LINKING REAL AND FINANCIAL CONNECTEDNESS

by

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Abstract

In this study, we investigate the relationship between the fundamental and market values of U.S. industry-portfolio returns. In particular, we first map and compare how real and financial connectedness in industry networks behave and co-move over time. Second, we use ordinary least squares regression analysis to quantify whether the real linkages between industries predict the industry-portfolio based financial connectedness. We have four different real economic network measures based on: (1) the flow of specialized inputs; (2) employment; (3) patent holdings; and (4) geographic proximity or co-agglomeration. To estimate industry-portfolio financial connectedness, we use Diebold-Yilmaz connectedness index methodology on industry-portfolio returns, which uses variance decompositions of vector auto-regressions. Using techniques from graph theory, we first find that several industries form observable clusters in real economic networks, whereas such clustering is not observed in financial networks. Second, industries having higher GDP shares (make values) in real economic networks are not the biggest drivers of the financial connectedness, which could be an evidence that dynamics of financial and production markets have subtle differences. Our empirical findings suggest that industry-portfolio financial connectedness and explanatory power of each real economic network on financial connectedness display opposite patterns. During tranquil times, each real economy linkage has a higher explanatory power on the determination of financial connectedness. However, during times of turmoil, industry-portfolio financial connectedness is not an inter-industry phenomenon, rather, it is due to each industry-portfolio being more susceptible to the overall financial environment.

Keywords: Industry-portfolio financial connectedness, Input-output network, Occupational employment network, Co-agglomeration, Patent citation network, Vector Autoregression, Nonparametric Estimation

Özet

Bu çalışma, Amerikan endüstriyel portföy getirilerinin temel ve piyasa değerleri arasındaki ilişkiyi incelemektedir. İlk olarak, endüstri bazında reel ve finansal bağlanmışlık hareketleri karşılaştırılmakta ve yıllar içinde beraber hareket edip etmedikleri sorgulanmaktadır. İkinci olarak, sıralı en küçük kareler regresyon yöntemi kullanılarak reel ekonomi bağlarının endüstriyel portföy getirilerinin finansal bağlanmışlığını tahmin etme gücü ölçülmeye çalışılmaktadır. Bu analizleri yapabilmek için, dört farklı reel ekonomi ağı kullanılmaktadır :(1) Özellikli girdi mallarının akışı ;(2) İstihdam ;(3) Patent sahipliği ve (4) Coğrafi yakınlık veya eş yığınlaşma. Portföy finansal bağlanmışlığı ölçmek için, vektör otoregresyon modeli içerisinde varyans ayrıştırması analizini temel alan Diebold-Yılmaz bağlanmışlık endeks metodolojisinden yararlanılmıştır. Grafik teorisi kullanılarak, ilk olarak, reel ekonomi ağları içerisindeki bazı endüstrilerin gözle görülür kümeleşmeleri tespit edilirken, bu tür bir kümeleşme finansal bağlanmışlık ağında görülmemektedir. İkinci olarak, reel ekonomi ağları içerisinde yüksek Gayri Safi Milli Hasıla (GSMH) oranlarına sahip öncü endüstrilerin finansal bağlanmışlığı açıklamada tetikleyici güç olmadıkları bulunmuştur, ki bu sonuç finans ile üretim piyasası dinamikleri arasında ciddi farklar olduğunu göstermektedir. Bu çalışmadaki ampirik bulgular, finansal bağlanmışlık ile her bir reel ekonomi ağının finansal bağlanmışlığı açıklama gücü arasında ters yönlü bir ilişki olduğunu göstermektedir. Yani, ekonominin sağlıklı olduğu dönemlerde, her bir reel ekonomi bağının finansal bağlanmışlık hareketlerini açıklama gücü yüksek seviyelerde bulunmuştur. Ancak, ekonominin kötüye gittiği (özellikle krizi içeren) dönemlerde, endüstriyel portföy finansal bağlanmışlık, reel ekonomi bağları tarafından açıklanamamaktadır. Bilakis, bu çalkantılı dönemlerde, portföy getiri performansı, genel finansal atmosfere daha duyarlı olmaya ve finans piyasasındaki dinamikler tarafından açıklanmaya başlamaktadır.

Anahtar Kelimeler: Endüstriyel portföy finansal bağlanmışlık, Girdi-çıktı ağı , Mesleki istihdam ağı , Eş yığınlaşma, Patent alıntılama ağı , Vektör otoregresyon, Parametrik olmayan kestirim

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1 Introduction

Recent studies point out that the structure of the real economic networks is key in determining whether and how microeconomic shocks affecting only a particular sector propagate to affect the economy as a whole and determine aggregate economic outcomes (Acemoglu et al. (2012)). The synchronized production decision in highly connected industries can redeem a sector level shock very critical for the aggregate economy. In particular, since each industry is strongly interdependent with respect to customer-supplier relationships, when even a small company fails, there is a strong chance that the entire industry would face severe disruption.

However, ignoring financial markets and just focusing on real economic networks will miss an important part of the modern and integrated production economies. The stock market is crucial as it channels funds to real economy. As part of this function, the stock market is also the place where real economic productions of firms are valued. Hence, the movements in stock prices are expected to reflect the changes in fundamental value of real economic activities. Thus, it is fair to expect a high and positive correlation between market and fundamental value of real economic linkages. In that respect, when there is a negative real economic shock to a firm, it will affect the future cash flow of this firm. In first-order effect, this in turn will be taken into account by the stock market and stock price of this firm will go down. In higher-order effects, since there are tight connections between industries through various real economic linkages, this particular negative shock would hit other firms and drag their stock prices down as well. Therefore, stock market has a very crucial role to reflect the developments on the real economy.

In that respect, Menzly and Ozbas(2010) suggest that economic links among certain individual firms and industries contribute significantly to cross-firm and cross-industry return predictability. They find that stock and industry-level returns exhibit strong cross-predictability effects based on lagged returns in supplier and customer industries. This observation is further supported by Ahern (2013), Aobdia et al. (2014), Birge and Wu (2014) and Rapach et al.(2015). However, all these studies identify economic links via customer-supplier relationships and ignore other possible relationships between real economy and financial market.

Differing from the literature, we try to estimate how real and financial networks are predictors of each other and how this predictability change temporally. In this study, our main contribution in methodological and substance level is that we have a unique approach and understanding in which we analyze how the dynamics in both networks affect and cross-predict each other. From our understanding, real economic linkages that we will introduce below are the main drivers between industries in the real economy. Above it, there is a financial network reflecting the developments in real economic networks through the movements in the stock market. To capture that we will use Diebold-Yilmaz framework which estimates industry-portfolio return financial connectedness based on the variance decomposition and gives a industry-portfolio based financial network.

How can we capture real networks? According to Marshall, industry pairs share goods, labor, or ideas. In that respect, a real economy is a linked web through sharing of specialized inputs, labor pooling, knowledge and technological transfer. In the literature, these are often studied to capture industry co-agglomeration (Ellison, Galeser & Kerr(2010)). On top of these networks, we also add geographic co-agglomeration to capture other forces that could result in industry spillovers. In sum, we have four different real economic networks:

1. A flow of specialized inputs

2. A flow of labor

3. A flow of knowledge and technology

4. Geographic proximity or Co-agglomeration

To estimate industry financial connectedness, we use Diebold-Yilmaz connectedness index methodology on industry-portfolio returns, which uses variance decompositions of vector auto-regressions and shows what fraction of the forecast error variance of each variable is explained by other variables. We also use the generalized variance decomposition which produces variance decompositions which are invariant to the ordering of variables in the VAR model. In order to improve the precision of high-dimensional models, we estimate the VAR model by using the elastic net shrinking and selection procedure, which combines Lasso and Ridge estimators.

In the end we have two different types of networks to analyze: industry-level real economic networks and industry-level financial connectedness network. First, since the structure of the network plays an important role in governing the outcome, we compare the network characteristics of both networks, such as how dense they are, whether some groups are segregated and which industries sit in central positions. Second, we compare the relative importance of each industry in the determination of real and financial connectedness. Last, in our empirical analysis, we estimate the predictive power of each real economic network on industry financial connectedness network.

Let us summarize our major findings when we analyze how real and financial links in industry-industry networks behave and co-move in different episodes. This comparison brings us to answer whether there is a wedge between the fundamentals driven by real economic activity and realized value in the financial market. There are four major differences between financial connectedness network and real economic networks. We first find that financial industries and wholesale trade are generating the bulk of connectedness in industry financial network. However, in real networks, manufacturing and real estate are important transmitters. Second, with the help of heat-map analysis, we show that dynamics in financial connectedness change substantially over time, whereas it is more static in IO network. The third difference is that several sectors form observable clusters in real economic networks, whereas such clustering is not observed in industy-portfolio financial connectedness network. Last, industries having higher GDP shares (make values) in real economic networks are not the biggest drivers of financial connectedness, which could be an evidence that dynamics in financial and production market have subtle differences.

A brief summary of our empirical findings is as follows. We first find several striking results when we compare the coefficients of each real economy linkage and industry-portfolio financial connectedness. In each regression classification financial connectedness and the coefficients of each real economy linkage move in the opposite/mirror image directions. Declining financial connectedness corresponds to tranquil times, when the determination of portfolio return is mainly coming from idiosyncratic effects. In these periods, the explanatory power of real economy dramatically increases. Hence, industry portfolio returns reflect their real fundamentals during good times. However, during bad times when the financial connectedness has skyrocketed, the explanatory power of real economy decreases. Hence, we suggest that industry portfolio returns deviate from their fundamentals, thus there is a divergence between market value and fundamental value during bad times. It also implies that during Great Recession industry financial connectedness is mainly explained by the factors outside the real connectedness (but we are agnostic to explain/investigate these factors) and financial connectedness during the crisis is no longer an inter-industry phenomenon, rather, it is due to each industry being more susceptible to the overall environment.

The remainder of the paper is structured as follows. In section 2, we review the literature related to our research questions. Section 3 describes our data sources methodology. In section 4, we describe our methodology which estimates financial connectedness. Section 5 discusses the comparison between financial connectedness network and real economic networks. Section 6 introduces our regression classifications. Section 7 interprets our empirical findings. We conclude by discussing our results and possible extensions.

2 Literature Review

There are two strands of the literature related to our paper. The first one focuses on the dynamics and propagation mechanism within real economic networks. The second strand studies inter-industry linkages and the cross predictability of stock returns. Here we briefly review the literature on each of these two topics.

2.1 Propagation mechanisms within real economic networks

Literature on the propagation mechanisms within real economic networks is recently very dense by focusing on observable large shocks to a set of firms or industries and having traced their impact through the input-output network. An important paper by Gabaix (2011) contributes a lot to the literature by showing that when the firm-size distribution has very fat tails, so that shocks hitting the larger firms cannot be balanced out by those affecting smaller firms, the law of large numbers need not apply. Hence, sizable macroeconomic fluctuations can occur from idiosyncratic firm-level shocks.

Being in line with this crucial finding from Gabaix(2011), the focal point of the recent literature is that input-output linkages can neutralize the force of the law of large numbers because shocks hitting sectors that are particularly important will not wash out and can translate into aggregate fluctuations(Carvalho (2008), Acemoglu et al. (2010, 2014), Acemoglu et.al (2012), Buraschi and Porchia (2012) and Baqaee (2015)).

The common feature of these studies is they only study the propagation of macroeconomic shocks through input-output network as a main driver of macroeconomic fluctuations. They do not study the propagation mechanism and interactions between real and financial networks. However, we argue that since financial market is crucial as it channels funds to real economy, the stock market is also the place where real economic productions of firms are valued. Hence, the movements in stock prices are expected to reflect the changes in fundamental value of real economic activities. Therefore, focusing on only real economic networks and ignoring its interactions with financial markets miss an important part of the propagation mechanism that is investigated in the studies that we have discussed so far.

2.2 Inter-industry linkages and the cross predictability of stock returns

Recently, there has been an increase in the efforts to find evidence of return predictability across economically linked firms. On the one hand, Menzly and Ozbas (2010) document that the market is segmented along the boundaries of industries and they identify economic links via customer-supplier relationships. They show that economic links among certain individual firms and industries contribute significantly to cross-firm and cross-industry return predictability. Empirically, they find stock and industry-level returns exhibit strong cross-predictability effects based on lagged returns in supplier and customer industries. On the other hand, Cohen and Frazzini (2008) focus on the customer-supplier links between firms, and find the stock prices of supplier firms have a predictable lag in reacting to the new information about their customers.

Birge and Wu (2014) study the relationship between supply chain linkages and firms' stock returns. Using recently available data on the relationships of public U.S. firms, they investigate the effects of supply chain connections on firm performance as reflected in stock returns. Their main argument is that if firm-level shocks propagate over supply chain linkages, they should have an impact on stock prices. In addition, Rapach et al. (2015) analyze the importance of industry interdependencies for cross-industry return predictability and argue that industries with the most pervasive predictive power on stock returns are among the key central nodes in the U.S. production network.

Our main motivation is on the same track with these papers but with several critical differences in methodological and substance manners. These studies only measure predictive power of customer-supplier relationships in the production network on firm or industry returns. However, there are other industry linkages in the real economy which can affect the cross-industry return predictability. We believe that ignoring other key interactions in the real economy would hurt the prediction accuracy and interpretability of the empirical analysis suggested in these studies. In order to capture these missing points, we will analyze the following three real economic interactions in addition to customer-supplier relationships : (1) a flow of labor; (2) a flow of knowledge and technology; and (3) geographic proximity or co-agglomeration. In our empirical findings, we find that all these additional three linkages have important explanatory power on industry-portfolio financial connectedness, which justifies our concern about the related studies we have discussed so far.

3 Data

To calculate industry-portfolio return financial connectednes, we use daily prices of all publicly-tradable stocks on CRSP from 2004 to 2015 and form value-weighted industry-level portfolios using industry definitions from BEA Input-Output (IO) 2002 and 2007 report years.

In order to analyze the flow of specialized inputs, we use industry-industry total requirements table which explains how much of one industry is required to deliver $1 worth of final good to the final users. We both use detailed level, which is reported every five year, and summary level, which is reported annually, industry-industry total requirements tables provided by Bureau of Economic Analysis (BEA). At the detailed level IO, we use 2002 IO detailed level, which reports 6-digit industries, industry by industry total requirement table with 432 industries (279 of which matches to CRSP) and 2007 IO detailed level table with 394 industries (275 of which matches to CRSP). At the summary level IO, we use annual IO summary level, which reports 3-digit industries, industry by industry total requirement tables 71 industries (64 of which matches to CRSP) from 2004 to 2015.

We capture industry similarities based on labor pooling with the help of Occupational Employment Statistics (OES) survey which provides the employment levels of 800 occupations in all NAICS 4 digit industries. We build labor similarities using this data.

In order to investigate the role of geographic proximity, we use County Business Patterns (CBP) which covers all counties of the U.S. and reports industries at NAICS 6-digit (some minor exceptions like agriculture and federal government employees). We use total employment in an industry in Commuting Zones to build co-agglomeration measure of Ellison et.al (2010).

Finally, we generate a measure of knowledge flow and transfer using all patent citations between 2004 and 2010 from NBER Patent Database. We first match each patent number to firm's CUSIP code and then match firm's CUSIP code to firm's NAICS code. In the end, we match firm's NAICS code to IO industry code.

4 Methodology

To estimate industry-portfolio financial connectedness, we use network connectedness measures that are based on variance decompositions of a large VAR of the sample which are proposed and developed in a series of papers (Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), and Diebold and Yilmaz (2014)).

We will now provide a brief description of the Diebold-Yilmaz Connectedness Measures and introduce the elastic net estimation of the VAR model used for dealing with the dimensionality problem.

4.1 Diebold-Yilmaz Connectedness Measures

In order to estimate industry-portfolio financial connectedness, we will use variance decompositions of vector autoregressions, using Diebold-Yilmaz connectedness measures as developed in Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), and Diebold and Yilmaz (2014). The variance decomposition matrix gives us an intuitively appealing connectedness measure. It gives what percentage of the future uncertainty in variable i is resulting from the shocks in variable j.

Let us explain why we use VARs. First, there could be the simultaneity in the determination of industry-portfolio returns so that we control this matter in VARs model. In this regard, we find the pure connectedness between the two industry-portfolio returns. Hence, we do not find spuriously high connectedness measures which result from a common shock transmitter.

We follow the Diebold-Yilmaz approach with three lags and use the generalized variance decompositions to obtain connectedness measures from the VAR model. Proposed by Pesaran and Shin (1998), generalized VAR approach produces variance decompositions which are invariant to the ordering of variables in the VAR model. It allows for correlated shocks but also separates the effects of each shock for the purposes of analysis.

4.1.1 Pairwise Directional Connectedness

A covariance stationary N-variable VAR with lag p can be represented as

$$x_t = \sum\nolimits_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \tag{1}$$

Moving average representation is as follows:

$$x_t = \sum\nolimits_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{2}$$

where A_i is a $N \times N$ matrix that satisfies $A_i = \sum_{j=0}^{p} \Phi_p A_{i-p}$

Variable j's contribution to variable i's H-step-ahead generalized forecast error variance, $\theta_{ij}^g(H)$, is calculated as

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \quad H = 1, 2, ..., \tag{3}$$

where Σ is the covariance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_i is the selection vector with one as the i^{th} element and zeros otherwise.

Since we are measuring directional connectedness, we are not assuming the effect of variable i on the variable j is identical to the effect of variable j on variable i.

We can normalize this measure to get well-defined percentages:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N} \theta_{ij}^g(H)}. \tag{4}$$

where $\sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H) = N$ follow by construction. We call $\theta_{ij}^g(H)$ the *pairwise connectedness* from variable j to variable i.

4.1.2 Total Directional Connectedness, “To" and “From"

When we calculate the pairwise connectedness measure between variables i and j, there are many analyses we can make. First, we can look at systemic measures, such that, what is the total directional connectedness from variable i to all remaining variables or what is the total directional connectedness to variable i from all remaining variables. We will call them as 'to connectedness' of variable i and 'from connectedness' of variable i respectively.[1]

Secondly, we can look at semi-systemic measures, such that what is the total directional connectedness from variable i to some subset S_j of the remaining variables

[1]Note that 'from connectedness' measure cannot be greater than 100%.

or what is the total directional connectedness to variable i from some subset S_j of the remaining variables.

Total directional connectedness to industry portfolio return i from all other industry portfolio returns is:

$$C_{i \leftarrow \bullet} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100. \tag{5}$$

Total directional connectedness from industry portfolio return i to all other industry portfolio returns is

$$C_{\bullet \leftarrow i} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100. \tag{6}$$

4.1.3 System-Wide Connectedness

In this study, we are interested in an even more systemic measure, such as what is the overall importance of shocks originating in all industry-portfolio returns. We calculate the total connectedness index as

$$C(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}. \tag{7}$$

We call this total connectedness as *system-wide* connectedness. It is simply the average of total directional connectedness measures whether “to" or “from".

4.2 Estimation

4.2.1 Selecting and Shrinking the Approximating Model

Our analysis of industry-portfolio financial connectedness relies on daily industry-portfolio returns by taking log of the ratio of the close price to the previous day's close price.

There is one problem for the estimation that increasing the number of variables, in a VAR setting, quickly consumes degrees of freedom. In order to solve this problem, we can increase the number of observations, but this inhibits the correct and consistent estimation of the change in the coefficients. To overcome this problem, we follow Demirer et al. (2015) and estimate sparse VAR of industry-portfolio returns using the elastic net estimator.

The elastic net estimator solves

$$\hat{\beta}_{Enet} = \arg\min_{\beta} \left(\sum_{t=1}^{T} \left(y_t - \sum_{i} \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} \left(\alpha |\beta_i| + (1-\alpha)\beta_i^2 \right) \right) \tag{8}$$

Elastic net is a hybrid of lasso and Ridge regression; that is, it combines a lasso L_1 penalty and a ridge L_2 penalty. There are two tuning parameters now, λ and $\alpha \in [0,1]$. While lasso shrinks insignificant coefficients to zero and drop these variables from the regression, elastic net makes sure that they are in or out of the model together. We will use 10-fold cross validation to choose λ and take $\alpha = 0.5$ without cross validation.

The adaptive elastic net estimator solves

$$\hat{\beta}_{AEnet} = \arg\min_{\beta} \left(\sum_{t=1}^{T} \left(y_t - \sum_{i} \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} \left(\alpha w_i |\beta_i| + (1-\alpha)\beta_i^2 \right) \right) \tag{9}$$

where $w_i = 1/\hat{\beta}_i^{\nu}$ with $\hat{\beta}_i^{\nu}$ the OLS estimate. Adaptive elastic net is an hybrid of adaptive lasso and elastic net. The advantage of adaptive elastic net is that it both inherits the oracle property of adaptive lasso and works better with highly correlated predictors.

We are safe to use adaptive elastic net on VAR estimation because Furman(2014) shows that the adaptive elastic net does not preclude the efficient equation by equation estimation of VAR. Moreover, it also produces accurate forecasts and valid impulse responses functions.

5 Comparison Between Financial and Real Connectedness

In order to compare how real and financial links in industry-industry networks behave and co-move in different episodes,we first investigate the evolution of financial connectedness throughout the sample period and analyze how the network structures of financial and real economic networks behave in different episodes. Second, with heat-map analysis, we try to figure out the speed of change in dynamics of financial and real connectedness. Let us summarize our major findings for each analysis.

5.1 Dynamic Evolution of Financial Connectedness

We use rolling-window analysis to deal with the time dimension of our coefficients. We choose the window length as 300 to achieve a balance between trend spotting and having acceptable degrees of freedom. More importantly, 300 observations roughly correspond to 12 months so that we have a consistent comparison between annual summary or detailed level real economic networks and financial connectedness network. We realize that 12 months is still a long period to assume constant coefficients, however since we use daily rolling window analysis, we are still able to catch significant changes in effects over time. We also replicated our results with smaller and bigger windows, but only the smoothness of the graph changed; the index still spikes in the same periods.

Figure 1: Evolution of Financial Connectedness at the Detailed and Summary level

Window size is the number of days we used to calculate connectedness for any given date. Here the window size is 300 days.

In Figure 1, we present the system-wide financial connectedness of U.S. value-weighted industry portfolio returns using industry definitions from BEA Input-Output 2007 report year. Our data sample consists of 275 industry-portfolio returns at the detailed level data and 64 industry-portfolio returns at the summary level data.

The first important result of the graph is that even if we switch the detailed level data to the summary level data, two series follow the same pattern throughout the sample period. However, magnitude of the overall connectedness measured with the summary level data is quite lower than the one measured with detailed level data. There is roughly a 2% difference between two series. This difference is not surprising because there is much more information and directed links in the detailed level data, which necessarily increases financial connectedness.

Second, financial connectedness is never below 91% at the summary level (93% at the detailed level), which implies that industry-portfolio returns are tightly connected and the variations of each industry-portfolio return is mainly explained by the connections with other industry-portfolio returns. Moreover, during and after the Great Recession until the end of 2015, the index is always above 94% at the summary level (96% at the detailed level), which strongly suggests that industry portfolios become more susceptible to system-wide risks during that period.

Third, the financial connectedness index has always increased during (also just before and after) the Great Recession, which shows that our framework is successful in capturing the significant events and turning points in the financial market. We can distinguish three sudden increases which correspond to important turning points in the last decade. The earlier turning point is in May 9, 2006 which corresponds to a FED decision about increasing federal funds target rate. After that decision, the system-wide connectedness index has increased 2 percentage points at the summary level (1 percentage point for detailed level) in 10 working days. The second hike corresponds to 26 July 2007, where the overall percentage of shocks in the decomposition of industry-portfolio returns increases nearly 1 percentage point both at the summary and detailed level. July 2007 was the month where the doubts about sub-prime lending built up. In July 26, Bear Sterns seized its assets from two of its problematic funds and it has caused a 4.2% fall in its shares in one day. In the following day, global stock markets have seen a big decline. The last critical point is the period from the beginning of September 2008 until the mid of October 2008 when Lehman Brothers collapsed and financial crisis officially began. During that period, the system-wide connectedness index has increased 2 percentage points and reached 96% at the summary level(98% at the detailed level). After Lehman's collapse, on October 3, President Bush has signed Emergency Economic Stabilization Act of 2008 which includes a $700 billion bailout program and system-wide connectedness has relieved.

After staying constant around 96% at the summary level(98% at the detailed level) in 2009, we see a slow but steady decrease in the system-wide connectedness from the beginning of 2010 until August 2011. The increase in system-wide connectedness during August 2011 corresponds that S&P downgraded US's credit rating. During that period Greece, France,Italy, Spain and Belgium has banned holding short-positions. The depressing global outlook caused an overall volatility increase in all markets, thus the index started a big climb to reach its highest points in the whole sample period. After the mid of 2012 until the end of sample period, the financial connectedness has steady but downward trend when the global outlook and specifically U.S. economy is getting healthier and more optimistic.

5.2 Network Structures of Financial and Real Connectedness

We will present network graphs as large as 64 nodes based on the summary level data, which implies 64^2 edges. Presenting the network completely would not be very informative and would require a high level of attention to identify patterns in the network structure. Therefore, we will present mostly half of the existing links by removing the smallest links in the graphs. We calculate all the network statistics using the full network.

5.2.1 Graphical Display

We use node size, node color, edge thickness, edge arrow size and edge color to convey extra and hard-to-spot information about the graph together with the node location.

We use Gephi, an open-source software for visualizing and analyzing large network graphs. We study complete, weighted and directed networks. Our networks are complete, since we are looking at 10 day ahead forecast errors in determining effects. We need directed networks since the effect of one industry-portfolio return to another is not necessarily same with the effect on the other direction. We obviously need weights, since the magnitude of effects differ between industry-portfolios.

Node Size Indicates GDP shares

We use GDP shares (make values) of industries based on annual IO total requirements to determine node sizes. According to this, an industry with a higher GDP share has a bigger node size while an industry with a low GDP share has a smaller node size. We intend to emphasize important input-supplier industries with this approach.

Node Color Indicates Total Directional Connectedness “To Others"

The node color indicates total directional connectedness “to others" ranging from 3DRA02 (bright green), to E6DF22 (luminous vivid yellow), to CF9C5B (whiskey sour), to FC1C0D (bright red), to B81113 (dark red; close to scarlet). That is, an industry-portfolio return in financial connectedness network and an industry in real economic networks that is less influential in the sample will be colored close to bright green while a highly influential one will be colored closer to dark red. We decide on the cutting points by taking the 25%, 50% and 75% percentiles of the ’to’ connectedness measures in financial network and 25%, 50% and 75% percentiles of industry links in real economic networks.

Figure 2: Network Graph Color Spectrum

Node Location Indicates Strength of Average Pairwise Directional Connectedness

We determine node location using the ForceAtlas2 algorithm of Jacomy et.al (2014) as implemented in Gephi. The algorithm finds a steady state in which repelling and attracting forces exactly balance, where (1) nodes repel each other, but (2) edges attract the nodes they connect according to average of the pairwise directional connectedness measures, “to" and “from."

Edge Thickness Indicates Average Pairwise Directional Connectedness

Edge color is lighter for the weakest links and same for all the others.

5.2.2 Comparative Analysis

We now compare the network structures of financial connectedness and IO total requirements corresponding to the years before, during and after Great Recession. It is important to notice that we use the cutoff points from our main analysis with 64 industries. We will present 25% of the edges by removing the weakest edges.

There are striking differences and similarities in the evolution of financial connectedness and IO total requirements network. The dynamics in financial connectedness network between 2004/2014 and 2008 has a subtle difference. There is a gravitational force resulting from greater financial connectedness in 2008 compared to 2004 and 2014, which implies that industry-portfolio returns are strongly connected and sensitive to any shock in the network during the crisis. However, IO total requirements network connectedness stays constant in each three year, which delivers that the formation and evolution of input relations between industries is persistent throughout the years. It gives an valuable information that real economic relations are much more immune to any shock in the real economy.

We now proceed to dig more deeply into the comparison between financial connectedness and IO total requirements network for each three year. First, when we analyze both networks in 2004 as shown in Figure 3 and Figure 4, financial network is more dense and connected and financial industries and wholesale trade are generating the bulk of financial connectedness. However, in IO total requirements networks wholesale trade, manufacturing and real estate are important transmitters. Moreover, several industries form observable clusters in IO network, such as the visible strong connections between (1) Oil and gas extraction(211) and Petroleum and coal products(324) industries; (2) Securities, commodity contracts, and investments(523) and Funds, trusts, and other financial vehicles(525) industries; and (3) Chemical products(325) and Plastics and rubber products(326) industries.

Second, when we analyze both networks in 2008 as shown in Figure 5 and Figure 6, it is apparent that pairwise directional and system-wide financial connectedness in 2008 is much higher than the ones in 2004 and more financial industries are getting closer to the center of the network and become the main drivers of financial connectedness. However, the network structure and main transmitters of IO network have not changed much compared to 2004 IO network (with one exception that Petroleum and coal products(324) which becomes one of the main transmitter in 2008) and same types of clustering still exist in this network.

Last, when we analyze both networks in 2014 as shown in Figure 7 and Figure 8, we find that pairwise directional and system-wide financial connectedness in 2014 is lower than the ones in 2008, which implies that industries have relieved from the financial stress and risks that give vulnerability to them. At the same time, financial industries and wholesale trade are still at the central position in the financial connectedness network. The dynamics of relations and relative importance of each industry in IO total requirements network are almost the same with ones in 2008 IO network.

Although there are several differences within and between two networks in each three year, the network graphs serve two distinct features. First, several industries form observable clusters in real economic networks, whereas clustering is not seen in industry financial connectedness network. Second, industries having higher GDP shares (make values), which are shown bigger node sizes, are not the biggest drivers of the financial connectedness, which could be an evidence that dynamics in financial and production market have subtle differences.

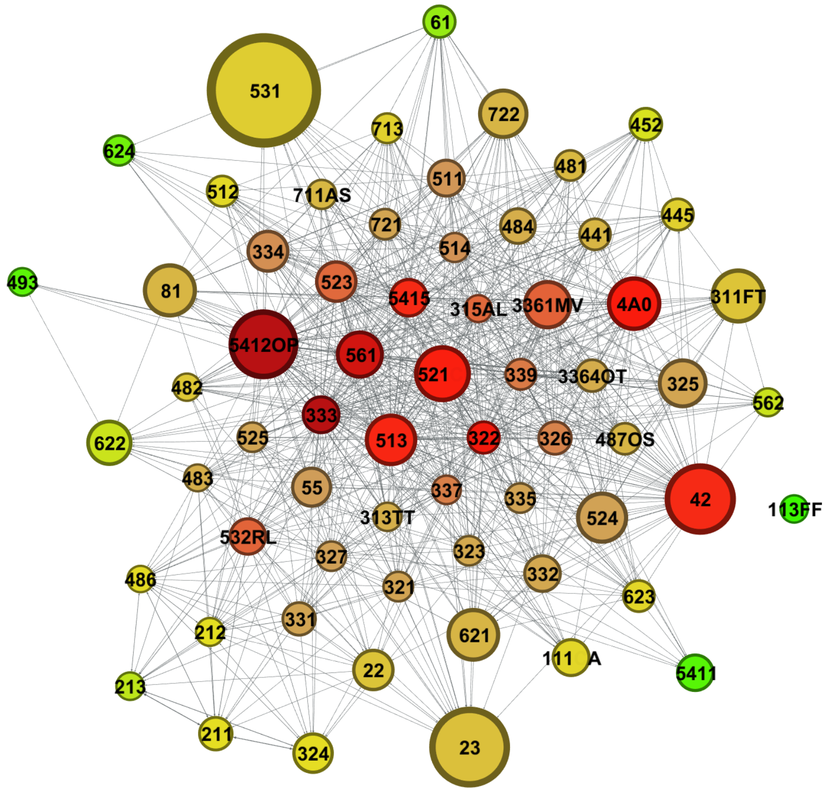

Figure 3: Financial Connectedness in 2004

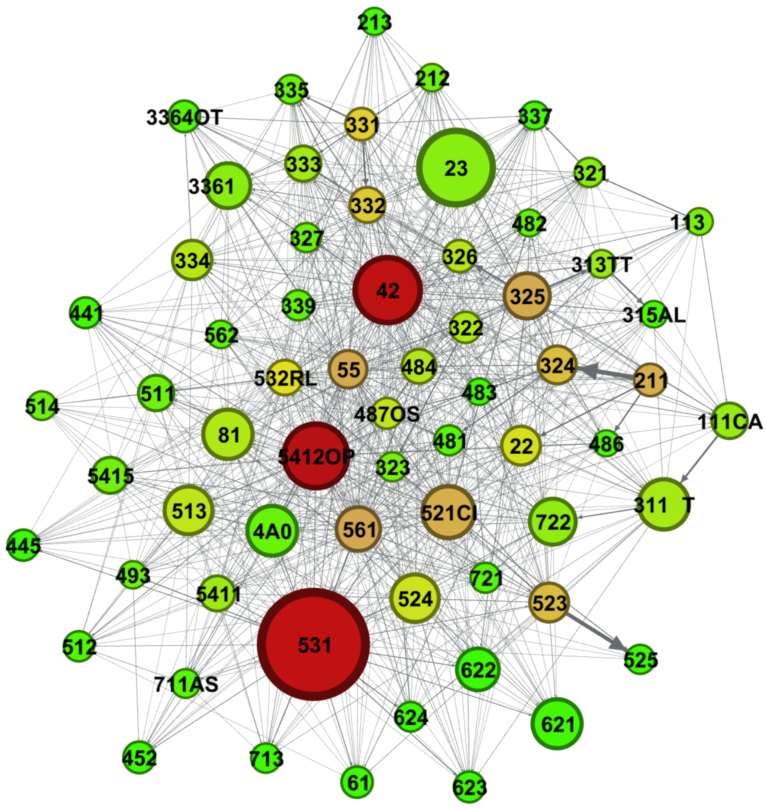

Figure 4: IO in 2004

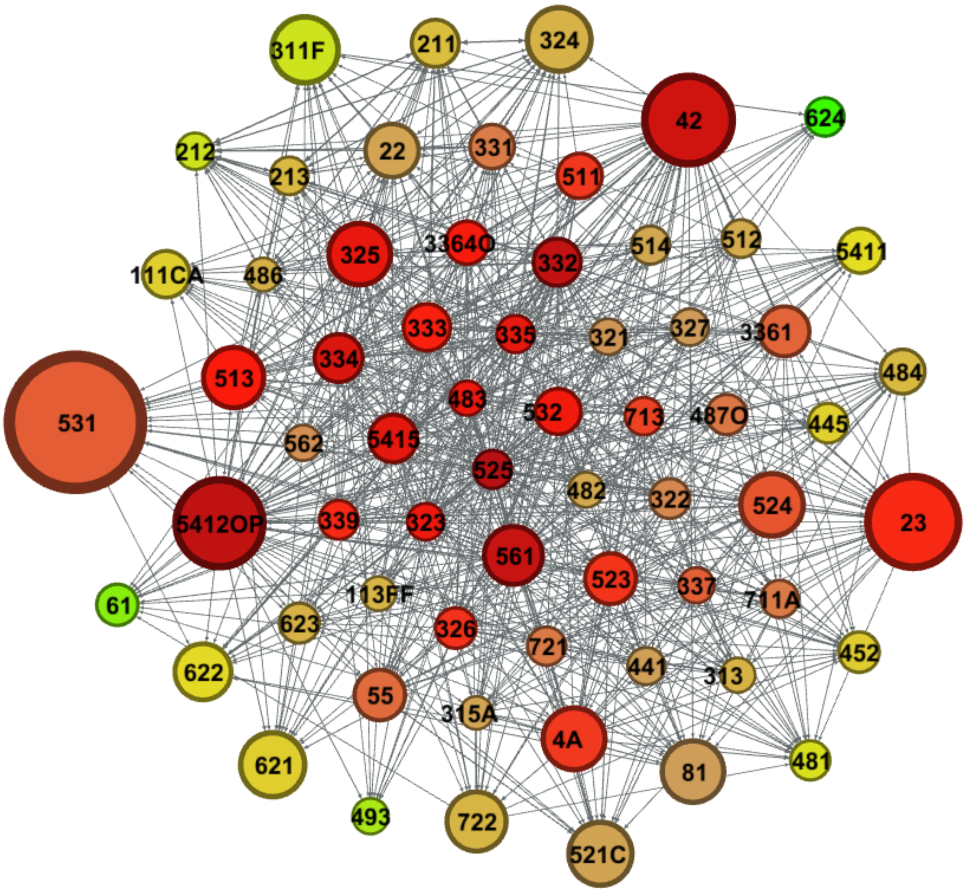

Figure 5: Financial Connectedness in 2008

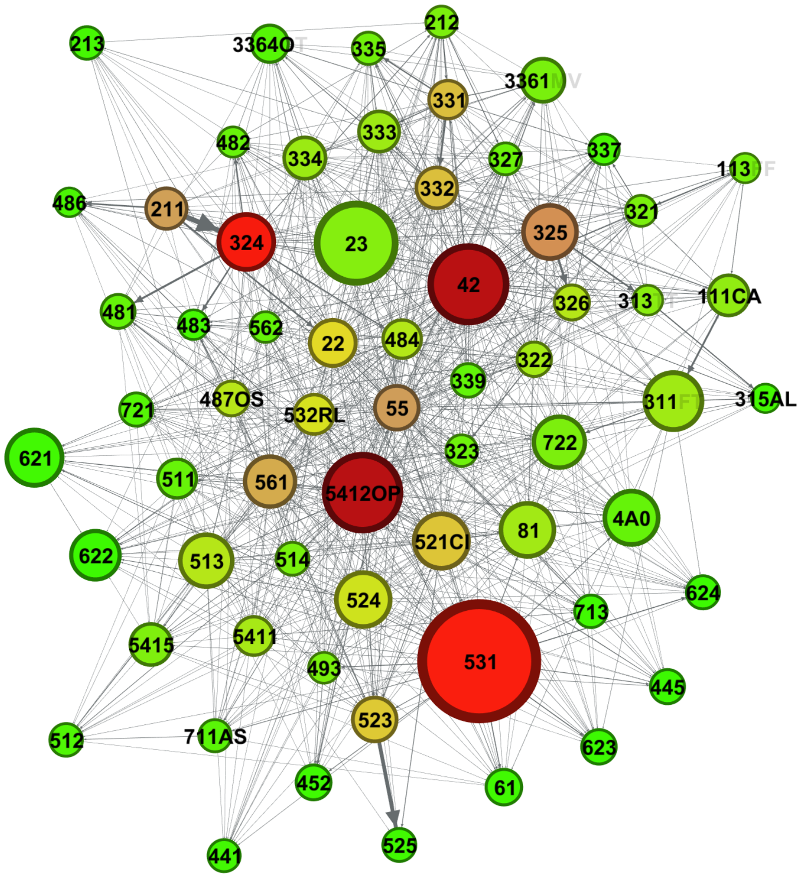

Figure 6: IO in 2008

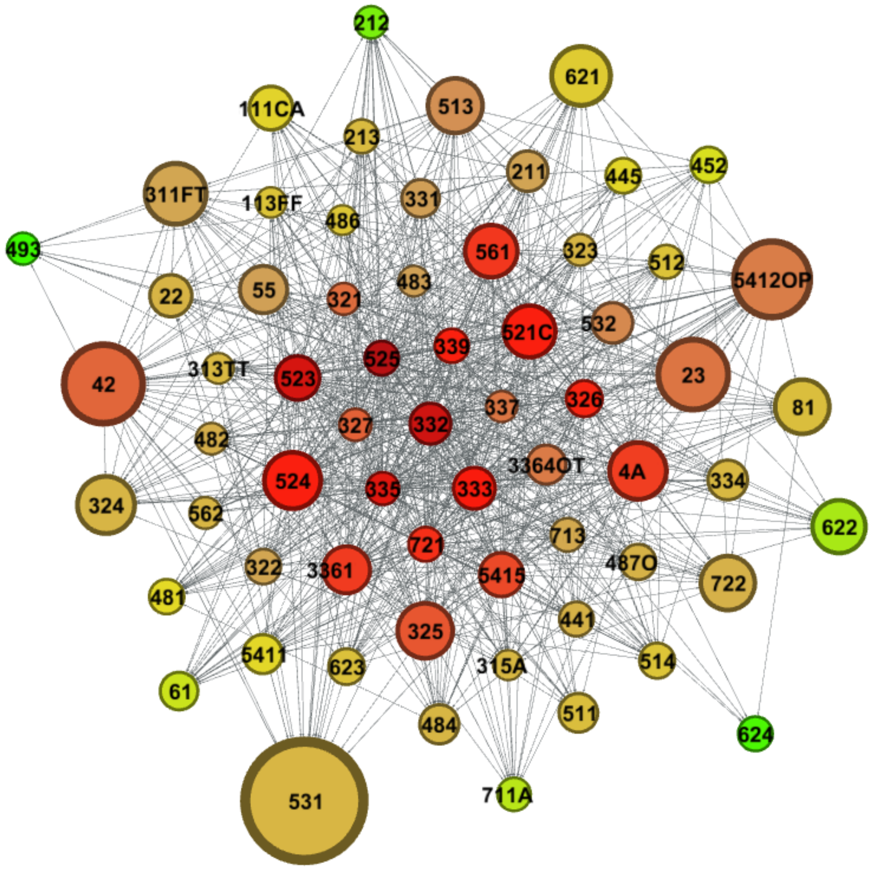

Figure 7: Financial Connectedness in 2013

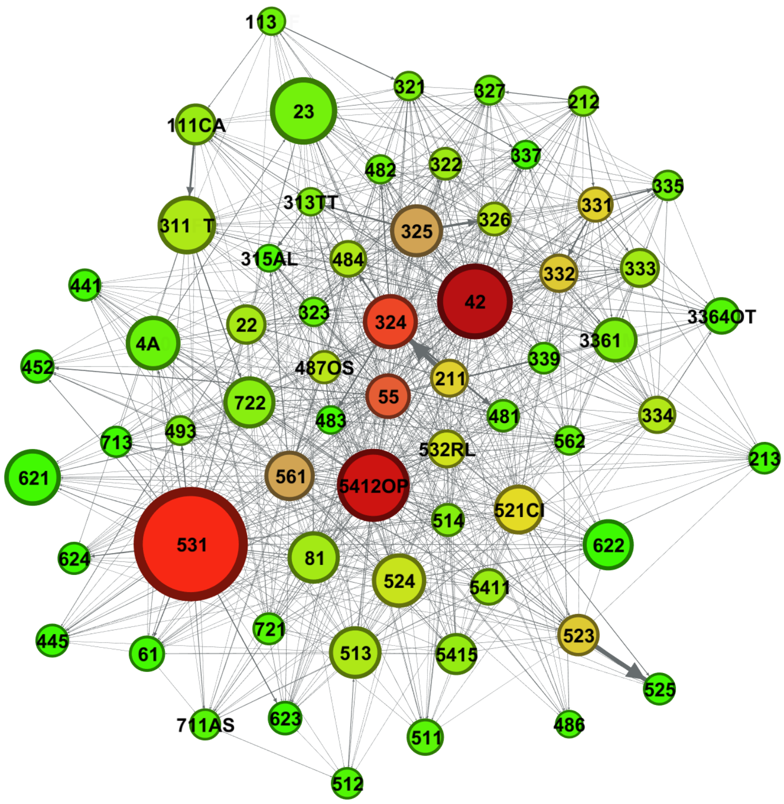

Figure 8: IO in 2013

5.3 Evolution in Major Drivers of Financial and Real Connectedness

In this section, we investigate both the evolution of ranking of industries in terms of their net connectedness in financial network and in terms of their make values in IO total requirements network throughout the whole year.

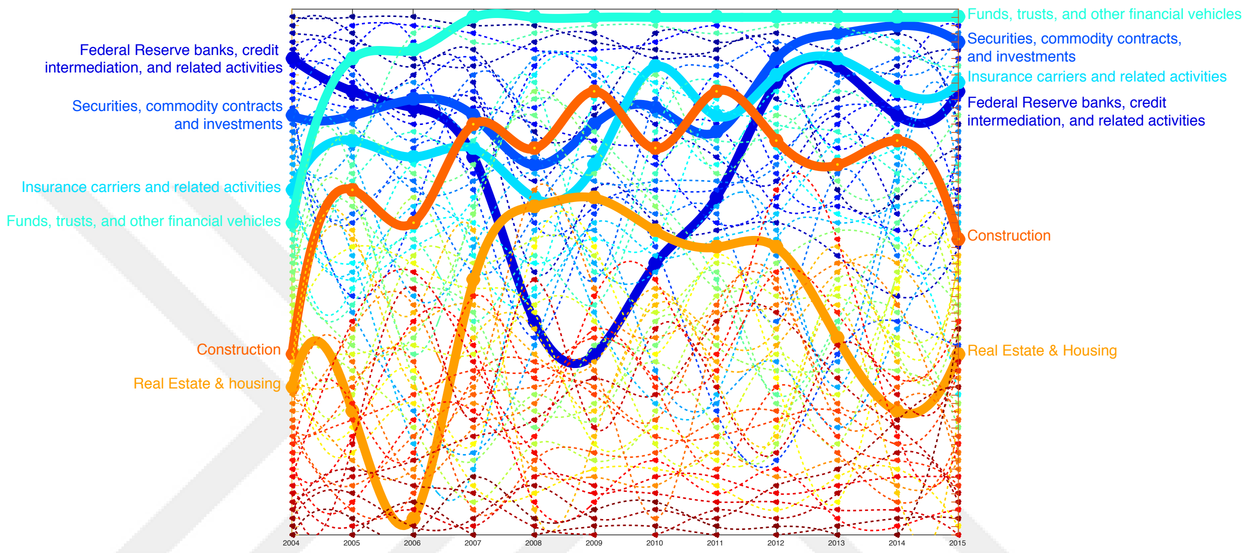

Figure 9: Ranking of Industries in Financial Connectedness Network

Figure 9 shows the ranking of industries is in terms of their net connectedness from 2004 to 2015. Here, each line represents an industry and the lines are colored according to their rank at the beginning of the time period. We highlight some financial industries as well as real estate and construction industries.

The change in the connectedness index is also reflected in the changes of industry rankings based on the total net-degree of industries in the financial connectedness network as evident in Figure 9. It is obvious that the dynamics for the determination of financial connectedness has changed frequently due to being more susceptible to the news and shocks in the financial market. We find that the net-connectedness of Real Estate & Housing as well as the Construction industries increase during the crisis. Financial industries such as funds, securities and insurance always keep their importance throughout time. However, the industry that contains federal reserve banks, credit intermediation and related activities loses its ranking through the crisis period. We speculate that the decline in the industry could be the result of heterogeneity of the firms within the industry which lead to a great spread in terms of their performances.

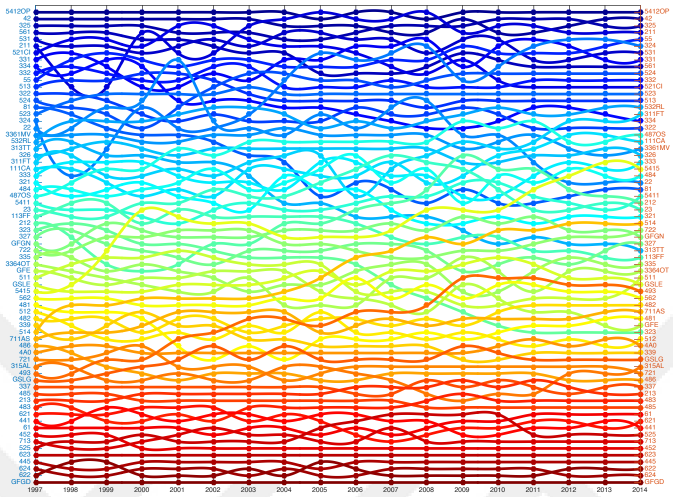

Figure 10: Ranking of Industries in Input-Output Network

Figure 10 shows the ranking of industries is in terms of their make values from 1997 to 2014. Here, each line represents an industry and the lines are colored according to their rank at the beginning of the time period.

Unlike in financial connectedness network, in IO total requirements network, as we see in Figure 10, dynamics for the determination of real connectedness has not changed much throughout the whole year with several exceptions. We can speculate that it is due to the fact that substitutability is low in total requirements and real economic activities and relations are much more persistent and stable even if there would be a negative shock in the real economy. We show that financial industries, manufacturing industries and wholesale trade always keep their importance in each year. Specifically, Miscellaneous professional, scientific, and technical services, Wholesale Trade and Chemical products are always the biggest three drivers in IO total requirements network. However, as in financial connectedness network, the industry that contains federal reserve banks, credit intermediation and related activities loses its ranking after 2005.

5.4 Change in Dynamics of Financial and Real Connectedness

In this section, we will investigate the change in dynamics of financial and real connectedness with the help of heat-map analysis. We analyze financial connectedness network and IO total requirements network at the summary level. In financial connectedness matrix, each row represents an industry portfolio transmitting a shock to the industry-portfolios represented by each column. The entries of this matrix correspond to the share of forecast error variance of each industry-portfolio in a given row. In IO total requirements matrix, each row represents an industry supplying inputs to the industries represented by each column. The entries of the matrix correspond to the share of intermediate good usage of each sector in a given column. In order to compare these two heatmaps, we take log of each entry in both matrices. Lighter colors reflect higher pairwise directional connectedness in financial network and more intensive input requirement in IO network while darker colors reflect lower pairwise directional connectedness in financial network and less intensive input requirement in IO network.

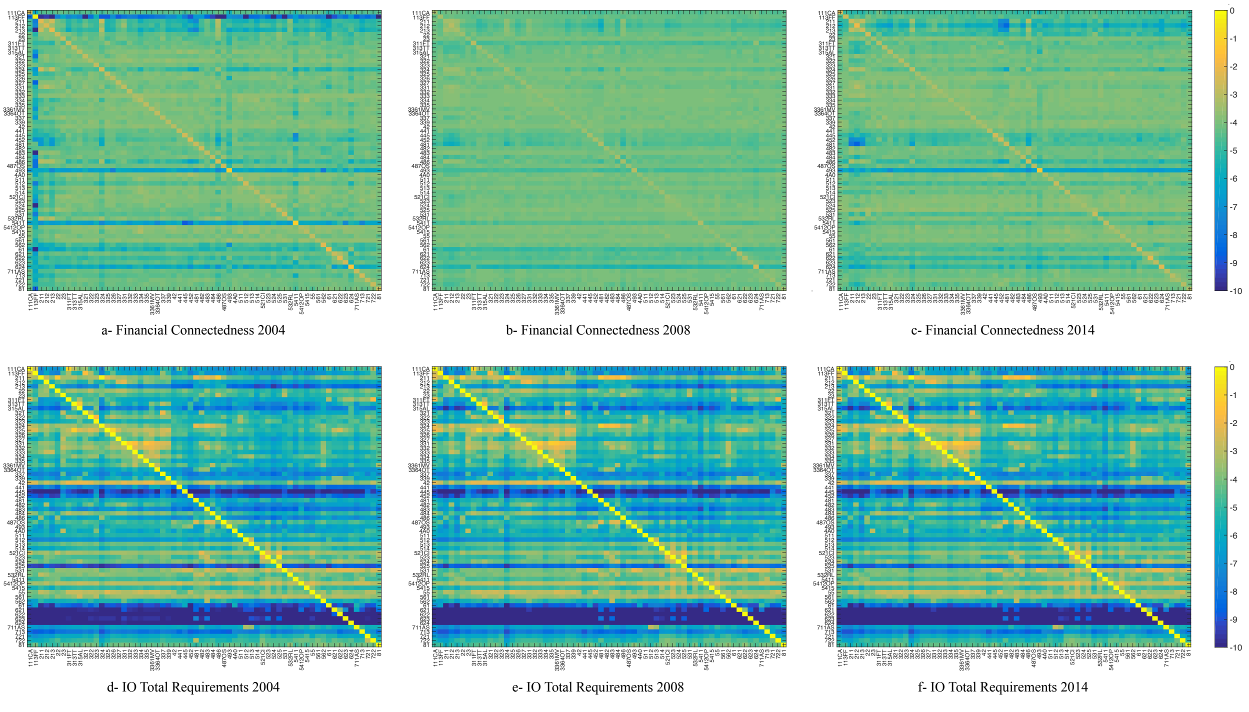

Figure 11: Financial Connectedness and IO Total Requirements Heatmaps
Heat-maps are at the summary level for years 2004, 2008 and 2014

Several patterns emerge from Figure 11. First, in both heat-maps we observe that the diagonal features light colors. This reflects the fact that in IO relationships many intermediate good transactions occur within the same industry. In financial connectedness matrix, most fraction of forecast error variance of each industry-portfolio return is explained by itself.

Next, there are different features between two heat-maps. First, we find a high concentration of light colors along certain rows in IO total requirements matrix. This indicates particular sectors that supply inputs to many other sectors. For example, the rows corresponding to wholesale trade and manufacturing industries are light for almost all column entries reflecting the need for manufacturing and sale services by all sectors. A similar pattern is found for financial service industries, which is a reflection that there is a substantial amount of outsourcing of professional tasks outside the firm. On the other hand, the rows corresponding to educational services, health care, and social assistance industries are dark for almost all column entries.

This certain feature does not exist in financial connectedness matrix. Almost all industry-portfolio returns are tightly connected with each other, which makes financial connectedness matrix more dense, connected and diversified. At the same time, it is evident that pairwise directional connectedness of industry-portfolio returns has changed a lot in each three year. Almost all rows in 2008 are lighter than the corresponding rows in 2004 and 2014, which shows that during the crisis pairwise directional connectedness of almost all industries has increased dramatically. This also implies that financial connectedness index we analyzed in Section 5.1 is dynamic and sensitive to new developments in financial market. However, as shown in Figure 11, IO total requirements is such a static matrix that there is no even slight change in each three year. This finding also suggests that substitutability of inputs and commodities is not a common feature in input-output linkages.

6 Regression Classifications

Our empirical analysis between real and financial connectedness relies on three different regression classifications :

- Individually:

$$C_{ij}^t = \beta_0^t + \beta_1^t M_{ij} + \varepsilon_{ij}^t$$

  where M could be any of our real Industry - Industry matrices.

- Together:

$$C_{ij}^t = \beta_0^t + \beta_1^t IO_{ij} + \beta_2^t OES_{ij} + \beta_3^t CBP_{ij} + \varepsilon_{ij}^t$$

$$C_{ij}^t = \beta_0^t + \beta_1^t IO_{ij} + \beta_2^t OES_{ij} + \beta_3^t CBP_{ij} + \beta_4^t Citing_{ij} + \beta_5^t Cited_{ij} + \varepsilon_{ij}^t$$

- Together with industry fixed effects (For robustness purposes):

$$C_{ij}^t = \beta_0^t + \beta_1^t IO_{ij} + \beta_2^t OES_{ij} + \beta_3^t CBP_{ij} + \nu_i + \mu_j + \varepsilon_{ij}^t$$

$$C_{ij}^t = \beta_0^t + \beta_1^t IO_{ij} + \beta_2^t OES_{ij} + \beta_3^t CBP_{ij} + \beta_4^t Citing_{ij} + \beta_5^t Cited_{ij} + \nu_i + \mu_j + \varepsilon_{ij}^t$$

  where

- C_{ij}: Financial connectedness between industries i and j generated by Diebold & Yilmaz method using industry portfolio returns

- IO_{ij}: $(i, j)^{th}$ entry of the Leontieff-Inverse of the IO matrix (Total industry by industry requirements)

- OES_{ij}: Correlation between the occupational compositions of industries i and j

- CBP_{ij}: Correlation between the locational distributions of industries i and j
- $Citing_{ij}$: Share of patents from industry i citing a patent from industry j
- $Cited_{ij}$: Share of patents citing industry i that are from industry j
- ν_i and μ_j: Industry fixed effects

We have two different type of aggregation and frequencies (detailed level versus summary level) in IO total requirements network. Hence, we follow two different rules for daily regressions as follows :

1. At the detailed Level data, we only have IO 2002 and 2007 Detailed Level tables available with 432 industries (279 of which matches to firms with these industry codes in CRSP) and 394 industries (275 of which matches to firms with these industry codes in CRSP). Hence, while the industry financial connectedness in LHS will change daily, same IO 2002 or 2007 Detailed Level tables in RHS will be used in all days.
2. At the summary Level data, we have yearly IO Summary Level tables availabe with 71 industries (64 Industries matching to firms in CRSP).Hence, while the industry financial connectedness in LHS will change daily, IO Summary Level tables will be updated in RHS every year. We combine each yearly results.

7 Empirical Findings

We will start with the empirical findings at the detalied level regressions. It is important to remember that at the detailed level regressions, the industry financial connectedness in LHS will change daily, however same IO 2002 or 2007 Detailed Level tables in RHS will be used in all days. Hence, we keep track of the importance of detailed level real economic networks on daily change in financial connectedness.

We first find that all real economy variables in each classification are statistically significant throughout the period. It means that each real economy linkage has a significant power while predicting financial connectedness. This finding justifies our concern with the current studies in the literature which only investigate input–output linkages to understand the cross predictability of stock returns. We estimate that not only input-output linkage but also each of other real economic network plays a measurable role in the determination of industry-portfolio financial connectedness. It suggests that all available real economic linkages should be taken into account to understand the dynamics in financial market.

Among the real economic networks, we find that input-output relationships have the strongest effect. These input-ouput linkages are closely followed by our proxy for knowledge spillovers. More importantly, we estimate that being cited from other industries has much stronger effect than being citing to other industries. Our proxies for co-agglomeration and labor pooling are weaker than other real economic linkages but still economically and statistically important.

When we analyze the evolution of each coefficient, it is crucial to notice that all coefficient values in each regression classification, except OES, decreases from the end of 2008 until the beginning of 2013. It indicates that during times of turmoil the power of all real economy connections, except OES, die out. In that regard, we have an interesting result about the pattern of OES. OES does not lose its importance even during the crisis and its performance shows a countercyclical trend within certain periods. It implies that the formation of a large labor pool for industries induces higher pairwise directional connectedness between even during the crisis.

When we analyze R^2 values of different regressions, Figure 12 delivers that the explanatory power of each regression, except the regression with fixed effects, is at remarkably good level during tranquil times. However, explanatory power of each regression, except the regression with industry fixed effects, declines during (also just before and after) the Great Recession, which means that our real economic networks are not able to explain financial connectedness as much as they explain during good times.

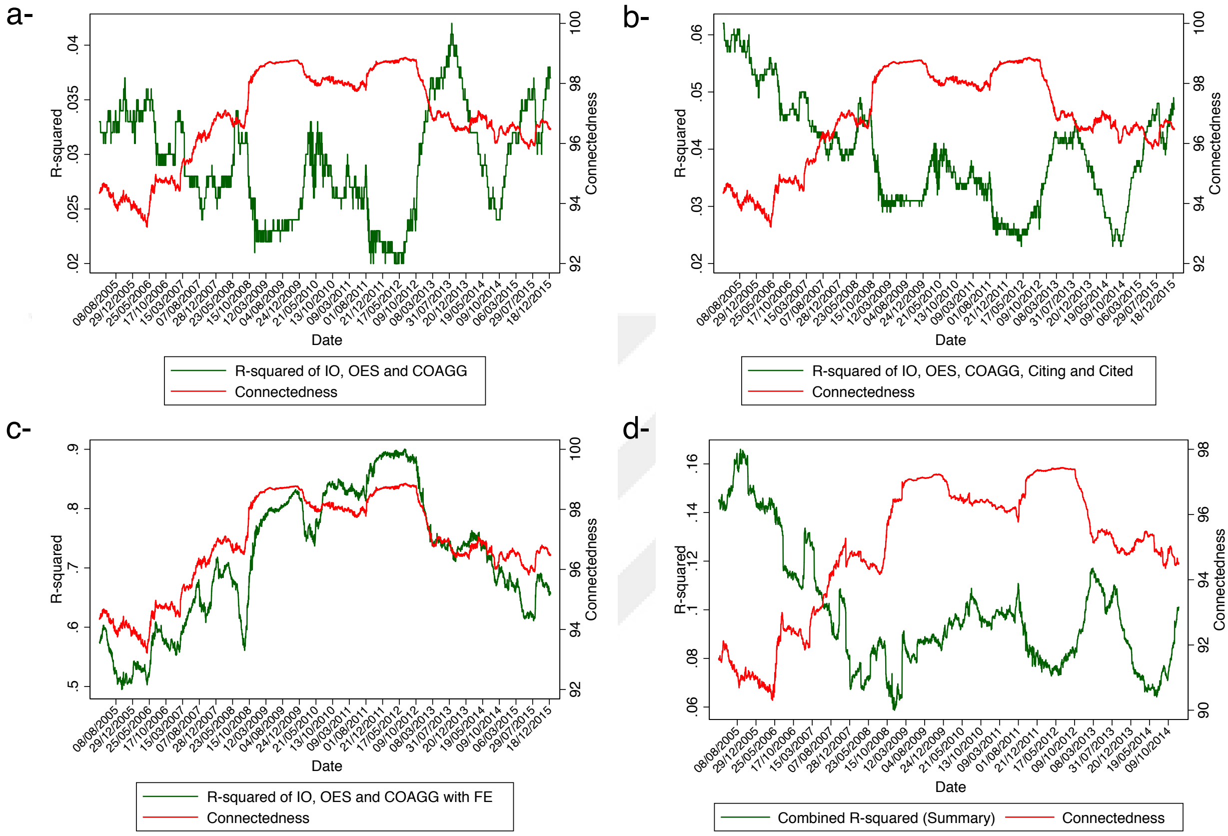

Figure 12: R^2 values of different regressions
a-, b- and c- are at detailed level, d- is at summary level. d- does not include patent citations.

When we analyze the relative importance of patent citations at the detailed level, we find that the inclusion of patent citations increases regression R^2 dramatically. However, the increasing explanatory power is coming from the *Cited* variable, not from *Citing*. Therefore, being cited from other industries increases the financial connectedness of this cited industry, which implies the citing industry is eventually becoming financially dependent on the cited industry.

As we include industry fixed effects for both source and target industries separately into the regression, we see that financial connectedness and R^2 of this regression move in similar direction (Figure 12-c) with a striking increase in the explanatory power during the crisis. If the increase during the crisis period was not captured by the fixed effects this well, we could have argued that the resultant increase in the connectivity was a result of inter-industry dynamics. Nevertheless, we observe the opposite. This result implies that the connectedness during the crisis is not an inter-industry phenomenon, rather, it is due to each industry being more susceptible to the overall environment.

When we move to the summary level, we first find that the regression R^2 follow similar trends as the ones in the Detailed Level with one exception. As evident in Figure 12-d, it moves up almost 3-fold.

However, our findings on the coefficients at the summary level slightly differs from what we found at the detailed level. First, as expected, all coefficients at the summary level are higher than the ones in detailed level due to being more frequent and aggregate. Second, among the real economic networks, we find that labor pooling has the strongest effect. This is closely followed by input-output linkages and our proxy for being *Cited*. At the summary level, we again estimate that being cited from other industries has much stronger effect than being citing to other industries, which again serves us the importance of being cited from other industries.

Our proxy for co-agglomeration is again weaker than the other real economic linkages and is not economically and statistically important during some periods. There are several possible explanations behind this crucial finding. According to Marshall's theories of agglomeration, input-output linkages, labor market pooling and knowledge transfer together explain the agglomeration of industries. Elliison et.al (2010) empricially studies the relative importance of each three real economic linkage on the agglomeration of industries. They suggest that these three links are significant drivers of industry agglomeration. In that respect, we can speculate that including these three real economic linkages in the regression dies out the importance of co-agglomeration.

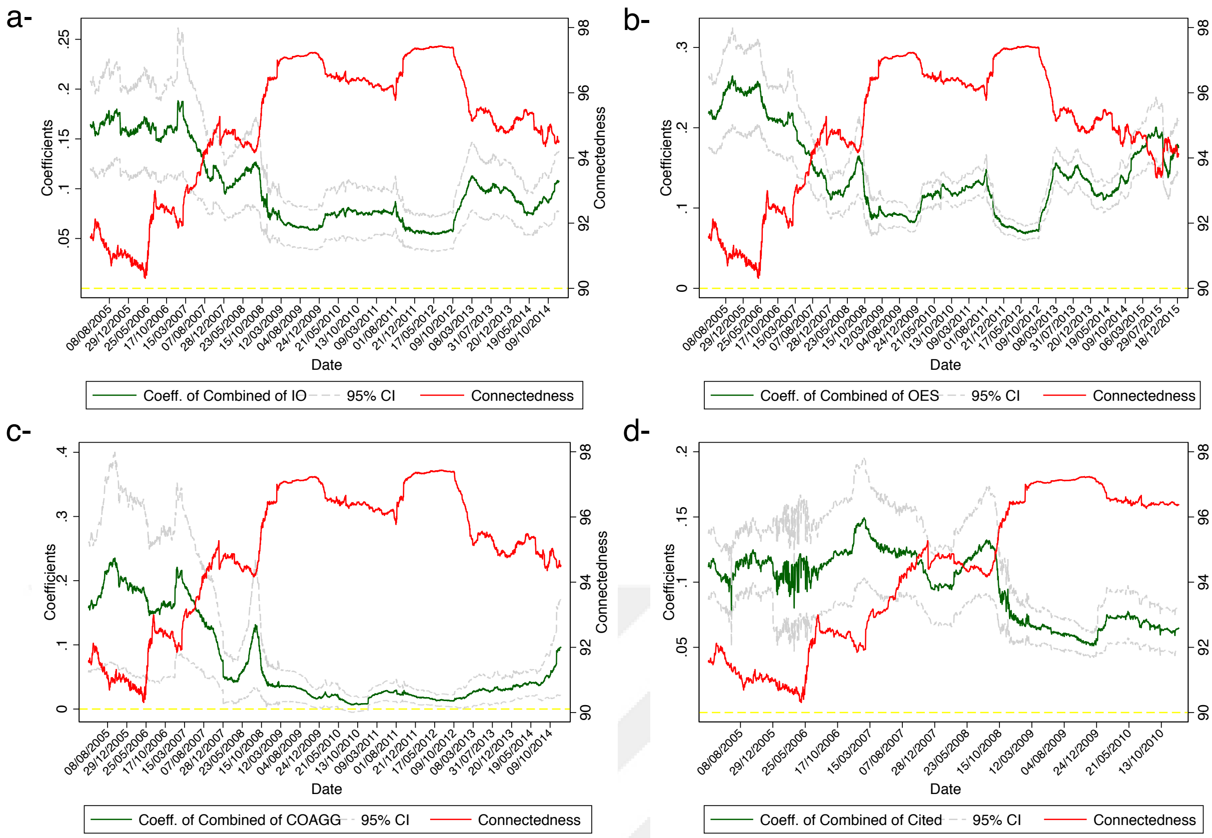

Figure 13: Coefficients of Real Network Parameters
Coefficients are from the individual regression at summary level. All the variables were normalized before the regressions. Dashed yellow lines represent 0 level. All coefficients are significant if 95% Confidence Intervals (CI) does not intersect with the dashed yellow line.

Last, we find several striking results when we compare the coefficients of each real economy linkage and industry financial connectedness at the summary level. Figure 13 shows that in each regression classification, financial connectedness and the coefficients of each real economy linkage move in the opposite/mirror image directions throughout the years. Declining financial connectedness corresponds to tranquil times, when the determination of portfolio return is mainly coming from idiosyncratic effects. In these periods, the explanatory power of real economy dramatically increases. Hence, industry portfolio returns reflect their real fundamentals during good times. However, during bad times when the financial connectedness has skyrocketed, industry portfolio returns deviate from their fundamentals, thus there is a divergence between market value and fundamental value during bad times.

Overall, our findings deliver that industry financial connectedness and explanatory power of real connectedness on financial connectedness display opposite/mirror image patterns. It is fair to say that during times of turmoil, industry financial connectedness is mainly explained by the factors outside the real connectedness. On the contrary, during tranquil times, each real economy linkage has a higher explanatory power on the determination of financial connectedness.

8 Conclusion

We have two purposes beginning this paper. First, we want to estimate U.S. industry-portfolio return financial connectedness and quantify whether the industry linkages in the real economy predict the estimated financial connectedness. This motivation is crucial to investigate the relationship between the fundamental and market values of US industry portfolios and their returns. Second, we want to map and compare how real and financial links in industry-industry networks behave and co-move in different episodes. It would help us understand the evolution of dynamics within financial and real economic networks and figure out the main drivers of financial and real connectedness in different episodes.

We estimate industry-portfolio financial connectedness with 64 industry-portfolios at the summary level data and 275 industry-portfolio returns at the detailed level data. We use four different real economic networks : (1) Input-Output Total Requirements Network; (2) Occupational Employment Network; (3) Patent Citation Network; and (4) Co-agglomeration. Then, we follow ordinary least squares regression analysis to understand the interactions between financia connectedness network and four real economic networks. Our paper is the first and the only one in the literature investigating the relation between financial interconnectedness and different real economic links.

We first find that the ordinary least squares relationships support the importance of all real economic networks on industry-portfolio return connectedness. Each of the real economic network plays a measurable role in the determination of industry-portfolio return connectedness. Among the real economic networks, input-output relationships have the strongest effect at the detailed level data and labor correlation/pooling (OES) has the strongest effect at the summary level data. Those are closely followed by our proxies for knowledge spillovers. More importantly, we estimate that being cited from other industries has much stronger effect than being citing to other industries. Our proxy for co-agglomeration is weaker than the other factors, which suggests that including input-output linkages, labor market pooling and knowledge transfer together into the regressions dies out the importance of co-agglomeration.

Second, in each regression classification we find that financial connectedness and the coefficients of each real economy linkage move in the opposite/mirror image directions. Declining financial connectedness corresponds to tranquil times, when the determination of portfolio return is mainly coming from idiosyncratic effects. In these periods, the explanatory power of real economy dramatically increases. Hence, industry portfolio returns reflect their real fundamentals during good times. However, during bad times when the financial connectedness has skyrocketed, industry portfolio returns deviate from their fundamentals, thus there is a divergence between market value and fundamental value during bad times. This result implies that the connectedness during the crisis is not an inter-industry phenomenon, rather, it is due to each industry being more susceptible to the overall environment. These findings are completely intuitive in the literature where high and positive correlation between market and fundamental value has been anticipated. We clarify this by suggesting that the stock market is crucial as it channels funds to real economy. As part of this function, the stock market is also the place where real economic productions of firms are valued. Hence, the movements in stock prices are expected to reflect the changes in fundamental value of real economic activities.

When we map and compare how real and financial links in industry-industry networks behave and co-move in different episodes, there are four major differences between the financial and real economic networks. First, during the crisis financial industries and wholesale trade are generating the bulk of connectedness in industry financial network. However, in real economic networks, we find that wholesale trade, manufacturing and real estate are important transmitters during the crisis. Second, industries having higher GDP shares (make values) are not the biggest drivers of the financial connectedness, which could be an evidence that dynamics in financial and real economy have subtle differences. Third, with the help of heat-map analysis, we find that dynamics in financial connectedness change substantially over time, whereas it is more static in real networks. Last, with the help of graph theory, we find that several sectors form observable clusters in real networks during tranquil times, whereas clustering is not seen in industry financial connectedness network.

Our contribution in methodological and substance level has particular advantages going forward. In the next step, we plan to investigate the relationship between world real economy connections (trade, labor mobility, technological spillovers) and global financial connectedness. It would help us to understand the mechanism behind global economic connections and how this mechanism responds to global financial crises like U.S financial crisis and Euro crisis.

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Appendix

Code	Title
22	Utilities
23	Construction
42	Wholesale trade
55	Management of companies and enterprises
61	Educational services
81	Other services, except government
211	Oil and gas extraction
212	Mining, except oil and gas
213	Support activities for mining
321	Wood products
322	Paper products
323	Printing and related support activities
324	Petroleum and coal products
325	Chemical products
326	Plastics and rubber products
327	Nonmetallic mineral products
331	Primary metals
332	Fabricated metal products
333	Machinery
334	Computer and electronic products
335	Electrical equipment, appliances, and components
337	Furniture and related products
339	Miscellaneous manufacturing
441	Motor vehicle and parts dealers
445	Food and beverage stores
452	General merchandise stores
481	Air transportation
482	Rail transportation
483	Water transportation
484	Truck transportation
486	Pipeline transportation
493	Warehousing and storage
511	Publishing industries, except internet (includes software)
512	Motion picture and sound recording industries
513	Broadcasting and telecommunications
514	Data processing, internet publishing, and other information services
523	Securities, commodity contracts, and investments
524	Insurance carriers and related activities
525	Funds, trusts, and other financial vehicles
531	Real estate
561	Administrative and support services
562	Waste management and remediation services
621	Ambulatory health care services
622	Hospitals
623	Nursing and residential care facilities
624	Social assistance
713	Amusements, gambling, and recreation industries
721	Accommodation
722	Food services and drinking places
5411	Legal services
5415	Computer systems design and related services
111CA	Farms
113FF	Forestry, fishing, and related activities
311FT	Food and beverage and tobacco products
313TT	Textile mills and textile product mills
315AL	Apparel and leather and allied products
3361MV	Motor vehicles, bodies and trailers, and parts
3364OT	Other transportation equipment
487OS	Other transportation and support activities
4A0	Other retail
521CI	Federal Reserve banks, credit intermediation, and related activities
532RL	Rental and leasing services and lessors of intangible assets
5412OP	Miscellaneous professional, scientific, and technical services
711AS	Performing arts, spectator sports, museums, and related activities

Table 1: Input Output 2007 Summary Level Codes and Titles