemic risk index as early warning signal for financial crisis. This study also tests whether the vulnerabilities of the Euro Area periphery countries (Portugal, Ireland, Greece and Spain) that were severely affected by the crisis could have been identified well before 2007 in terms of network properties. However, this study differ from Markose et al (2017) by o quantify implied loss in case of the failure the systemically most important banking system, and by filling in major data gaps in the within country sectoral flow of funds in the BIS data, and analysing the sectoral cross-border flows (non-financial sectors across and within countries). In addition, while Castrén and Rancan (2014) macro-net is based on some confidential data, this study uses flow of funds public available data.

The within countries sectoral flows of funds data analysis and the notion of macro-net used in this study follows from Castrén and Rancan (2014), as depicted in Figure 2.1.

Figure 2.1 : Macro-net for the Euro Area

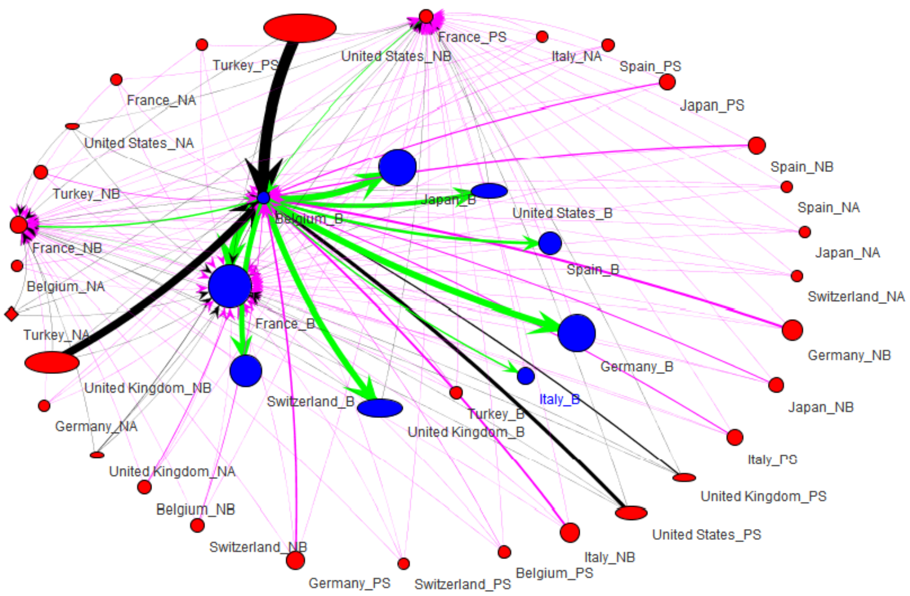


Source: Castren-Rancan (2014)

Figure 2.1 shows the Macro-Network of eleven Euro area countries. The nodes in the centre are the national banking systems with the hub denoting data similar to the BIS consolidated cross-border banking flows. The nodes radiating from the national banking system are the other sectors of the economy of each country: the non-financial corporations (NFC), the banks (monetary financing institutions, MFI), the insurance and pension fund companies (INS), the other financial intermediaries (OFI), the general government (GOV), the households (HH), and the rest of the world (ROW). The numbers and the colours refer to the countries. This study develops a similar cross-border macro-network to the one first proposed by Castrén and Racan (2014) using publicly available data.

It is worth noting that the sectoral BIS data that used in this study, yield Figure 2.2 (for 2010Q4 data) with missing within country sectoral flows of funds. In this study we fill this gap using countries' flows of funds data to yield a complete macro-network similar to the model suggested by Castrén and Rancan (2014), for 10 countries: Belgium, France, Germany, Italy, Spain, Switzerland, Turkey, and the US, UK and Japan.

Figure 2.2 : Macro-net for the Euro Area



Source: Plotted by author using BIS consolidated sectoral banks statistics for 2010.

The rest of the paper is organised as follows: Section 2.2 presents the theoretical and empirical literature review; Section 2.3 the methodology for the financial network, contagion and the stability Analysis, while Section 2.4 is reserved for the empirical results. Finally, Section 2.5 presents the summary and conclusions of the study.

2.2 Theoretical and Empirical Literature Review

This section is divided into two parts. Section 2.2.1 presents the theoretical economic literature, and section 2.2.2, the interbank network and cross-border empirical literature. The objective is to provide a holist view of the developments in the theoretical and empirical sphere on financial network modeling.

2.2.1 Theoretical Economic Literature

Modern financial systems are characterized by a complex network, with connections between financial institutions stemming from both the asset and the liability sides of their balance sheets (Allen and Babus (2009)). This makes the financial network a powerful macropudential policy tool for systemic risk and contagion analysis implied by national and cross-border direct and indirect linkages. However, the theoretical literature on financial network, particularly on the importance of interconnectedness for financial stability and contagion, focuses on interbank markets and presents mixed results.

For instance, early research by Allen and Gale (2000) investigates the effect of different interbank network structures in propagating shocks. They show that if the market is complete and each bank is connected to all others, and each bank's total exposure is equally divided among its counterparties, then risk is shared equally at a very small rate. Therefore, the failure of a single counterparty has a very small impact on the system, suggesting that better connected networks are more resilient. In contrast, in an incomplete network where each bank is exposed to only one other for the total of its receivables, then the failure of any bank in the circle will trigger the failure of the entire banking system. Babus (2016) also investigating the effect of high interbank market connectivity on contagion, argues that increased connectivity enhance stability, as banks form links with each other as an insurance mechanism to reduce the risk of contagion. Similar results are also presented in Castiglionesi and Navarro (2007), Freixas et al. (2000), Gai and Kapadia (2010).

However, Battiston et al (2010), studying whether the financial network architecture can make the financial system more resilient to global crises, finds a non-linear relationship between increased connectivity system stability. Battiston et al (2010) argues that a financial network can be more resilient for intermediate levels of risk diversification up to a certain point, beyond which connectivity in network increases instability. Although the theory does not provide a clear identification of the threshold, there is almost a consensus that applying network theory to financial systems is a useful approach to evaluate systemic risk and test for contagion analysis.

2.2.2 Interbank and Cross-border Empirical Literature

There is an extensive empirical literature on financial network, but it is mainly concentrated on the analysis of interbank market inter-linkages and their importance as a channel of contagion. Most of the research uses balance sheet information to estimate bilateral credit relationships for different banking systems, and then tests the stability of the system by triggering one bank default. This includes Angelini et al (1995) and Mistrulli (2010) who assess the potential size of contagion in the Italian interbank market, Wells (2002) who studys interbank exposures on the UK, Upper and Worms (2004) on Germany, and Furfine (2003) on the US. Some of these studies are based on observed interbank bilateral data and others on maximum entropy method in light of bilateral data unavailability. The main results seem to agree that interconnection plays a key role for contagion.

The literature on cross-border bank exposure includes Von Peter (2007), Hattori and Suda (2007), Degryse et al (2010), Allen et al (2011), Minoiou and Reyes (2013) and Castrén and Rancan (2014). In general this research is based on the cross-border bilateral data provided by the Bank of International Settlements (BIS), and in some exceptions, on the maximum entropy methodology to overcome the data limitations problem. The main findings show that the network of cross-border bank exposures has become more tightly connected over time and systemic risk in international markets is likely to increase, reflecting increased connectivity and clustering, and allowing for more widely spread spillover effects across countries. However, connectivity tends to fall during and after systemic banking crisis and sovereign debts.

Von Peter (2007) investigates the topological properties of the global networks based on BIS locational bank statistics. Using centrality measures such as degree, closeness, betweenness and weighted centrality, the author has highlighted the core-periphery structure in global banking network, with the UK and US as the main international banking centres that can explain the market share dominance in attracting foreign deposits. Although Von Peter (2007) does not explore the network property in terms of early warning signal for instability, this study evidence how a financial network approach might be used in assessing the soundness of international banking centres.

Also using BIS locational bank statistics, Minoiu and Reyes (2013) analyse the global banking network metrics of centrality, connectivity and clustering, using cross-border bank lending data for 184 countries over the period 1978-2009. They find that the global banking network was relatively unstable, exhibiting structural breaks in network indicators resulting from several waves of capital flows. Further, they show that connectivity tend to fall during and after systemic banking crisis and sovereign debts. However, they stress out that although connectivity may be important for shock contagion, other factors such as the location of the initial shock to the core of the network, have contributed to the severity of the 2007 financial crisis.

The pro-cyclical behaviour of global connectivity evidenced in Minoiu and Reyes (2013), is also observed in market price based measure of systemic risk such as the Conditional VaR (CoVaR) proposed by Adrian and Brunnermeier (2009), System Expected Shortfall (SES) by Acharya et al. (2010), Co-risk by Chau-Lan (2010), DIP (Distress Insurance Premium) by Huang et al. (2010), POD (Probability that at least one bank becomes distressed) by Segoviano and Goodhart (2009), a phenomenon that became known as the paradox of volatility (Minsky, 1982) or financial instability by Borio and Drehman (2009). Indeed, Markose (2012, 2013) shows that this models underestimate the risk (volatility) ruling the market price booms, when systemic risk is building up on the balance sheets of the financial and non-financial institutions, underscoring the need to focus on a network model of direct financial exposures and obligations.

Models on network of direct financial exposures include Hattori and Suda (2007) that investigate cross-border network topology using BIS international banking statistics on cross-border bank exposures over the period 1985 – 2006. They show that the cross-border network of bank exposures has become more tightly connected over time. It is now characterized by higher connectivity, a shorter average path length, a higher average degree and higher clustering coefficient than in the past. However, Hattori and Suda (2007) expect systemic risk in international markets to increase, but also the efficiency of international financial markets in terms of capital and risk allocation.

Conforming with Hattori and Suda (2007), Degryse et al (2010) analysing cross-border exposures contagion risk over the period 1999-2006, using BIS consolidated statistics for 17 countries, show increased density of the banking system in recent years and increased speed of propagation of contagion, where a shock to a single country's liabilities may threaten the stability of the entire financial system. Degryse et al (2010) shows that the potential failure of the US banking system represents the most devastating contagion effect. For instance, the study shows that a shock eroding 25% (35%) of US (UK) cross-border liabilities against non-US (non-UK) banks could lead to bank domino losses of at least 94% (45%) of the counterparty countries' banking assets.

Similar results on connectivity dynamics over time are found by Castrén and Rancan (2014). Using data from the Euro Area flows of fund statistics, for 11 countries that corresponding to 77 sector level over 199Q1 to 2012Q1. Castrén and Rancan (2014) pioneer macro-network analysis that depicts the linkages across financial and non-financial sector of each country and between the country-level sector networks through the individual banking sectors. Their results suggest that the propagation effects of any financial shocks depend on the underlying network structure, which evolves over time. Furthermore, they show that connectivity increased in the run up to the 2007 and contracted sharply after the financial crisis, reflecting the surge in counterparty risk and the de-leveraging process. However, Castrén and Rancan (2014) argue that even after this process, vulnerabilities remained in the euro area financial system.

2.3 Financial Network analysis Methodology

2.3.1 The Theoretical Framework for Network Analysis

As in Markose (2012), Markose et al (2012, 2017) and Degryse et al (2010), we define the global financial system as network G containing a pair of finite sets (N, E) . Where $N = \{1, 2, ..., n\}$ is a set of nodes and E , the set of links (edges) connecting one node to others. We built a directed weighted network where each of banking system of BIS reporting countries, referred simply as banking system (or sectors) analysed in this study, represent a node, and each link (edge) the directional borrowing/lending relationship between two reporting country's banking systems. The direct link from banking system i to banking system j stands for banking system j contractual obligation (liabilities) to make payments to banking system i and banking system i's right to receive payments (a claim) from j . These links are also known as "out" and "in-degree", respectively.

The bilateral relationship between banking system of BIS reporting countries, identified as foreign claims of the baking system of BIS reporting country i of the borrower banking system in reporting country i can be represented by $N \times N$ gross flow matrix $\mathbf{X}$ defined as

$$
\begin{array}{c|c}
 & \Gamma = \sum_i G_i \\
X = \begin{bmatrix} 0 & x_{12} & x_{13} & ..x_{ij}. & .... & x_{1N} \\ x_{21} & 0 & x_{23} & .... & .... & x_{2N} \\ . & . & 0 & .... & .... & . \\ x_{i1} & . & . & 0 & & x_{iN} \\ . & . & . & & 0 & \\ x_{N1} & . & . & x_{Nj} & ... & 0 \end{bmatrix} & \begin{array}{c} G_1 \\ G_2 \\ . \\ G_i \\ . \\ G_N \end{array} \\
\Phi = \sum_j B_j \quad B_1 \quad . \quad . \quad B_j \quad .... \quad B_N N &
\end{array}
\qquad (2.2)
$$

Where x_{ij} are the flows of gross liabilities of banking system of country i to the banking system of country j. $G_i = \sum_j x_{ij}$ is the total foreign liabilities of country i's banking system over j counterparties. $B_i = \sum_i x_{ij}$, represents the total gross foreign claims (receivables) of banking system of the BIS reporting country j taken across the i rows. Since the country's banking system does not lend to itself, x_{ii} and x_{jj}, the diagonal entries are equal to zero.

The equivalent netted matrix is given by $\mathbf{M}$ with entries $m_{ij} = (x_{ij} - x_{ji})$ that represent the netted positions between banking system (sector) *i* and *j*. Where $m_{ij} > 0$ ($m_{ij} < 0$), in row *i* indicates banking system i's net financial claims (liabilities) against the banking system of country *j*. The sums of positive entries ($m_{ij} > 0$) denoted by $\sum_j (x_{ij} - x_{ji})^+$ and of the negative entries ($m_{ij} < 0$), denoted by $\sum_j (x_{ij} - x_{ji})^-$ for all banking system *i*, correspond to the total bilaterally netted financial claims and liabilities across counterparties, respectively.

The matrix $\mathbf{M}$ is a skew symmetric with entries $m_{ij}^+ = m_{ji}^-$. For the contagion dynamics analysis across the reporting countries' banking system, we consider as in Markose (2012) the positive entries, the matrix $\mathbf{M}^+$. Since $m^+ = (x_{ij} - x_{ji})^+$ is the netted position between banking system of country i and j, the causal direction of the contagion and the systemic risk a country's banking system, follows from the failed ("triggered") banking system i, owing its counterparty j more than country j owes to i's banking system.

Then, the matrix $\mathbf{\Theta}$ shows the positive entries for net foreign liabilities from country i to j relative to country j's capital, that is $\theta_{ij} = \frac{(x_{ij} - x_{ji})^{+}}{C_{j^0}}$.

$$
\Theta = \begin{bmatrix}
0 & \frac{(x_{12}-x_{21})^{+}}{C_{20}} & \frac{(x_{13}-x_{31})^{+}}{C_{30}} & 0 & \dots. & 0 \\
0 & 0 & \frac{(x_{23}-x_{32})^{+}}{C_{30}} & \dots. & \dots. & \frac{(x_{3N}-x_{N3})^{+}}{C_{N0}} \\
. & . & 0 & \dots. & \dots. & . \\
\frac{(x_{i1}-x_{1i})^{+}}{C_{10}} & . & \dots & 0 & \dots & \frac{(x_{iN}-x_{Ni})}{C_{N0}} \\
. & . & \dots & \dots & 0 & . \\
\frac{(x_{N1}-x_{1N})^{+}}{C_{10}} & . & \dots & \frac{(x_{Nj}-x_{jN})^{+}}{C_{j0}} & \dots & 0
\end{bmatrix} \tag{2.3}
$$

2.3.2 Generalization to Include Within Country Sectoral Flow of Funds

The BIS sectoral cross-border data over 2010-2013 does not provide the exposures of the reporting countries' banking system to sectors within countries. For the Macro-network in this study we fill the gap by using countries' Flows of Funds statistics. The sectoral BIS bilateral statistics can be represented by matrix $\mathbf{\Psi}$ in (2.11)

$$
\boldsymbol{\Psi} = \begin{vmatrix}
0 & 0 & \cdots & 0 & x^1_{11,2} & x^1_{12,2} & \cdots & x^1_{1N,2} & x^1_{11,N} & x^1_{12,N} & \cdots & x^1_{1N,N} \\
0 & 0 & \cdots & 0 & x^1_{21,2} & x^1_{22,2} & \cdots & x^1_{2N,2} & x^1_{21,N} & x^1_{22,N} & \cdots & x^1_{2N,N} \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & \cdots & 0 & x^1_{N1,2} & x^1_{N2,2} & \cdots & x^1_{NN,2} & x^1_{N1,N} & x^1_{N2,N} & \cdots & x^1_{NN,N} \\
x^2_{11,1} & x^2_{12,1} & \cdots & x^2_{1N,1} & 0 & 0 & \cdots & 0 & x^2_{11,N} & x^2_{12,N} & \cdots & x^2_{1N,N} \\
x^2_{21,1} & x^2_{22,1} & \cdots & x^2_{2N,1} & 0 & 0 & \cdots & 0 & x^2_{21,N} & x^2_{22,N} & \cdots & x^2_{2N,N} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\
x^2_{N1,1} & x^2_{N2,1} & \cdots & x^2_{NN,1} & 0 & 0 & \cdots & 0 & x^2_{N1,N} & x^2_{N2,N} & \cdots & x^2_{NN,N} \\
x^N_{11,1} & x^N_{22,1} & \cdots & x^N_{2N,1} & x^N_{11,2} & x^N_{12,2} & \cdots & x^N_{1N,2} & 0 & 0 & \cdots & 0 \\
x^N_{21,1} & x^N_{22,1} & \cdots & x^N_{2N,1} & x^N_{21,2} & x^N_{22,2} & \cdots & x^N_{2N,2} & 0 & 0 & \cdots & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
x^N_{N1,1} & x^N_{N2,1} & \cdots & x^N_{NN,1} & x^N_{N1,2} & x^N_{N2,2} & \cdots & x^N_{NN,2} & 0 & 0 & \cdots & 0
\end{vmatrix}
$$

(2.4)

Where $x^p_{ij,r}$ are the flows of gross liabilities of sector i of country p to the sector j of country r. As in matrix (2.2), we assume that the diagonal entries are equal to zero. That each of sectors within a country does not lend to itself. The matrix (2.3) also does not provide links between within countries sectors, as the entries $x^p_{ij,p}$ and $x^r_{ij,r}$ are equal to zero. Thus, to form a complete Macro-network we extend this matrix to include non-zero values of $x^p_{ij,p}$ and $x^r_{ij,r}$ entries, using countries' Flows of Funds statistics, such that matrix 2.11, can be expressed as,

$$
\boldsymbol{\Psi}^* = \begin{vmatrix}
0 & x^1_{12,1} & \cdots & x^1_{1N,1} & x^1_{11,2} & x^1_{12,2} & \cdots & x^1_{1N,2} & x^1_{11,N} & x^1_{12,N} & \cdots & x^1_{1N,N} \\
x^1_{21,2} & 0 & \cdots & x^1_{2N,1} & x^1_{21,2} & x^1_{22,2} & \cdots & x^1_{2N,2} & x^1_{21,N} & x^1_{22,N} & \cdots & x^1_{2N,N} \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
x^1_{N1,1} & x^1_{N2,1} & \cdots & 0 & x^1_{N1,2} & x^1_{N2,2} & \cdots & x^1_{NN,2} & x^1_{N1,N} & x^1_{N2,N} & \cdots & x^1_{NN,N} \\
x^2_{11,1} & x^2_{12,1} & \cdots & x^2_{1N,1} & 0 & x^2_{12,2} & \cdots & x^2_{1N,2} & x^2_{11,N} & x^2_{12,N} & \cdots & x^2_{1N,N} \\
x^2_{21,1} & x^2_{22,1} & \cdots & x^2_{2N,1} & x^2_{21,2} & 0 & \cdots & x^2_{2N,2} & x^2_{21,N} & x^2_{22,N} & \cdots & x^2_{2N,N} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\
x^2_{N1,1} & x^2_{N2,1} & \cdots & x^2_{NN,1} & x^2_{N1,2} & x^2_{N2,2} & \cdots & 0 & x^2_{N1,N} & x^2_{N2,N} & \cdots & x^2_{NN,N} \\
x^N_{11,1} & x^N_{22,1} & \cdots & x^N_{2N,1} & x^N_{11,2} & x^N_{12,2} & \cdots & x^N_{1N,2} & 0 & x^N_{12,N} & \cdots & x^N_{1N,N} \\
x^N_{21,1} & x^N_{22,1} & \cdots & x^N_{2N,1} & x^N_{21,2} & x^N_{22,2} & \cdots & x^N_{2N,2} & x^N_{21,N} & 0 & \cdots & x^N_{2N,N} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
x^N_{N1,1} & x^N_{N2,1} & \cdots & x^N_{NN,1} & x^N_{N1,2} & x^N_{N2,2} & \cdots & x^N_{NN,2} & x^N_{N1,N} & x^N_{N2,N} & \cdots & 0
\end{vmatrix}
$$

(2.4)

Then, we analyse the network topology, identify the most systemically important within country sectors, networks, and test for the contagion effects given by triggering the top most systemically most important sectors.

To characterise the network, we compute various network statistics that identify the number and strength of the relationships between the nodes (countries), the main lenders and borrowers, and the dynamic of these relationships is over time. This statistics include degrees, connectivity, clustering coefficients and eigenvector centrality.

Following Markose et al (2012) and Minoiu and Reyes (2013), Degree is a number of links that connects each country to others. When a link originates from country i to j it represents an out-degree (foreign claim) for country i and in-degree for country j (liabilities). Each country's out-degrees and in-degrees are expressed, respectively, as:

$$k_i^{out} = \sum_{j \in \vartheta(i)} a_{ij} \tag{2.5}$$

Where the sums run over the set $\vartheta(i)$ of neighbours i, i.e $\vartheta(i) = \{j | a_{ij} = 1\}$, and

$$k_j^{in} = \sum_{i \in \varsigma(j)} a_{ij} \tag{2.6}$$

Where the sums run over the set $\varsigma(j)$ of neighbour i, i.e. $\varsigma(j) = \{j | a_{ij} = 1\}$.

Connectivity is the number of connected links as a share of total possible links. According to Minoiu and Reyes (2013) and Markose (2012) it represents the likelihood of any two countries (nodes) in a network to be connected, such that:

$$Conect = \frac{\psi}{N(N-1)} \tag{2.7}$$

Here, ψ is for the number of the existing links, that represents the θ^{+} in the matrix $\mathbf{\Theta}$, and $N(N-1)$ is the total possible direct links.

One other indicator is the clustering coefficient. This shows how each country's direct counterparties are interconnected with one another. The assumption underlying this measure is that there should be an increased likelihood for two countries that share common counterparty to be connected (Markose et al (2012)). Thus, the clustering coefficient (CC) can be expressed as:

$$CC = \frac{L_i}{k_i(k_i-1)} \tag{2.8}$$

The numerator denotes the number of existing links between country i's direct counterparties, and the denominator is the total number of possible country i's counterparties direct links between them.

Other important network metrics are the systemic risk and country vulnerability indexes based on eigenvector centrality. Markose (2012) and Markose et al (2012) show that eigenvector centrality measure is correlated with loss stemming from stress test based on Furfine (2003). According to Markose (2012) eigenvector centrality assigns relative centrality scores to all nodes in the network given the importance of their neighbours in the global connectivity, in such a way that a node that is connected to very important or high-scoring nodes tend to be more important than a node with the same number of connections but to low-scoring nodes. Thus, Markose et al (2012) show that the higher the centrality of a given financial institution the larger is the loss implied by its failure to the system.

Leting $\tilde{\upsilon}_i$ be the right eigenvector centrality for the i^{th} node for matrix $\mathbf{\Theta}$, the centrality score is proportional to the sum of the centrality scores of all nodes to which it is connected (i.e., out-degree), such that:

$$\tilde{\upsilon}_i = \frac{1}{\lambda} \sum_j \boldsymbol{\theta}_{ij} \tilde{\upsilon}_j \qquad (2.9)$$

For the centrality measure (2.9), the largest eigenvalue, λ_{max}, and its associated eigenvector are considered, such that the i^{th} component of this eigenvector gives the centrality score of the i^{th} node in the network. Using vector notation, the eigenvalue equation for the matrix for the eigen-pair (λ_{max}, $\tilde{\boldsymbol{\upsilon}}_1$) is given as:

$$\mathbf{\Theta} \tilde{\boldsymbol{\upsilon}}_1 = \lambda_{max} \tilde{\boldsymbol{\upsilon}}_1 \qquad (2.10)$$

Where, right eigenvector of matrix $\mathbf{\Theta}$ given in Equation 2.10 is the country's systemic risk index – it measures the impact of the country's total liabilities relative to the respective capital of each of its counterparties. This is given by the row sums of matrix $\mathbf{\Theta}$ on the stability of the system characterized by the maximum eigenvalue. The left eigenvector of $\mathbf{\Theta}$ matrix, $\boldsymbol{\upsilon}_1$ is defined as

$$\boldsymbol{\upsilon}_1\boldsymbol{\Theta} = \boldsymbol{\Theta}'\boldsymbol{\upsilon}_1 = \lambda_{\max}\boldsymbol{\upsilon}_1 \tag{2.11}$$

The left eigenvector centrality is the vulnerability index, it measures the impact of the exposures of each country to others. Note both the left and right eigenvectors yield the same maximum eigenvalue for the matrix $\boldsymbol{\Theta}$.

2.3.3 Contagion and Stability Analysis

The contagion analysis in this study is based on the Furfine (2003) methodology as applied by Markose (2012) and Degryse et al (2010). Assuming no novation in credit contracts and a zero recovery rate on trigger country's liabilities, the sequential algorithm for simulating contagion from Furfine (2003) starts with a failure of the trigger country i that fails at time 0. Then the effects are transmitted to the system by the failure of its direct counterparty, country j, if j's net losses from i, taken as a ratio of j's capital is greater than a threshold ρ, such that:

$$\frac{(x_{ij} - x_{ji})^{+}}{C_j} > \rho \tag{2.12}$$

Where ρ is the percentage of bank capital that can be regulated as specifically to be held to buffer losses in these countries. ρ is assumed equal to 0.06, and to be the same for all bank in all countries[2].

[2] Where 6% is the Basel III capital ratio of 6% for risk weighted assets, i.e. Tier1 Capital has to be higher than 6% of RWA.

If the losses incurred by country z from i and j's default are less than ρ then the country survives to the second-round effect of contagion, such that $z \notin D^1$. In this round the contagion effect follows if there are some countries/banking systems that did not fail in the first round, it suffer losses due to counterparty failure such that the net losses are greater than a proportion ρ of its capital:

$$\frac{[(x_{iz} - x_{zi})^+ + \sum_{j \in D^1} (x_{jz} + x_{zj})]}{C_z} > \rho \tag{2.13}$$

The summation term aggregates the net loss suffered by z from all countries j, $j \neq i$, which demised in the first iteration. Following Markose et al (2012) this then interacts to the *qth* round of defaults if there is some country/sector v, $v \notin D^1 \cup D^2 \ldots \cup D^{q-1}$, that is, has not failed till $q-1$, such that:

$$\frac{\left\lfloor (x_{iv} - x_{vi})^+ + \sum_{j \notin \cup_s^{q-1}} (x_{jv} - x_{vj}) \right\rfloor}{C_v} > \rho \tag{2.14}$$

The contagion is assumed to have ended at the round $q^{\#}$ when there are no more countries left or none of those that have survived fail at $q^{\#}$.

2.3.4 Network stability analysis

Based on Markose (2012) and Markose et al (2012), the dynamics of the contagion and rate of failure of country i's banking system from failure of the trigger bank system can be given as,

$$\mathbf{U}_{iq+1} = (1-\rho)u_{iq} + \sum_j \frac{\left(x_{ji} - x_{ij}\right)^+}{C_{i0}} u_{jq}^1 = \left(1-\rho\right)\left(1 - \frac{C_{iq}}{C_{i0}}\right) + \sum_j \frac{\left(x_{ji} - x_{ij}\right)^+}{C_{i0}} u_{jq}^1, \quad 0 < u_{jq+1} < 1.$$

(2.15)

Where u_{iq} is the probability of a banking system i being 'infected' at the qth-iteration. The $u_{iq} = 1 = u_{iq}^1$ represents the banking systems that fail at the qth iteration and infect all non-failed counterparties with probability 1. The initial probability of failure is assumed to be $u_{i0} = 1/C_{i0}$ while $u_{iq} = 1-(C_{iq}/C_{i0})$. That is, the probability of failure is determined by the rate at which country i's banking system capital is depleted by losses from failed counterparty countries. The matrix notation of the dynamics of bank system failures is given by:

$$\mathbf{U}_{q+1} = \left[\mathbf{\Theta}' + \left(1-\rho\right)\mathbf{I}\right]\mathbf{U}_q. \tag{2.16}$$

Here, $\mathbf{\Theta}'$ is the transpose of the matrix in (2.2) with each element $\mathbf{\theta}_{ij}' = \mathbf{\theta}_{ji}'$ and $\mathbf{I}$ is the identity matrix. The system stability of (2.16) is evaluated on the basis of the power iteration of the initial matrix

$$\mathbf{Q} = \left[\mathbf{\Theta}' + \left(1-\rho\right)\mathbf{I}\right] \tag{2.17}$$

Thus, $\mathbf{U}_q$ takes the form:

$$\mathbf{U}_q = \left[\mathbf{\Theta}' + \left(1-\rho\right)I\right]^q \mathbf{U}_0 = \mathbf{Q}^q \mathbf{U}_0 \tag{2.18}$$

Markose et al (2013) show that the stability of the system is defined by the maximum eigenvalue of the initial matrix (2.16) which requires that the conditions $\lambda_{\max}(\mathbf{Q}) < 1$ and

$\lambda_{\max}(\boldsymbol{\Theta}') < \rho$ are satisfied. If these conditions are not satisfied the system is considered instable, and any shock can propagate though the system as a whole and cause system failure.

2.4 Empirical Results

2.4.1 Data and Source of Data

This study uses consolidated cross-border banking statistics on ultimate risk basis from the international banking statistics published by Bank of International Settlements (BIS)[3]. This data includes the country level data on 21 countries[4] over 2005Q4-2013Q4, and sectoral data on 10 countries[5] with 4 sectors (Banking, Non-banking[6], Public and Non-Allocated) covering the period from 2010-2013. In the BIS statistics this data corresponds to Table 9D and 9C, respectively[7]. The data represents foreign claims and other exposures of the reporting countries' banking systems to all the sectors of other countries. Since the BIS sectoral cross-border data over this period does not provide the exposures of the reporting countries' banking system to sectors within countries', this study fills this gap by using countries' flows of funds statistics. In the present analysis we consider within countries' flows of funds data, for the US, the UK and Euro Area given the data unavailability.

[3] The BIS international banking statistics (IBS) comprise the following two data sets: The *Locational banking statistics (LBS)*, which measure claims and liabilities, including inter-office positions, of banking offices resident in reporting countries. These statistics are reported using principles that are consistent with balance of payments methodology. The *Consolidated banking statistics (CBS)*, measure worldwide consolidated claims of banks headquartered in reporting countries, including claims of their own foreign affiliates but excluding inter-office positions. These statistics build on measures used by banks in their internal risk management systems. Both sets of statistics are reported at a country rather than individual bank level; https://www.bis.org/statistics/bankstatsguide.pdf

[4] Australia, Austria, Belgium, Canada, Chile, Finland, France, Germany, Greece, India, Ireland, Italy, Japan, Netherlands, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States of America.

[5] Belgium, France, Germany, Italy, Japan, Spain, Switzerland, Turkey, United Kingdom and United States of America.

[6] The non-banking private sector, in the BIS sectoral classification refers collectively to non-financial corporations and households, i.e. the non-financial sector excluding general government. https://www.bis.org/statistics/glossary.htm?&selection=278&scope=Statistics&c=a&base=term

[7] https://www.bis.org/statistics/consstats.htm. Recent updates show that Tables 9C and 9D are now denominated B3 and B4 as describe in https://www.bis.org/statistics/annex_map.htm

The data on banking system equity capital is collected from the Bankscope statistics. The level and dynamic of countries' banking system equity capital is fundamental for risk and vulnerability analysis, as it is related to the ability of the banking system to absorb negative shocks. Table 2.1 presents the capital for the 21 countries. As shown, the level of capital follows an upward trend over time with the US, Japan and United Kingdom holding on average 32 per cent, 12.9 and 12.08 per cent of the global capital, respectively. Note that in 2011Q4 and 2012Q4 the Greek banking system has negative capital in light of the sovereign debt crisis.

Table 2.1 Level of Equity Capital

	2005Q4	2006Q4	2007Q4	2008Q4	2009Q4	2010Q4	2011Q4	2012Q4	2013Q4
Australia	32.34	87.95	122.51	131.78	166.24	208.68	231.88	247.48	233.18
Austria	63.54	101.35	140.29	132.80	140.09	147.58	140.02	154.06	126.68
Belgium	110.41	141.96	194.46	129.20	156.42	153.27	126.39	149.26	134.67
Canada	94.27	105.23	141.33	121.23	145.24	344.20	383.93	428.90	424.15
Chile	0.96	1.13	0.76	15.65	22.75	26.94	32.66	40.26	36.24
Finland	24.07	30.86	31.99	31.04	34.77	34.03	33.83	33.84	36.97
France	401.32	599.36	722.65	730.05	903.06	944.18	927.38	992.83	922.35
Germany	247.19	439.17	682.41	595.21	869.94	867.05	914.19	1019.11	508.50
Greece	13.12	21.81	37.21	31.90	39.64	33.72	**-3.32**	**-8.21**	35.86
India	49.86	59.09	95.62	90.12	121.26	149.39	155.35	170.19	153.36
Ireland	37.89	53.68	64.76	46.03	52.84	49.41	77.92	73.86	55.22
Italy	223.98	321.18	410.66	391.29	447.86	433.96	397.70	423.61	388.24
Japan	673.06	724.70	953.90	874.32	1239.56	1485.10	1674.03	1644.61	1115.34
Netherlands	166.61	223.83	320.47	226.19	287.63	282.31	275.80	289.54	264.09
Portugal	19.39	29.46	35.51	31.34	41.42	36.10	33.54	43.33	42.11
Spain	124.90	163.36	213.89	239.90	289.77	319.49	323.49	321.77	385.82
Sweden	49.16	67.77	82.17	75.87	95.44	108.07	112.63	126.01	133.45
Switzerland	179.67	225.77	258.17	230.65	250.46	288.37	293.93	312.92	317.10
Turkey	26.13	36.70	65.41	70.20	90.37	105.83	98.64	129.63	108.01
United Kingdom	637.18	816.10	1028.81	756.84	1101.44	1227.20	1311.75	1339.55	1294.14
United States	1774.46	2022.40	2226.87	2226.96	2902.47	3243.35	3517.58	3765.27	3701.50

Source: Bankscope

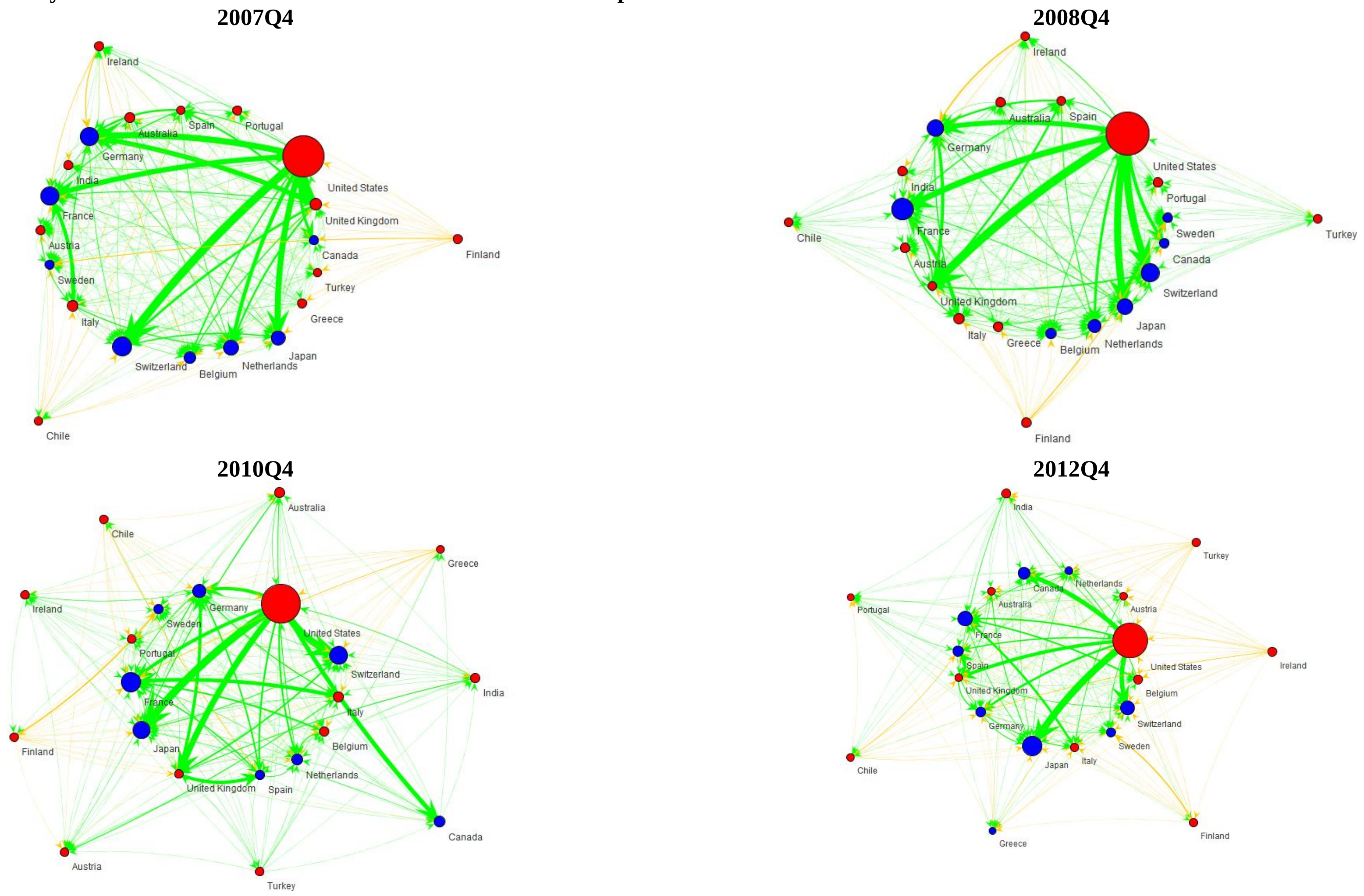
2.4.2 Country Cross-Border Analysis

2.4.2.1 Preliminary Checks by Network Visualization and Statistics

Figure 2.3 presents the visualization of the cross-border bank exposure network in 2007Q4, 2008Q4, 2010Q4 and 2012Q4 to characterize the pre-crisis, crises, post-crisis, and the

Eurozone crisis. The red nodes represent the net borrower countries, and the blue the net lender. The size of the nodes and the thickness of the arrows show the importance of the country and of the relationship between them, respectively. The network is highly connected in the pre-crisis period until 2007Q4, particularly in the core. During and after the crisis the connectivity tends to decrease with some countries, such as Turkey and Greece, moving from the core to the periphery. Over the sample, the United States, United Kingdom and Italy are the biggest net borrowers among the 21 countries that form the network, raising funds mainly from Switzerland, Germany, Sweden, France and Netherlands, the biggest net lenders.

Figure 2.3: Country Level Network Visualization Cross-border Bilateral Exposures



Source: Plotted by author using matrix (2.2) from the BIS and Bankscope Capital. .

The increased connectivity up to 2007 and its decline after the crisis as shown in Figure 2.2 can also be summarised by the network statistics in Table 2.2. The results show that on average the number of lender and borrower countries, measured as in/out-degree, increased over 2005Q4 to 2007Q4, followed by a decline up to 2013Q4. From 2005Q4 to 2007Q4 the number of borrowers and lenders (in and out-degree) increased from 9.76 to 9.86 lenders, and declined to 9.57 in 2013Q4. This trend is evidenced by the numbers of contractual linkages between countries. For instance, from 2005Q4 to 2007Q4 the number of edges increased from 205 to 207, respectively, and declined to 201 in 2013. In terms of volume it represents an increase in net lending by 36.8 per cent to US$7,7999.08 billion in 2007Q compared to 2005Q4, and declined by 37.9 per cent to US$4,840.5 billion in 2013 compared to 2007Q4.

Figure 2.4 plots the connectivity and the network maximum eigenvalue. Connectivity indicator, which measures the likelihood that two countries are connected by cross-border flows, also shows an upward trend from 2005Q4 to 2007Q4, and a decline up to 2013Q4. Although this index increased from 2010Q4 to 2012Q1, that increment was still well below the levels observed in 2004Q7.

Similar trend can be observed in the network maximum eigenvalue. This statistic measures the degree of the instability of the global net liabilities adjusted to the equity capital buffer of exposed countries' banking systems. *i. e.* measures the systemic risk for the system as a whole[8]. The result shows that the maximum eigenvalue stood well above the 0.25[9], over 2005Q4-

[8] Following Markose (2012) the eigenvector centrality of financial institution can be large if its total liabilities and/or its capital is low and also it is connected to counterparties with high eigenvector centrality.
[9] Markose (2011), show that the Basel III capital ratio of 6% for risk weighted assets implies capital ratio of 25% for total assets. So the $\rho = 0.25$ can be viewed as a proxy for capital adequacy ratios of banking systems.

2013Q4, with an increase of 68%, to 0.43 in 2007Q1. Moreover, it rose to over 0.49 in 2007Q3 giving ample early warning of the upcoming distress with the collapse of the BNP Paribas hedge funds followed by that of Bear Sterns. Then, the maximum eigenvalue continued to increase peaking at about 0.51 in 2008Q1 followed by decline to 0.30 in 2013, indicating a system instability that can trigger losses that can exceed 25% of any of the national banking capital buffers (i.e. exceeding about US$705,02 billion in case the of US, US$264 in the United Kingdom and Italy – the main borrower countries).

Table 2.2 : Network Statistics – Country Level Network

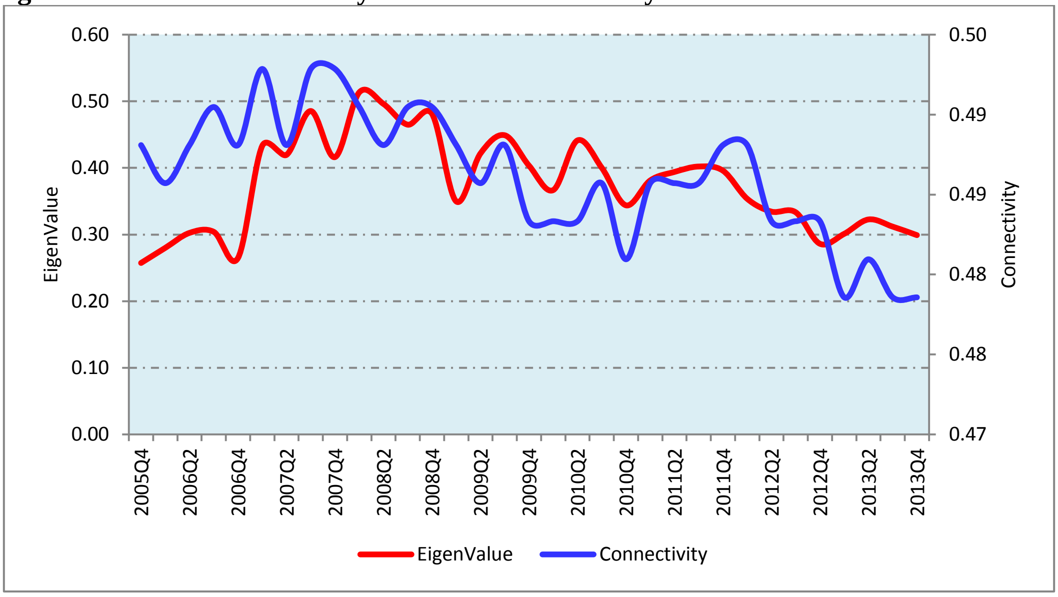
	2005Q4	2006Q1	2006Q2	2006Q3	2006Q4	2007Q1	2007Q2	2007Q3	2007Q4	2008Q1	2008Q2	2008Q3	2008Q4	2009Q1	2009Q2	2009Q3	2009Q4
Nodes	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21
Edges	205	204	205	206	205	207	205	207	207	206	205	206	206	205	204	205	203
Connectivity	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.48
CC	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
Mean in	9.76	9.71	9.76	9.81	9.76	9.86	9.76	9.86	9.86	9.81	9.76	9.81	9.81	9.76	9.71	9.76	9.67
Std in	5.40	5.90	5.82	5.78	5.76	5.59	5.65	5.62	5.62	5.79	5.61	5.75	5.61	5.72	5.65	5.60	5.59
Skew in	-0.23	0.12	0.07	0.13	0.12	0.20	0.16	0.14	0.18	0.13	0.18	0.14	0.23	0.31	0.34	0.30	0.30
Kurt in	-1.03	-1.03	-1.07	-1.12	-1.07	-0.89	-0.93	-0.98	-0.91	-1.03	-0.81	-1.01	-0.91	-0.92	-0.88	-0.79	-0.65
Mean out	9.76	9.71	9.76	9.81	9.76	9.86	9.76	9.86	9.86	9.81	9.76	9.81	9.81	9.76	9.71	9.76	9.67
Std out	5.92	5.21	5.32	5.42	5.32	5.33	5.15	5.37	5.37	5.47	5.11	5.34	5.24	5.30	5.05	5.15	4.89
Skew out	0.09	-0.41	-0.22	-0.21	-0.20	-0.28	-0.34	-0.20	-0.25	-0.17	-0.35	-0.27	-0.35	-0.40	-0.58	-0.46	-0.60
Kurt out	-1.03	-1.14	-1.14	-1.17	-1.08	-0.99	-1.02	-1.07	-1.01	-1.07	-0.78	-1.09	-0.98	-0.93	-0.88	-0.85	-0.58
EigenValue	0.26	0.28	0.30	0.30	0.26	0.43	0.42	0.49	0.42	0.51	0.50	0.46	0.48	0.35	0.42	0.45	0.40

	2010Q1	2010Q2	2010Q3	2010Q4	2011Q1	2011Q2	2011Q3	2011Q4	2012Q1	2012Q2	2012Q3	2012Q4	2013Q1	2013Q2	2013Q3	2013Q4
Nodes	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21
Edges	203	203	204	202	204	204	204	205	205	203	203	203	201	202	201	201
Connectivity	0.48	0.48	0.49	0.48	0.49	0.49	0.49	0.49	0.49	0.48	0.48	0.48	0.48	0.48	0.48	0.48
CC	0.49	0.48	0.49	0.48	0.49	0.49	0.49	0.49	0.49	0.48	0.49	0.49	0.48	0.48	0.48	0.48
Mean in	9.67	9.67	9.71	9.62	9.71	9.71	9.71	9.76	9.76	9.67	9.67	9.67	9.57	9.62	9.57	9.57
Std in	5.67	5.27	5.55	5.49	5.51	5.33	5.23	5.32	5.09	5.00	5.08	5.21	5.22	5.16	5.46	5.05
Skew in	0.11	0.08	0.11	0.18	-0.05	-0.05	0.02	-0.05	-0.09	-0.25	-0.17	-0.19	-0.16	-0.01	-0.06	-0.02
Kurt in	-0.65	-0.83	-0.46	-0.74	-0.77	-0.73	-0.74	-0.89	-0.37	-0.01	-0.40	-0.33	-0.50	-0.12	-0.44	0.12
Mean out	9.67	9.67	9.71	9.62	9.71	9.71	9.71	9.76	9.76	9.67	9.67	9.67	9.57	9.62	9.57	9.57
Std out	4.83	4.58	4.83	4.70	4.71	4.54	4.46	4.77	4.50	4.41	4.36	4.49	4.51	4.49	4.63	4.27
Skew out	-0.58	-0.38	-0.49	-0.52	-0.36	-0.35	-0.42	-0.06	-0.14	0.29	-0.06	-0.07	0.11	-0.12	-0.12	-0.26
Kurt out	-0.85	-0.86	-0.37	-0.63	-0.75	-0.62	-0.62	-0.61	-0.15	0.95	-0.11	-0.34	-0.01	0.17	-0.20	0.29
EigenValue	0.37	0.44	0.40	0.34	0.38	0.39	0.40	0.40	0.35	0.33	0.33	0.29	0.30	0.32	0.31	0.30

Source: Calculated by author.

In general, these results conforms with Hattori and Suda (2007) and Degryse et al (2010) who also shows that financial interconnectedness in international financial markets increased overtime, at least up to 2007 financial crisis. However, they are in contrast with Minoiu and Reyes (2013) and Castrén and Rancan (2014) who suggests that connectivity of financial networks decreased at the onset of global financial crisis.

Figure 2.4 : Network Instability Index and Connectivity

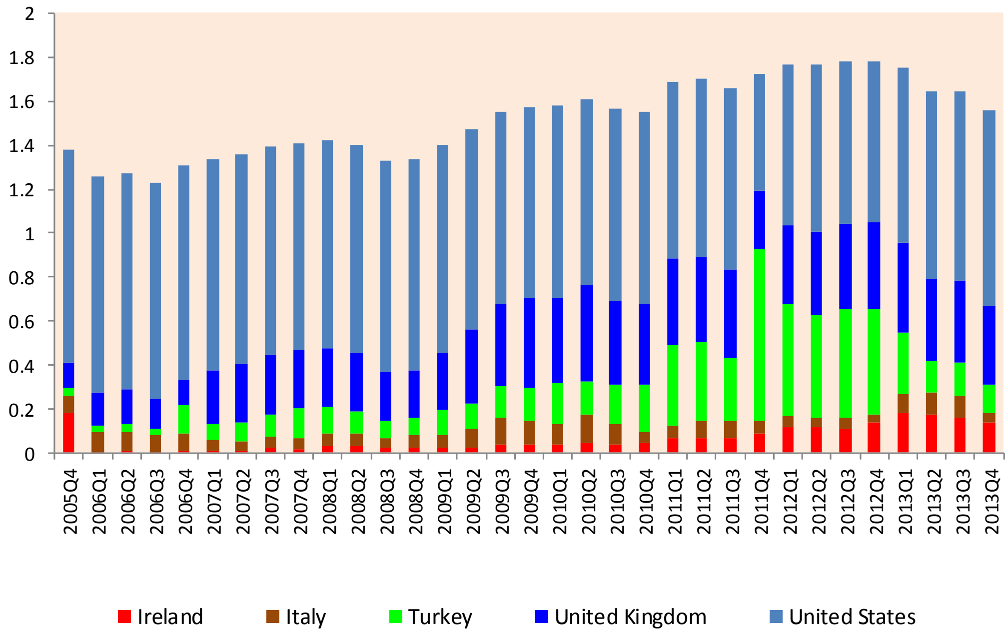


Source: Calculated and plotted by author.

Having investigated the stability of the system, in Figure 2.5 and 2.6 we shows the evolution of the right and left eigenvectors centrality to identify, as in Markose (2012), the systemically most important and the most vulnerability banking systems, respectively. Our results show that the United States, the United Kingdom and Turkey are predominantly the systemically most important countries over 2005Q4-2013Q4. While the US and UK systemic risk indexes are almost stable over time, the maximum eigenvalue for Turkey increased significantly from 2010Q4 to 2013Q1, period during the euro area crisis. One other important change is observed in the systemic risk index for Ireland which increased notably from 2012Q4 to 2013Q4. Figure

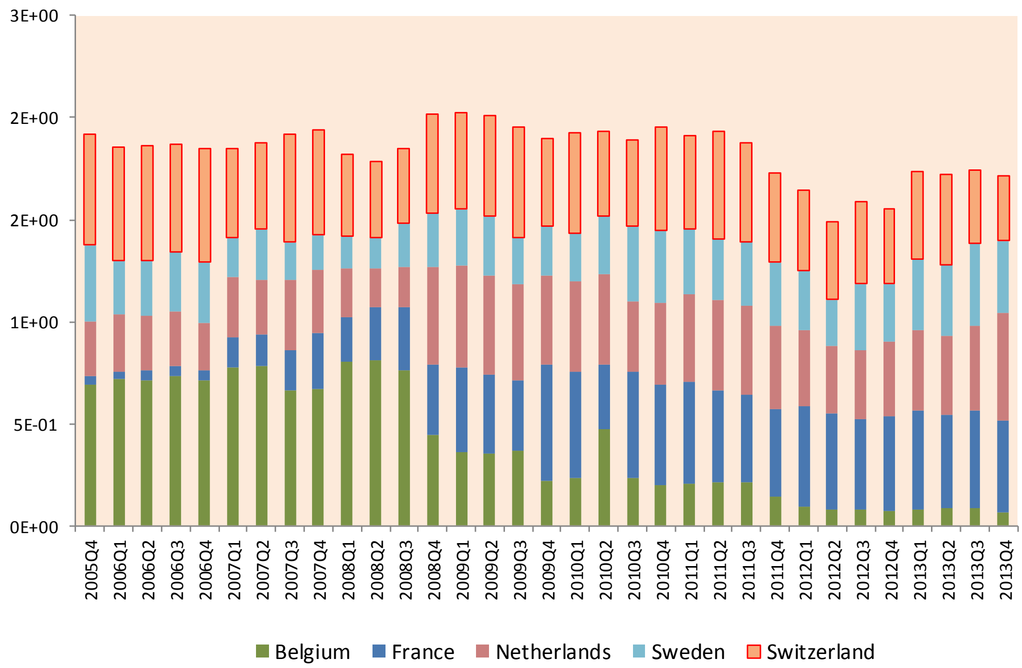
2.6 shows that Belgium, Switzerland and Sweden/Netherlands (Figure 2.5), are the most exposed to the network, as they are also the main lender banking system to the US and UK.

Figure 2.5: Dynamic of Systemic Importance (Right eigenvector centrality)



Source: Calculated (Eq 2.10) and plotted by author

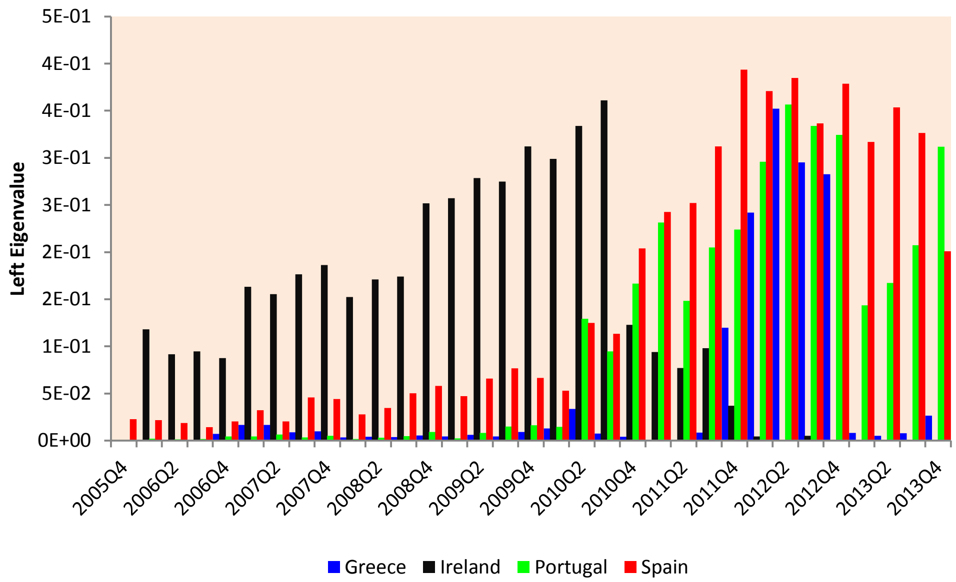
Figure 2.6 : Dynamic of Countries' Vulnerability Index (Left eigenvector)



Source: Calculated and plotted by author (using Eq. 2.11)

Regarding the vulnerability analysis for the Euro area periphery countries, Figure 2.7 presents the left eigenvalue (vulnerability index) for Greece, Portugal, Spain and Ireland. As indicated the left eigenvalue for Ireland trended upward from 2005Q4 to 2010Q3, coinciding with the bailout agreement of 29 November 2010 (Lojsch et al (2011)). Then it declined sharply until 2013Q4. In line with the Table 2.1 that shows a negative capital, Figure 2.7 shows that between 2011Q3 and 2012Q4 Greece was completely defaulted. We also evidence an increased Spain and Portugal vulnerability formed in the most recent quarters. In fact, on 3 August 2014, *Banco de Portugal* announced that *Banco Espirito Santo* would be split in two after losing the equivalent of US$ 4.8 billion in the first 6 months of 2014, sending its shares down by 89 per cent (BoP, 2014)..

Figure 2.7: The Euro Area Periphery Countries' Vulnerability Index (Left eigenvector)



Source: Calculated and plotted by author (Eq. 2.11).

2.4.2.2 Contagion Analysis

In the previous section we analyzed the stability of the cross-border banking system and identified the systemically most important and vulnerable banking systems. In this section we conducted a contagion analysis to assess the impact of the failures of the top three systemically important countries. We focused each quarter over 2005Q4-2013Q4. The results are presented in Table 2.3. As shown the Unites States stands as the most devastating banking system, followed by the United Kingdom and Turkey banking systems, with Italy and Ireland alternating with Turkey in 2005Q4 and 2013Q2-2013Q4, respectively. Over the sample, the losses implied by triggering these countries are immense in the period before and during the 2007 financial crisis, observing a decline after the crisis. For instance, a failure of the USA would imply to its counterparty global and domino losses equivalent to 125.7 per cent and 116.2 per cent of the total the 21 countries' banking systems equity capital in 2007Q4, 124 and 112.2 per cent in 2008Q4, 64.7 and 53.5 per cent in 2010Q4 and 52.8 and 43.6 per cent in 2012Q4. Although less frequently identified as a systemic important country over the period, and with lower systemic risk index than the United Kingdom, the potential of failure of Turkey (it ranks third after the UK) in 2008 implies capital losses of 62.6 per cent of total capital i.e. 8.1 percentage points higher that the United Kingdom effect.

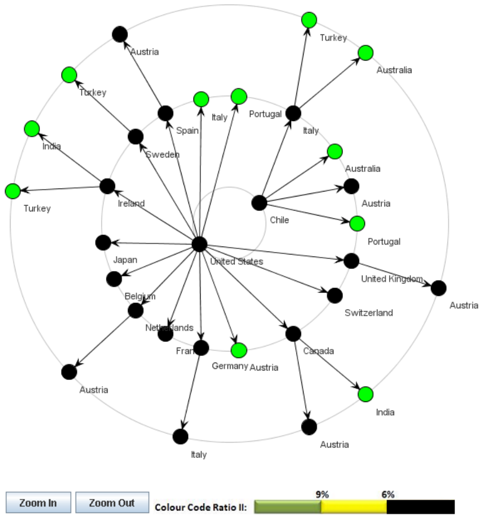
Table 2.3 : Total Global and Domino Losses

`	USA		UK		TURKEY		IRELAND	
	Global Losses % Equity Capital	Total Domino Losses % Equity Capital	Global Losses % Equity Capital	Total Domino Losses % Equity Capital	Global Losses % Equity Capital	Total Domino Losses % Equity Capital	Global Losses % Equity Capital	Total Domino Losses % Equity Capital
2005Q4	127.0	126.0	41.4	38.2			70.7	63.8
2006Q4	128.1	128.1	42.8	40.4	26.4	13.7		
2007Q4	125.7	116.2	55.4	44.3	62.2	25.9		
2008Q4	124.1	112.2	53.5	39.8	62.6	22.6		
2009Q4	79.6	65.0	45.4	32.5	33.6	17.8		
2010Q4	64.7	53.5	31.3	28.4	33.6	12.8		
2011Q4	62.5	50.9	29.2	26.1	30.7	19.4		
2012Q4	52.8	43.6	23.9	21.7	25.6	11.1		
2013Q4	65.4	54.9	29.7	26.2			19.4	18.0

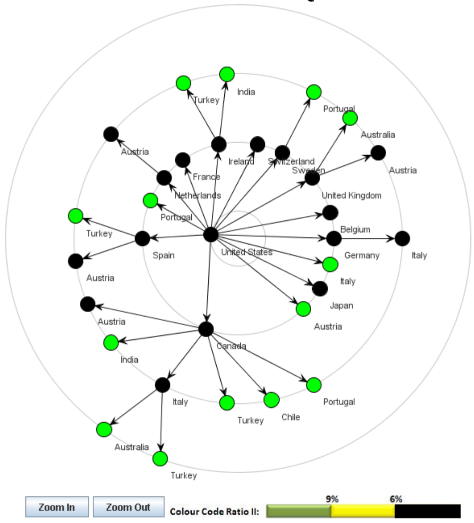
Source: Calculated by author.

Figure 2.8 Contagion Analysis Potential Impact of US Failure

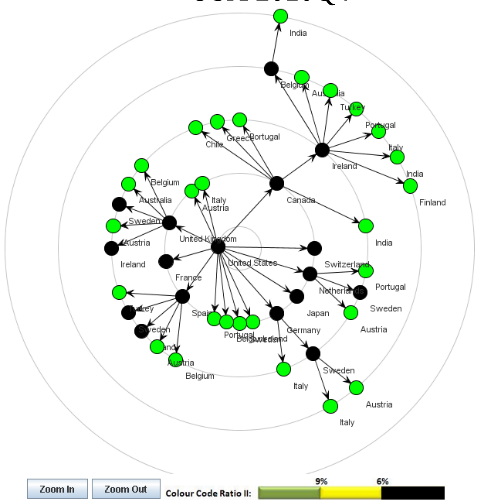
USA 2007Q4



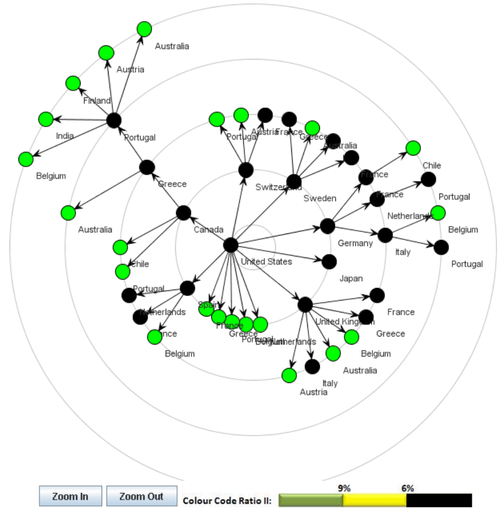
US 2008Q4



USA 2010Q4



US 2012Q4



Source: Calculated and plotted by author. The black nodes shows the defaulted bank systems ($\rho < 0.06$), the yellow noted are nodes are banking system with $0.06 < \rho < 0.09$. The green nodes are the banking systems with $\rho > 0.09$

2.4.3 Within Country Sectoral Flow of Funds

This section presents the sectorial analysis in two stages. First, we look at the BIS sectorial data on its own; second, we analyze the BIS sectoral data including within countries sectoral flows of funds data obtained from the countries' (US, UK and the Euro Area) flows of funds statistics over 2010-2013. Figure 2.9 visualize the sectorial network based on the BIS sectorial data. It shows an intense financial activity between the 10 countries' baking systems working as a hub for the non-banking, public and non-allocated sectors. The Turkish is identified as the only net borrower banking system. Over the period, in general, the eigenvalue stood above 60, having experienced downward trend from 71 in 2012 to 48 in 2012, increasing again to 60 in 2013 (Table 2.4). These levels are very high indicating problems with the data. It may reflect the fact that the capital for the non-banking sectors are set to 1 given the unavailability of data. The alternative calculation of capital is to subtract sector liabilities from the sector Assets, but this data is also unavailable.

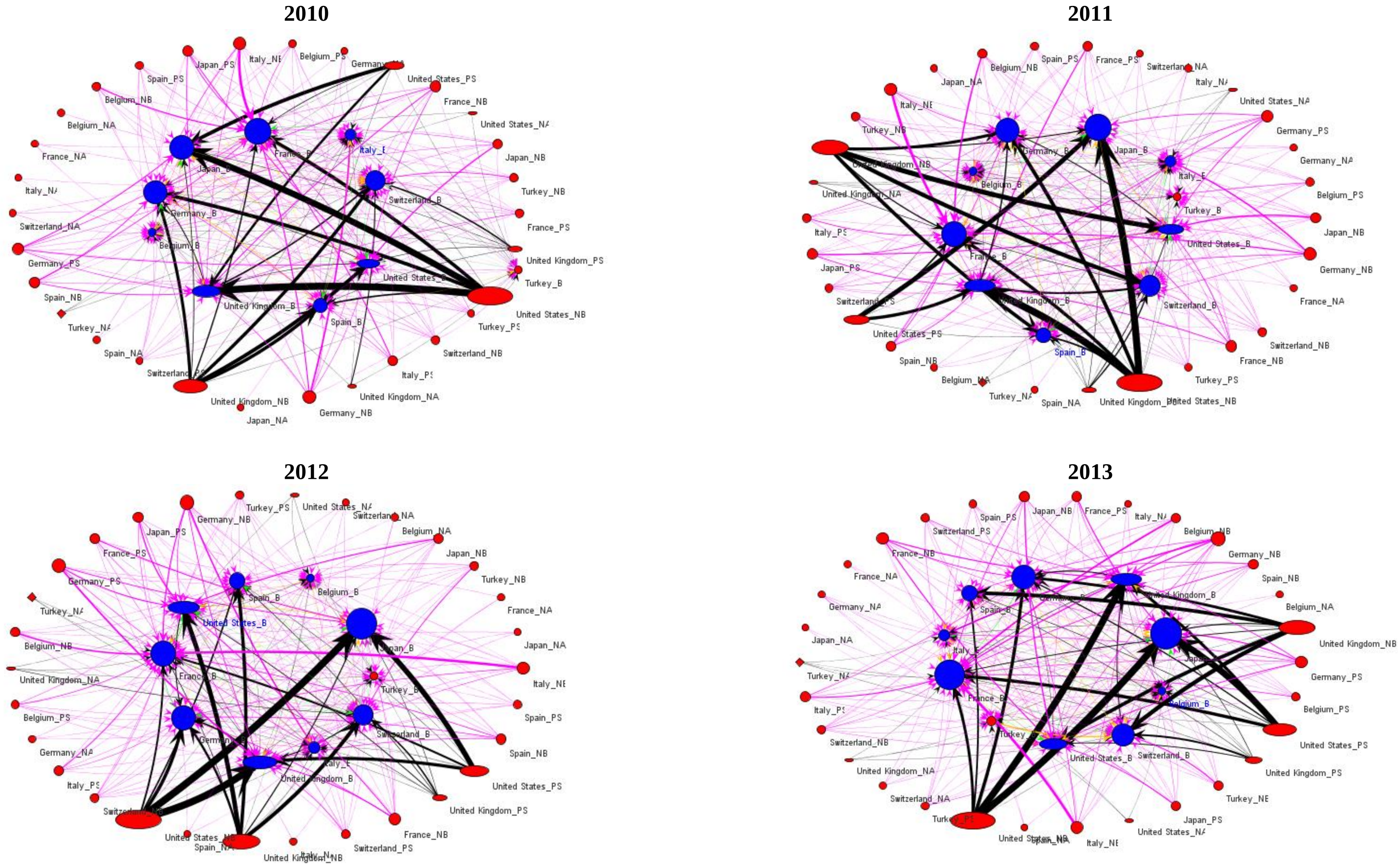
Table 2.4 Network Statistics on Cross-border Sectoral data

	2010	2011	2012	2013
Nodes	40.00	40.00	40.00	40.00
Edges	242.00	246.00	246.00	243.00
Connectivity	0.16	0.16	0.16	0.16
CC	0.46	0.43	0.43	0.43
Mean in	6.05	6.15	6.15	6.08
Std in	10.88	11.07	11.05	10.91
Skew in	1.36	1.37	1.36	1.36
Kurt in	0.08	0.09	0.04	0.10
Mean out	6.05	6.15	6.15	6.08
Std out	2.81	2.63	2.68	2.62
Skew out	-0.36	-0.23	-0.19	-0.30
Kurt out	-1.44	-1.54	-1.75	-1.62
EigenValue	70.98	60.33	48.00	60.02

Source: Calculated by author.

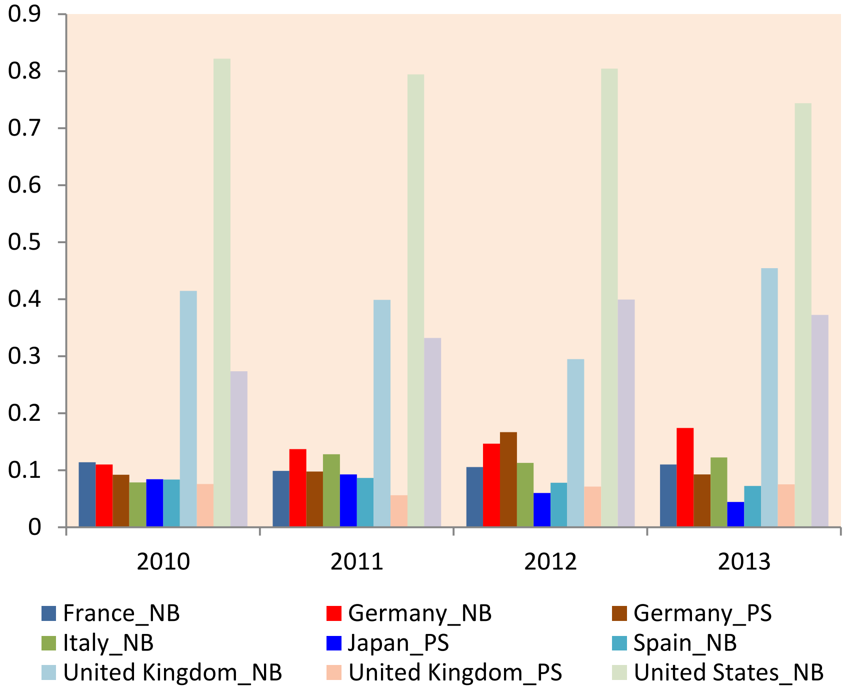
While the results from the country level data analysis suggested that over 2010-2013, the US and UK were the systemically most important countries, the sectorial data analysis (as Figure 2.10 and 2.11) shows the systemically most important sectors are the US Non-Banking and the Public sectors, and UK's Non-banking sectors, raising funds mainly from Switzerland, Belgium and Germany (also Italy) banking sectors. Triggering the three systemically most important, the effects are devastating resulting in the default of all the sectors including other sectors in the same countries (See Figure 2.12). Since this data do not provide exposure of the banking sector to other sectors within countries, this result suggests that failure of the US banking system is a feedback impact from the default in other countries triggered by the default in the US Public and Non-banking.

Figure 2.9: Sectoral Data Network



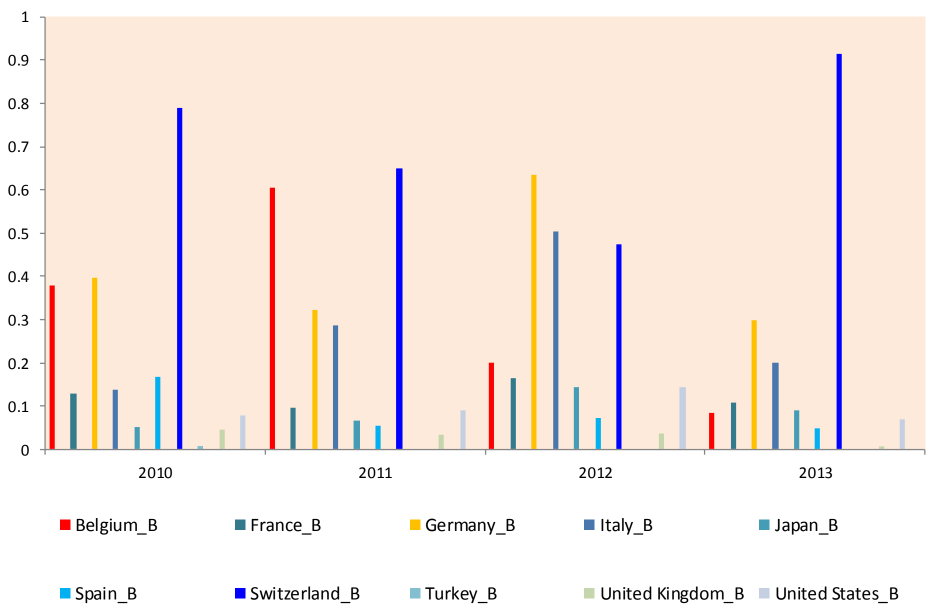
Source: Plotted by author.

Figure 2.10 : Country's Sector Systemic Risk Index (Right EigenValues)



Source: Calculated and plotted by author.

Figure 2.11 : Country's Sector Vulnerability Index (Left Eigenvalue)



Source: Calculated and Plotted by author.

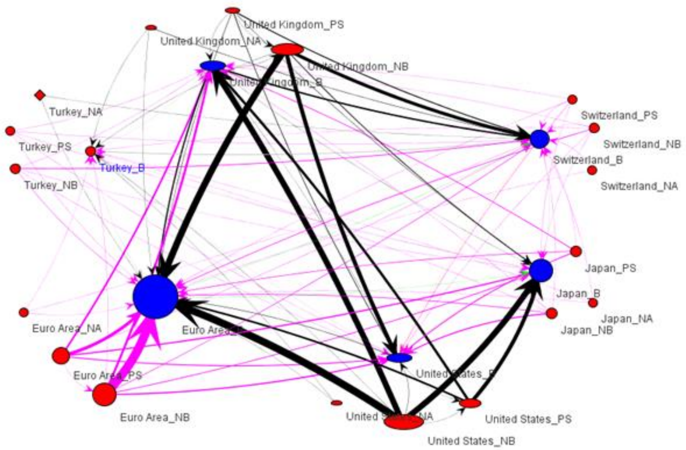
Figure 2.12 visualizes the Macro-network as in Castrén and Rankan (2013). As shown the United States Non-banking sector, the United Kingdom public sector and the United States Public sector are the systemically most important sectors of the network. While the UK non-banking, Switzerland banking and Turkey non-banking are the most exposed sectors of the network. The above stated about the abnormal level of the network measure on degree of instability, eigenvalue also applies to this analysis.

After triggering the systemically most important sectors the results are presented in Figure 2.12. It shows important within country sectorial direct contagion effect. Indicating for instance, that a failure in the UK public sector (in 2013) would default the UK banking and non-banking sectors, as well as the US, Japan, Switzerland and the Euro Zone banking sectors – as the first-round effect. This is followed by the US public sector and the Turkey banking sector as the second-round effect.

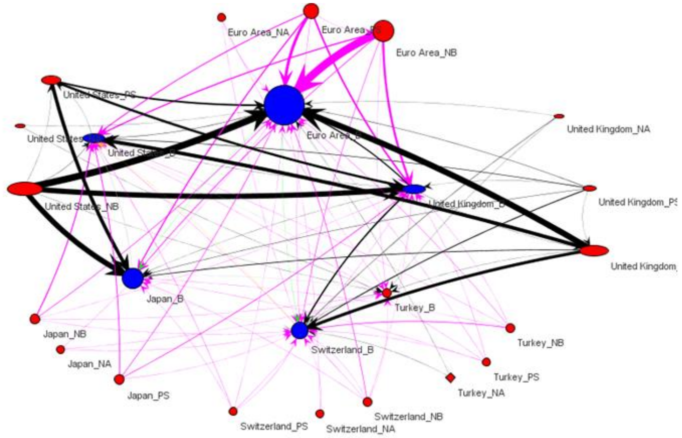
Although providing important details for systemic risk and vulnerability analysis, these results must be interpreted with caution, given the inconsistences found when dealing with the countries' flows of funds, as follows. First, the flows of funds statistics in most countries are presented in terms of sectoral balance sheets that include only the financial assets and financial liabilities. Then, the financial flows between two sectors are obtained by aggregation of the balance sheet asset and liabilities elements that seem to be of the same sector. In this process error may occur. Second, the sectoral breakdown in the countries flows of funds is different across countries and contrast with the BIS sectorial statistics breakdown.

Figure 2.12: Sectorial Data Network

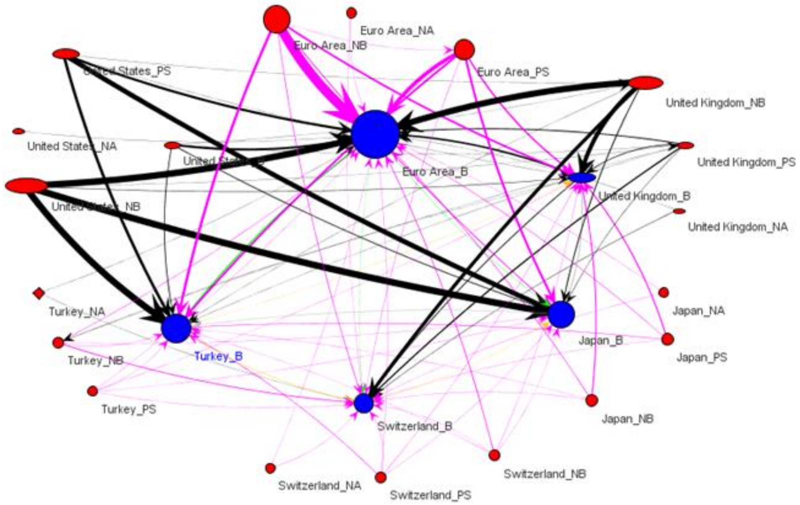
2010



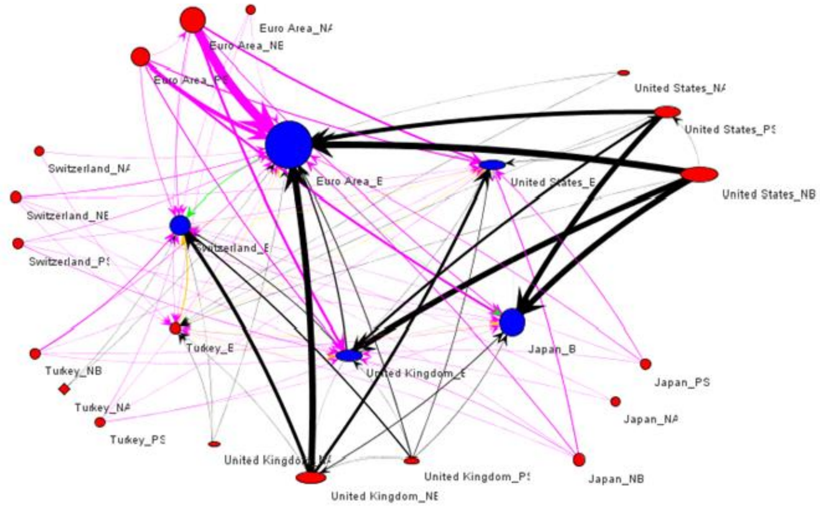
2011



2012



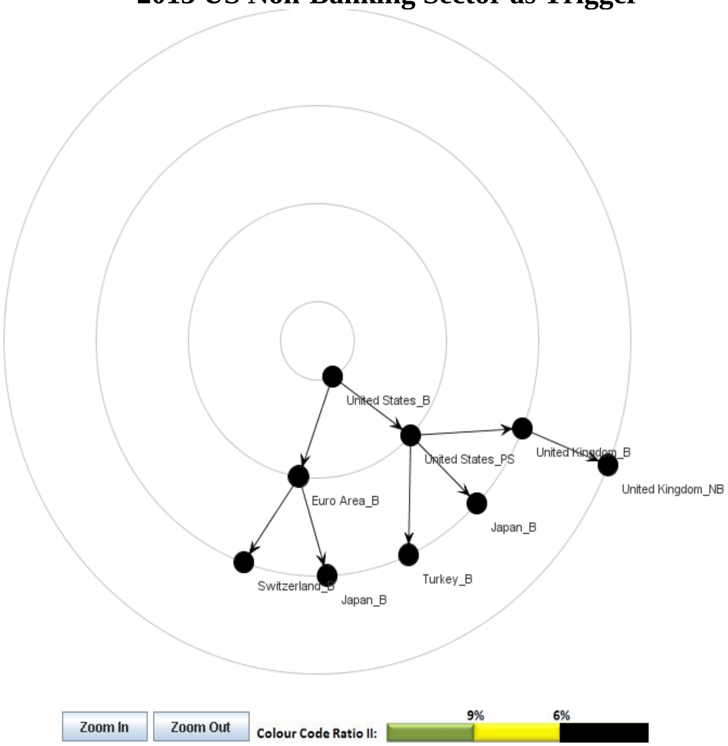
2013



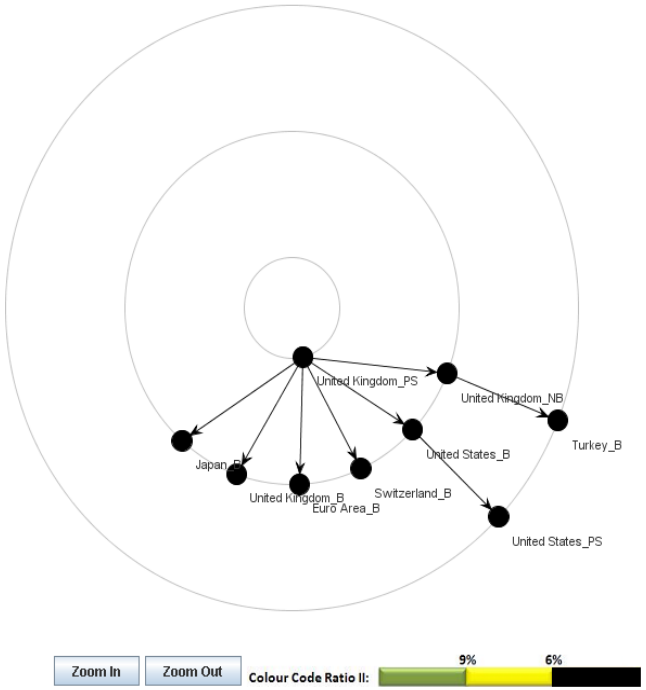
Source: Plotted by author

Figure 2.13: Contagion Analysis using Within Country Sectoral Data

2013 US Non-Banking Sector as Trigger



2013 UK Public Sector as Trigger



Source: Plotted by author

2.5 Summary and Conclusion

The study re-examines the properties and stability of cross-border bank exposures for 21 countries using bilateral data for the period 2005Q4 – 2013Q4 and within country sectoral flows of fund data over the period 2010 to 2013, to identify the systemically important sector of the identified country. To this end the study develops a visualization of the interconnectedness and analyses the dynamics network topology measures over time, including the number of in and out-degrees, the connectivity, clustering coefficients and the left and right eigenvalues as countries' systemic risk and vulnerability indexes.

Then we simulate contagion analysis for the top three systemically important banking systems to assess the magnitude of the related losses. Furthermore, we test whether the systemic and vulnerability index based on the eigenvector centrality yields early warning signal for financial crisis; we also test whether the Euro Area periphery countries' (Portugal, Ireland, Greece and Spain) crisis could have been identified well before 2007 in terms of network properties.

In general, our results suggests that financial interconnectedness in international financial markets increased overtime, at least up to 2007, and decreased after the financial crisis. In general, these results conform with Hattori and Suda (2007), and Degryse et al (2010) that financial interconnectedness in international financial markets increased overtime in the run up to the 2007 GFC. However, there is a contradiction with the hypothesis of Minoiu and Reyes (2013) and Castrén and Rancan (2014) that connectivity of financial networks decreased at the onset of global financial crisis.

Our results also show that the banking system of Belgium, Switzerland and Sweden/Netherlands are the more vulnerable, exposed essentially to the United States, the United Kingdom and Turkey, which have been identified as the systemically most important countries over 2005Q4-2013Q4. After simulating contagion analysis, we find that a failure of the US has a devastating contagion effects, implying to its counterparty a global and domino losses equivalent 93 per cent and 84 per cent of total the 21 countries' banking systems equity capital (average from 2005Q4-2013Q4), respectively. The analysis of the sectoral data shows that the systemic most important sectors are US Public and Non-Banking sectors, and the UK's by the Non-banking sectors. Further, we find that the failure of one sector in the US and UK has an important implication for sectors within countries.

Finally, the study suggests that the maximum eigenvalue based systemic risk index provides important information as an early warning signal to the run up of the crisis, as it revealed important information on the impact of Euro area crisis in the periphery countries, Greece, Portugal, Spain and Ireland.

3 Chapter 3

Granular Macroeconomic Model for Advanced Economies: The Role of Offshoring and Financial Sector Growth on Falling Wage share and Output Growth

Abstract

In recent years, advanced economies experienced falling wages, rising wage and income inequality and low GDP growth. The literature has identified the increased offshoring operations in key sectors and the fast growth of the financial sector relative to the rest of the economy, respectively, as the determinants of falling wages and low GDP growth. This study explores the relationship between offshoring and wages, and the impact of high financial sector growth on economic growth. While the existing literature uses an econometric approach, we use cross-border sectoral data input-output data. In order to identify the impact of the increased financial sector share of gross operating profits and surplus (GOPS) and fall wages share on GDP growth, this study provides an innovative method using the Ghosh inverse for the US input-output model. We show that a decline in wages in the US is associated with sectors that suffered most from offshoring. We also find that a decline in wage share of the top three most offshored sectors has a negative impact on total output growth. Further, we argue that an increase in financial sector profits share relative to the rest of sectors of the economy has a negative effect on total output. The impact of a 1% increase in financial sector share of gross operating profit on US output is higher in 2009 than in 2000, implying a greater within country sectoral imbalance.

Keywords: Networks, offshore, wages compression, cross-border analysis

3.1 Introduction

Globalisation of trade and financialisation are two mega trends that characterise the global economy in the last few decades. As a process of international integration of markets for goods, factors and technology (Slaughter and Swagel (1997)), globalisation has led to the reorganization of production activities to a network at global scale. Phenomena such as offshoring has experienced non-trivial upward trend over the years in search of exploring low factor cost differentials (Bramucci (2016)). Defined as the reallocation of production processes abroad, either to a foreign affiliate or to an external supplier (Olsen (2006)), offshoring is reported to have increased in many OECD countries by 30% between 1970 and 1994 (Hummels et al (2001)). In the UK it increased by 33% in 1984 and by 40% in 1995 (Hijzen et al. (2005)), while in EU(27) it rose from 26% of value added in 1995 to 42% in 2008 (Parteka and Derlacz (2013)).

This trend has been associated with lower input prices which accounted, up to 2008, for a cost savings in the range of 20% to 60% and higher profit margins and profits (Milberg and Winkler (2009)). These gains were expected to increase investment and raise productivity and output. However, evidence shows that the rise in profits fails to translate into capital investment, as since the 1980s non-financial corporations have shifted their investment strategies toward investing in financial instruments of various sorts, including shares buyback (Tomaskovic-Devey at al. (2015)), and on maximising shareholder value (retaining net gains to shareholders and paying higher dividend) out of capital accumulation and long-term growth.

This phenomenon led to an impressive expansion of the financial sector and the arrogation of a very large percentage of corporate surpluses (over 60% in the US), underscoring the paucity of real investment in this economy and also the growing income inequality (Stockhammer, 2004). In fact, Johnson (2009) as cited in Moosa (2010) reports that from 1973 to 1985, the financial sector in the US earned less than 16 per cent of domestic corporate profit. However, in 1986, that figure reached 19 per cent, and it then fluctuated around 21 per cent during the 1990s. In the first decade of the 21st century it reached 41 per cent.

This and the recent macroeconomic malaise in advanced economies characterised by falling wages, rising wage and income inequality, and low GDP growth accompanied by high GDP volatility, have motivated extensive research on theoretical models and empirical studies on the effects of offshoring on macroeconomic variables, and on the re-assessment of the impact of financialisation on economic growth. These studies identify increased offshoring operations in key sectors as one of the determinants of falling wages, and the growth of the financial sector (measured has the growth of Gross Operating Profits and Surplus (GOPS)) relative to the rest of the economy as the factor explaining low growth.

The general view is that, increasing industry offshoring of less efficient activities accompanied by increased focus on their core components improves productivity (Oslen (2006)). However, it may have an adverse effect on wages. On the re-assessment of the impact of the financial sector on growth, recent studies such as Tomaskovic-Devey at al., (2015), Cecchetti and Kharroubi (2012), and Stockhammer (2004), show a non-linear relationship between financial sector and GDP growth. They argue that at low levels, a larger financial system has a positive effect on economic growth, up to a point, a threshold above which this relationship turns negative.

Thus, this study contributes to this debate. It investigates the role of globalization and offshoring on wages, and the effects of wage decline and economic growth, and the effects of increased size of financial sector on economic growth in US economy. We study the US as a leading exponent for the loss of wage share in production and the growth of financial sector. While most of the studies analyse these hypotheses using econometric technics, the novelty of our research is to explore these relationships using cross-border sectoral data and the Ghosh inverse input-output supply driven model. We use 2000 and 2009 detailed OECD Inter-Country Input-Output tables of inter-sectoral flows of intermediate and final goods and services within and across countries, condensed into 13 sectors for the US economy, plus the rest of the world sector that captures the exported and imported intermediate input from and to US sectors.

The chapter is organised as follows. Section 3.2 presents the literature review on the measure and the impact of offshoring on wages, and of the relationship between financial growth and economic growth; section 3.3 presents the methodology of study and the source of data; section 3.4 ICIO data analysis for the US; section 3.5 gives the analysis of the impact of sectoral GOPS and wage changes on output. Lastly but not least, in section 3.6 we present the conclusion.

3.2 Literature Review

This section presents the literature review covering two parts of this study: subsection 3.2.1 presents the role of offshoring on the wage; and subsection 3.2.2 presents the related research on the effects of the financial sector growth on GDP growth.

3.2.1 On the Role of Offshoring on Wages

Globalisation and the progress in the transportation and communication technologies allows firms to explore the possibility of fragmenting the production process globally, taking advantage of lower factor cost in countries like Indonesia, Malaysia and China (Sethupathy, 2013). Yeats (2001) reports that trade in intermediate goods has been growing at a much faster rate than trade in final goods and accounts for 30% of world trade in manufacturing. This result is also presented by Hummels et al (2001) and Borga and Zeile (2004). The literature on the effect of the fast-growing offshoring is almost consensual in that it creates winners and losers (Mankiw and Swagel (2006)). However, the identification of winners and losers, the quantification of offshore aggregated effects on the labour markets, and also the mechanism through which these effects are transmitted, lead to different conclusions.

Sethupathy (2013) investigates the offshoring effects on wage and employment using firm-level data on US offshoring to Mexico. He finds that offshoring has mixed effects on wages, depending whether the firm is likely or not to take advantage of the offshoring opportunities. Sethupathy (2013) argues that domestic wages rise at US firms likely to take advantage of this new offshoring opportunity, whilst domestic wages fall at US firms unlikely to take advantage of this opportunity. Further, they show that firms likely to take advantage of new offshoring opportunities increase their productivity and profitability at the expense of their competitors. This leads to higher domestic wages at the former firms relative to the latter.

Other studies analyse the effect of offshore on wages, with respect to the categories of skilled and unskilled workers. Feenstra and Hanson (1996), exploring the impact of offshoring of intermediate goods on the demand for labour in the U.S., find that offshoring can account for a 30.9 per cent increase in skilled worker wage. Similar results are found in Geishecker and Gorg (2008). Using large household panel data and industry-level information on industries offshoring activities from input-output tables, Geishecker and Gorg (2008) find that a 1 percentage point increase in offshoring reduced the wage for workers in the lowest skill categories by up to 1.5%, while it increased wages for high-skilled workers by up to 2.6%. The evidence of the positive effect of offshoring on high-skilled wages, is also presented by Hummels et al (2001) using Danish worker-firm data, Hijzen et al (2005) investigating the relationship between offshoring and the skill structure of labour demand in the UK, and by Bramucci (2016) who analyses the impact of imports of intermediate products on labour demand and wages in five European countries (Germany, Spain, France, Italy, and the United Kingdom).

Further, Feenstra and Hanson (1999) investigate the relative effects of offshoring of intermediate inputs and of high-technology capital on wages in the US over the period 1979-1990. They find that high-technology explains about 35 per cent increase in the relative wage of skilled workers, while outsourcing explains 15 per cent fall in wage of low skilled workers. However, Chowdhury (2009) contends that it is neither technology nor offshoring individually, but rather the combined effects of both that have contributed to widening wage inequality.

Others contend that the impact of offshoring on wages differs depending on the source of the input imports. For instance, Yamashita (2010) conforms with Chowdhury (2009), Hummels et al (2011) and Feenstra and Hanson (1999) on the effect of offshoring on skilled, unskilled wages. However, he argues that this impact differs depending on whether inputs are imported from developing or developed countries. Increased parts and components imports from developing countries tend to increase wage inequality, but imports from developed countries have no such effect. Geishecker (2006), analysing the effect of offshoring on the relative demand for manual workers in Germany, finds that this effect differs depending whether the inputs are imported from Central and Eastern Europe (CEEC) or from the European Union (EU15) and the rest of the world, with offshoring towards CEEC playing a major role.

However, Ebenstein et al (2014) contend that offshoring can adversely affects all wages irrespective weather it is for skilled or unskilled workers. The negative effects of offshoring on labour market and on the economic growth are also stressed by Milberg and Winkler (2009).

According to Milberg and Winkler (2009) offshoring is expected to lower prices of inputs and outputs, raising demand for both and consequently the demand for labour too. In addition, lower input prices should raise profit margins and profits, leading to investment that should further raise productivity and output. However, offshoring weakens labour demand by substituting foreign labour for domestic labour, causing firms’ labour demand curve to shift inward and lower wages. This effect is also expected via raising productivity. Furthermore, only part of the entire rise in profit is translated into investment on capital. Thus, benefits from offshoring may not be realised as expected.

3.2.2 Financialisation and Economic Growth

Epstein (2005) defines financialisation as the increasing role of financial motives, financial markets, financial actors and financial institutions in the operations of domestic and international economies. However, for the purposes of this study, we follow Orhangazi (2008), who defines financialisation as the changes that have taken place in the relationship between the non-financial corporate sector and financial markets. Particularly, we focus on the resulting fast growth of the financial sector profits relative to the rest (non-financial sectors) of the economy.

Economic theories relying on the assumption of efficient financial markets contend that financial sector deepening fosters economic growth. This includes Goldsmith (1969), MacKinnon (1973), Shaw (1973), and King and Levine (1997), and argues that financial sector growth and development promotes growth, through at least five channels, namely: 1) improved information production about investment opportunities and allocation of capital; 2) enhancing saving mobilization and pooling; 3) monitoring of investments and performance; 4) financing of trade and consumption; and 5) through the provision of liquidity, facilitation of secondary market trading, diversification, and risk management. This view has dominated for quite a sometime and has motivated many reforms, such as the advent of the financial liberalization processes undertaken in many developing countries during the early 80's and 90's (Gemech, 2003).

However, the fast growth of the financial sector in recent years, particularly, in the light of the 2008 financial crisis, has motivated a re-assessment of the finance-growth nexus aiming to understand the nature of the financial sector growth and its implications on the real economy.

Contrasting with the above-mentioned literature, Cecchetti and Kharroubi (2012) find that the relationship between financial sector and productivity growth is non-linear. The financial sector growth may foster economic growth, but up to a point[10], a “threshold[11]” beyond which the finance-growth relationship turns negative.

The negative effect of financial sector growth on GDP growth is due to fact that the growing size of the financial sector in recent years was characterised by a rise in financial investment, replacing investment on capital which is a driving force for growth. For instance, Stockhammer (2004) investigates the effect of financialisation on physical capital accumulation, using time series data for the USA, the UK, France and Germany. He shows that the shareholder revolution and the development of a market for corporate control have shifted power to shareholders and thus changed management priorities, leading to a reduction in the desired growth rate. This led to a negative effect of financialisation on capital accumulation, particularly in the USA, the UK and France. Similarly, Orhangazi (2008) explore the effects of increased financialisation on the real investment decisions of Non-financial Corporation (NFC) in the US. Their main findings conform with Stockhammer (2004), and show a negative relationship between financialisation and real investment, through two channels. First, increased investment and increased financial profit opportunities may have crowded out real investment by changing the incentives of firms’ managers and directing funds away from real investment; and second, increased payments to the financial markets may have impeded real investment by decreasing available internal funds, shortening the planning horizons of the firm management and increasing uncertainty.

[10]Arcand et al (2011) identifies the turning point to be approximately at 110 per cent private credit to GDP, with the relationship between finance and growth turning significantly negative at around 150 per cent of private credit to GDP.
[11]Cecchetti and Kharroubi (2012) argue that many advanced economies have already passed that threshold long ago.

Indeed, Crotty (2005) shows an increasing investment in financial assets by the non-financial firms, buying or expanding financial subsidiaries, and shortening their planning horizons. In addition Duménil and Lévy (2004) show increased interest and dividend payments to financial markets, and argue that NFCs are therefore left with smaller amounts of funds for real investment. This view is also emphasized by Aglietta and Breton (2001) who argue that an active market for corporate control pushes firms to boost their share price through dividend pay-outs or stock buybacks and, as a consequence, the share of earnings devoted to financing growth is reduced. Also, Stockhammer (2006) investigates the effects of increased shareholder power to influence management decisions. Based on microeconomic analysis, they find that Shareholder power is found to reduce investment and output, while increasing profits. Other studies supporting these views include Onaran et al (2011) and Bolton et al (2011).

3.3 Methodological Framework and Source of Data

3.3.1 Methodological Framework – The Input-Output Model

This section presents the standard Leontief (demand driven) and Ghosh (supply driven) input-output model based on Dietzenbacher (1997) and Miller and Blair (2009). The Leontief Model provides multipliers that can be used to estimate the impact of initial changes in final demand (such as increase in government purchases, investment and private consumption and investment) on output, and the Ghosh model estimates the effect of initial change in value added (such as increase in profits or wages) on total gross output. Since this study aims to test the impact of increased financial sector profit shares and falling wages share in most offshored sectors on total gross output, we use the Ghosh input-output model, presented by Ghosh (1958). However, the underlying mathematical characterization is inspired and represents an alternative for the Leontief input-output model, based on Leontief (1958).

The model assumes an economy where production takes place at n sectors. Each sector produces an output x_i which is sold to domestic and the rest of the world's sectors as intermediate input, and to domestic and foreign as final demand. However, for the production of the output x_i, sector i also uses domestically and foreign (imported) produced output. So that,

$$
\begin{aligned}
x_1 &= x_{11} + \cdots + x_{1j} + \cdots + x_{1n} + x_{1m} + d_1 \\
&\vdots \\
x_i &= x_{i1} + \cdots + x_{ij} + \cdots + x_{in} + x_{im} + d_i \\
&\vdots \\
x_n &= x_{n1} + \cdots + x_{nj} + \cdots + x_{nn} + x_{nm} + d_n \\
&\vdots \\
x_m &= x_{m1} + \cdots + x_{mj} + \cdots + x_{mn} + x_{mm} + d_m \\
&\vdots \\
v &= v_1 + \cdots + v_j + \cdots + v_n \cdots + v_m
\end{aligned}
$$

(3.1)

Here x_i denotes sector i's output, x_{ij} is the amount of sector i's output used as input in the production of sector $\boldsymbol{j}$'s, and x_{im} the amount of sector i's output used by the rest of the world sector m's as intermediate input. The x_{mj} and x_{mm} represent the amount of the rest of the world sector m's output used as intermediate input in the production of sector $\boldsymbol{j}$'s and of the other rest of the world's sector output, respectively. The vector $\mathbf{d}$ is the sectoral final demand, and the vector $\mathbf{v}$ is the sectoral value added. The sectoral gross output can be expressed as the column sum of the portions allocated as intermediate inputs through the domestic sectors and the rest of the world, and the final demand, also as the row sum of each sector total intermediate inputs and the value added (payments for the primary factors, labour and capital). Thus, the sectoral total output based on Leontief and Ghosh model can be expressed in equations (3.2) and (3.3), respectively.

$$\mathbf{x} = \mathbf{Xe} + \mathbf{d} \tag{3.2}$$

$$\mathbf{x}' = \mathbf{e}'\mathbf{X} + \mathbf{v}' \tag{3.3}$$

Where $\mathbf{x}$ is a vector of sectoral output, $\mathbf{e}$ denotes the n element summation vector, that is $\mathbf{e}' = (1, \ldots, 1)$, and $\mathbf{X}$ is the $N \times N$ matrix of intermediate flows. More explicitly, the exact nature of the input-output inter-sectoral relationship within and across countries is expressed by the technical *coefficient* (also known as input-output coefficient and direct input coefficient) denoted as,

$$a_{ij} = \frac{x_{ij}}{x_j} \tag{3.4}$$

Thus, in a matrix notation the Leontief technological matrix composed by elements a_{ij} can be given as $\mathbf{A} = \mathbf{X}\hat{\mathbf{x}}^{-1}$, where $\hat{\mathbf{x}}$ denotes a diagonal matrix of total outputs of each sector, so that:

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \\ x_m \end{pmatrix} = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} & a_{1m} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} & a_{2m} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} & \\ a_{m,1} & a_{m,2} & & a_{mn} & a_{mm} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \\ x_m \end{pmatrix} + \begin{pmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \\ d_m \end{pmatrix}$$

(3.5)

That is:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{d} \tag{3.6}$$

The Ghosh sectoral input-output relationship can be expressed as

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \\ x_m \end{pmatrix}' = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \\ x_m \end{pmatrix}' \begin{pmatrix} b_{1,1} & b_{1,2} & \cdots & b_{1,n} & b_{1m} \\ b_{2,1} & b_{2,2} & \cdots & b_{2,n} & b_{2m} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nn} & \\ b_{m,1} & b_{m,2} & & b_{mn} & b_{mm} \end{pmatrix} + \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \\ v_m \end{pmatrix}'$$

(3.8)

Where, as opposed to technical coefficient a_{ij}, b_{ij} is frequently called allocation coefficient. It represents the distribution of the sector i's output across sectors j, as a share of sector i's (the seller's) output (x_i), such that:

$$b_{ij} = \frac{x_{ij}}{x_i} \tag{3.7}$$

matrix 3.8 can be written as,

$$\mathbf{x'} = \mathbf{x'B} + \mathbf{v'} \tag{3.9}$$

Where $\mathbf{B}$ is a matrix with b_{ij} elements. After re-writing, equations (3.6) and (3.9) becomes $\mathbf{(I - A)x} = \mathbf{d}$ and $\mathbf{(I - B)x'} = \mathbf{v'}$ for the Leontief and Ghosh models, respectively. The standard Leontief model assumes that input coefficients are fixed. Under this assumption, given some demand vector ($\mathbf{d}$), the required output vector ($\mathbf{x}$) can be defined as

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{d} \tag{3.10}$$

Where $(\mathbf{I} - \mathbf{A})^{-1} = \mathbf{L}$ is usually called the Leontief inverse matrix. Thus, $\mathbf{x} = \mathbf{Ld}$. As opposed to the Leontief model, the Ghosh (supply-driven) model rests on the assumption of fixed output coefficients. So that, for a given new value-added $(\mathbf{v'}_{\mathbf{new}})$ the required new output is calculated as

$$\mathbf{x'}_{\mathbf{new}} = \mathbf{v'}_{\mathbf{new}}(\mathbf{I} - \mathbf{B})^{-1} \tag{3.11}$$

Where $(\mathbf{I} - \mathbf{B})^{-1} = \mathbf{G}$ is usually called the output inverse matrix. Thus, $\mathbf{x'} = \mathbf{v'G}$.

Given our hypothesis, we generate the new value of valued-added compatible with the increase of the financial sector's gross operating profit shares at 1% and with the decline in most offshored sector wage shares of the same magnitude. Then the impact on output is given by the growth rate of the new output relative do the original output. Such that:

$$\Delta Y_{new} = \left(\frac{Y_{new}}{Y_{orig}} - 1 \right) * 100$$

(3.12)

Where $Y = \sum x_i$ is the total output.

3.3.2 The Methodology on Increased Sectoral Financial Sector GOPS Share relative to Other Sectors

The research using the Leontief and Ghosh model for input-output studies the effect of a per cent increase in the absolute value of final demand and value added, respectively. For the purpose of this study, we analyse the effect of a percentage increase in the financial sector gross operating profit share on output, and the effect of fall wage share on output. This section describes the methodology used to calculate these changes.

To simulate for the impact of increased share of financial sector GOPS on output growth, we assume an increase in the financial sector GOPS by μ followed by a correspondent decline in the rest of the sectors, to keep the total GOPS unchanged[12]. The declining rate of each of the other sectors is determined by their weight in total GOPS. Algebraically, we split the total value added into two. A vector of sectoral Value Added excluding GOPS denoted by $\mathbf{V}_{XGOPS}$ and a vector the gross operating profits and surplus denoted by $\mathbf{G}_{GOPs}$. Letting v_{XGOPSi} be the sectoral value added excluding GOPS, and $gops_i$ be the sectoral gross operating profit, we define

$$VAXGOPS = \sum_{i=1}^{n} v_{XGOPSi} \qquad (3.13)$$

and

[12] This assumption is in line with the argument presented in Cecchetti and Karroubi (2012) the effect of the financial sector growth on GDP growth can results from the fact that, the financial industry competes for resources with the rest of the economy. Thus, excessive growth of the financial sector may bids away not only physical capital, in the form of buildings, computers and the like, but highly skilled workers as well from other sectors.

$$GOPS = \sum_{i=1}^{n} gops_i \tag{3.14}$$

Then, assuming an increase in the financial sector gross operating profit and surplus ($gops_{FINANCE}$) by μ we get

$GOPS\_F > GOPS$ by $\mu * gops_{FINANCE}$. Thus, to keep $GOPS\_F = GOPS$, we need to subtract the $\mu * gops_{FINANCE}$ from the rest of the sector. The percentage of $\mu * gops_{FINANCE}$, deducted from each sector's gross operating profit, is based on the share of each on the non-financial sector ($gops\_non\_fin$) on total non-financial ($GOPS\_non\_fin$), given by,

$$\psi_i = \frac{gops\_non\_fin_i}{GOPS\_non\_fin} \tag{3.16}$$

The absolute value to be subtracted in each non-financial sector is the given by $\psi_i * \mu * gops_{FINANCE}$. So that,

$$gops\_New_i = (gops_i - \psi_i * \mu * gops_{FINANCE}) \tag{3.17}$$

The magnitude of the change in sectoral $gops$ is then calculated as:

$$\Delta gops_i = \left(\frac{(gops_i - \psi_i * \alpha * gops_{FINANCE})}{gops_i} \right) * 100 \tag{3.18}$$

Where the intended profit share growth rate is obtained by changing the value of μ. The new sectoral GOPS ($gops\_New_i$) gives a vector of new $GOPS\_New$. The new vector of total value added is then obtained as

$$V_{New} = VXGOPS + GOPS\_New \tag{3.19}$$

The required output, $\mathbf{x}_{New}$, is calculated using equation 3.11. As the global output is defined as $Y_{New} = \sum x_i$, the effect of the changes in the financial sector profit share, relative to other sector, on output is then calculated using equation 3.12.

3.3.3 Source of Data

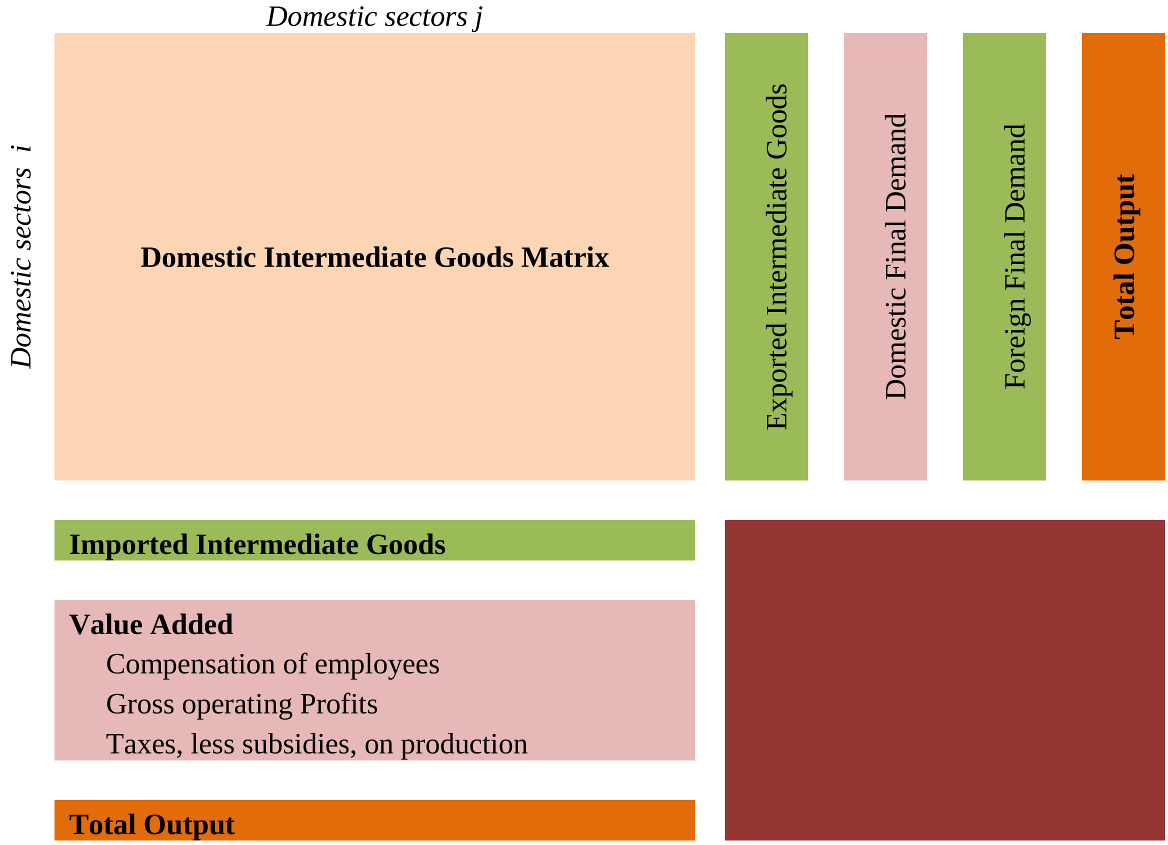
This study uses a detailed OECD Inter-Country Input-Output (ICIO)[13] tables spanning the years 2000 and 2009. These tables present the matrices of inter-sectoral flows of intermediate and final goods and services within and across countries, evaluated in USD million. The data includes 62 countries with 34 sectors and 6 final good and services use items each[14]. For the purpose of the present study, we condense the 34 sectors into 13 sectors as described in the Appendix A, and focus on the US economy. We also add up the sectors of all other (61) countries into a single row of imported input to US sectors and one column of exported inputs from the US sectors. The remaining disaggregated US sectors correspond to the matrix that expresses domestic inter-sectoral flows of intermediate goods in the US.

[13] http://www.oecd.org/sti/ind/inter-country-input-output-tables.htm
[14] Include all OECD countries and 27 non-member economies (including all G20 countries).

More specifically, the basic structure of input-output tables used in this study is illustrated in the figure 3.1. The sectors in the rows supply inputs to the sectors in the columns. The domestic intermediate goods matrix provides data on the interactions between domestic suppliers and domestic users of domestically produced input. It is a square matrix comprised by 13 sectors. It can be extended to a 14×14 matrix by including the row and columns of imported and exported inputs, respectively. Next, we have the rows that make up value added (at basic prices). This includes compensation of employees (such as wages and salaries) and gross operating surplus and taxes, less subsidies on production. It is worth noting that the VA's breakdown into these components is fundamental for the present study. However, the ICIO database provides only the aggregated VA value. Therefore, the data on value added breakdown was collected from STAN database[15] at the OECD statistics. Finally, the upper right of Figure 3.1 accounts for the supply of goods that are not consumed by domestic industries, but as final consumption (both by households and general government), gross fixed capital formation (investment) and exports.

[15] https://stats.oecd.org/Index.aspx?DataSetCode=STAN08BIS

Figure 3.1: The Structure of the Input-Output Tables



Source: Developed by author

3.4 ICIO Data Analysis for U.S.

The data shows that over 2000-2009 total US output increased 33% to US$ 22.96 trillion. This was followed by a 26 % increase in intermediate input use to US$ 10.0 trillion in 2009, and by almost a 40% increase in total value added to a total of US$ 12.9 trillion. In terms of its components it is worth noting that the total gross profit share increased by 53% to US$ 5.34 trillion in 2009, while the total wages ad salary increased by 30% increase to a total of US$ 6.3 trillion[16].

Given the purpose of this study, Table 3.1 presents the sectoral offshoring index, defined according to Feenstra and Hanson (1996, 1999), as a ratio of imported intermediate inputs to the total purchase of individual industries. The results shows that the most offshored sectors, between 2000 and 2009, are Computer and Electric Equipment importing about 30.2 per cent of its total input in 2009, and 27.67 per cent in 2000; Manufacturing 2, with imported input at the share of 22 per cent of total input to the sector in both years; Mining (22.5%), representing highest sectoral outsourcing growth of 7.1% compared to the level of 2000; followed by the Energy and Water sector where outsourcing increased by 6.3% per cent between 2000-2009, to 20%. Other sectors are Construction that outsourced 16% of its input in 2009 against 14% in 2000, and Manufacturing 1 with 16% after 13% in 2000.

[16] Still in this period unemployment declined slightly (0.7%), representing a loss of almost 1.1 million jobs.

Table 3.1: Outsourcing Indicators US

	DOMESTIC INPUT			IMPORTED INPUT		
	2000	2009	CHANGE	2000	2009	CHANGE
USAAGRFISH	92.84	90.80	-2.04	7.15	9.20	2.04
USAMINING	84.65	77.52	-7.12	**15.35**	**22.48**	**7.12**
USAMANUF1	86.67	83.92	-2.75	13.33	16.08	**2.74**
USACOMELEC	72.33	69.75	-2.58	**27.67**	**30.25**	**2.57**
USAMANUF2	77.77	77.80	0.03	**22.23**	**22.20**	**-0.02**
USAENERWAT	86.42	80.14	-6.29	**13.58**	**19.86**	**6.29**
USACONS	86.03	83.93	-2.09	13.97	16.06	2.09
USATRADERENT	94.64	95.08	0.44	5.36	4.91	-0.44
TRANSCOM	93.94	91.86	-2.08	6.05	8.14	2.08
USAFINANCE	97.03	95.74	-1.29	2.96	4.25	1.29
R&D AND COMP	95.30	93.80	-1.51	4.69	6.19	1.50
PUBLIC	93.59	94.21	0.62	6.41	5.78	-0.62
USAPVH	0.00	0.00		0.00	0.00	0.00

Source: Calculated by author. AGRIFISH stands for Agriculture and Fish, MANUF1 for Manufacture 1, COMELEC is Computer and Electric Equipment, MANUF2 is Manufacture 2, ENERWAT is Energy and Water, TRADERENT , the Trade and retail, TRANSCOM is the Transport and Communications, R&d SOFTWARE is Research and Development and Software, FINANCE, PUBLIC, PVH stand for Financial, Public and Private sector.

Analysing the dynamics of these sectors' main components of value added, we find, as shown in Figure 3.2-3.5, that in general the wages and salaries in the most offshored sectors declined steadily over 2000-2009, except in Mining. In this sector wages show an upward trend up to 2008, followed by a decline. In contrast, in the non-outsourcing sectors the wages and salaries have been volatile, except in the sectors of services (Trade and Retail) and transport and communication, where it shows a steady decline.

The gross operating profits, as a percentage of the total profits (Figure 3.6-3.11), show mixed results among the sectors. The Mining and Computer and Electronic Equipment sectors show a steady increase in profit share up to 2008, while the profit in Manufacturing 1, exhibits a volatile behaviour. Manufacturing 2 and Construction profit share fell, while the profit share in the sector of Energy and Water is stable. The data also shows that each of the most offshored sector's gross operating profit share to the total gross profit is still lower relative to less outsourced sectors. The financial sector, one of the non-outsourced sector generates the biggest share of the economy gross profits recording an average of 38% over the period.

Figure 3.2 Most Offshored Sectoral Wages and Salaries % of the total

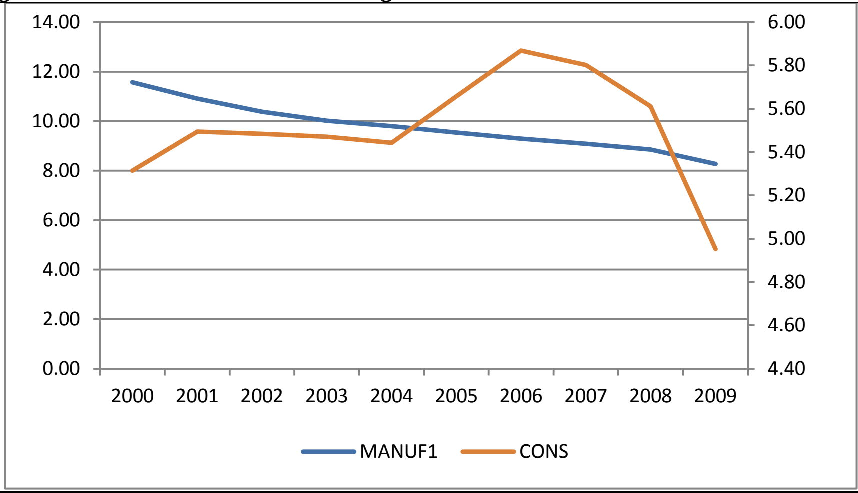


Figure 3.3 Most Offshored Sectoral Wages and Salaries % of the total

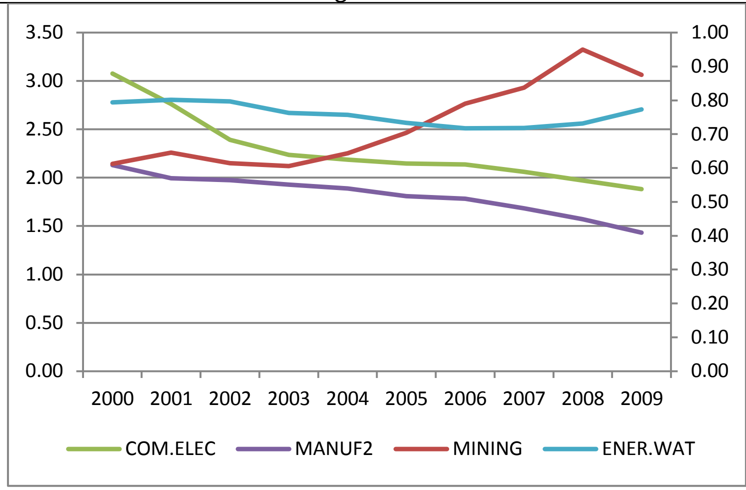


Figure 3.4 Less Offshored Sectoral Wages and Salaries % of the total

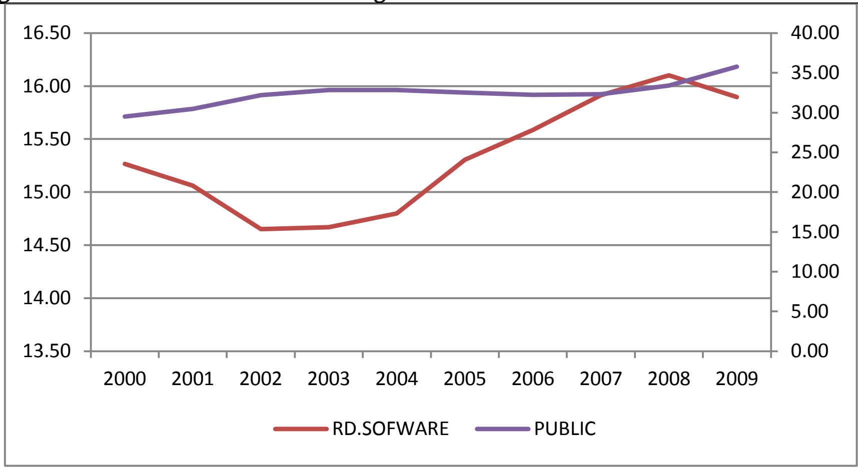
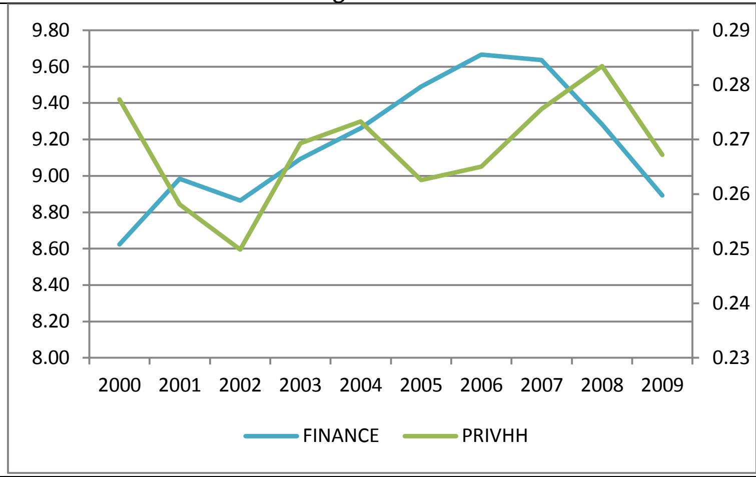


Figure 3.5 Less Offshored Sectoral Wages and Salaries % of the total



Source: Plotted by author

Figure 3.6 Sectoral GOPS share to Total GOPS

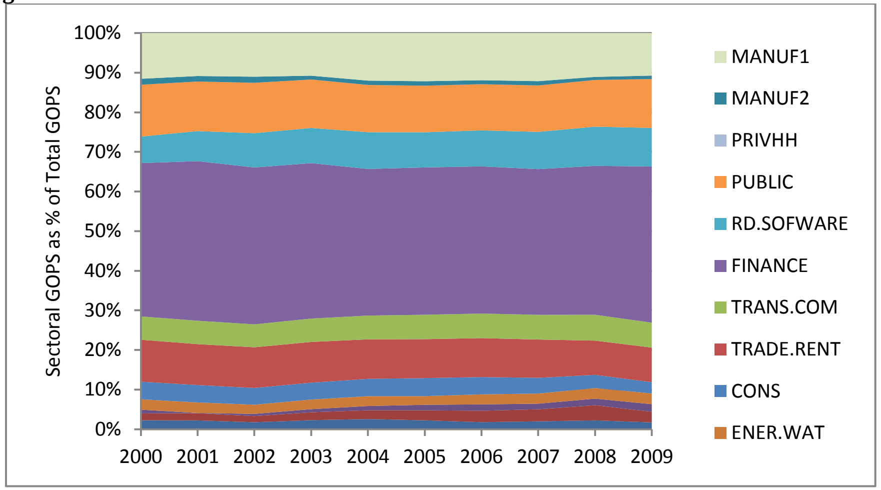


Figure 3.7 Most Offshored Sectoral GOPS share to Total GOPS

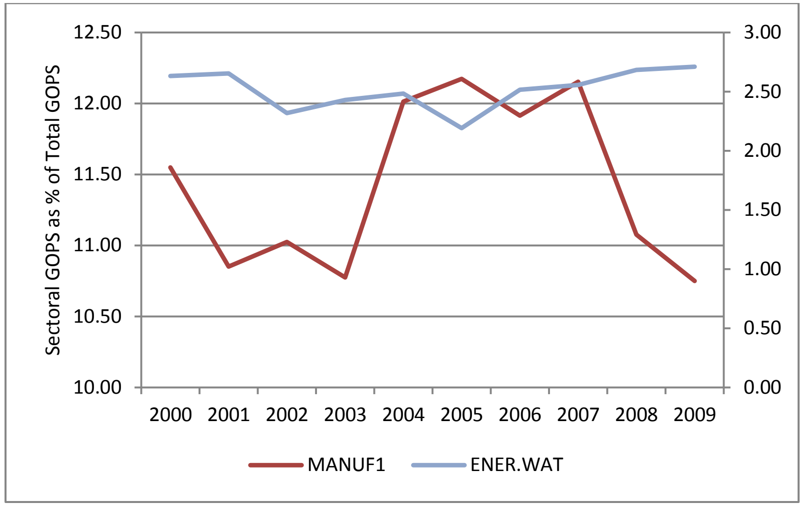


Figure 3.8 Most Offshored Sectoral GOPS share to Total GOPS

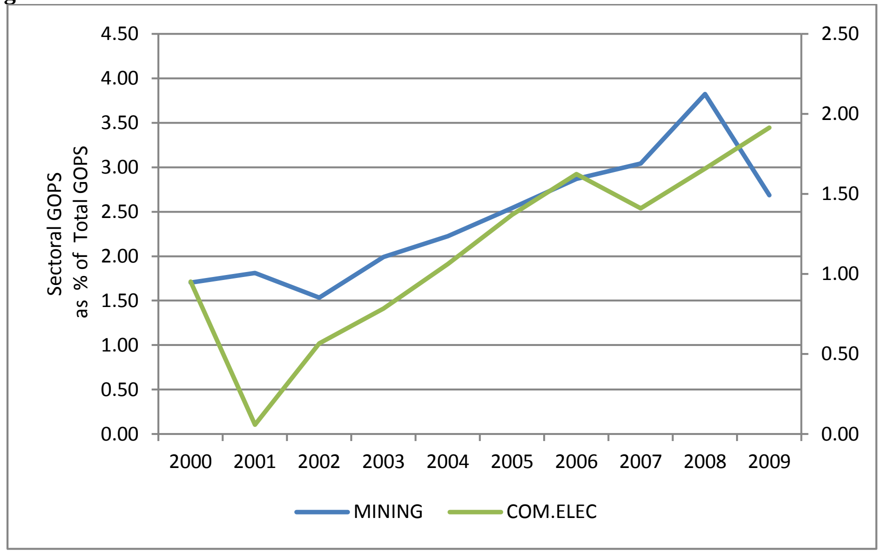
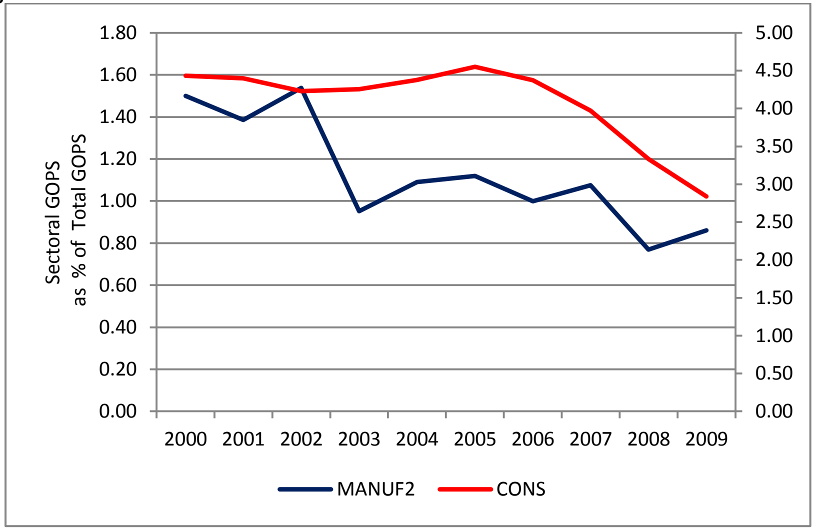


Figure 3.9 Most Offshored Sectoral GOPS share to Total GOPS



Source: Plotted by author

Figure 3.10 Less Offshored Sectoral GOPS share to Total GOPS

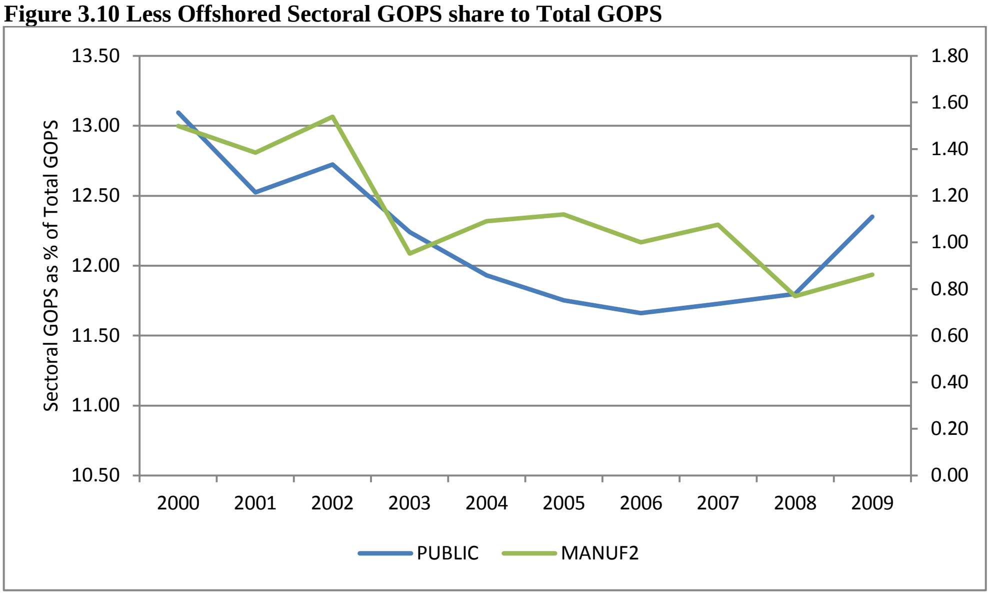
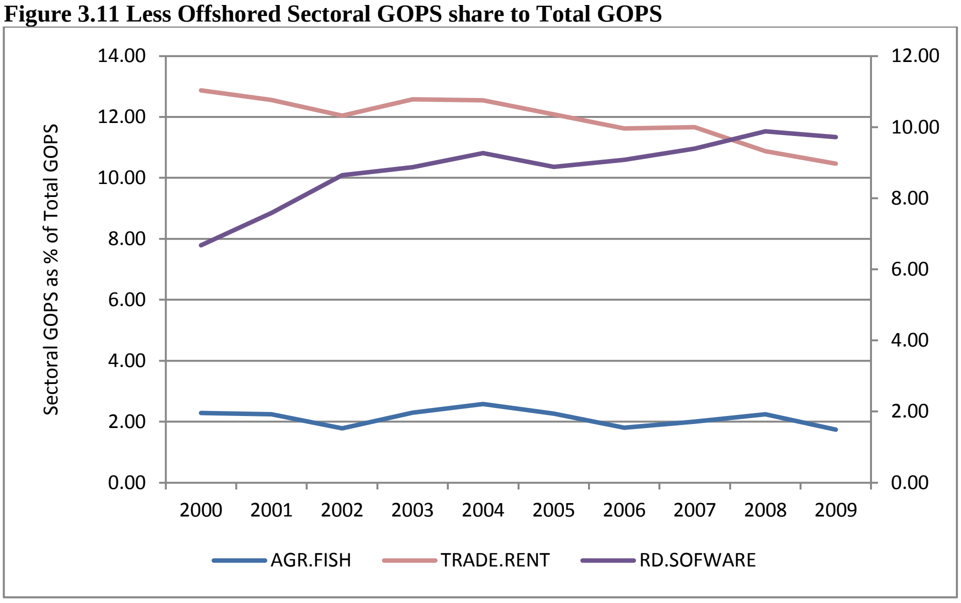


Figure 3.11 Less Offshored Sectoral GOPS share to Total GOPS



3.5 The Impact of Change in Sectoral GOPS and Wages shares on Output growth

In this section we use the Ghosh inverse (equation 3.11) to test the impact of increased financial sector gross operating profits share, and the effect of a decline in wages share – of top three most foreign outsourced sectors – on total output growth. We simulate the impact of such changes for two periods, 2000 and 2009. This allows us to understand how the output response to increase in the financial sector profit share, and to a decline in wages in the offshored sectors, differs given the change in the structure of the output technology matrix between the two periods.

3.5.1 The Impact of Increase of Financial Sector GOPS Share on Output

The results on the impact of increased financial sector profit share on output are summarised in Table 3.2. It shows that a 1 per cent increase in the financial sector's gross operating profits share, relative to rest of the economy sectors profits share, results in total output decline by 0.015 per cent for the 2000's Ghosh "technological matrix" structure, and by 0.256 per cent in 2009. This shows that the changes in the production technology structure between the 2000 and 2009 may have magnified the effect by almost 10 times the impact in 2000.

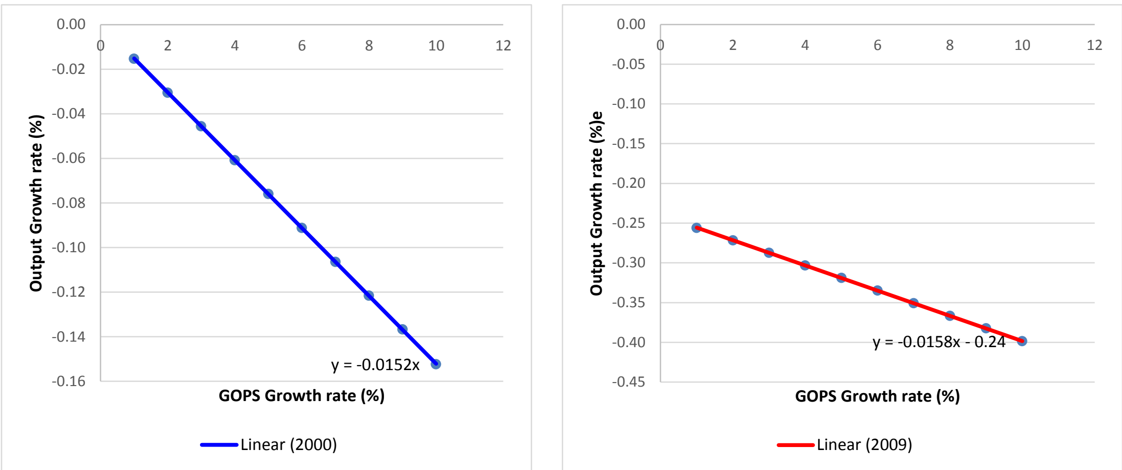
Table 3.2: The Impact of Financial Sector profit share increase on US GDP (in US$ millions) [17]

Sectors	x_0_2000	x_1_2000	Change	x_0_2009	x_1_2009	Change
AGRI.FISH	231978	230489.3	-2.31	328404.6	326618.1	-0.54
MINING	186581.7	185525.7	-1.96	331407.1	328038.3	-1.02
MANUF1	3004623	2993381	-1.33	3492701	3461990	-0.88
COM.ELEC	480576.2	479577.2	-0.73	311891.2	309149.5	-0.88
MANUF2	706819	704985.5	-0.92	612713.9	607575.7	-0.84
ENER.WAT	335963.5	334456.3	-1.59	320276.2	317284.2	-0.93
CONST	892402.7	889067.5	-1.33	1035897	1028667	-0.70
TRADE.RETAIL	2088808	2083115	-0.96	2561540	2545961	-0.61
TRANS.COM	1114949	1111058	-1.22	1349652	1338911	-0.80
FINANCE	2936055	2974744	5.07	4370113	4543047	3.96
RD.SOFTWARE	1760162	1756704	-0.68	2576800	2449809	-4.93
PUBLIC	3456129	3449313	-0.70	5638712	5614309	-0.43
PRIV.HH	13168.8	13168.8	0.00	16594.37	16594.37	0.00
Total Output	**17208216**	**17205585**	**-0.01529**	**22946702**	**22887953**	**-0.25602**

Source: Calculated by author

Furthermore, we simulated for the impact different financial profit shares growth rate (from 1% to 10% increase) on output (Figure 3.14). It shows that given the 2000 and 2009 technological structures of the economy, there is a negative linear relationship between changes in financial sector gross operating profit share and output growth. With the 2009 linear relationship[18] showing higher slope, confirming the greater financial sector gross operating profit share growth impact on output in this year relative to 2000.

Figure 3.12: Changes in GOPS vs. Change in Output -2000 and 2009



Source: Plotted by author.

[17]x_0 stands for original Gross Output (before the increase in the financial sector profit share) and x_1 notes the new Gross Output (after an increase in the financial sector profit share).
[18] This relationship is based on the Ghosh Model, using different GOPS growth rate.

3.5.2 Impact of falling Wage Share in the most Outsourced Sectorial on Output

Tables 3.3-3.5 show the results of the impact of falling wages in the most input offshored sectors on total output. The results are as follows: a 1 per cent decline in wages in the sector of Computer and Electronics implies a decline in total output by 0.058 per cent in 2000 and by 0.247 per cent in 2009; a 1 per cent decline in Mining sector wage share resulted in global output decline by 0.35 per cent in 2000 and by 0.51 per cent in 2009; finally, a 1 per cent fall in Manufacture 2 is associated with a total output fall by 0.016 per cent in 2000 and 0.24 per cent in 2009.

As in the analysis of the effects of financial sector profit share on output, these results reinforce the evidence that the 2009 technology matrix structure magnifies the effect of sectoral falling wages shares on output relative to the Ghosh technological structure of 2000.

Table 3.3: The Impact of Computer and Electronics wages share falling of Output[19]

Sectors	x_0_2000	x_1_2000	Change	x_0_2009	x_1_2009	Change
AGRI.FISH	231978	232502.6	-2.31	328404.6	329154.3	0.23
MINING	186581.7	187023.6	-1.96	331407.1	331348.7	-0.02
MANUF1	3004623	3010796	-1.33	3492701	3485046	-0.22
COM.ELEC	480576.2	426245.1	-0.73	311891.2	250039.8	-19.83
MANUF2	706819	705913.4	-0.92	612713.9	608478.8	-0.69
ENER.WAT	335963.5	336678.1	-1.59	320276.2	320393.5	0.04
CONST	892402.7	895178.3	-1.33	1035897	1035596	-0.03
TRADE.RETAIL	2088808	2096897	-0.96	2561540	2563202	0.06
TRANS.COM	1114949	1118092	-1.22	1349652	1346858	-0.21
FINANCE	2936055	2937387	5.07	4370113	4490742	2.76
RD.SOFTWARE	1760162	1767424	-0.68	2576800	2466876	-4.27
PUBLIC	3456129	3470650	-0.70	5638712	5645555	0.12
PRIV.HH	13168.8	13297.12	0.00	16594.37	16750.97	0.94
Total Output	**17208216**	**17198085**	**-0.05887**	**22946702**	**22890040**	**-0.24693**

Source: Calculated by author

Table 3.4: The Impact of Mining wages share falling of Output

Sectors	x_0_2000	x_1_2000	Change	x_0_2009	x_1_2009	Change
AGRI.FISH	231978	231648.3	-2.31	328404.6	328006.8	-0.12
MINING	186581.7	137680.7	-1.96	331407.1	267215.3	-19.37
MANUF1	3004623	2976942	-1.33	3492701	3440528	-1.49
COM.ELEC	480576.2	482052.2	-0.73	311891.2	312096.9	0.07
MANUF2	706819	706651.7	-0.92	612713.9	609353.4	-0.55
ENER.WAT	335963.5	326854	-1.59	320276.2	315510.5	-1.49
CONST	892402.7	891642.1	-1.33	1035897	1031362	-0.44
TRADE.RETAIL	2088808	2095340	-0.96	2561540	2562383	0.03
TRANS.COM	1114949	1116865	-1.22	1349652	1347493	-0.16
FINANCE	2936055	2934838	5.07	4370113	4489653	2.74
RD.SOFTWARE	1760162	1767444	-0.68	2576800	2468434	-4.21
PUBLIC	3456129	3465967	-0.70	5638712	5640695	0.04
PRIV.HH	13168.8	13295.29	0.00	16594.37	16750.59	0.94
Total Output	**17208216**	**17147220**	**-0.35446**	**22946702**	**22829484**	**-0.51083**

Source: Calculated by author

Table 3.5: The Impact of manufacture 2 wages share falling of Output

Sectors	x_0_2000	x_1_2000	Change	x_0_2009	x_1_2009	Change
AGRI.FISH	231978	232463.6	-2.31	328404.6	329128.8	0.22
MINING	186581.7	187003.8	-1.96	331407.1	331352.5	-0.02
MANUF1	3004623	3012746	-1.33	3492701	3486463	-0.18
COM.ELEC	480576.2	482196	-0.73	311891.2	312055	0.05
MANUF2	706819	653876	-0.92	612713.9	541087.2	-11.69
ENER.WAT	335963.5	336746.5	-1.59	320276.2	320439	0.05
CONST	892402.7	894080.9	-1.33	1035897	1034024	-0.18
TRADE.RETAIL	2088808	2097238	-0.96	2561540	2563766	0.09
TRANS.COM	1114949	1118229	-1.22	1349652	1348781	-0.06
FINANCE	2936055	2937995	5.07	4370113	4492213	2.79
RD.SOFTWARE	1760162	1768509	-0.68	2576800	2468929	-4.19
PUBLIC	3456129	3471083	-0.70	5638712	5646713	0.14
PRIV.HH	13168.8	13296.13	0.00	16594.37	16750.83	0.94
Total Output	**17208216**	**17205461**	**-0.01601**	**22946702**	**22891702**	**-0.23969**

Source: Calculated by author

[19] x_0 stands for original Gross Output (before the increase in the financial sector profit share) and x_1 notes the new Gross Output (after an increase in the financial sector profit share).

3.6 Summary and Conclusions

In recent years, advanced economies have experienced the following types of macroeconomic malaise: falling wages, rising wage and income inequality, a reduced share of surplus in most economic sectors except the financial sector, and low GDP growth accompanied by high GDP volatility. This study explores the relationship between outsourcing and wage decline, the effect of falling wage share and the impact of high financial sector gross operating profit share on output growth.

To test these hypotheses the study follows three steps. First, we measure outsourcing as a ratio of imported intermediate inputs to the total purchase of individual industries to identify the most outsourced sectors. Second, we analyse the dynamic of their respective wages and salaries and gross operating profits. Third, using an innovative approach based on the Ghosh inverse input-output model, we investigate the impact of increase in financial sector gross operating profits share and the effects of falling wages share, in the top three most offshored sectors, on total output. This approach has the advantage of testing directly the argument presented in Cecchetti and Karroubi (2012) excessive growth of the financial sector may bids away not only physical capital, in the form of buildings, computers and the like, but highly skilled workers as well from other sectors, leading to lower GDP growth. Additionally, our approach also consider the information of the sectoral relationship contained in the input-output matrices, which is not often explored by the econometric approach on this subject.

Our results show that between 2000 and 2009, the Computer and Electronics, Mining and Manufacturing 2 are most offshored, importing about 30.25%, 22.5% and 22.2% of their total inputs, respectively. The results also show that, in general, wages and salaries in these sectors declined steadily over the period. In less-offshored sectors we find wages and salaries to be volatile. This suggests that, over the period, a decline in wages may be associated with increased offshoring. Further, we show that a decline in wages shares in the top three most offshored sectors has a negative impact on total output growth

On the analysis of the dynamic of sectoral gross operating profits, we find no clear pattern in the effect of offshoring on improvements of sectoral profits. The results show mixed behaviour among the sectors. The Mining and Computer and Electronic Equipment sectors show a steady increase in profit share up to 2008, and a decline in Manufacturing 2 profits. However, the share of each of this sectors gross profit to the total gross profit is still lower relative to the less outsourced sectors. The Financial sector, one of the non-outsourced sectors, has the biggest share of the economy gross profits recording an average of 38% over the period.

Testing the impact of increase on Financial sector GOPS on total output using Ghosh inverse matrix, we argue that Financial sector gross operating profits share growth has negative effect on total output. The magnitude of this impact is higher in 2009 compared to 2000. Further, we show that falling wage in the most offshored sector has reduces output growth.

Our findings conforms with Cecchtti and Karroubi (2012), Stockhammer (2004), Orhangazi (2008), Crotty (2005) and Duménil and Lévy (2004) that find negative relationship between financial sector growth and GDP growth, reflecting the rapid financial sector growth relative to the other sectors of the economy.

4 Chapter 4

Granular Macroeconomic Model for Advanced Economies: The Impact of Financial Sector on GDP Volatility

Abstract

The 2007 financial crisis and the excessive growth of the financial sector, particularly in advanced economies, has renewed interest in the role of the financial sector for GDP growth and volatility, and in the importance of microeconomic sectoral shocks on aggregate volatility. The objective of this study is twofold. First, it proposes a demand driven GDP volatility measure and compares its performance with the original supply side GDP volatility based on the Carvalho-Gabaix (2013) granular macro-economic model. Secondly, we estimate the role of the financial sector on GDP volatility given its centrality in the production network. The main results show that demand-driven GDP volatility explains about 60 per cent of actual GDP volatility and replicates the most important swings in macroeconomic volatility. It is able to capture the low volatility of Great Moderation and the increased volatility from the 1990s up to 2007. In general, these results conform with the granular macroeconomic hypothesis on the relevance of sectoral shocks on aggregate volatility such as affirmed by Gabaix (2011). More importantly, we find that the surge in the centrality of the financial sector is the main factor that determined the increased volatility from the 1990s to the run up to the 2007 financial crisis.

Keywords: Networks, financial sector, Sectoral Final Demand Shocks, GDP volatility, granular macroeconomics

4.1 Introduction

The 2007 Global Financial Crisis and the excessive size of the financial sector, especially in the US and UK, have refuelled the debate on the role of financial sector on GDP growth and volatility (see, Rajan (2010), Philipon (2010), Moosa (2010), and Schularik and Taylor (2012)). The approaches in these analyses have gained new contours with the granular macroeconomic movement which emphasises the relevance of the interconnections in the production networks of an economy to explain GDP fluctuations. The granular macroeconomics based on the input-output links between sectors of an economy, given at a high level of granularity in the industrial classification began with Acemoglu et al (2012), Carvalho (2014), Carvalho and Gabaix (2013), and to a lesser extent with Stella (2015), Weinstein (2013) and Buch and Neugebauer (2011). This was predated by the work of Gabaix (2011) who challenged highly aggregated macroeconomics relying on aggregate shocks for driving GDP fluctuations as being a flawed model. In Gabaix (2011), the degree of granularity goes to the level of firms in an economy and as the firm-size distribution is fat-tailed, individual firm level shocks matter and they cannot be aggregated into a single shock, as in the macro-economic model. Once the framework of interconnectedness and networks is used, as seen in financial sector models for systemic risk, highly central nodes drive the instability of the system (Markose (2012))

To operationalize the analysis of the role of microeconomic shocks on aggregate GDP fluctuations, based on neoclassical production function, the literature proposes two quantitative measures. First, the "fundamental volatility" (Carvalho and Gabaix (2013)) which consists of the product of the ratio of sectoral output to total output and productivity growth standard deviation. The second measure is called the "influence vector" (Carvalho (2014)[20]) which is a more network-related measure of centrality, consisting of the product of network centrality and productivity growth standard deviation. Using these frameworks, the granular macroeconomic approach has shown that GDP volatility that is the result of the propagation through the economy of idiosyncratic sectoral or firm-level productivity shocks (fundamental volatility) accounts for the swings in macroeconomic output growth. Further, it is shown that the recent rise of macroeconomic volatility is chiefly due to the growth of the financial sector (Carvalho and Gabaix, 2013). The growth of the financial sector as a ratio of GDP, which accelerated in late 2005 relative to other sectors, is the key factor for the end of Great Moderation – defined as "a decline in the volatility of U.S. output growth starting from 1984 up to 2007" (Carvalho and Gabaix, 2013).

It is worth noting that both the fundamental volatility and the influence vector are designed to derive the effects of sectoral idiosyncratic productivity (supply side) shocks on the aggregate fluctuations. However, from a theoretical view point, it has been argued that the impact of the financial sector on GDP volatility is based on the presence of financial or credit market frictions (Bernanke and Gertler (1990), Greenwald and Stiglitz (1991) and Kiyotaki and Moore (1997)). These manifest not only via shocks to the supply side arising, for example, from tighter lending criteria by the lenders, but also through shocks to demand for credit, such as those that arise from deterioration of creditworthiness of borrowers (Adrian et al, 2012). In particular, we start with the evidence in the US of an oversized financial sector contributing to a credit fuelled private consumption led GDP growth. This has been highlighted by various studies such as

[20]Carvalho (2014) shows that the fundamental volatility index proposed by Carvalho and Gabaix (2013) is equivalent to "influence vector"

IMF (2017), Mian et al. (2017b) and Mian and Amir (2018). The challenge is to quantify this based on our input-output demand shock driven approach.

Thus, following an approach similar to Carvalho-Acemoglu-Gabaix, the objective of this study is twofold. First, we develop a measure of demand side shocks driving aggregate volatility, in contrast with the volatility that would arise only from idiosyncratic sectoral or firm-level production shocks. Second, we explore the impact of a demand shock to financial sector on GDP volatility, given that this sector has high centrality in the production network. One straightforward rationale based on "macro-net granular" hypothesis is that, once the size of financial sector is considerably bigger relative to other sectors of the economy, becoming systemically important sector in the network, it has the potential to account for a significant portion of GDP volatility

This chapter is organised as follows. Section II presents the literature review on the role of the financial sector on macroeconomic volatility, and the literature review on granular macroeconomics and GDP volatility. Section III gives the methodology of study and the source of data. Sector IV presents the analysis and interpretation of the results on the impact of the financial sector on the production network and on the GDP volatility. Finally, section V provides the conclusion.

4.2 Why Demand Side Shocks Matter?

The Carvalho and Gabaix (2013) and Acemoglu et al (2012) granular macroeconomic models, the "fundamental volatility" and the "influence vector", are designed to derive the effects of sectoral idiosyncratic productivity (supply side) shocks on aggregate fluctuations. We develop a demand-driven model that investigates the impact of sectoral demand side shocks on GDP volatility. Our focus on demand side shocks in this study is motivated by the data and the theoretical and empirical literature showing that understanding of demand side shocks to the financial sector is important to elucidate macroeconomic fluctuations.

Our data shows private consumption as the biggest component of the final demand, which defines the expenditures side based GDP. As shown in Table 4.1, private consumption represents about 67.4 % of the total final demand. In contrast, private investment accounts for 16.7%, net exports, -3.4%, government consumption 15.5%, and government investment, 3.8%.

Table 4.1: Share of the 5 Final demand components in total US Final Demand (in per cent)

	1966-1975	1976-1985	1986-1995	1996-2005	2006-2015
Private Consumption	**59.71**	**61.35**	**63.66**	**65.49**	**67.40**
Private Investment	17.23	19.25	17.64	19.33	16.71
Net Exports	0.21	-1.16	-1.58	-3.28	-3.43
Govt. Investment	5.44	4.62	4.61	3.87	3.88
Govt. Consumption	17.40	15.94	15.68	14.58	15.45

Source: Calculation done by author using BEA's final demand data.

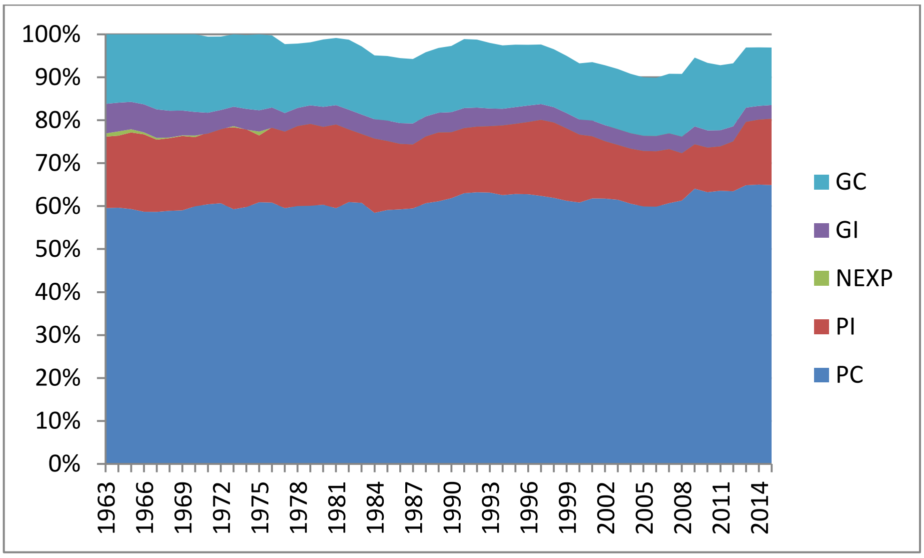
Private consumption is also the main determinant of final demand growth. As shown in Table 4.2 and Figure 4.1, on average private consumption contributes to about 69.75% of the GDP growth, followed by private investment contributing for 27.1%, government consumption with 10.1%, Government investment with 2.2, while the net exports, contributed for a decline by 9.1 %.

Table 4.2: Contribution of the Final demand components in total Final Demand growth (in per cent)

	1966-1975	1976-1985	1986-1995	1996-2005	2006-2015
Private Consumption	**35.58**	**108.85**	**69.41**	**72.41**	**69.75**
Private Investment	17.81	48.39	13.72	20.74	27.14
Net Exports	32.02	-89.24	-1.31	-14.03	-9.13
Gov. Investment	1.86	6.53	2.94	4.22	2.16
Gov. Consumption	12.72	25.46	15.24	16.67	10.08

Source: Calculation done by author using BEA's final demand data.

Figure 4.1: Share (%) of the Final Demand Components in Total US Final Demand from 1963-2015



Source: Plotted by author from BEA's final demand data. Note PC denotes Private Consumption, PI is Private Investment, GC is Government Consumption, GI is Government Investment and NEXP is the net exports.

The growth in the private consumption is mostly determined by the growth of the financial sector, which has the biggest share of this component of the final demand. As shown in Table 4.3, and Figure 4.2, on average over a 10-year period 2006-2015 the financial sector represents 23% of the private consumption, and contributed to the private consumption growth by 23.15% before the 2007 financial crisis, as shown in Table 4.4.

Table 4.3: Sectoral Shares of Private Consumption

	1966-1975	1976-1985	1986-1995	1996-2005	2006-2015
AGRI.FISH	1.13	0.95	0.74	0.69	0.65
MINING	0.00	0.00	0.00	0.00	0.00
ENER.WAT	2.69	3.48	3.07	2.49	2.37
CONST	0.00	0.00	0.00	0.00	0.00
MANUF1	21.97	20.00	15.81	13.21	14.21
COM.ELEC	1.41	1.22	1.15	1.14	1.07
MANUF2	3.71	3.46	3.16	2.89	1.97
TRADE.RETAIL	26.98	25.56	23.67	23.03	22.31
TRANS.COM	2.20	2.30	2.20	2.32	2.17
RD&SOFTWARE	5.00	5.14	6.07	7.05	6.63
FINANCE	**18.66**	**19.69**	**21.99**	**23.15**	**22.95**
PUBLIC	10.09	13.18	17.38	19.28	21.46
PRIV.HH	5.82	5.10	5.32	5.38	4.87

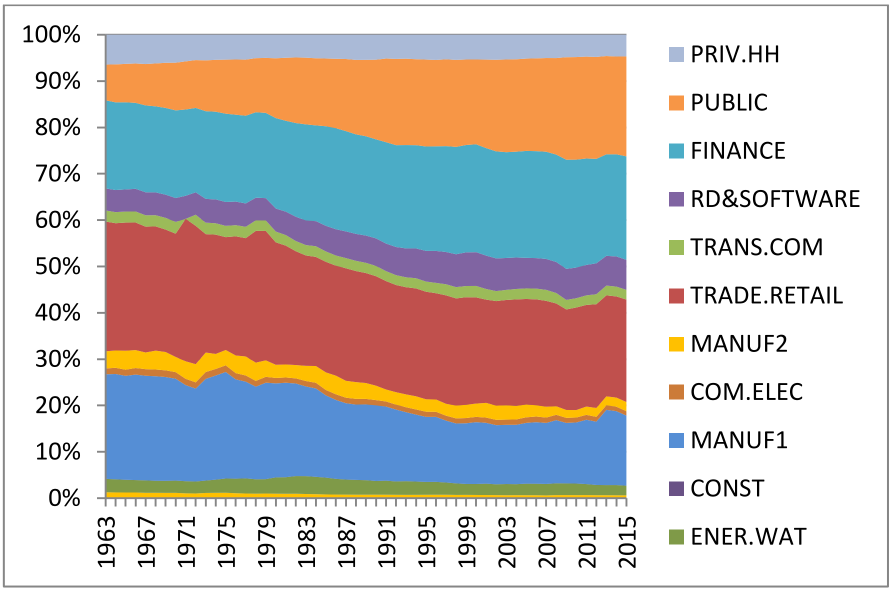
Source: Calculation done by author using BEA's sectoral final demand data.

Table 4.4: Sectoral Contribution to the Private Consumption Growth

	1966-1975	1976-1985	1986-1995	1996-2005	2006-2015
AGRI.FISH	1.01	0.56	0.61	0.52	0.62
MINING	0.00	0.00	0.00	0.12	0.04
ENER.WAT	2.83	4.54	1.80	1.97	1.64
CONST	0.00	0.00	0.00	0.00	0.00
MANUF1	22.12	14.05	9.13	10.83	21.74
COM.ELEC	1.46	0.89	1.06	1.26	0.92
MANUF2	2.23	4.03	1.15	3.24	1.41
TRADE.RETAIL	17.26	22.24	22.14	22.02	24.77
TRANS.COM	12.20	2.15	2.02	2.31	3.20
RD&SOFTWARE	5.29	5.74	7.88	6.77	6.49
FINANCE	**17.51**	**23.46**	**24.10**	**23.58**	**18.17**
PUBLIC	13.55	17.40	24.77	22.36	15.59
PRIV.HH	4.53	4.94	5.35	5.03	5.42

Source: Calculation done by author using BEA's sectoral final demand data.

Figure 4.2: Sectoral Share in US Private Consumption (in per cent)



Source: Plotted by author from BEA's sectoral Final demand data.

This evidence supports the studies done by the IMF (2017), Mian et al. (2017) and Mian and Amir (2018). These studies argue that an expansion in credit supply, as opposed to technology shocks or permanent income shocks, is a key force in generating a boom-bust cycle to the real economy. The effect of expansionary credit to the real economy is transmitted primarily through boosting household demand, as opposed to boosting productive capacity of firms in the economy – this is a mechanism that Mian and Amir (2018) called a "credit-driven household demand channel". This view conforms with Mian and Sufi (2009); focusing on the rapid growth in household leverage in the years before the recession, they show that household leverage growth performs remarkably well in explaining four facts that collectively define the recession: the sharp rise in household defaults, the fall in house prices, the drop in consumption (especially durables), and the rise in unemployment. Further, Mian and Sufi (2009) show that the dramatic increase in household leverage from 2000 to 2007 was a primary driver of the recession of 2007 to 2009. The importance of household leverage on the business cycle is also highlighted by the fact that the initial indicators of economic difficulty led to a rise in household default rates and a decline in house prices, both of which reflected an overstretched household sector. Further, Mian and Sufi (2009) draw our attention to the fact that the components of GDP that initially declined in 2007 and early 2008 were fixed residential investment and durable consumption, the two components that most heavily rely on the willingness of households to obtain additional debt financing, i.e. evidence of demand and not supply side shock.

The evidence in table 4.2 and 4.3 is also in line with the theoretical literature such as Bernanke and Gertler (1990), Greenwald and Stiglitz (1991) and Kiyotaki and Moore (1997), which shows that in presence of financial friction, the impact of the financial sector growth on the real economy can manifest not only via supply side shock, but also through shocks to demand for credit. This include shocks such as those arising from deterioration of creditworthiness of borrowers (Adrian et al, 2012), including the low willingness of borrowers to obtain additional debt financing, as in the case of the households discussed above.

4.3 Literature Review

This section is divided into two parts. Subsection 4.3.1 presents the literature review on the role of finance on macroeconomic volatility. Section 4.3.2 covers the literature review on the granular macroeconomics and the network approach in the context of determinants for GDP volatility dynamics.

4.3.1 The Role of Finance in Macroeconomic Volatility

The impact of finance on macroeconomic volatility has been extensively investigated in the last 20 years. This began in the wake of the East Asian financial crisis of the 1997-8 (Denizer et al. (2002), Beck et al. (2006), Cecchetti et al. (2006), Dynan et al. (2006) and Raddatz (2006)) followed more recently by the 2007-2009 Global Financial Crisis, when the financial sector was found to be instrumental in the propagation of the crises (Brunnermeier et al. (2012), Quadrini (2011), Sanjani (2014) and Fuentes-Albero (2014)).

The theoretical literature such as Bernanke and Gertler (1989), Greenwald and Stiglitz, (1991) and Kiyotaki and Moore (1997) attribute the relevance of the financial sector in business cycle fluctuations to the financial and credit market frictions. Financial frictions[21] have been shown to have a central role in propagating and amplifying the supply and demand credit shocks to the real economy. For instance, a negative shock that may result from deterioration of

[21]Financial frictions can be defined as the "stickiness" involved in making financial transactions; the total process including time, effort, money, and tax effects of gathering information and making a transaction such as buying a stock or borrowing money. https://financial-dictionary.thefreedictionary.com/Frictions

creditworthiness of borrowers increases agency costs by worsening the potential conflict between lenders and borrowers. This leads to higher external finance premium, which magnifies the fluctuations in borrowing and investment, thereby having an impact on the real economy (Adrian et al, 2012). A negative shock to the supply side that may arise from tighter lending criteria applied by the lender, or from other conditions that limit the availability of funds or increase the cost of funds, reduces spending leading to lower real GDP (Dabla-Norris and Srivisal (2013)).

However, there is no consensus in the empirical literature about the role of the financial sector on GDP volatility. Some argue that there is a linear negative relationship between financial development and macroeconomic volatility. This is facilitated through a number of channels, such as, (i) by reducing financial frictions that result from asymmetric information, adverse selection and moral hazards problems (Da Silva (2012)); (ii) through liquidity provision to firms facing cash- flow shortage or net worth problems (Raddatz (2006)); and (iii) by relaxing borrowing constraints and facilitating greater diversification, reducing risk and dampening fluctuations, as contended by Caballero and Krishnamurty (2001); and Acemoglu and Zilibotti (1997), Basu and Taylor (1999), Buch et al., (2002), and Buch and Pierdzioch (2005).

Others support positive linear relationship, as they argue that financial sector growth which occurs via financial deregulation can lead to increased macroeconomic volatility, and hence, increased instability. For instance, Wagner (2010) analysing the effect of diversification in financial institutions and systemic risk, argues that even though diversification reduces each institution's individual probability of failure, it makes the systemic crises more likely. Shliefer and Vishny (2010) argue that financial development can lead to more risk-taking by entrepreneurs and banks or facilitate over-leverage, both of which can potentially drive up volatility. In turn, Brunnermeier et al. (2012) and Quadrini (2011) show that propagation and amplification mechanisms within the financial sector and from the financial sector to the real economy can exacerbate GDP volatility. Similar results are also presented by Sanjani (2014) and Fuentes-Albero (2014), who base their analyses on an estimated New Keynesian DSGE model with an explicit financial intermediary sector, and financial stress. They show that financial shocks play a key role in explaining the volatility of macroeconomic variables.

The literature also has a very long pedigree starting from the Austrian School, leading to Hyman Minsky (1977), and the most recent rendering of this is Schularick and Taylor (2012) who states that the global financial crisis (GFC) was the result of a credit boom that went bust. This follows from the financialisation literature of Stockhammer (2004), and a more recent literature such as Moosa (2010) and, Philipon (2010).

Many of the discussions on the destabilizing role of the excessive growth of the financial sector and the increasing financial sector share of gross operating profits in the economy have been covered in Chapter 2 under the section financialisation and economy growth.

Finally, a growing literature, including Easterly et al (2000), and more recently Dabla-Norris and Srivisal (2013) and Cechetti et al. (2012), contends that the relationship between financial development and macroeconomic volatility is non-linear. They argue that financial development reduces volatility, but up to a certain threshold. At higher levels (such as those observed in many advanced economies), as the financial sector continues to grow relative to GDP, financial development can imply higher leverage and more risk, contributing to higher macroeconomic volatility.

4.3.2 Network Approach to Input-Output Macro-economic Modelling for GDP Volatility

There are two related issues in the granular macroeconomics: the granularity and the interconnectedness of the economies. In contrast with the dominant macroeconomic approaches that deal with highly aggregated stylized agents, granularity requires the break-down of the economy into smaller incompressible units of economic activity, such as, at the level of sectors and firms (Gabaix, 2011). Interconnectedness is modelled, at a given level of granularity, as the interactions between the sectors or firms using network methods. Thus, the level of disaggregation of the economy and the structure of the network connecting the different sub-units is key, in determining whether and how microeconomic shocks — affecting only a particular sector or firm — propagate throughout the economy and shape aggregate outcomes (Carvalho, 2014).

The practice of mainstream macroeconomic models which aggregate the supply chains and production networks into a single output equation with an aggregate supply shock is found to be highly flawed by the original proponents of granular macroeconomics, such as Gabaix (2011), Acemeglou (2010, 2012) and Carvalho (2014). In particular, they argue that microeconomic idiosyncratic shocks play an important role in explaining macroeconomic fluctuations.

The theory underlying the current view of granular macroeconomics started with Long and Plosser (1983). Using a model with six sectors (Agriculture, Mining, Construction, Manufacturing, Transport and Trade, and Services and Miscellaneous), Long and Plosser (1983) found that sectoral shocks and its propagation through the economy determines aggregate output volatility. However, subsequent studies, using more disaggregated data failed to show the relevance of the microeconomic shocks on aggregate volatility. The main argument is motivated by the Gaussian assumption and central limit theorem which implies that individual shocks cancel one another out in the limit (Lucas, 1981). For instance, Dupor (1999) testing the validity of the diversification hypothesis, found that if all sectors are equally important as input-suppliers, then independent sector-level shocks will have no role in generating aggregate volatility in a large economy, a result that is known as Dupor's Irrelevance.

Essentially, the micro shock irrelevance for aggregate volatility assumes equal importance of sectors and the fast volatility decline at the rate of $1/\sqrt{N}$ implied by the law of large numbers. Thus, the common feature of the subsequent research is to explore the micro shock effect on macroeconomic fluctuations, assuming heterogeneous sectoral importance and factors that can limit the law of large numbers and preserve the aggregate volatility. This includes models that assume asymmetries or threshold effects and limited interactions, such as Jovanovic (1987), Durlauf (1993), Bak et al (1993) and Horvath (2000).

A pioneering paper proposing a mechanism that generates a non-vanishing effect of microeconomic shocks on aggregate fluctuations is Jovanovic (1987). Based on game theory model to explain idiosyncratic shocks on aggregate risk, Jovanovic (1987) shows that independent shocks to players generate significant amounts of aggregate risk with size proportional to $\sqrt{N}$, rather than the $1/\sqrt{N}$ contended by the diversification hypothesis. However, Jovanovic's theoretical multiplier of $\sqrt{N} \cong 1000$ has been criticized as being much larger than what is empirically plausible (Gabaix, 2011). Durlauf (1993), studying the dynamic behaviour of an economy with N sectors, shows that in the presence of local interactions between sectors or firms and the existence of leading sectors – defined as industries which trade with all other industries – an idiosyncratic shock, particularly to these sectors, can explain aggregate fluctuations. This view is also emphasized in Bak et al (1993) who argue that the effects of the small independent shocks fail to cancel out in the aggregate due to two non-standard assumptions: local interaction between productive units (linked by supply relationships), and non-convex technology, as the main factors limiting the law of large numbers to hold.

Other studies include Horvath (2000), who presents a multi-sector dynamic general equilibrium model, calibrated to the US economy. The model assumes limited interaction, characterized by a sparse intermediate input-use matrix. This reduces substitution possibilities among intermediate inputs, strengthening co-movement in sectoral value-added and limiting the law of large numbers to hold in the volatility of aggregate value-added. Under such circumstances, they show that the model is able to match empirical reality as closely as standard one-sector business cycle models without relying on aggregate shocks.

A recent break-through is Gabaix (2011), who pioneered what became known as granular macroeconomics. Gabaix (2011) shows that the diversification argument breaks down if the distribution of firm sizes is fat-tailed. Specifically, he contends that when firm size is power-law distributed, aggregate volatility decays according to $1/\ln N$ rather than the speed of $1/\sqrt{N}$ which implies that idiosyncratic shocks do not die out in aggregate. Using U.S economy input-output data, Gabaix (2011) shows that idiosyncratic shocks to the largest 100 firms in the United States appear to explain about 1/3 of variations in output growth. Since then, the microeconomic shock relevance on aggregate volatility has been also reported by

Foerster, Sarte and Watson (2011) who argue that the role of idiosyncratic shocks increased considerably after the mid-1980s, accounting for half of the quarterly variation in industrial output. The similar magnitude of the effects of industry-specific shock on aggregate output is also reported by Atalay (2017). In addition, Di Giovanni, Levchenko, and Mejean (2014), analysing French input-output data, finds even bigger effects, that the standard deviation of the firm- specific shocks' contribution to aggregate sales growth amounts to 80% of the standard deviation of aggregate sales growth in the whole economy.

While Gabaix (2011) takes the firm size distribution as given, Acemoglu et al (2010), endogenise the firm size distribution as a function of a network structure based on the input-output linkages between the different units of production. The main finding suggests that structural properties of the supply network play an important role in determining whether idiosyncratic shocks have non-negligible aggregate effects. Similarly, Carvalho (2010) analysing the U.S intermediate inputs-output flows across sectors, shows that the presence of sectoral hubs – by coupling production decisions across sectors – leads to fluctuations in aggregates. These results conform with Carvalho (2014) and Acemoglu et al (2010, 2012), who show that that aggregate effect of sectoral idiosyncratic shocks is non-negligible, only if there is a significant asymmetry in the roles that sectors play as suppliers to others. In fact, Carvalho (2014), analysing the network perspective of production linkages using detailed US input-output data based on a standard general equilibrium setup, shows that the central sectors productivity co-moves with aggregate productivity, suggesting that idiosyncratic shocks to these sectors can play an important role in explaining aggregate fluctuations.

In addition to the studies on the real sector of the economy, the relevance of the idiosyncratic shocks on aggregate volatility is also true in the studies on the financial sector. For instance, Buch and Neugebauer (2011) analyse whether the effect of idiosyncratic shocks to loan growth at large banks affect aggregate credit growth and real GDP growth in the Eastern European countries. They find that bank idiosyncratic shocks account for about 11 per cent of the variation in aggregate credit growth and 10% in GDP growth. Amati and Weinstein (2013), who investigate the effect of idiosyncratic bank-specific shocks on investment, found that individual bank supply shocks explain 40% of aggregate loan and investment fluctuations.

In general, this literature shows a move against the excessive aggregation in macroeconomics, as also highlighted in Blanchard et al (2013), to the point that sectoral contributions and problems are overlooked in the explanation of the patterns in macroeconomic volatility (Gabaix (2016)). The main insight here is that the famous Leontief inverse function of input-out models can be shown to correspond to network centrality measures that propagate final demand shocks commensurate to produce economy wide GDP volatility.

4.4 Methodological Framework and Source of Data

In this section we present the methodology in two parts: in subsection 4.4.1 we present the network analysis methodology and in 4.4.2 the methodological framework for GDP volatility measures.

4.4.1 Production Network Analysis

We consider an economy where input-output flows can be represented by a network $G = (N, E)$. Where $N = \{1, 2, ..., n\}$ is a set of finite nodes corresponding to a production sector, each specialised in different goods. E denotes the edges, the input-output trading relationship among the sectors. The structure of this relationship is given as $N \times N$ input-output matrix $\mathbf{X}$:

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & x_{13} & ..x_{ij}. & .... & x_{1N} \\ x_{21} & x_{22} & x_{23} & .... & .... & x_{2N} \\ . & . & \ddots & .... & .... & . \\ x_{i1} & . & . & x_{ii} & & x_{iN} \\ . & . & . & & \ddots & \\ x_{N1} & . & . & x_{Nj} & \cdots & x_{NN} \end{bmatrix}$$

(4.1)

Where x_{ij} denotes the amount of sector i 's output used in production of sector j. The diagonal entries, x_{ii} and x_{jj}, denote what a sector consumes from its own outputs. Then the production network is based on the Leontief technological matrix $\mathbf{A}$ defined as:

$$\mathbf{A}=\begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{1j}. & .... & a_{1N} \\ a_{21} & a_{22} & a_{23} & .... & .... & a_{2N} \\ . & . & \ddots & .... & .... & . \\ a_{i1} & . & . & a_{ii} & & a_{iN} \\ . & . & . & & \ddots & \\ a_{N1} & . & . & a_{Nj} & \cdots & a_{NN} \end{bmatrix}$$

(4.2)

Where $a_{ij}=\dfrac{x_{ij}}{x_j}$ is the technological coefficient – which measures the value of sector i's output used in the production of one unit of sector j's output, x_j[22].

To infer how a production network can propagate shocks and to analyse the role of the financial sector in this network, we focus on five network metrics, namely, the degrees, connectivity, clustering coefficients and the eigenvector centrality, concepts described in Chapter 2, section 2.3.1. Here we discuss other important network metrics, the weighted in and out degree, and the Katz-Bonacich centrality. Following Carvalho (2014) we define weighted out degree of a sector i as the row sum of all the weights of the network (Leontief technological coefficients) in which this sector is the input supplier. Such that,

$$d_i^{out}=\sum_{i=1}^{n}a_{ij} \tag{4.3}$$

Where a_{ij} is the technological coefficient (4.2) and d_i^{out} measures the contribution of sector i's output to the production of other sectors of the economy, including to the production of its own

[22] x_j is equal to the row sum plus sector j's value added.

output. The weighted in degree can be defined as

$$d_i^{in} = \sum_{j=1}^{n} a_{ji} \tag{4.4}$$

Similarly, d_i^{in} measures the contribution of the all other sectors in the economy to the production of sector i's output.

4.4.1.1 Katz-Bonacich Centrality

As noted in Gabaix (2011), Acemoglu et al (2010, 2012) and Carvalho (2014), sectoral idiosyncratic shocks have significant effects on aggregate fluctuations, but only if there exists significant asymmetry in the roles that sectors play as suppliers to others. Thus, other important network metrics to consider are the centrality measures that indicate which are the most important or central sectors in a network. Thus, beside the eigenvector centrality, our analysis focus on Katz-Bonacich centrality. The Katz–Bonacich centrality is of particular importance in this chapter, as it is key to the link between centrality of a sector in the productions network and its effects on aggregate volatility through the Leontief inverse. This is discussed in the next section 4.4.3. Following Carvalho (2014) and Newman (2011), Katz–Bonacich centrality assigns to each sector a centrality score that is the sum of some baseline centrality level (equal across sectors), and the centrality score of each of its downstream sectors. Katz–Bonacich eigenvector centrality assigns to each sector j a centrality weight, $v_{KB\,j} > 0$, which is defined by some baseline centrality level β (equal across all sectors), plus a term proportional to the weighted sum of the centrality weights of its downstream sectors for some parameter $\lambda > 0$, such that,

$$v_{KBi} = \lambda \sum_j a_{ij} x_j + \beta \qquad (4.5)$$

Where λ and β are positive constant. In matrix notation, with $\mathbf{A}$ being the Leontief technology matrix for our production network, with elements a_{ij} as defined in (4.2), and $\mathbf{1}$ being a vector of ones, the vector of centrality scores, v_{KBj} 's, is given by:

$$v_{KB} = \beta(\mathbf{I} - \lambda\mathbf{A})^{-1}\mathbf{1} \qquad (4.6)$$

It is worth noting that, normally, the centrality analysis in the network literature is concerned only with identifying the relative centrality of the nodes, not with the absolute magnitude of the centrality (Newman (2011)). Thus, the positive constant, β, is set equal to one[23]. For convenience, we consider a simple Katz-Bonacich centrality such that

$$v_{KB} = (\mathbf{I} - \lambda\mathbf{A})^{-1}\mathbf{1} \qquad (4.7)$$

However, the measure of Katz–Bonacich centrality is sensitive to the choice of the level of λ . Following Newman (2011), λ should not be arbitrarily large. If it tends to zero, $\lambda \to 0$, all nodes will have a centrality equal to β (see equation (4.5)). As λ increases the centralities increase and eventually there comes a point at which they diverse, i.e. when $\det(\mathbf{I} - \lambda\mathbf{A})$ - in equation 4.7 - passes through zero. That is when

[23]However, an "extended" version of Katz-Bonacich centrality can allow for $\beta > 1$ and this is different across sectors (see Newman, 2011). For instance, Carvalho (2014) assumes $\beta = 0.5$.

$$\det(\mathbf{A} - \lambda^{-1}\mathbf{I}) = 0 \qquad (4.8)$$

As stated in Newman (2011), equation (4.8) can be seen as a characteristic equation whose roots λ^{-1} are equal to the largest eigenvalues of the adjacency matrix[24] $\mathbf{A}$, the κ_1. Thus, the literature advises the use of λ less than $1/\kappa_1$ for the centrality to converge. In this paper we use λ equal to $1/\kappa_1$, which over the period under analysis is very close to $\lambda = 0.5$, as assumed in Carvalho (2014) and Acemoglu et al (2010, 2012).

[24]The eigenvalues being defines by $\mathbf{Av} = k\mathbf{v}$, we see that $(\mathbf{A} - \kappa\mathbf{I})\mathbf{v} = 0$, which has non-zero solutions for $\mathbf{v}$ only $(\mathbf{A} - \kappa\mathbf{I})$ cannot be inverted, i.e., if $\det(\mathbf{A} - \kappa\mathbf{I}) = 0$, and hence this equation gives the eigenvalues κ (Newman, 2011).

4.4.2 Methodological Framework on GDP Volatility Measures

4.4.2.1 The Granular Gabaix-Carvalho-Acemoglu Model and Measures of GDP Volatility

The measure of GDP volatility implied by idiosyncratic productivity shocks based on Acemoglu et al (2012), and Carvalho (2014), and the Fundamental volatility in Carvalho and Gabaix (2013), are derived from a static competitive markets equilibrium model. As described by Acemoglu et al (2012), the model consists of an economy with n different sectors whose input-output flows among them are described by a technological matrix A_n. There is one representative consumer that makes decisions on their labour and consumption, by maximising their preferences,

$$\max_{l,\{c_i\}_{i\in I_n}} \quad \frac{1}{n}\sum_{i=1}^{n}\log(c_i)+\log(W_n) \tag{4.9}$$

Subject to budget constraint defined as

$$\sum_{i=1}^{n} p_i c_i = hl \tag{4.10}$$

Where p_i is price, h denotes wage, l is total amount of labour, and W_n is a normalisation constant which depends on the inter-sectoral supply structure of the economy.

The representative firm in sector i maximizes profits,

$$\max_{l,\{c_i\}_{i\in I_n}} \quad p_i x_i - hl_i - \sum_{j=1}^{n} p_j x_{ij} \tag{4.11}$$

Subject to its production possibilities, i.e. the sector's Cobb-Douglas production technology given as:

$$x_i = z_i^{\alpha} l_i^{\alpha} \prod_{j \in \mathrm{N}_i} x_{ij}^{(1-\alpha)a_{ij}} \tag{4.12}$$

Where x_i is the sectoral output, and x_{ij} is the amount of commodity j used in production of i[25]. z_i is the idiosyncratic productivity shock to firm i, which is assumed to be independent across-sectors. So that the market clearing conditions for this economy are given by

$$c_i + \sum_{j=1}^{n} x_{ji} = x_i \tag{4.13}$$

$$\sum_{i=1}^{n} l_i = l \tag{4.14}$$

Assuming that the commodity prices and wage are given, the optimal consumption bundle of the consumer is given by $c_i = h/np_i$. On the other hand, taking first-order conditions with respect to l_i and x_{ij} in firm i's problem implies that

$$l_i = \frac{\alpha p_i x_i}{h} \tag{4.15}$$

$$x_{ij} = \frac{(1-\alpha) p_i a_{ij} x_i}{p_j} \tag{4.16}$$

[25] Note that in this paper we denote x_{ij} as the amount of output (commodity) i used in production of j .

Substituting (4.15) and to (4.16) in the production function (4.12) gives

$$\alpha \log(h) = \alpha\varepsilon_i - H_{(\alpha)} + \log(p_i) - (1-\alpha)\sum_{j=1}^{n} a_{ij} \log(p_j) - (1-\alpha)H_i \tag{4.17}$$

Where $H_{(\alpha)} = -\alpha \log(\alpha) - (1-\alpha)\log(1-\alpha)$ and H_i is the input weight entropy of sector i, defined as $H_i \equiv -\sum_{j=1}^{n} a_{ij} \log(a_{ij})$. Writing the above equality in vector form, and pre-multiplying both sides by the influence vector $v'_n = \frac{\alpha}{n} 1'\left[I-(1-\alpha)A_n\right]^{-1}$ yields

$$\log(h) = v'_n\,\varepsilon + \frac{1}{n}\sum_{i=1}^{n} \log(p_i) - \frac{H_{(\alpha)}}{\alpha} - \frac{1-\alpha}{\alpha} v'_n\,H \tag{4.18}$$

Where $H = \left[H_1 ... H_n\right]'$ is the vector of input entropies of all sectors. Finally, by setting

$$W_n = n \exp\left(\frac{1}{\alpha}\left[H_{(\alpha)} + (1-\alpha)v'_n\,H\right]\right) \tag{4.19}$$

And by normalising the ideal index to 1, i.e.,

$$\frac{n}{W_n}(p_1 p_2 \dots p_n)^{\frac{1}{n}} = 1 \tag{4.20}$$

They obtain

$$y_n = \log(h) = v'_n\,\varepsilon\,. \tag{4.21}$$

This defines aggregate output as the logarithm of the real value added in the economy, and corresponds to a weighted sum of sector-specific productivity shocks $\boldsymbol{\varepsilon} \equiv [\varepsilon_1 \ldots \varepsilon_n]$, where the weights are determined by n- dimensional vector $\mathbf{v}_n$, the influence vector, defined as

$$v_n \equiv \frac{\alpha}{n}\left[I-(1-\alpha)A_n^{'}\right]^{-1}\mathbf{1} \tag{4.22}$$

Assuming that the productivity shocks to all sectors are mutually independent, aggregate volatility is defined as

$$\sigma_y = \sqrt{\sum_{i=1}^{n} v_i^2 \sigma_{\rho_T i}^2} \tag{4.23}$$

This explicitly accounts for the role of sectoral centrality of the sectors on GDP volatility. Where v_i is the sectoral Katz-Bonacich centrality and $\sigma_{\rho_T i}$ is the standard deviation of sectoral productivity growth. So that the evolution of σ_{Ft} will reflect the centrality of sectors in the economy and the micro-level TFP volatility over time.

An alternative measure is the fundamental volatility presented in Carvalho and Gabaix (2013)) given as

$$\sigma_{Ft} = \sqrt{\sum_{i=1}^{n}\left(\frac{S_{it}}{GDP_i}\right)\sigma_{\rho_T i}^2} \tag{4.24}$$

Where S_{it} is the gross output of sector i, and $\sigma_{\rho_T i}$ is the standard deviation of the total factor productivity (TFP) in the sector.

4.4.2.2 The Granular Gabaix-Carvalho Measures of Actual GDP Volatility

Carvalho and Gabaix (2013) use two measures to proxy actual GDP volatility. The first is the so called, rolling window GDP volatility (σ_{Yt}^{Roll}) and the second is the Hodrick-Prescott (HP) filtered GDP volatility (σ_{Yt}^{HP}). The rolling window based actual GDP volatility consists of the standard deviation of the cyclical component of actual quarterly real GDP, which is obtained using Hodrick-Prescott filter (HP). Considering that the observed real GDP series y_t consists of two unobservable components, the trend denoted by τ_t, and the cyclical component, c_t, the HP filter is applied to decompose the log of quarterly real GDP into these two components by solving

$$\min_{\tau} \left(\sum_{t=1}^{T} (c_t)^2 + \lambda \sum_{t=2}^{T-1} \left[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}) \right]^2 \right) \tag{4.25}$$

Subject to

$$y_t = \tau_t + c_t . \tag{4.26}$$

Here T is the number of samples and λ, the smoothing parameter. Then, the 10 years (41 quarters) rolling window standard deviation of the cyclical component, σ_{Yt}^{Roll}, centred at quarter t, is computed as:

$$\sigma_{Yt}^{Roll} = \left[\frac{1}{10} \sum_{\tau=-4}^{+5} (\gamma_{t+\tau} - \bar{\gamma}_t)^2 \right]^{1/2} . \tag{4.27}$$

$\bar{\gamma}_t$ is the average real GDP cyclical component between $t-4$ and $t+5$. Essentially, this consists of replacing each of the observation c_t by the average of itself and its neighbours. The corresponding annual counterpart, for a given year t, is then given by the average σ_{Yt}^{Roll} over the four quarters of that year.

The HP-based GDP volatility consists of the HP filtered cyclical component of the instantaneous quarterly GDP standard deviation. Based on McConnell and Perez-Quiros (2000), the procedures consist of fitting a first order autoregressive AR(1) model to real quarterly GDP growth rates:

$$\Delta y_t = \vartheta + \omega \Delta y_{t-1} + \varepsilon_t , \qquad (4.28)$$

where y_t is log GDP in quarter t and Δ denote growth. Then assuming that an unbiased estimator of the annualized standard deviation is given by $2\sqrt{\pi/2}|\hat{\varepsilon}_s|$, where the factor 2 converts quarterly volatility into annualized volatility, and the $\sqrt{\pi/2}$ comes from the fact that if $\varepsilon \sim N(0,\sigma^2)$, then $\sigma = E\left\lfloor\sqrt{\pi/2}|\varepsilon|\right\rfloor$. Thus, the annual measure of volatility in year t, is made of the average of the four measures $2\sqrt{\pi/2}|\hat{\varepsilon}_{t:q}|$ of quarterly volatility (where date $t:q$ is the *qth* quarter of year t). The annualized volatility in year t is then given by $\sigma_{Yt}^{Inst} = \frac{1}{2}\sqrt{\frac{\pi}{2}}\sum_{q=1}^{4}|\hat{\varepsilon}_{t:q}|$, the "instantaneous" measure of GDP volatility in year t. The σ_{Yt}^{HP}, is the Hodrick-Prescott smoothing of the instantaneous volatility σ_{Yt}^{Inst}.

4.4.2.3 Methodology for Estimating Sectoral Productivity Shock

The sectoral productivity is obtained based on Joergenson, Ho and Stiroh (2005) and Basu, and Kimball (2006). Using private-sector output[26], the productivity index for each industrial sector consists of the trans-log of the rate of productivity growth $\{\rho_T^i\}$ given as;

$$\rho_T^i = [\ln Z_{i,t} - \ln Z_{i,t-1}] - \rho_X^i [\ln X_{i,t} - \ln X_{i,t-1}] - \rho_K^i [\ln K_{i,t} - \ln K_{i,t-1}] - \rho_L^i [\ln L_{i,t} - \ln L_{i,t-1}]$$

(4.29)

Where ρ_X^i, ρ_K^i, ρ_L^i are the average shares of sectoral intermediate, capital, and labour inputs in the value of sectoral output, respectively. Where the technological shock is then defined as the variance over the sample,

$$\sigma_{\rho_T i,t} = \left[\frac{1}{m} \sum_{t=1}^{m} (\rho_{T,t,i} - \bar{\rho}_{T,i})^2 \right]^{1/2} \tag{4.30}$$

With $\bar{\rho}_{T,i}$ denoting average productivity.

[26]excluding services produced by government but including purchase of private sector and services by the government

4.4.3 Macro-Net GDP Measure Based on Sectoral Final Demand Shocks

In this study we propose a GDP volatility measure implied by idiosyncratic demand shocks, derived from the Leontief input-output model. We assume an economy where production takes place in n sectors. Each sector produces an output x_i, which is sold to other sectors as intermediate input, and consumed as final goods. However, for the production of the output x_i, this sector uses other sectors' produced output, so that:

$$\begin{bmatrix} x_1 \\ \vdots \\ \\ x_n \end{bmatrix} = \begin{bmatrix} a_{11} & a_{ij} & \cdots & a_{1N} \\ & \ddots & & \\ & & \ddots & \\ a_{N1} & & & a_{NN} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix}$$

(4.31)

Here x_i denotes sector i's output, and d_i is the sector i's final demand. Letting $\mathbf{A}$ be the technological matrix with elements a_{ij} as defined in matrix (4.3), and $\mathbf{x}$ and $\mathbf{d}$ the vectors of sectoral gross output and final demand, respectively, the total output can be expressed as

$$\mathbf{x} = \mathbf{Ax} + \mathbf{d} \tag{4.32}$$

Re-writing,

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{d} \tag{4.33}$$

Where $(\mathbf{I}-\mathbf{A})^{-1}=\mathbf{L}$ this is usually called the Leontief inverse matrix. Thus, the gross output is equal to $\mathbf{x}=\mathbf{Ld}$. Given the Katz–Bonacich centrality,

$$\mathbf{v_{KB}}=(\mathbf{I}-\lambda\mathbf{A})^{-1}\mathbf{1} \tag{4.34}$$

To obtain the sectoral final demand effect on the output aggregate volatility, given the sectoral centralities, we approximating the output vector (equation 4.33) to the product of sectoral centrality vector $\mathbf{v_{KB}}$ and the vector of final demand $\mathbf{d}$, such that,

$$\mathbf{x}^{c}=\mathbf{v_{KB}}\mathbf{d}. \tag{4.35}$$

Here,

$$\mathbf{v_{KB}}=(\mathbf{I}-\lambda\mathbf{A})^{-1}\mathbf{1}=L\mathbf{1} \tag{4.36}$$

The aggregate gross output, $Q=\sum_{i=1}^{n}x_i$ generated by the Leontief inverse is then approximated to:

$$Q^{c}=\sum_{i=1}^{n}(v_{KBi}d_i) \tag{4.37}$$

Given that in the input-output identity $GDP=\sum_{i=1}^{n}(x_i-\bar{x}_i)$, where $\bar{x}_i=\sum_{j=1}^{n}x_{ij}$, in terms of GDP equation 4.37 can be written as

$$\sum_{i=1}^{n}(x_i - \bar{x}_i) = \sum_{i=1}^{n}\left(v_{KBi}d_i - \bar{x}_i\right) \tag{4.38}$$

So that, denoting GDP by Y^c,

$$Y^c = \sum_{i=1}^{n}\left(v_{KBi}d_i - \bar{x}_i\right) \tag{4.39}$$

Assuming the centralities as "sectoral weights" and taking the log of both sides, the aggregate GDP volatility implied by the volatility of sectoral final demand given the sectoral centralities is,

$$\sigma_{y_{FD}} = \sqrt{\sum_{i=1}^{n}\left(v_{KBi}^2\sigma_{\varepsilon_d i}^2 - \sigma_{\bar{x}i}^2\right)} \tag{4.40}$$

Where σ_{yFD} is the demand driven GDP volatility, v_{KBi} is the Katz–Bonacich centrality of sector i in the production network, σ_{di} the standard deviation of the logarithm of sectoral final demand, and $\sigma_{\bar{x}i}$ is the standard deviation of intermediate input growth[27].

[27] As static approach this model has no uncertainty, but a fixed standard deviation of the sectoral final demand growth, σ_{di}, as proxy of the sectoral final demand shocks.

4.4.3.1 Methodology for Measuring Final Sectoral Demand Volatility

We estimate two measures of sectoral final demand volatility. One is based on standard deviation of sectoral final demand growth, and is calculated in the following two steps. First, we calculate the sectoral final demand growth, $\gamma_{d,i,t}$, defined as

$$\gamma_{d,i,t} = \ln(d_{i,t}) - \ln(d_{i,t-1}) \tag{4.41}$$

Where $d_{i,t}$ denotes the final demand of the sectors i at time t. Then we calculate the respective simple standard deviation over the sample as[28]

$$\sigma_{\varepsilon_d t} = \left[\frac{1}{m}\sum_{t=1}^{m}(\gamma_{di,t} - \bar{\gamma}_{di,t})^2\right]^{1/2} \tag{4.42}$$

$\bar{\gamma}_{di,t}$ is the average final demand growth.

4.4.3.2 Methodology for Measuring Sectoral contribution of demand driven aggregate GDP Volatility

Following Carvalho and Gabaix (2013), we use the equation (4.40) to calculate the "demand driven GDP volatility". By this we mean the volatility that would be derived from macroeconomic demand side shocks for the output of each sector. If the aggregate shocks come in large part from demand shocks, augmented by the sectoral interconnectedness propagation effect, then our measure of demand fundamental volatility should explain a

[28]We also estimated and tested other measure of final demand volatility, such as, 10 years rolling window standard deviation, a simple and 10 years rolling window standard deviation of the cyclical component of final demand decomposed using HP filter. However, the results were not meaningful.

significant part of GDP volatility (Carvalho and Gabaix (2013)). Thus, we estimate a simple ordinary least square of type

$$\sigma_{yt} = \alpha + \beta \sigma_{yFD} + \varepsilon_t \,. \tag{4.44}$$

Here σ_{yt} is the actual GDP volatility, α is the constant and β the parameter that measures the relationship between our measure of demand driven GDP volatility and the volatility of actual GDP. ε_t denotes the error term.

Then, the sectoral contribution to GDP volatility $SC_{i,t+1}(t,t+1)$ is defined as

$$SC_{i,t+1} = \frac{(v_{KBit+1}^2 \sigma_i^2 - \sigma_{\bar{x}i}^2) - (v_{KBit}^2 \sigma_i^2 - \sigma_{\bar{x}i}^2)}{\sigma_{y_{FDt+1}}^2 - \sigma_{y_{FDt}}^2} \tag{4.45}$$

The numerator is change in sectoral demand-driven GDP variance, while the denominator measures the change of total demand driven GDP variance. In other words, Equation (4.45) measures the percentage of the change in total demand driven variance between time t and $t+1$ brought about by changes in the variance of the sector i in the same period. By construction $\sum_i H_{i,t+1}(t,t+1) = 1$ for all $t \neq t+1$.As will be seen in the empirical section, this ratio given in (4.45) will be found to be the largest for the financial sector for the period 1990 -2007. This constitutes the major result of this chapter.

4.5 Empirical Analysis

4.5.1 Source of Data

In this study we use detailed Bureau of Economic Analysis (BEA) Input-Output tables for the US economy over the period from 1963 to 2015. These Tables present the matrices of inter-sectoral flows of intermediate and final goods, evaluated in USD million, with 46 sectors for the period between 1963-1996 and 71 sectors for 1997-2015. For the purpose of the present study we condensed all these sectors into 13 sectors as shown in the Appendix A. The quarterly real GDP data is obtained from the Federal Reserve Economic Data (FRED) at the Federal Reserve Bank of St. Louis.

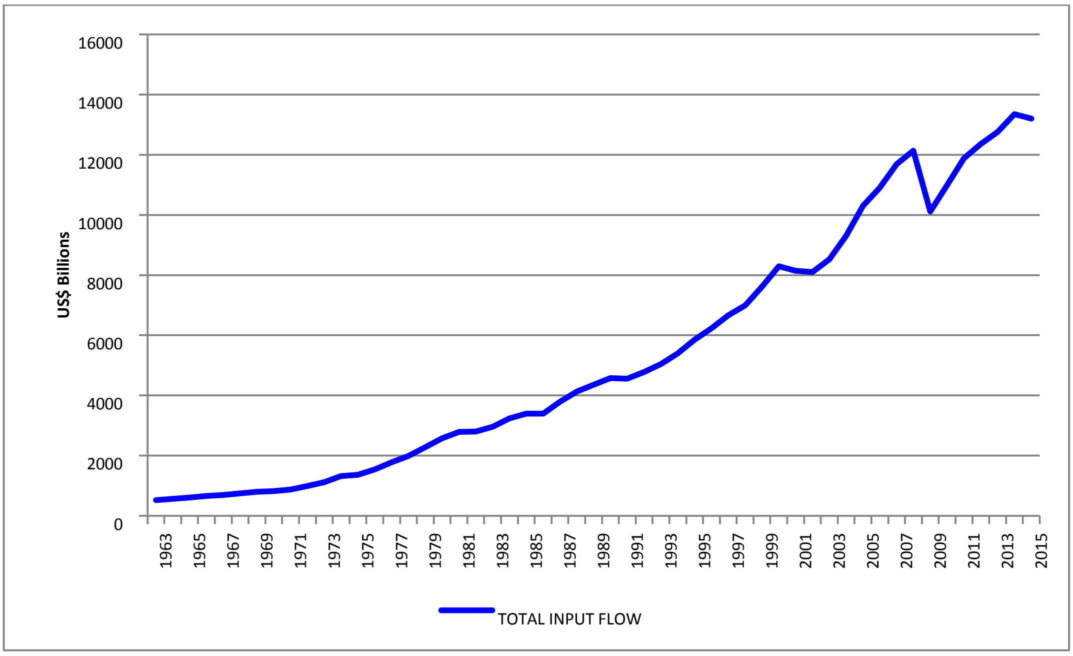
4.5.2 Preliminary Data Analysis

4.5.2.1 Sectoral Trends of the Intermediate Input Flows

As we can see from Equation 4.40, our analysis focus on the intermediate input-flows matrix and on the final demand, from which we calculate the centralities and the demand-driven sectoral shocks, respectively. We have already discussed the evolution of the final demand and the role of each sector in each of the final demand components in section 4.2, as a motivation to this study. This section analyses the statistical properties of the intermediate input flows and sectoral contribution to its dynamics.

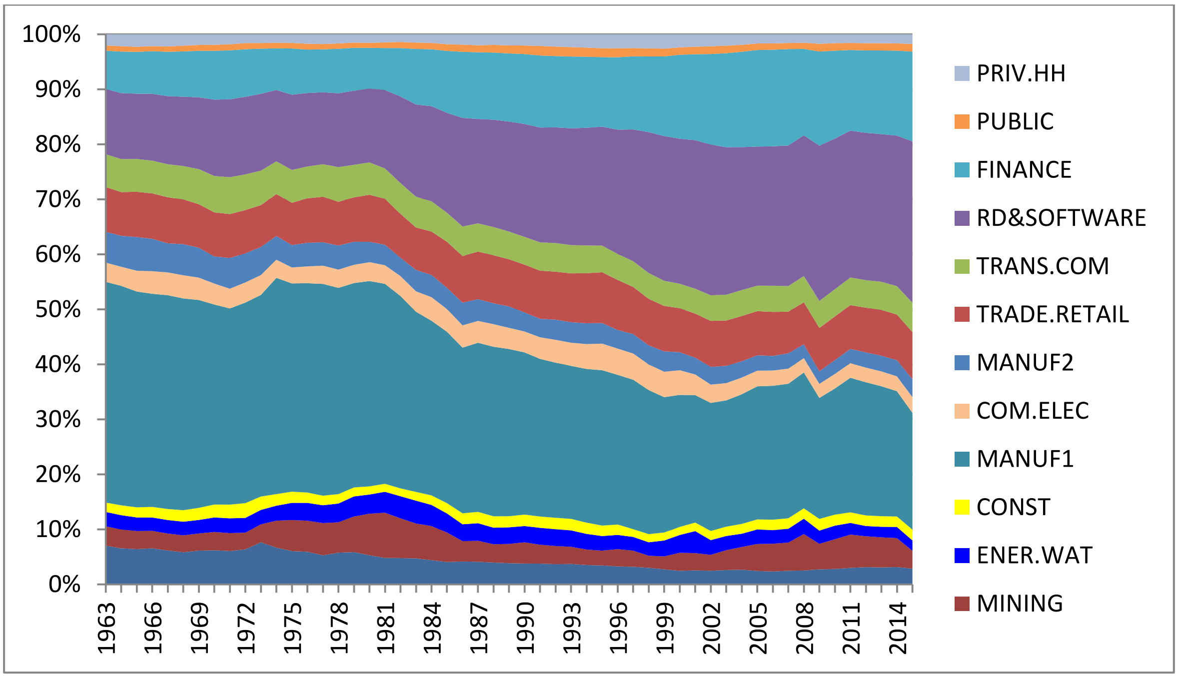
Figure 4.3 shows the total intermediate input used by the US economy over the period 1964 - 2015. It evidences an impressive growth, particularly from the 1970s. While the total input used was estimated at US$ 559.258 billion in 1964, in 2015 the total input is US$ 13206.183 billion.

Figure 4.3: US Total Intermediate Input Flows (in US$ Billions)



Source: Plotted by author using intermediate input flows from BEA input-output data Note:

Figure 4.4: US Sectoral intermediate Input flow from 1963-2015 (in per cent)



Source: Plotted by author using sectoral intermediate input flows from BEA input-output data: Note: Figure 4.4 shows that the top three biggest input suppliers are the Manufacturing 1, R&D software and the Financial sectors. The Manufacturing 1 declines in recent years while the shares of the financial and R&D and software increase.

In terms of its components, Figure 4.4 shows that the top three biggest input suppliers are the Manufacturing 1, R&D software and the Financial sectors. However, in recent years, we evidence a decline in Manufacturing 1 share, while the shares of the financial and R&D and software experience a continuous growth, particularly from 1980.

For a better understanding of the behaviour of these variables, Table 4.5 presents the descriptive statistics of the sectoral input over the period 1964-2015. The results shows that in the average of US$ 5316.7 billion of input used in the economy, US$ 3439.3 billion (about 65 per cent) are supplied from only the three sectors, namely, the sector of Manufacturing 1 supplying an average of US$ 1396.8 billion (26.3%), R&D Software supplying US$ 1276.6 billion (24%) and Finance supplying US$ 765.9 billion (14.4%).

Table 4.5 Descriptive statistics of the sectoral intermediate inputs (US$ billions)

	Mean	Median	Standard Deviation	Sample Variance	Kurt.	Skews	Min	Max
AGRI.FISH	173.7	166.8	101.0	10202	-0.126	0.635	36.4	418.3
MINING	235.9	157.4	217.2	47164	0.448	1.229	18.2	804.0
ENER.WAT	141.6	131.2	95.9	9192	-1.079	0.260	13.6	339.4
CONST	98.5	88.1	78.2	6116	-0.744	0.716	8.8	258.5
MANUF1	1396.8	1305.8	902.2	813968	-0.994	0.398	207.8	3041.6
COM.ELEC	179.9	169.4	122.6	15041	-1.573	0.077	18.1	377.1
MANUF2	172.1	156.7	109.8	12046.7	-0.894	0.398	29.0	431.8
TRADE.RETAIL	438.3	373.2	335.3	112395	-0.998	0.506	42.1	1130.9
TRANS.COM	266.3	219.3	197.9	39170	-0.626	0.692	30.9	703.3
RDSOFTWARE	1276.6	870.7	1189.0	1413694.4	-0.926	0.698	61.3	3874.7
FINANCE	765.9	539.4	711.6	506344	-1.076	0.667	36.0	2157.9
PUBLIC	70.3	63.3	55.3	3062	-1.194	0.367	4.9	182.7
PRIV.HH	100.9	88.1	75.1	5638	-1.639	0.191	10.5	232.0
TOTAL	**5316.7**	**4353.4**	**4129.5**	**17053170**	**-1.022**	**0.562**	**517.7**	**13347.8**

Source: Calculated by author using sectoral intermediate input flows from BEA input-output matrices.

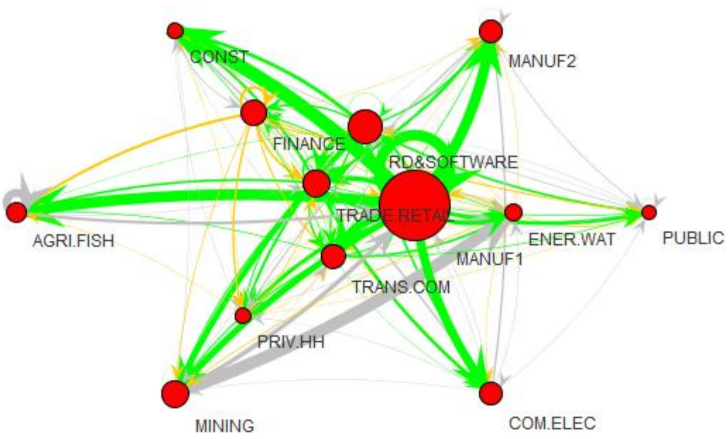
4.5.2.2 Network Analysis of US Production Network

The study of the implications of sectoral shocks on aggregate volatility requires an understanding of the topology and structure of the production network (Carvalho (2014)) and Acemoglu et al (2012)). Figure 4.5 presents a production network based on Leontief technological matrices, connecting individual sectors within the US economy for 1980, 2007, and 2015. These years correspond to the period in which the total input growth starts to increase significantly, its peak, and the most recent date in the data, respectively. The size of the nodes is comparable with the importance of the sector as input supplier. The thickness of the link connecting two sectors expresses the magnitude of the input flows.

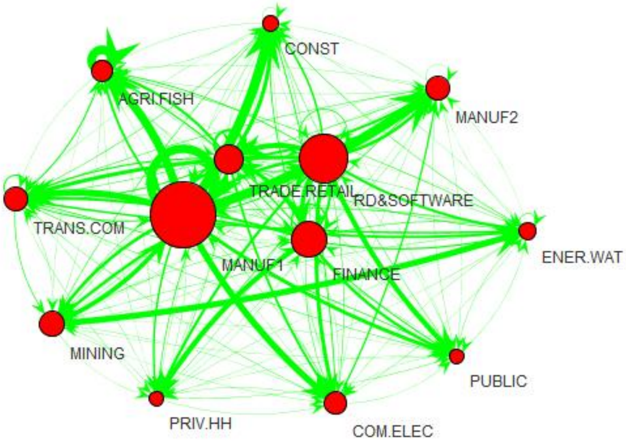
With a closer look at these networks, we see that they are characterized by high density. However, they are very heterogeneous, with a small number of sectors playing a disproportionately important role as input suppliers, as we can see from the size of the nodes in the networks.

Figure 4.5: Production Networks Based on Leontief technological Matrices

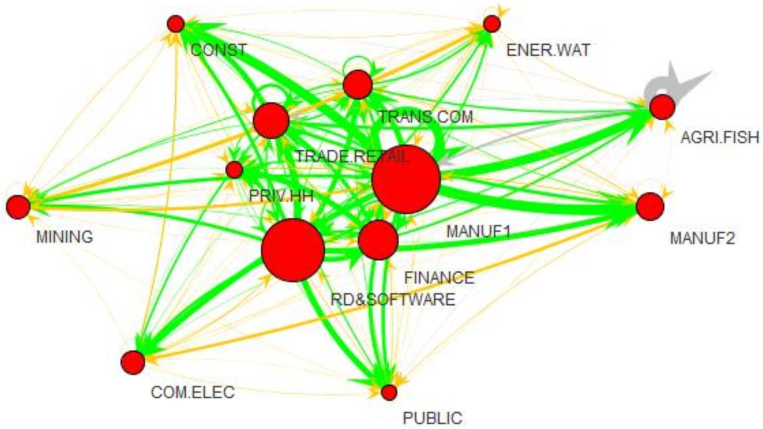
1980



2007



2015



Source: Constructed by author using Leontief technological matrix from BEA's input-output data

These can also be conveniently summarized by the key statistics of these networks presented in Table 4.6, which shows high and increasing density of the network which can be seen from the average number of in and out-degrees of about 8.9 in 1980, 12.9 in 2007 and 11.5 in 2015. The results also show a high connectivity of almost 73, 100 and 96 per cent in 1980, 2007 and 2015, respectively. The distribution of out degrees from production sectors shows important asymmetry on both the in and out-degrees in terms of all higher moments given by standard deviation, skewness and the kurtosis.

Table 4.6 Network statistics US production Network

	1980	2007	2015
Nodes	13	13	13
Edges	115	168	149
Connect	0.737179	1.076923	0.955128
CC	0.795158	1.076923	0.955666
Mean in	8.846154	12.92308	11.46154
Std in	1.281025	0.27735	1.126601
Skew in	0.334316	-3.60555	0.112481
Kurt in	-0.36441	13	-1.28014
Mean out	8.846154	12.92308	11.46154
Std out	3.912505	0.27735	2.366974
Skew out	-0.14992	-3.60555	-1.94849
Kurt out	-1.74205	13	4.084217
EigenValue	0.520701	0.473998	0.410156

Source: Calculated by author using Leontief technological matrices from BEA input-output data
Note: CC is Clustering coefficient; Connect is connectedness; Mean in and out is mean for in and out-degrees; Std in and out are the standard deviation for in and out-degrees. Kurtosis in/out is the Kurtosis for in and out-degrees; Skewness in/out is the Skewness for in and out-degrees; and Eigen Value is the maximum eigenvalue.

Further, Table 4.7 presents the sectoral weighted out degree of sector i (Equation 4.4), defined as the row sum of all the weights (Leontief technological coefficients) of the network in which sector i is the input supplier (Carvalho, 2014). The results show important changes over the years. For instance, in 1980 the input supply was dominated by Manufacturing 1, R&D – Software, Trade and retail, with the Financial sector ranking fourth. However, in 2007 we evidence a decline in input supply by almost all the sectors, except the R&D Software, Financial and the Public sector. The biggest decline in input supply in 2007 occurred in the sector Manufacturing 1. However, it remains the biggest supplier followed by the R&D Software and the Financial sector. From 1980 to 2007 the Financial sector moved from the fourth to the third biggest input supplier in the economy. From 2007 to 2015, we also find a further decline in sectoral input supply in almost all the sectors, except in Agriculture and Fisheries, Trade and Retail, Transport and Communication, and R&D Software. In post 2007 the biggest decline is again in the Manufacturing 1, but now followed by the Financial sector.

Table 4.7: Sectoral weighted out-degree (d_i^{out})

	1980	**2007**	$d_{i,2007}^{out} - d_{i,1980}^{out}$	**2015**	$d_{i,2015}^{out} - d_{i,2007}^{out}$
AGRI.FISH	0.267	0.258	-0.008	0.281	0.023
MINING	0.483	0.389	-0.094	0.220	-0.169
ENER.WAT	0.161	0.123	-0.038	0.081	-0.042
CONST	0.085	0.092	0.007	0.079	-0.013
MANUF1	2.126	1.589	-0.537	1.255	-0.334
COM.ELEC	0.352	0.281	-0.071	0.245	-0.036
MANUF2	0.361	0.331	-0.030	0.326	-0.004
TRADE.RETAIL	0.520	0.492	-0.027	0.503	0.011
TRANS.COM	0.405	0.330	-0.075	0.352	0.022
RD&SOFTWARE	0.800	1.112	0.311	1.157	0.046
FINANCE	**0.443**	**0.712**	**0.269**	**0.624**	**-0.088**
PUBLIC	0.049	0.054	0.005	0.052	-0.002
PRIV.HH	0.100	0.065	-0.034	0.065	0.000

Source: Calculation done by author using Equation 4.3

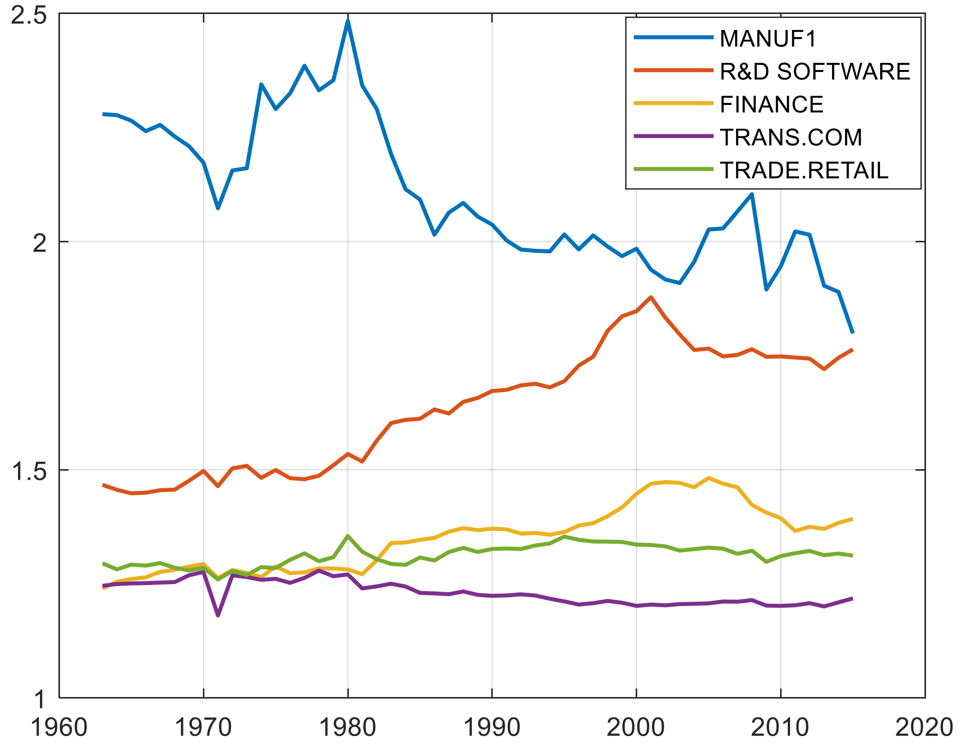
The empirical analysis of the dominant sectors in the input-output flows is summarized in Table 4.8, in terms of their network connectivity and their eigenvector, and in Figure 4.6 in terms of Katz-Bonacich centralities. It shows that there is considerable difference in the ranking of sectors with regards to their systemic importance index, as measured by the right eigenvector of matrix (4.2). Table 4.8 shows that the top three most important sectors in 1980 are Manufacturing 1, with an index of 0.87, the R&D software (0.27), with the Financial sector (0.13) ranking the seventh after the Mining sector (0.24), Trade and Retail (0.19), and Transport and Communications (0.14). However, in 2007 we evidence an impressive decline in the centrality of these sectors, but a considerable increase in the centrality of the R&D software and of the Financial sector, conforming with the sectoral trends of input supply described in subsection 4.5.2.1. Manufacture 1 is still the most central sector, followed by the R&D software and the Financial sector. Note that in 2015 the centrality ranks R&D software as the most central sector, followed by Manufacture 1 and then by the Financial sector. Similar results are also found in Katz-Bonacich centrality presented in Figure 4.6. It clearly shows that the Manufacturing sector is the most central node in the production network over the 60's and 70's. However, from 1980's its centrality shows an impressive decline while the R&D Software and Financial sector centralities increase.

Table 4.8: Eigenvector Centralities of Leontief technological matrices

	1980	**2007**	**2015**
AGRI.FISH	0.18	0.14	0.14
MINING	0.24	0.24	0.11
ENER.WAT	0.06	0.06	0.04
CONST	0.01	0.03	0.03
MANUF1	0.87	0.71	0.56
COM.ELEC	0.05	0.06	0.08
MANUF2	0.03	0.04	0.06
TRADE.RETAIL	0.19	0.18	0.20
TRANS.COM	0.14	0.12	0.14
RD&SOFTWARE	0.27	0.53	0.70
FINANCE	0.13	0.28	0.30
PUBLIC	0.01	0.02	0.02
PRIV.HH	0.02	0.03	0.03

Source: Calculated by author using Eq. 2.9 on Leontief technological matrices

Figure 4.6: Katz-Bonacich Centrality for the top 5 most central Nodes over 1964-2017

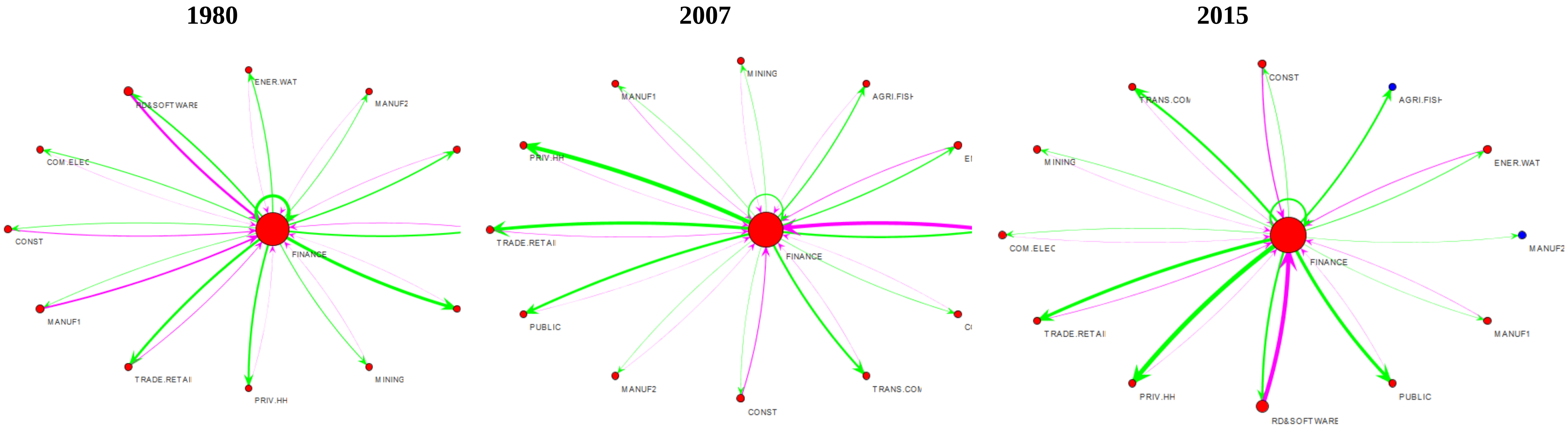


Source: Calculated and plotted by author using Eq. 4.34 on Leontief technological matrices

4.5.2.3 Network Analysis of US Financial Sector Production Network

Table 4.7 in the previous section shows an increase in the Financial sector contribution to the production of other sectors from 1980 to 2007, as described by equation 4.3, and a decline following the financial crisis in 2007 up to 2015. In this section, we plot only the relationship between the Financial sector and the rest of the sectors of the economy, i.e. only the in-degree and out-degrees of the Financial sector. This is for better understanding of the changes in the allocation of the Financial sector output to the production of other sectors output, over the years. The results are presented in Figure 4.7. They show that in general the Financial sector was always connected to all the other sectors in the three periods.

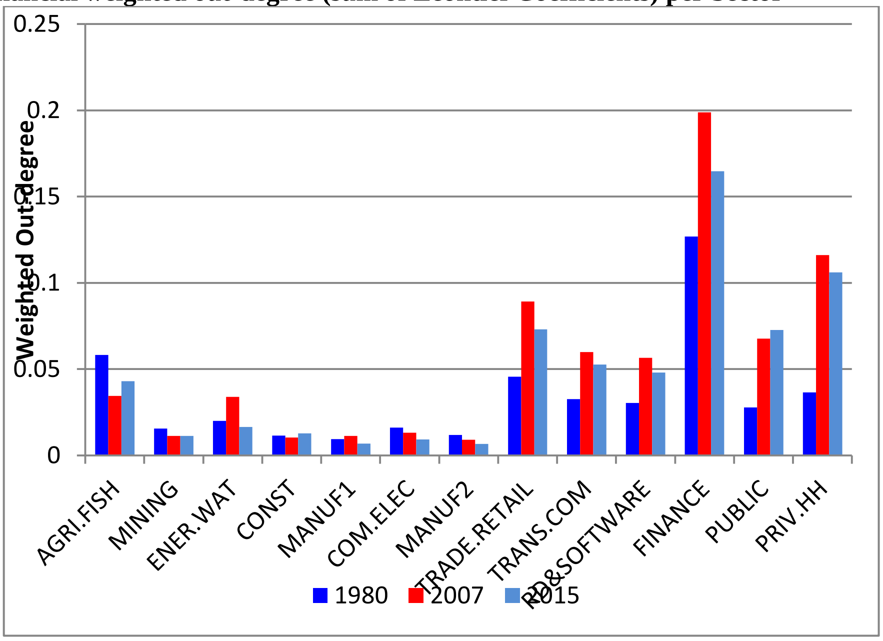
Figure 4.7: Production Networks Based on Leontief Coefficients



Source: Constructed by author using Leontief technological matrices from BEA's bilateral input-output data.

However, as shown in Figure 4.8, the contribution of the financial sector output to itself is the largest, followed its contribution to Private household, Trade and Retail, Public sector, Transport and Communication, R&D Software and to Agriculture and Fisheries. Figure 4.8 also shows that over 1980-2007, the Financial sector input supply increased considerable, as we also describe in section 4.5.2.1. This increase was mainly to private household sector, to itself to Trade and Retail, Public, Transport and communication, R&D Software, Energy and Water, and to Manufacture 1 (Figure 4.8). The Financial sector input supply to the remaining sectors declined, except to Mining which remained almost constant. The data also shows that the decline of the financial sector input supply to the economy, following the 2007-crisis, was mainly to its biggest users, namely, the Financial sector itself, the Trade and Retail and to Private Household. However, we find an increase in the Financial sector input supply to Agriculture and to the public sector.

Figure 4.8: Financial weighted out-degree (sum of Leontief Coefficients) per Sector



Source: Plotted by author using Eq. 4.3 and.4 on Leontief technological matrices from BEA's input-output data.

4.5.3 Empirical Results for Demand and Supply Side and GDP Volatility from Granular US Macro-Net Model

This section presents our measure of demand-driven GDP volatility (σ_{yFD}) based on Equation (4.40), defined as the GDP volatility that would be derived only from demand side sectoral shocks. Then, we test to what extent this measure explains the actual GDP volatility measured in terms of HP filtered GDP volatility (σ_{Yt}^{HP}) and by the rolling window GDP volatility (σ_{Yt}^{Roll}), as described in section 4.4.2.2. Further, we analyse the role of the financial sector in the GDP volatility.

Table 4.9 compares the statistical properties of the demand-driven GDP volatility and the actual GDP volatility measures. The results show that, in general, the GDP volatility based on the sectoral demand shocks is statistically similar to the actual GDP volatility measures, as it shows mean, median, kurtosis and skewness values very close to rolling window actual GDP (σ_{Yt}^{Roll}). We find that the standard deviation and the variance of the demand-driven volatility are considerable different from the actual GDP measures. However, these demand-driven statistics are much closer to the rolling window statistics than the variance and the standard deviation of the HP filtered actual GDP volatility (σ_{Yt}^{HP})

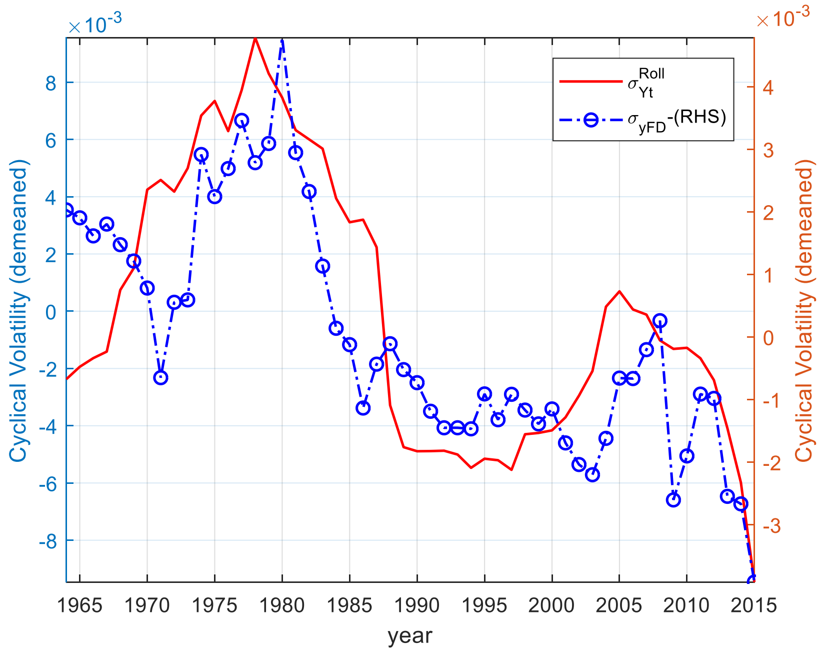
Table 4.9: Comparison of the Volatility Measures σ_{Yt}^{HP}, σ_{Yt}^{Roll} and σ_{yFD}'s Descriptive Statistics

	σ_{Yt}^{HP}	σ_{Yt}^{Roll}]	σ_{yFD}
Mean	0.058	0.0142	0.0182
Median	0.0498	0.0129	0.0176
Standard Deviation	0.0215	0.0047	0.0019
Variance	4.61E-04	2.24E-05	3.5681-e6
Kurtosis	1.8555	1.9769	2.5178
Skewness	0.5759	0.3221	0.4543

Source: Calculation done by author. Note: σ_{Yt}^{HP} is given in Equation (4.25), σ_{Yt}^{Roll} is given in Equation (4.27) and σ_{yFD} is given in Equation (4.40).

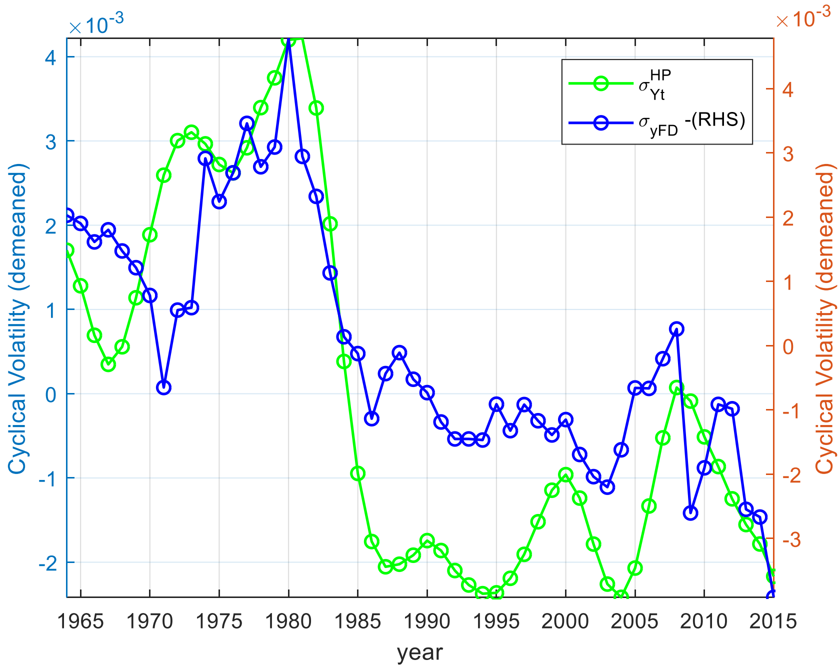
In addition, Figure 4.9 and 4.10 plot the demand driven GDP volatility σ_{yFD} versus two measures of the actual GDP volatility viz. σ_{Yt}^{HP} and σ_{Yt}^{Roll}, respectively, from Carvalho and Gabaix' (2013). We find that, over the period 1964 to 2015, the demand-driven GDP volatility performs well in tracking actual GDP volatility. In general, our measure on demand driven GDP volatility is also similar to Carvalho and Gabaix's (2013) supply drive volatility measure as shown in Figure 9.1, in Appendix C. Given the lack of data we were unable to extend the Carvalho and Gabaix's (2013) supply drive volatility measure up to 2015. Thus, Figure 9.1 compares the demand and the supply driven GDP volatility, σ_{yFD} versus two measures of the actual GDP volatility viz. σ_{Yt}^{HP} and σ_{Yt}^{Roll}, over the period 1964-2008

Figure 4.9: Demand-Driven GDP Volatility and Rolling window actual GDP Volatility



Source: Calculated and plotted by author from Equations 4.40 and 4.27

Figure 4.10: Demand-Driven GDP Volatility and HP actual GDP Volatility



Source: Calculated and plotted by author from Equations 4.40 and 4.25

$\sigma_{y_{FD}}$ is our measure, the demand-driven GDP volatility. σ_{Yt}^{Roll} and σ_{Yt}^{HP} are the rolling window and HP based actual GDP volatility, respectively. All the volatilities are in terms of demeaned standard deviation. Where the full sample $\sigma_{y_{FD}}$ mean is 0.0182, σ_{Yt}^{Roll} is 0.0142 and σ_{Yt}^{HP} is 0.0058. The RHS stands for Right Hand Scale.

This relationship is also presented in Table 4.10 that shows the regression results between the demand-driven GDP volatility ($\sigma_{y_{FD}}$) and actual GDP volatility, measured by σ_{Yt}^{HP} and σ_{Yt}^{Roll}. It shows a positive and statistically significant relationship with these variables. Here, the demand-driven GDP volatility indicator explains 60 per cent of the actual GDP volatility σ_{Yt}^{Roll} and about 40 per cent of σ_{Yt}^{HP}. These results conform with the literature on the effect of microeconomic shocks on aggregate volatility, in particular, with Carvalho and Gabaix (2013). Also Atalay (2017) argues that the role of idiosyncratic sectoral supply shocks account for half of the quarterly variation in industrial output.

Table 4.10: Demand-driven GDP Volatility Vs. Supply Led Carvalho-Gabaix Volatility: Regression Results for and Rolling window and HP actual GDP Volatility

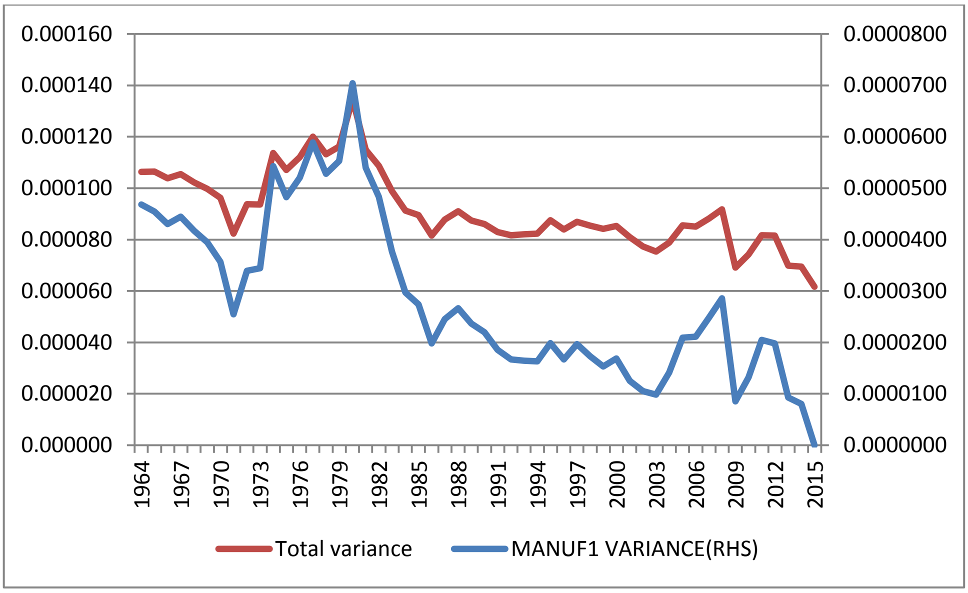
	Demand driven GDP Volatility		Supply Driven GDP Volatility (The Carvalho and Gabaix results)	
	σ_{Yt}^{Roll}	σ_{Yt}^{HP}	σ_{Yt}^{Roll}	σ_{Yt}^{HP}
$\hat{\alpha}$	-0.021	-0.134	-0.029	-0.0483
	(-5.158)	(-3.966)	(-5.53)	(-4.47)
$\hat{\beta}$	1.942	10.585	4.815	7.015
	(8.665)	(5.734)	(8.39)	(5.89)
R^2	0.60	0.40	0.60	0.43

Source: Computed by author, Carvalho and Gabaix (2013) (RHS). The figures in brackets are the t-statistics which show the coefficients are statistically significant at 5% level.

4.5.4 Evidence for Impact on Financial Sector on GDP Volatility

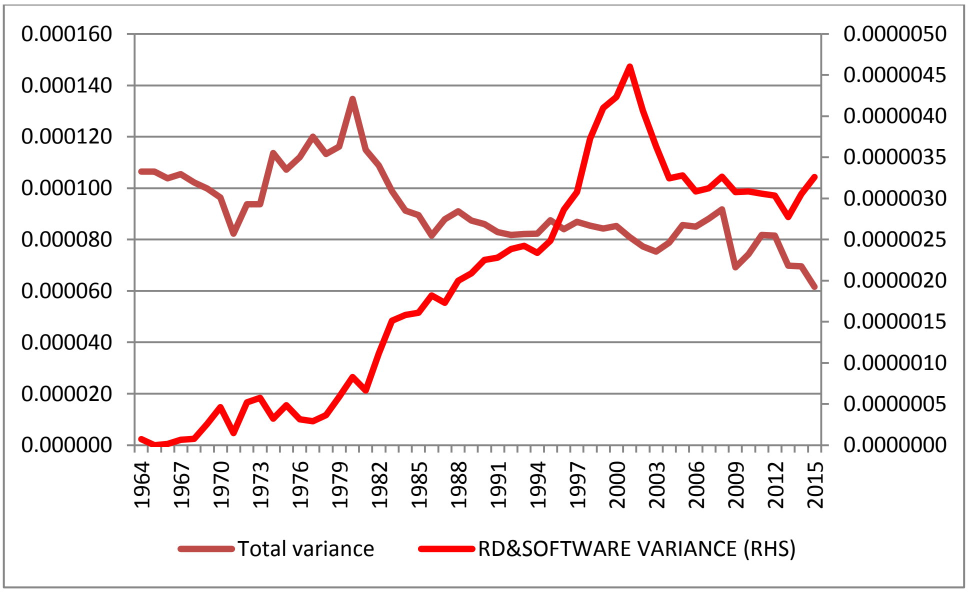
To analyse the impact of the financial sector on the GDP volatility, we start by looking at the historical evolution of the demand-driven GDP volatility, particularly, in periods showing big changes. We focus on the large decline of volatility from the 1960s to the early 1990s, the relative increase in volatility from 1990 up to 2007-2008, and the decline in volatility up to 2015. Then, we analyse sectoral contribution to the GDP volatility using Equation 4.45. We find that the large decline in total volatility between 1960s to the early 1990s is essentially due the decline in Manufacture 1 variance, as shown in Figure 4.11.

Figure 4.11: Total Demand-Driven GDP Variance versus Manufacturing 1 Variance



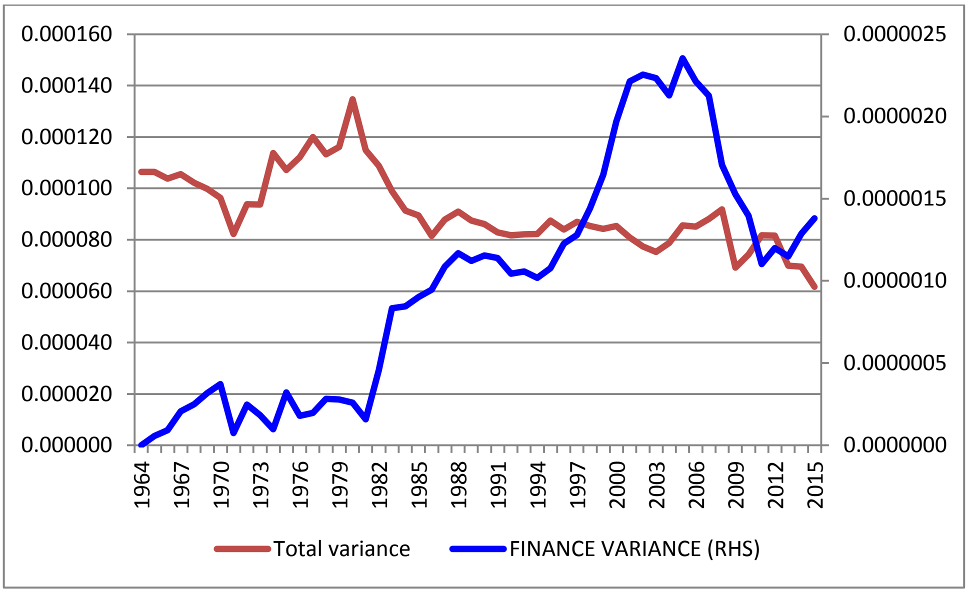
Source: Calculated and Plotted by author using Equation (4.40).

Figure 4.12: Demand-driven GDP variance and RD& Software variance



Source: Calculated and Plotted by author from Equations 4.40.

Figure 4.13: Demand-driven GDP variance and financial sector variance



Source: Calculated and Plotted by author from Equation 4.40

However, as we can see from Figure 4.11, in 1981, the variance of the Manufacture 1 sector starts to decline faster that total demand-driven GDP variance, widening the gap between the two. As shown in Figure 4.12 and 4.13, this coincides with the period where we observe increase in the R&D software and Financial sector variances, which offset the decline in manufacture variance on the total demand-driven GDP variance. Given that equation 4.40, assumes time-invariant final demand and intermediate input volatilities, the decline in the variance of Manufacture 1 sector and the increase in the volatility of the Financial sector and R&D software is determined by change in the centrality of the sectors (see Figure 4.6 in subsection 4.5.2.2). Furthermore, Table 4.11 shows the sectoral Katz-Bonacich centrality growth. It shows that the highest growth rate among the three most central sector was recorded by the R&D software and the Financial sector. Actually the centrality of the Manufacture 1, essentially, declined over these periods.

Table 4.11: Sectoral Katz-Bonacich Centrality Growth Rate

	1990-2005	1990-2006	1990-2007
AGRI.FISH	0.517	0.561	0.502
MINING	8.834	6.812	7.192
ENER.WAT	-0.561	-1.311	-0.911
CONST	0.210	0.332	0.742
MANUF1	-0.529	-0.412	1.411
COM.ELEC	-2.651	-3.202	-3.209
MANUF2	0.569	0.259	1.170
TRADE.RETAIL	0.228	0.049	-0.793
TRANS.COM	-1.344	-1.017	-1.056
RD&SOFTWARE	5.565	4.536	4.738
FINANCE	8.110	7.197	6.620
PUBLIC	-0.209	-0.269	-0.244
PRIV.HH	-2.299	-2.552	-2.915

Source: Calculated by the author using Equation 4.34.

Then from mid-1980 to 2007 we see lower GDP volatility, a period known as the Great Moderation. However, as in Carvalho and Gabaix (2013) we find a relative increase in our GDP volatility between the 1990s and 2007, which become more accentuated in the run up to the 2007 financial crisis, where it reached its peak. Using the Equation (4.45) sectoral variance contribution to the total variance growth (SC), we find that increase in the GDP volatility between 1990 and 2007 is due, primarily, to the increase in the centrality of the Financial sector. As shown in Table 4.12, the increase in total GDP variance over 1990-2005 and 1990-2006, was determined, essentially, by the Financial sector with the contribution of 183 and 179, respectively, and by the R&D and Software with SC(1990-2005)=100 and SC(1990-2006)=90. The Manufacture 1 volatility declined with SC (1990-2005) = -192 and SC (1990-2006) =-166. However, this effect was not enough to offset the increase in the Financial sector and in the R&D software variances. In addition, we also find that with the eruption of the financial sector in mid-2007, and the consequent decline in its centrality in the production network, between 1990-2007 the Financial sector contribution on GDP fell to SC(1990, 2007) = 20 per cent, and the Manufacture 1 stood at 70 per cent.

Table 4.12: Sectoral Contribution to % Change GDP Variance

Sectors	1990-2005 $\Delta\sigma_i^2$	SC	1990-2006 $\Delta\sigma_i^2$	SC	1990-2007 $\Delta\sigma_i^2$	SC
AGRI.FISH	0.000000073	**2.85**	0.0000001	**3.42**	0.0000001	**0.38**
MINING	0.000000196	**7.62**	0.0000001	**6.45**	0.0000002	**0.84**
ENER.WAT	-0.000000012	**-0.46**	0.0000000	**-1.19**	0.0000000	**-0.10**
CONST	0.000000115	**4.49**	0.0000002	**7.88**	0.0000004	**2.18**
MANUF1	-0.000004924	**-191.73**	-0.0000038	**-165.59**	0.0000133	**70.71**
COM.ELEC	-0.000000190	**-7.38**	-0.0000002	**-9.85**	-0.0000002	**-1.22**
MANUF2	0.000000107	**4.16**	0.0000000	**2.10**	0.0000002	**1.17**
TRADE.RETAIL	0.000000226	**8.78**	0.0000000	**2.07**	-0.0000008	**-4.15**
TRANS.COM	-0.000000058	**-2.27**	0.0000000	**-1.91**	0.0000000	**-0.24**
RD&SOFTWARE	0.000002567	**99.94**	0.0000021	**89.78**	0.0000022	**11.60**
FINANCE	**0.000004695**	**182.78**	**0.0000041**	**178.91**	**0.0000038**	**20.27**
PUBLIC	-0.000000165	**-6.43**	-0.0000002	**-9.18**	-0.0000002	**-1.03**
PRIV.HH	-0.000000060	**-2.34**	-0.0000001	**-2.88**	-0.0000001	**-0.41**
Total Variance	**0.000002568**	**100**	**0.0000023**	**100**	**0.0000188**	**100**

Source: Calculated by author from equation (4.45)

Note: $\Delta\sigma_i^2 = [(v_{KBit+1}^2 - \sigma_i^2 - \sigma_{\bar{x}i}^2) - (v_{KBit}^2 - \sigma_i^2 - \sigma_{\bar{x}i}^2)]$ is sectoral variance and corresponds to the numerator of Equation (4.45). The $\Delta\sigma_{yFDt+1}^2 = (\sigma_{yFDt+1}^2 - \sigma_{yFDt}^2)$ is change in total variance and corresponds the denominator in Equation (4.45). $SC_{i,t+1}$ is defined in Equation (4.45). It is the sectoral contribution on total GDP variance. The dates are based on Carvalho and Gabaix (2013), who find increased volatility between 1990 and 2007(in cumulative terms), particularly in the run up to the 2007 financial crisis.

4.6 Summary and Conclusions

This study investigates the role of the financial sector on GDP volatility, using granular macroeconomics, based on the input-output links between sectors of the US economy. The literature on the granular macroeconomic such as Acemoglu et al (2012) and Carvalho (2014) and Carvalho and Gabaix (2013), proposes two GDP volatility measures of Carvalho and Gabaix (2013) and Carvalho (2014), "the fundamental volatility" and the "influence vector". However, both measures are supply driven micro shock volatility, as they derive the impact of sectoral productivity shock on the aggregate fluctuations. In this study we proposes a similar measure, but it derives GDP volatility arising from sectoral idiosyncratic demand shocks. Then we explore the role of the Financial sector in aggregated GDP volatility.

We find that the demand-driven GDP volatility explains about 60% of actual GDP volatility and replicates the most important swings in macroeconomic volatility. It is able to feature the great moderation and the relative increase in volatility from the 1990s up to 2007. It also shows that the surge in the centrality of the financial sector, particularly in the 1990s, was the main factor that determined the increased volatility in the run up to 2007 financial crisis. In general, these results conform with the granular macroeconomic hypothesis on the relevance of idiosyncratic shocks on aggregate volatility such as Gabaix (2011).

5 Conclusion

This thesis contributes to the applications of network analysis to the areas of macro-prudential policy and granular macroeconomics for GDP growth and volatility, with emphasis on the role of the financial sector on real economy. . First, chapter 2 investigates the properties of the global banking system flows, as a cross-border banking system using BIS consolidated banking statistics, (i) to quantify impliyed loss in case of the failure the systemically most important banking system, using the Eigen-pair method of Markose-Giansante yielding the right and left eigenvector centralities as measures, respectively, for systemic importance and systemic vulnerability of banking systems; and (ii) by filling in major data gaps in the within country sectoral flow of funds in the BIS data, and analysing the sectoral cross-border flows (non-financial sectors across and within countries). Findings suggest that financial interconnectedness in international financial markets increased in the run up to the 2007 financial crisis and declined after the crisis. The United States banking system was the systemically most important one. A failure of the US banking system would result in massive loss amounting to on average about 93% of the aggregated 21 countries' total capital of their banking systems. However, the sectoral data analysis including the sectoral shows the US Non-Banking and the Public sector as the most systemically important.

The second chapter explores the relationship between outsourcing and wage decline, the effect of falling wage share and the impact of high financial sector gross operating profit share on output growth. Our results show that between 2000 and 2009, the Computer and Electronics, Mining and Manufacturing 2 are most offshored, importing about 30.25%, 22.5% and 22.2%

of their total inputs, respectively. We also argue that, over the period, a decline in wages may be associated with increased offshoring. Further, we find that a decline in wages shares in the top three most offshored sectors has a negative impact on total output growth. On regards to the impact of increase on Financial sector GOPS on total output using Ghosh inverse matrix, we argue that Financial sector gross operating profits share growth has negative effect on total output. The magnitude of this impact is higher in 2009 compared to 2000. Further, we show that falling wage in the most offshored sector has reduces output growth.

The third chapter derives GDP volatility arising from sectoral idiosyncratic demand shocks to investigate the impact of the Financial sector in aggregated GDP volatility. Findings shows that the demand-driven GDP volatility explains about 60% of actual GDP volatility and replicates the most important swings in macroeconomic volatility. It is able to feature the great moderation and the relative increase in volatility from the 1990s up to 2007. It also shows that the surge in the centrality of the financial sector, particularly in the 1990s, was the main factor that determined the increased volatility in the run up to 2007 financial crisis. In general, these results conform with the granular macroeconomic hypothesis on the relevance of idiosyncratic shocks on aggregate volatility such as Gabaix (2011).

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7 APPENDIX A

The detailed OECD input-output tables used in the present study were downloaded from: http://www.oecd.org/sti/ind/input-outputtablesedition2015accesstodata.htm. The data is available for the years 1995, 2000, 2005, 2008, 2009, 2010 and 2011. . The tables represent matrices of inter-sectoral flows of intermediate and final goods and services within and across countries, evaluated at current prices (USD million). The data comprise 67 countries with 34 sectors and 6 final good and services use items, each. However, for the purpose of the present study the 34 sectors were condensed to 14 sectors, and we focus on the US economy. For the aggregation of the sectors we used the International Standard Industrial Classification of All Economic Activities, Rev.4, http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=27. Detailed information on the aggregation is presented in the table below.

For the detailed analysis of the value added and its components use an OECD STAN data obtained from http://stats.oecd.org/Index.aspx?DatasetCode=STAN08BIS&lang=en

1	• C01T05 Agriculture, hunting, forestry and fishing HC Household Consumption;	AGRI.FISH
2	• C10T14 Mining and quarrying NPISH Non Profit Institution Serving Household;	MINING
3	• C15T16 Food products, beverages and tobacco GGFC General Government Final Consumption; • C17T19 Textiles, textile products, leather and footwear GFCF Gross Fixed Capital Formation; • C20 Wood and products of wood and cork INVNT Changes in Inventories; • C21T22 Pulp, paper, paper products, printing and publishing CONS_ABR Direct purchases abroad by residents (Export to Non-residents); • C23 Coke, refined petroleum products and nuclear fuel DISC Discrepancies (exports to unspecified partner); • C24 Chemicals and chemical products C25 Rubber and plastics products; • C26 Other non-metallic mineral products Output rows Description; • C27 Basic metals; • C28 Fabricated metal products OUT Output at basic prices; • C29 Machinery and equipment, nec • C36T37 Manufacturing nec; recycling;	MANUF1
4	• C30T33X Computer, Electronic and optical equipment;	COM.ELEC
5	• C31 Electrical machinery and apparatus, nec; • C34 Motor vehicles, trailers and semi-trailers • C35 Other transport equipment	MANUF2
6	• C40T41 Electricity, gas and water supply;	ENER.WAT
7	• C45 Construction;	CONST
8	• C50T52 Wholesale and retail trade; repairs • C55 Hotels and restaurants;	TRADE.RETAIL
9	• C60T63 Transport and storage; • C64 Post and telecommunications;	TRANS.COM
10	• C65T67 Financial intermediation • C70 Real estate activities;	FINANCE
11	• C71 Renting of machinery and equipment • C72 Computer and related activities • C73T74 R&D and other business activities	RD.SOFTWARE
12	• C75 Public admin. and defence; compulsory social security • C80 Education • C85 Health and social work • C90T93 Other community, social and personal services	PUBLIC
13	C95 Private households with employed persons;	PRIV.HH

8 APPENDIX B

8.1.1.1 The Output of Financial Sector

The US System of National Account (SNA)of 2008, defines the financial sector output as the sum of the output generated from the central bank services, the financial services other than those associated with insurance and pension funds, and from the financial services associated with insurance and pension schemes.

Given its non-market nature, the central output is valued in terms of the total costs of three groups of services, the monetary policy services, financial intermediation and borderline cases, which includes supervisory services overseeing the financial corporations.

The output of the financial services other than those associated with insurance and pension funds, consists of financial intermediation, the services of financial auxiliaries and other financial services. The financial intermediation involves financial risk management and liquidity transformation, activities in which a financial institution incurs financial liabilities, by taking deposits and issuing bills, bonds or other securities, used to acquire mainly financial assets. Thus, by making advances or loans to others and to purchase bills, bonds or other securities. The Auxiliary financial activities are those that facilitate risk management and liquidity transformation activities.

This concept of financial sector output also captures other financial services, such as, those provided in return for explicit charges in association with (i) interest charges on loans and deposits; (ii) the acquisition and disposal of financial assets and liabilities in financial markets; and (iii) the financial services associated with insurance and pension schemes.

Examples of financial services provided in return of explicit charges associated with interest rate includes, deposit taking institutions, such as banks, that charge households to arrange a mortgage, manage an investment portfolio, give taxation advice, administer an estate, and so on. The most pervasive charge in this category of financial services is the direct fee charged by credit card issuers to the agents that accept credit cards as a means of payment for the goods and services they provide, and annual fee to the card holder for holding the card and for using (when it applies) the credit facilities offered by the card.

The financial services provided in association with interest charges on loans and deposits are essentially those related to the financial intermediation activity, where, the lender and borrows pays a fee to the bank for the service provided. This consists of the difference between the rate paid to banks by borrowers and the reference rate plus the difference between the reference rate and the rate actually paid to depositors, which represent charges for financial intermediation services indirectly measured (FISIM).

On the financial services associated with the acquisition and disposal of financial assets and liabilities in financial markets, the financial sector output accounts for the charges levied when a financial institution offers for sale or purchase a security. The margins on sales and purchases are defined in terms of mid-prices. Also, accounted in this category of financial services is the property income (other than interest rate) generated by equities and investment fund shares.

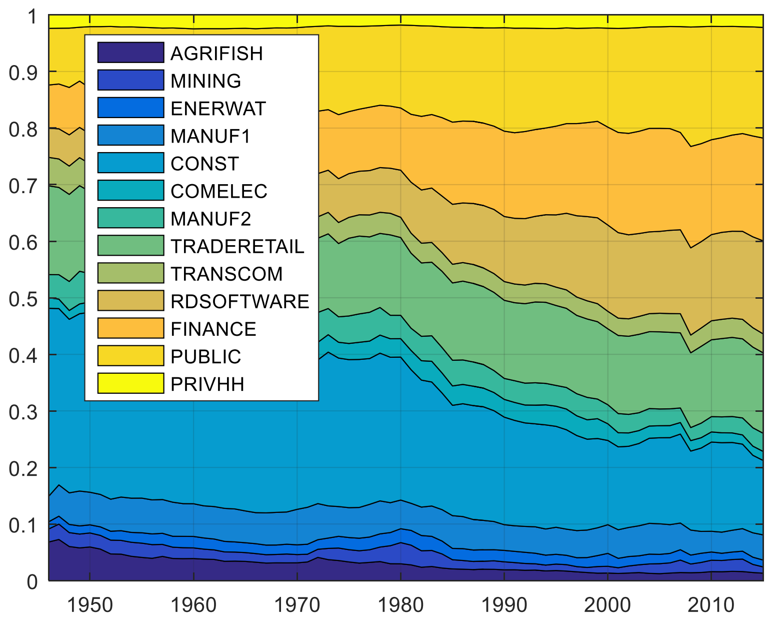
On their turn, the financial services associated with insurance and pension schemes consist of non-life insurance, life insurance and annuities, reinsurance, social insurance schemes, and standardized guarantee schemes. Where the output on the non-life insurance, reinsurance and of the standardized guarantee schemes is measured as the sum of total premiums earned plus premium supplements, less adjusted claims incurred. The output of life insurance is derived as the premiums earned, plus premium supplements, less benefits due, less increases (plus decreases) in life insurance technical reserves. However, the output on the social insurance schemes accounting depends on how it is organised. When it is run as part of the operation of general government, and when it is operated by an employer on his own social insurance scheme, the output is determined as the sum of incurred costs. In the latter case, it includes estimate for a return to any fixed capital used in the operation of the scheme. When an employer uses an insurance corporation to manage the scheme on his behalf, the value of the output is the fee charged by the insurance corporation, while for a multiemployer scheme, the output is valued the same as for life insurance policies.

8.1.1.2 Financial Sector Output Dynamics over 1964-2015

Figure 4.9 shows the share of the US financial sector output in terms of total gross output, estimated from 1964-2015. The results evidence an impressive increase in the economic importance of the Financial sector over the period, particularly from the 1980s. After remaining almost stable from the 1960s to 1980 at around 10%, the financial sector output increased from 11 per cent in 1981 to 18.3 per cent in 2005. This growth is attributed to the finance of the Information Technology (IT) revolution (Phillipon (2008)) and the Financialisation phenomenon (Tomaskovic-Devey et al (2015)). It was then followed by a slight decline to 17.2 during the financial crisis, after which it recovered from 2012 back to the 18.2 per cent of the gross output in 2015. In fact, this growth was accompanied by important changes in the structure of the economy, with sectors such as the financial sector, R&D and Software, and Trading and Retail gaining more relevance while others, namely, the Manufacturing and Transport and Communications where losing preponderance. This can be also seen on the structure of the inter-sectoral input-output flows in terms of production network, as we will discuss later in the next section.

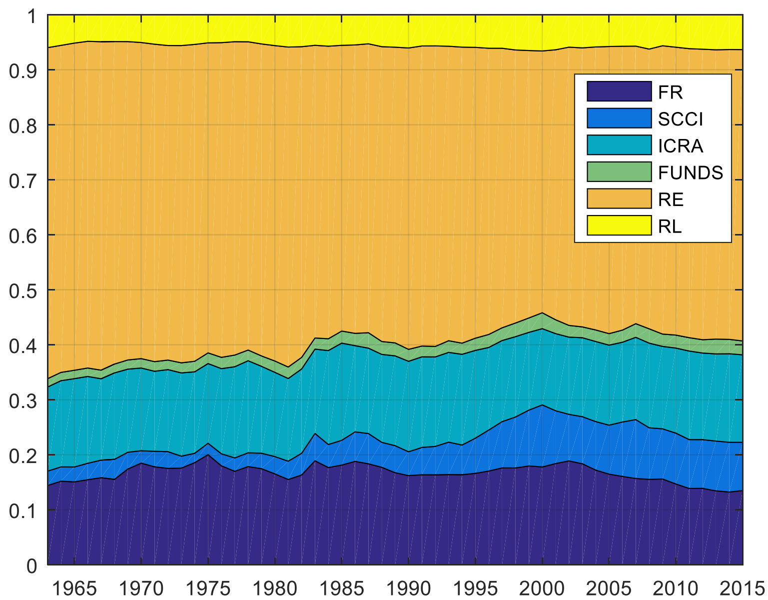
Figure 4.10 shows the evolution of the components of financial sector output. In the estimates of Industry Economic Accounts of the Bureau of Economic Analysis (BEA) the financial sector consist of six subsectors: (i) Federal Reserve banks, credit intermediation, and related activities (FR), (ii) Securities, commodity contracts, and investments; (iii) Insurance carriers and related activities; (iv) Funds, trusts, and other financial vehicles; (v) Real estate; and (vi) Rental and leasing services and lessors of intangible assets. Figure 4.10 shows an upward trend over the period (1964-2015) driven mainly by the component of real estate (RE) whose annual growth accounts for an average of 52.5 per cent of the total financial sector output growth; the growth in the Insurance carriers and related activities (ICRA) which represents 16 per cent, and Federal Reserve banks, credit intermediation, and related activities (FR) remains stable over the period, notwithstanding the weight of 15.5 in the total financial sector output. The output in the component of the securities, commodity contracts, and investments (SCCI) accounts for 8.14 per cent, whilst rental and leasing services and lessors of intangible assets (RL) account for 5.6 per cent, with the Funds constituting for 2.34 per cent of the financial sector output growth.

Figure 8.1: US Financial Sector Output as a percentage of all industries Gross Output



Source: Plotted by author from BEA Gross Output by Industry data

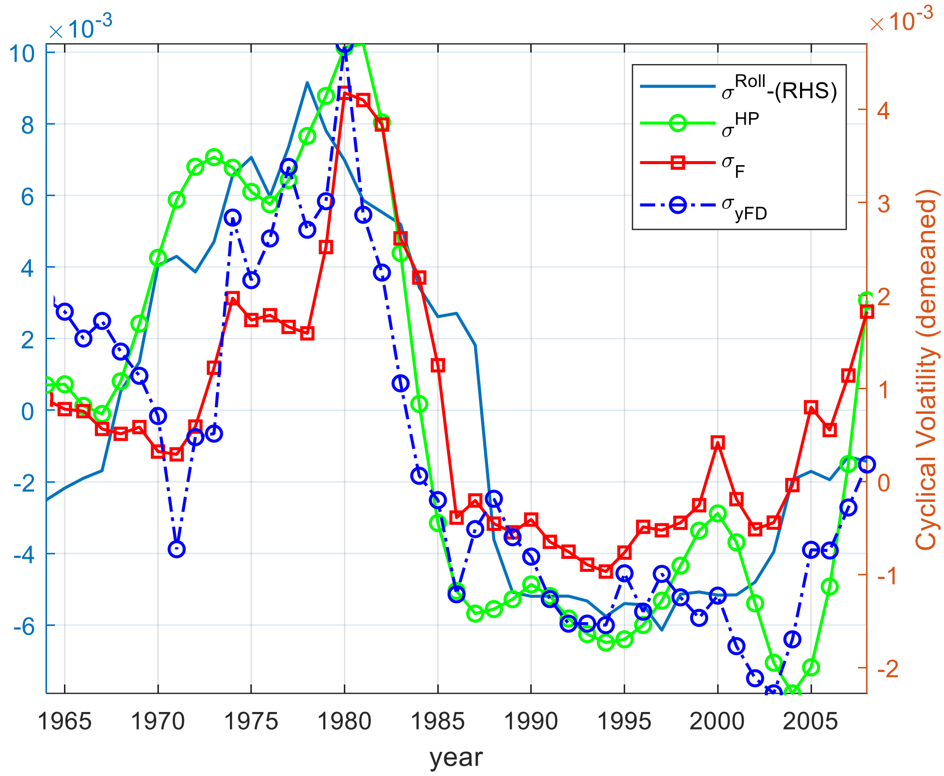
Figure 8.2: US Financial Sector Output and its main Components



Source: Plotted by author from BEA Gross Output by Industry data

9 APPENDIX C

Figure 9.1: Demand and Drive-Driven GDP Volatility and Rolling window actual GDP Volatility



Source: Plotted by author from Equations (4.40), (4.25) and (4.27)

$\sigma_{y_{FD}}$ is our measure, the demand-driven GDP volatility. σ_F is the fundamental volatility, the Carvalho and Gabaix (2013) supply driven GDP volatility. σ_{Yt}^{Roll} and σ_{Yt}^{HP} are the rolling window and HP based actual GDP volatility, respectively. The RHS stands for Right Hand Scale