Inter-Sectorial Transactions of the U.S. Economy– An Evolutionary Network Analysis Approach

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Abstract

This paper analyzes the evolution of the U.S. industrial sectors in term of shock susceptibility and spillover from any hypothetical shock. First, it develops the temporal connectedness (network) of U.S. industrial sectors from 1997 to 2015. Then, it ranks the sectors based on their inter-sectorial transactions. A higher ranking represents a richer connectedness to the overall production system. The connectedness of sectors are defined by PageRank, CheiRank, Hub and Authority scores. A higher PageRank represents higher input dependencies and a higher CheiRank represents higher connectivity to supply chain. A higher authority score of a sector denotes its significance for absorbing the final product as the input from other hub sectors. And, a higher hub score indicates a sector's significance to outflow their final product to other authority sectors. We transformed the Leontief inverse (published by the Bureau of Economic Analysis (BEA) from 1997-2015) to technical coefficient matrix and defined it as the weighted directed temporal network then ran above algorithms. Given any hypothetical shock, we found that manufacturing, construction and agricultural sectors are highly susceptible for shock as these sectors are highly dependent on inputs, while, manufacturing, finance and business services sector can spillover shocks to other sectors as these sectors' final products are highly demanded as the input.

Keywords: PageRank, HITS, Hubs, Authorities, Networks, IO

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1. Introduction

The U.S. Input-Output (I-O) Accounts, published by Bureau of Economic Analysis (BEA), provides supply and use tables. The supply table delivers a detailed elaboration of the total domestic supply of goods and services from both domestic and foreign producers while the use table shows the use of supply across U.S. economy. These tables provides a detailed "internal workings of the U.S. economy" in-terms of flows of goods and services purchased by each industry (inter-industry transaction), the incomes generated from production in each industry, and the dissemination of sales for each commodity [1].

The inter-industry transaction is the flow of the demand made by each industry j for each industrial input i. Bott and Mayberry's paper on "Matrices and Trees" described the possibility of network analysis in such inter-industry transactions [2]. Since then, "a small but steady flow of literatures" have emerged [3], but, the network analysis have not maneuvered extensively in input-output framework [4]. Several studies developed the networks of inter-industry transactions by binarizing [2] on some arbitrary threshold value of inter-industry transaction (see [5]–[11]). Because of these arbitrary cut-offs, their study were branded as qualitative input-output analysis (QIOA).

The goal of this paper is to assess the potential quantitative applications of network characterizations on the U.S. inter-sectorial[3] transactions. This can provide some insights on sector's shock susceptibility and shock spillover from any hypothetical shock. Post 1990 (especially after the dot-com boom and, more recently, the social media boom) the network analysis advanced rapidly to study higher complexities of connectivity of interlinked webpages, computer networks and social network clusters. Hence, there is scope to explore and use advanced network algorithms to analyze the complexities of connectives associated with inter-sectorial transactions.

In this paper, we studied the temporal evolution of key U.S. sectors in term of shock susceptibility and spillover to any hypothetical shock. As a proxy of inter-sectorial transaction, we have used the technical coefficient matrix of U.S. (discussed later) from 1997-2015 as

[2] When inter-industry transaction occurs above some arbitrary threshold, then, it is assigned value of 1 and 0 otherwise

[3] A sector refers to a large segment of the economy, while the term industry describes a much more specific group of companies or businesses (http://www.investopedia.com/ask/answers/05/industrysector.asp).

weighted directed temporal networks. The data were downloaded from the Bureau of Economic Analysis website. We implemented advanced network algorithms like the Google PageRank, CheiRank, Authority and Hub index to identify the shock susceptibility and shock spillover capability of the key sectors based on their inter-sectorial transactions.

2. Literature Review

One of the primary concerns of the input-output (IO) method is to rank the industries based on the degree of inter-industry interdependence. In much of this research since the seminal works of Leontief [12]–[14], the ranking of industries has been based on the Leontief Inverse and the Ghosh Inverse [15]. Leontief inverse/Ghosh inverse is derived from technical/sales coefficient matrix, in fact, the power series sums of technical/allocation coefficient matrix gives the Leontief/Ghosh Inverse.

Technical coefficient or the direct requirement shows the value of the input demanded by the sector j from the sector i per monetary unit of output in the sector j [4]. The Leontief inverse or the total requirements matrix captures the total direct and indirect outputs in sector i per unit of final demand in sector j [16]. The allocation coefficient or direct sales coefficient shows the value of input sold to sector j by sector i per monetary unit of output in the sector i. The Ghosh Inverse reflects the total (or direct plus indirect) dependence of sector i on sector j [17].

In the Leontief Inverse, the column sum is a measure backward linkages [18], while in the Ghosh Inverse, the row-sum is a measure of forward linkages. A higher backward-linkage value indicates industry's greater dependence on inputs while a higher forward-linkage indicates a greater dependence on sales. The backward-linkage captures the demand-side interconnections while the forward-linkage captures the supply-side interconnections. Rasmussen and Hirschman have implemented these linkages to rank the key industry [18], [19], and several others have enriched the ranking techniques by assigning different types of weights to these linkages [20]–[22]. Sonis & Hewings have extended the analysis to trace the hierarchy of backward and forward linkages. in the context of an economic landscape associated with the cross structure of the matrix product multiplier (MPM) [23]. These studies tried to rank inter-industry interdependence using the Leontief and/or Ghosh Inverse. However, the ranking problem also can be approached from a network theoretic conceptual framework.

Network analysis found its way into input-output analysis from operations research and electrical engineering [3]. After, Bott and Mayberry developed some foundation of network analysis on technical coefficient matrix [2], slow and steady progress in literature have been seen [3] but not fully-fledged [4]. The studies that have implemented network analysis in IO were known as qualitative input-output analysis (see [5]–[11]) and had primary motives to rank industry based on the inter-industry relations.

Interestingly, ranking the billions of interlinked web-pages based on the search query is also the primary concern of search engines like Google. Google's unprecedented success is rooted in the Brin and Page's PageRank algorithm known as Google PageRank [24], [25]. This algorithm ranks the importance of web pages according to an eigenvector of a weighted link matrix, alternatively known as the "$25,000,000,000 eigenvector" [26]. Another similar algorithm to rank web pages is known as the hyperlink-induced topic search (HITS) algorithm [27], [28], which iteratively finds the hub and authority. Higher authority scores are associated with the nodes that are pointed to by many other nodes that have a high hub score, while the higher hub scores identify the nodes that are pointed to by many other nodes with a high authority score [29].

After After Serrano and Bogun revamped the study on world trade network in 2003 [30], several papers have embraced the above stated network algorithms to analyze the world trade and global IO networks (see [29], [31]–[34]). These studies, in general, tried to analyze the importance of linkages and ranked them.

3. Data and Methodology

The data of Leontief Inverse or total requirement matrix (from 1997-2015) are published by BEA for summary level of 15 sectors. Leontief Inverse is defined as: $L = (I - A)^{-1}$, where A is technical coefficient. Leontief Inverse represent the total direct and indirect outputs in sector i per unit of final demand in sector j.

3.1 Technical Coefficient Matrix and Leontief Inverse

The direct-requirement matrix is defined as $A = \{a_{ij}\}_{i,j=1,\cdots,n} = x_{ij} / x_j$, where x_{ij} is direct demand made by sector j for input of sector i, and x_j is the total output of sector j. The coefficient a_{ij} represents dollars' worth of output from sector i per dollar output from sector j or alternatively, it shows the value of the input demanded by sector j to sector i per monetary unit of output in sector j. The matrix A provides a quantitative representation of the internal structure of the economic system. These ratios are also called technical coefficients because they represent the technologies employed by the sectors to transform inputs into outputs.

We transformed the total requirement matrix to the direct requirement matrix (technical coefficient) as: $L^{-1} - I - 1 = A$. The transformed technical coefficient matrix had some negative values which were elevated to zero. For visual analytics only, values less than 0.0001 were suppressed to zero. The dimension of data is 15 sectors by 15 sectors by 19 years. We renamed the sectors using appropriate abbreviated first word. The actual names of sectors assigned by BEA are given in Annex.

3.2 Google PageRank and CheiRank

We defined the direct-requirement matrix as a weighted and directed network matrix A. We modified the general PageRank, CheiRank and Kleingberg's Hyperlink-Induced Topic Search (HITS algorithm) to be weighted and not binary. The weighted PageRank (PageRank henceforth) algorithm on A that ranks the network nodes' average proportionally to a number of ingoing links or ingoing connectivity at the global level. We also implemented a PageRank on an A^T, which is known as the CheiRank [33]–[35], and it ranks nodes in average proportionally to a number of out-going links. The PageRank highlights nodal popularity (higher incoming links), or which sector is highly demanding input from the global network of the direct-requirement matrix, while the CheiRank highlights communication and connectivity abilities of sectors in the global network on direct requirement matrix [33], [34]. The definition of PageRank requires the Google matrix $G = \{g_{ij}\}_{i,j=1,\cdots,n}$ and:

$$g_{ij} = \phi s_{ij} + (1-\phi)/n$$

Where, matrix $S = \{s_{ij}\}$ is obtained by normalizing to unity all columns of A and $\phi = 0.85$ is the dampening parameter used by Google search engine. The ϕ is introduced to ensure the existence of a unique solution by the Perron-Frobenius theorem. Then the PageRank $r = (r_1, \cdots, r_n)^T$ can be acquired by iterating the following algorithm until convergence:

$$r(t+1) = G^T r(t)$$

where t is the number of iteration and superscript T is transposition and initial condition $r_i(0) = 1/n$ Same PageRank algorithm can be run in A^T to define the CheiRank.

3.3 Kleingberg's Hyperlink-Induced Topic Search (HITS algorithm)

The PageRank and CheiRank only reflect the one-link network structure; to reflect a two-link network structure, we introduce the HITS algorithm of Kleinberg. Kleingberg's HITS algorithm ranks the node of a complex directed network using authority and hub values. The HITS authority vector $\alpha = (x_1, \cdots, x_n)^T$ and the HITS hub vector $h = (y_1, \cdots, y_n)^T$ are defined by the limits of the following set of iterations:

$$\alpha(t+1) = c(t) A^T h(t)$$

$$h(t+1) = d(t) A^T \alpha(t+1)$$

Where $c(t)$ and $d(t)$ are the normalization factors to make the sums of all the elements become unity,

$$\sum_{i=1}^{n} \alpha_i (t+1) = 1; \sum_{i=1}^{n} h_i (t+1) = 1$$

And $\alpha_i = 1/n$ and $h_i = 1/n$ initialize the above algorithms. α is the eigenvector for matrix $A^T A$ and h is eigenvector of AA^T and non-negative A ensures non-negatives authority and hub scores.

4. Results

The first section of results provides basic descriptive studies of the technical coefficient, inter-sectorial transaction and trends of U.S. industrial sectors from 1997 to 2015. And, in second section, we have presented the results of PageRank, CheiRank, Authority and Hub scores.

4.1 Basic Descriptive Studies

4.1.1 Time-series of Direct Input Requirements with the Quadratic Fit

The (Direct Input Requirements) technical-coefficient matrix gives the value of the input demanded by sector j from sector i per monetary unit of output in sector j. We traced 225 time-series of a_{ij} from 1997-2015 (15 sectors by 15 sectors) in Figure-A (See Annex and in Tableau Public for interactivity)[4], Each time series represents the technical coefficient of sector j for input i. As the 2008 financial crisis is very important event in U.S. economy, splits time series in pre and post 2008 era with dotted vertical line while flat horizontal line shows nonexistence of inter-sector relationship. Ceterius peribus and in general, higher value and or the positive trend represents higher dependency of sector j for industrial input i and in other hand it represents the significance of industrial input i for sector j. The sectors were renamed using appropriate abbreviated first word. The actual names of sectors assigned by BEA are given in Annex. There are several interesting sectorial inter-dependencies that are to be noted (inverted U-shaped and U-shaped relationships) in Figure-A at Annex. We have also released an online public domain application for interactivity of technical coefficient. In Figure-B at Annex, we showed a network of input requirement of each sectors for year 2015.

The demand of mining sectors in utilities, mining and manufacturing sectors were positive in pre 2008 but such trend sharply inverted to the negative trend after 2008. Such inverted U-shaped relationships are also marked by: a) the demand of manufacturing sector in agriculture sector and in utilities sectors; b) demand of finance sector in transport and finance sectors; c) and demand of business sector in the government sectors. While, the U-shaped relationships (negative trend in pre 2008 and then trend became positive after 2008) appeared in: a) demand of agriculture sector in agriculture sector; b) demand of manufacturing sector in information, manufacturing and

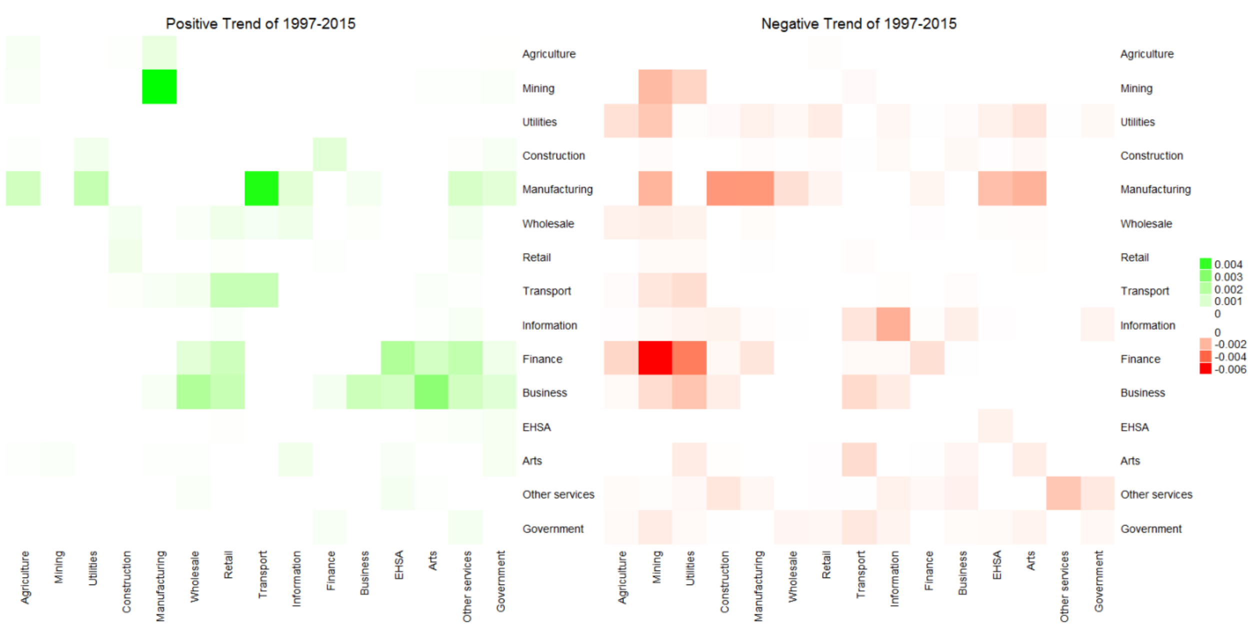
[4] Link of online Tableau application (Click here)

mining sector; c) demand of information sector in information sector; and d) demand of finance sector in mining sector.

4.1.2 Heat Map of Linear Trend of Direct Input Requirements.

To generalize the technological coefficient from 1997-2015, we averaged each of the a_{ij} 1997 to 2015 and represented them in the heat map (see Figure-1). The darker tone represents higher value of technical coefficient. The diagonal cell represents the degree of self-absorption. Each off-diagonal cell represents the value of the input demanded by column sector from the row sector in per monetary unit of output in column sector. Clearly, almost all the sectors demand intensely from manufacturing, finance and business services sectors while the agricultural sector demands inputs from many other sectors.

Figure 1: Heat Map of Trends of Technical Coefficient (1997-2015)



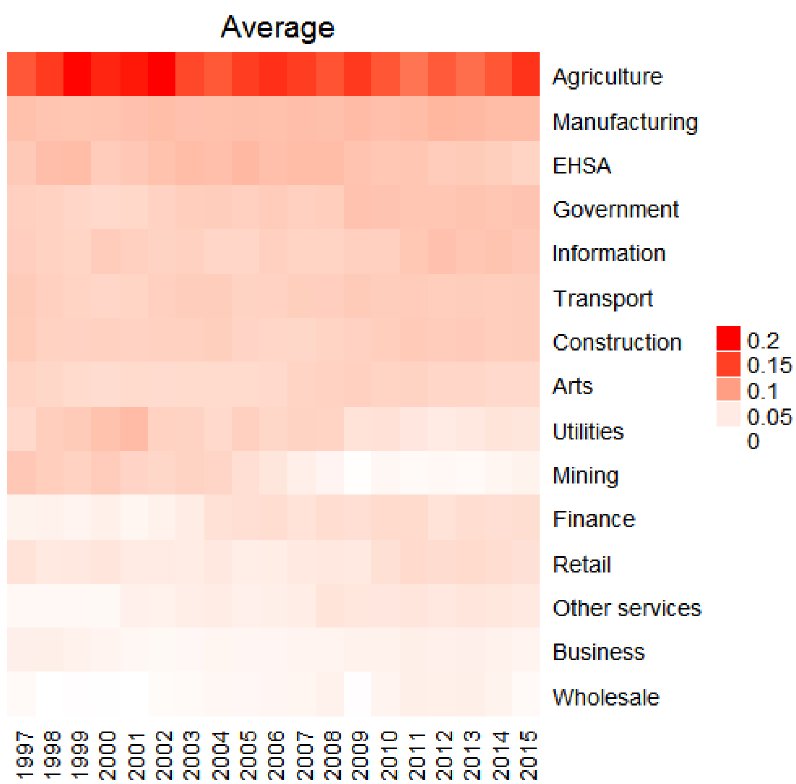
There exist two strong positive trends: a) demand of mining sector in manufacturing sector and b) demand of manufacturing sector in transportation sector. Thus, the manufacturing sector strongly depends on the mining sector for inputs while the transport sector strongly depends on the manufacturing sector for inputs. Overall, the demand of manufacturing, business and finance sector are in rise thus aftermaths of any shock can spillover faster from these sectors.

There exist several strong negative trends. The mining sector and utilities sectors were reducing their demand which represents these sector are less input dependent. Both of these sectors significantly reduce their demand from the finance sector. Sectorial input dependencies on the government, manufacturing, utilities and other service sectors have also declined. The trends of self-absorption (diagonal) have also in decline.

4.2 PageRank and CheiRank Index of US Sectors

We developed the PageRank and CheiRank of each U.S. sector from 1997 to 2015. The results are represented in the heat map and sectors are ordered in decreasing rate of averages of PageRank and CheiRank. Hence, each cell represents the intensity of Rank index of corresponding sector for corresponding year. Higher tone represents higher index while the gradual increase or decreases in tonal intensity is evidence of upward or downward trend of index.

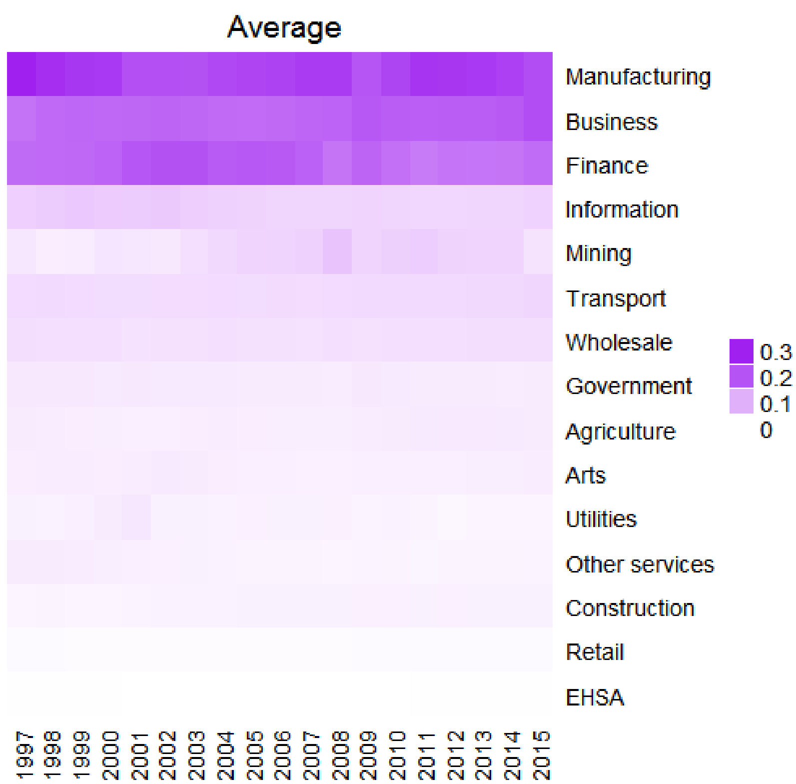
Figure 2: PageRank Index of US Sectors from 1997-2015



The PageRank index arranges the sector based on their high in-degree. High in-degree represents incoming link toward itself from many other relevant sectors. Hence, higher PageRank represents higher dependency on inputs from other sectors. Sectors with higher PageRank are always susceptible to be affected by supply-side shocks.

In the Figure-2, the agriculture sector has highest PageRank and its intensity is very high. Therefore, it demands inputs from many other sectors thus remains vulnerable to any hypothetical supply shocks. Agriculture PageRank is followed by manufacturing sector, EHSA and Government, but the intensity is relatively faint compared to agricultural sector. The PageRank index of EHSA and utilities have decline after 2008 while the PageRank of Government, transportation and retail has increased in post 2008. The PageRank of mining has declined from 2004 while the PageRank for the Finance have increased since then.

Figure 3: CheiRank Index of US Sectors from 1997-2015



Another, approach to look at the PageRank is CheiRank. The PageRank accounts for higher in-degree to relevant sectors while the CheiRank accounts the higher out-degree to more relevant sectors. Hence, CheiRank represents sector ability to remain as the inputs for other sectors. These sectors fulfill the demands of inputs for many other sectors thus has supply-side role.

The Figure-3 clearly shows manufacturing, business and finances sectors have higher CheiRank. These sectors are forward linked with many other sectors. Any hypothetical shocks on these sectors can spillover quickly toward its forward supply chain. The CheiRank of retail and EHSA are lowest and these are sectors which don't supply their final product as input to other sector.

4.3 Authority and Hubs Kleingberg's HITS Algorithm

The PageRank and CheiRank give the importance of sector in overall economic structure. However, it can be more interesting to study inter-sector importance based inter-sector linkages which are tightly feed backing toward each other. The economic term would be Authorities and Hubs.

In general, the authority represents sector with higher number of incoming link with large amount of inter-sector transaction, thus these sector has heavy inflows of the final product from other sectors. Similarly, the hub represents sector with higher number of outgoing links with a large amount of inter-sector transaction, thus these sector outflow their final product heavily to other sectors. Therefore, the sector having more in-degree from the sector which are hubs are known as authority sector while the sector having more out-degree to the sector which are authority are known as hubs. Because of the higher volume of transaction, the hubs are the connector which can spillover shock of shocks while the Authorities are the sectors which are more vulnerable to shock of such shocks.

The Figure-4 shows the rank of the authority index of US sectors from 1997-2015. This index ranks the sectors based on their susceptibility (incoming nodes) of shock from the sector which are prominent in their supply chain (hub sectors). Based on authority index, manufacturing sector followed by construction, agriculture and transportation sectors appears more susceptibility from the shocks from the hub sectors. The authority index in transportation sector has appears to increase after 2003.

Looking at post 2008 era, the tone of heat map breaks and intensifies which indicates that most of the sectors have become more susceptible to shocks from the hub sectors. However, the mining and utilities sector appears less vulnerable as the tone of heat map has fairly faded.

Apparently, the finance, retail and wholesale ranks last in authority index indicating they have less incoming input demand from the hubs.

Figure 4: Authority Ranks Index of US Sectors from 1997-2015

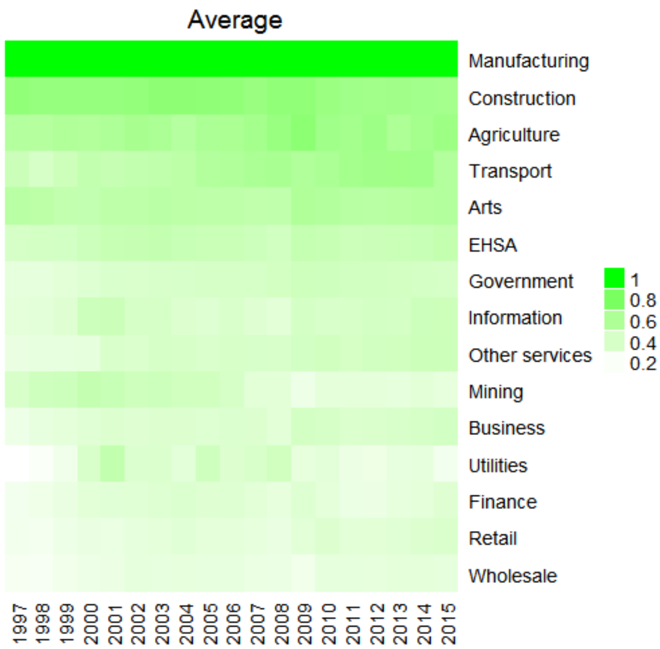
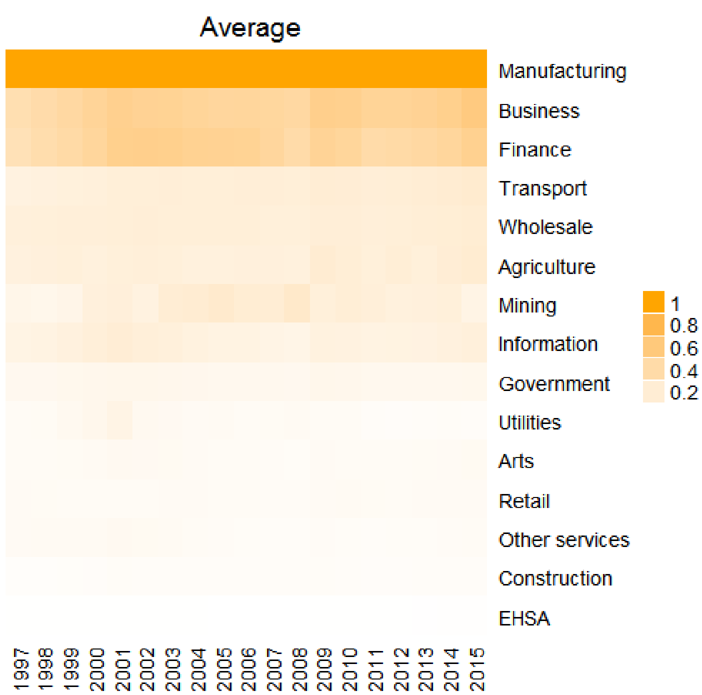


Figure 5: Hub Ranks Index of US Sectors from 1997-2015



The Figure-5 shows the rank of the hub index of US sectors from 1997-2015. This index ranks the sectors based on their spillover ability (outgoing nodes) of shock from the sector which are prominent in their supply chain (authority sectors). The manufacturing sector followed by business and finance appears more linked to high authority indexed sectors which represents these sector can behave as hub to spillover the shocks. The hub index of business and finance have increased in post 2008 era thus, they are evolving to become more connected in term of selling their final output to other sectors.

5. Conclusion, Discussion and Future Works

This study accessed some recent network algorithms like the Google PageRank [24], [25], CheiRank [33]–[35], Kleingberg's HITS algorithms [27], [28] to identify Authority and Hub index to analyze the US inter sector transaction from 1997 to 2015. We provided an insight on evolution of U.S. inter-sector shock susceptibility and spillover based on technical coefficient matrix. The technical coefficient matrix was retrieved from the Leontief Matrix published by BEA for 15 sectors. The technical coefficients matrix represented the weighted directed network of U.S. inter-sector transaction.

At first we performed general descriptive analysis. Firstly, we traced the trend of technical coefficient and pointed out several important reversals of trend of several U.S. inter-sector transactions. We realized that the trend of mining sector demand in utilities sector was positive in pre 2008 era then it sharply U inverted to negative trend after 2008 while, the self-absorption of information sector was in negative trended but became positive after 2008. Secondly, we develop the heat map of the average U.S. inter-sector transaction by averaging the technical coefficient from 1997 to 2015. We found that, all other sectors are dependent to manufacturing, finance and business for their production inputs. Thirdly, we layout the heat maps for general trend of technical coefficients. We found trend of mining sector dependency toward finance sector and many other have sharply declined. Sectorial dependencies in the government and utilities sectors have overall declined. Manufacturing has become more dependent toward the mining sector while the transport sector is more dependent toward manufacturing and retail sector. The professional business services and finance dependencies with themselves and with education health and social assistance (EHSA) and arts sector have increase.

Based on the PageRank index we found Agriculture is intensely susceptible to shocks while CheiRank provided strong evidence that manufacturing, business and finances sectors can spillover the shocks to all other sectors. The PageRank and CheiRank gave the importance of sector in overall economic structure. However, we also performed Kleingberg's HITS algorithms to analyze the inter-sector linkages which are feed backing toward each other. We found that the manufacturing sector followed by construction, agriculture and transportation are authority sector and they appears more susceptibility from the shocks from the hub sectors. The manufacturing, business and finances sectors behave as the hubs sectors and these hubs can spillover the shocks to the authorities sectors.

This study seeks future advancement on following grounds. We only considered the technical coefficient however; it's equally possible to apply this concept with sales coefficients. We use several Eigen value based centrality measure, however, there are several other possibilities which can equally provide useful insights. We have only ranked the sectors but ranking of the economics landscape is also possible.

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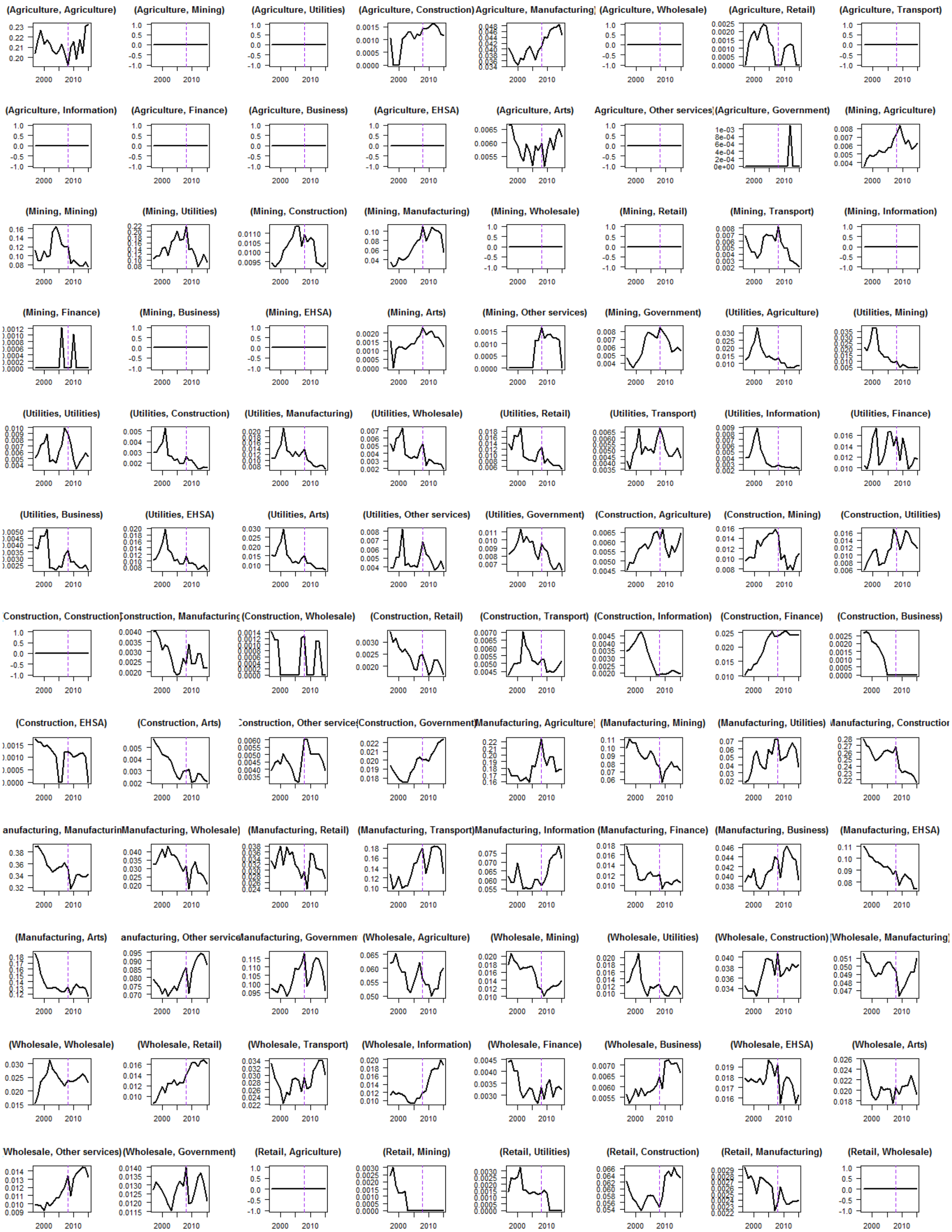
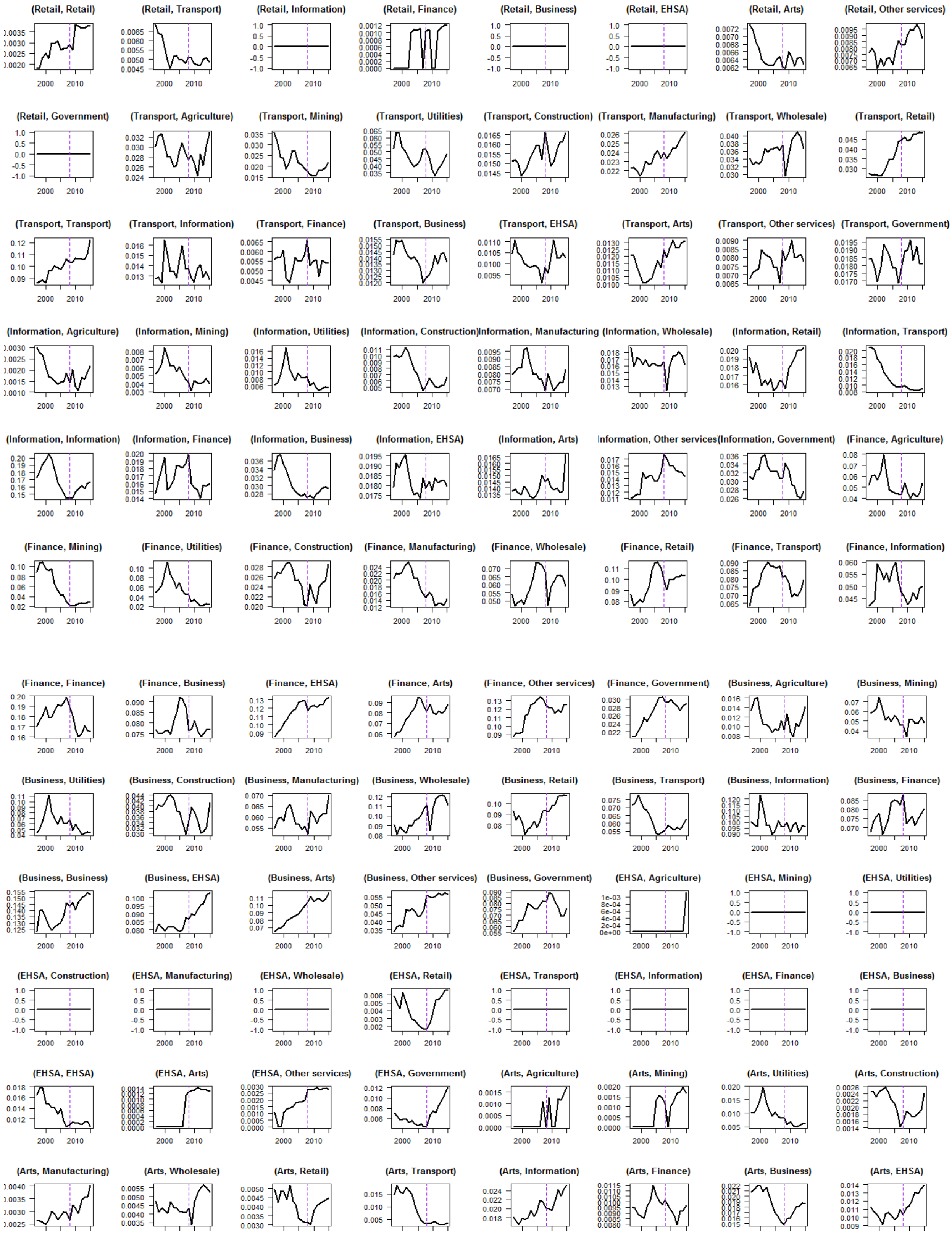
Annex

Table-A

S.N	Industry Codes and Aggregations in the Industry Economic Accounts (BEA)	Abbreviation for Sectors
1	Agriculture, forestry, fishing, and hunting	Agriculture
2	Mining	Mining
3	Utilities	Utilities
4	Construction	Construction
5	Manufacturing	Manufacturing
6	Wholesale trade	Wholesale
7	Retail trade	Retail
8	Transportation and warehousing	Transportation
9	Information	Information
10	Finance, insurance, real estate, rental, and leasing	Finance
11	Professional and business services	Business
12	Educational services, health care, and social assistance	EHSA
13	Arts, entertainment, recreation, accommodation, and food services	Arts
14	Other services, except government	Other services
15	Government	Government

Figure-A: Temporal Evolution of Technical Coefficients (Link of Tableau Public ([here](#)))

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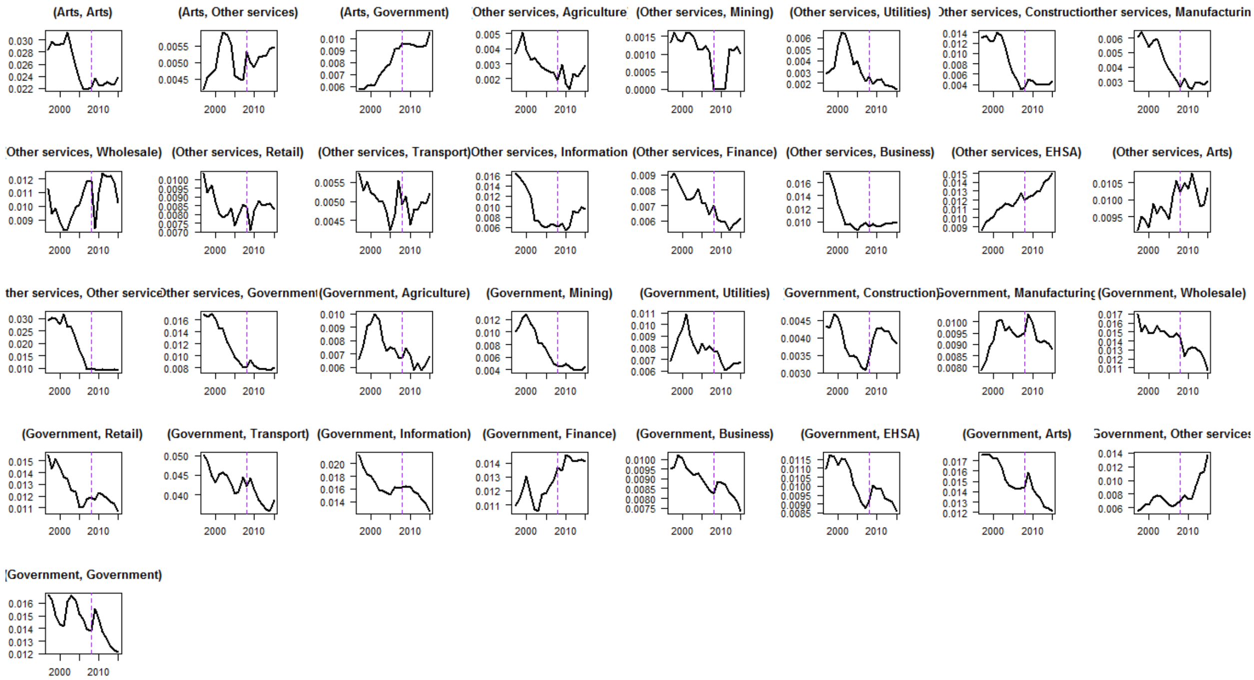
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Figure-B: A Network of Input Requirements (Year 2015)