Korea and the World Economy, Vol. 16, No. 1 (April 2015) 43-85

Aggregate Fluctuations and Industrial Network Effect: International Evidence*

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In this paper, I provide empirical evidence that the industrial network has effects on aggregate fluctuations by using data from 37 countries during 1995-2010. This empirical finding strongly implies that industrial bailouts are necessary in the short-term period of economic crisis, but, in long term, the policy should aim at supporting disadvantaged industries or sectors to reduce the risk of unstable aggregate growth. In addition, I further distinguish between the demand-side and supply-side network effects and find that both the supply-side and demand-side network effect on investment volatility is significantly stronger than the network effect on GDP volatility.

JEL Classification: D57, E32, L16

Keywords: input-output table, industrial network effect, aggregate fluctuations, log-log rank-size regression, economic development

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* Received March 17, 2015. Revised April 13, 2015. Accepted April 20, 2015. I am grateful to my Ph.D. advisor, Chih-Chiang Hsu, for his valuable guidance about this paper. I would also like to thank Yeonho Lee (Editor) and the anonymous referees for their valuable comments to improve this paper. Any remaining errors are my own.

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1. INTRODUCTION

Whether microeconomic shocks to firms or disaggregated sectors can generate significant aggregate fluctuations is a considerable debate in the literature. Lucas (1977) argued that idiosyncratic shocks to individual sectors would average out, and thus only have negligible impacts on the aggregate economy. Although macroeconomic shocks, such as wars, radical changes in policy and/or oil shocks, are highly systematic, many researchers have begun to emphasize the existence of the idiosyncratic shocks. Long and Plosser (1983) first developed a disaggregated-sector model to explain how input-output linkages propagate shocks across sectors and time periods. Early theoretical studies include Jovanovic (1987), Cooper and Haltiwanger (1990), and Bak *et al*. (1993) among many others. Shea (2002) and Conley and Dupor (2003) provided empirical evidence that input-output linkages play an important role in documenting the existence of interindustry comovements from disaggregate shocks.

Other works had focused on several restrictions of the diversification argument based on the law of large numbers. Because the Long-Plosser model only contains a small number of sectors, it is limited to discuss the argument why the effects of sectoral shocks may tend to dissipate due to the law of large numbers. Dupor (1999) provided conditions under which the input-output structures are irrelevant to aggregate fluctuations induced by sector-specific shocks and the law of large numbers holds. Horvath (1998, 2000) presented that the sparseness of the input-output matrix may amplify aggregate volatility caused by sectoral shocks and lead to a postponement of the law of large numbers.

Instead of stressing the role of input-output linkages, Gabaix (2011) showed that idiosyncratic shocks can cause aggregate fluctuations when the firm size distribution is fat-tailed. Gabaix (2011) named this granularity hypothesis. There are several possible channels for granularity hypothesis. First, larger firms buy more intermediate inputs from upstream suppliers. Second, larger firms sell more intermediate or final goods to downstream demanders. Third, larger firms occupy a large share of aggregate output and consume most of the goods and services in the economy. Therefore, idiosyncratic shocks to large firms may not average out promptly. Acemoglu *et al*. (2012) further argued that idiosyncratic shocks to a sector which is strongly interconnected with other sectors in the economy may cause aggregate fluctuations. Whether or not idiosyncratic shocks generate sizable aggregate effects depends on the intersectoral network structures. It has a policy implication that industrial bailouts, which are aimed at preventing more severe aggregate shocks, are actually necessary. Schweitzer *et al*. (2009) also emphasized the need to make economic networks more robust to reduce the risk of global failure.

In this paper, I use multi-country input-output tables to examine if network plays a significant role in affecting aggregate fluctuations. The main contribution of my study is presenting empirical evidence of the industrial network effect on aggregate fluctuations among advanced and developing countries. By regressing GDP volatility on network-effect variables and other control variables, I have robustly proved that the industrial network is one of the important sources of aggregate fluctuations. This empirical finding strongly implies that industrial bailouts on influential sectors or companies are necessary in the short-term crisis period, but in long run, the policy should aim at supporting disadvantaged sectors to reduce the risk of unstable aggregate growth.

In addition, I further distinguish between the demand-side and supply-side network effects. My empirical results indicate that the network effect of both demand-side and supply-side on GDP volatility is significant with the correct direction by eliminating the disturbance of systematic shocks such as the 2007-2008 financial crises. Furthermore, the supply-side and demand-side network effect on investment volatility is significantly stronger than the effect on GDP volatility. Besides, only demand-side network effect on the consumption volatility is significant with correct sign. The demand-side effect on consumption volatility is statistically stronger than the effect on GDP volatility.

The remainder of this paper is organized as follows. The next section briefly introduces the basic concept of how the industrial network could affect aggregate fluctuations and how to measure the network structure. Section 3 describes the empirical model and data sources. Section 4 presents the empirical results and analyses. Section 5 concludes the findings and proposes recommendations for further research.

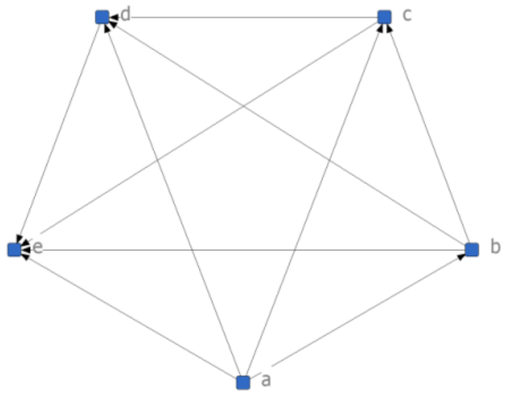
2. THE EFFECTS OF INDUSTRIAL NETWORK ON AGGREGATE FLUCTUATIONS: A BRIEF REVIEW OF THE THEORETICAL FRAMEWORK AND MEASUREMENT

2.1. Industrial Network Effects on Aggregate Fluctuations

Acemoglu *et al*. (2012) theoretically connected the structural properties of the sectoral network with micro-level shocks throughout the whole economy. For example, in one extreme case, an economy in which each sector relies equally on any other sectors is the network in which the law of large numbers applies, and independent sectoral shocks should average out rapidly at the rate of $\sqrt{n}$. Another extreme case is that where one sector is the only supplier of all other sectors. Here, the economy becomes unstable because, if the only supplier suffers a shock, the shock will be disseminated throughout the whole system and will last longer than the rate of $\sqrt{n}$. As I will demonstrate in sequential study, the economies in the real world are in the middle case. Therefore, the ability of micro-level shocks throughout the whole economy is also different depending on how the economy forms its industrial network structure.

I further introduce a graph system to visualize the industrial network structure. A graph (N, p) denotes a set of vertices $N = \{1, \ldots, n\}$ and an $n \times n$ matrix p, where $p_{ij} (\neq p_{ji})$ represents the directed edge from n_i to n_j. This adjacency matrix indicates how each vertex is connected to each

Figure 1 Graph System and Network Structure



other. A directed graph means that each vertex may have an indegree and/or outdegree, which is the number of edges directed from and/or to the other vertices. For example, the matrix A in figure 1 represents one of the special cases of the network structure. Each vertex has one or more one-way connections with other vertex ($p_{ij}=1$ for all $i<j$), except the sector e. The structure of matrix A thus exhibits a very special property. An independent shock on sector a should pass to other four sectors only throughout the 'outdegree' connections with them. By contrast, an independent shock on sector e should pass to other four sectors only throughout the reverse 'indegree' connections.

The network structure of matrix A

$$\text{matrix } A=\begin{pmatrix} 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}.$$

Back to the field of economic analysis, the input-output matrix has the most similar structure to above adjacency matrices, where $N=\{0, \ldots, n\}$

represents the sector that produces and consumes intermediate goods, and $p_{ij}(\neq p_{ji})$ represents the intermediate good flows among sectors. Any sector's numbers of edges directed from and/or to other sectors, the definition of indegree and outdegree, represent how many linkages a sector has in terms of consuming from and/or supplying to other sectors. Therefore, according to the data from the input-output table, we should be able to observe each country's industrial network structure during a period of time.

In order to measure industrial network structure, I define the *outdegree* and *indegree index* which plays the key role in my empirical analysis. In the input-output table with $n \times m$ matrix, where row sectors i=1, ..., n and column sectors j=1, ..., m, sector i's *outdegree index* is the sum of the share of sector i's intermediate output in all sectors' total intermediate input, including sector i itself. Equation (1) is the definition of *outdegree index* of row sector i:

$$\sum_{j=1}^{m}\left(p_{ij} / \sum\nolimits_{i=1}^{n} p_{ij}\right) \ for \ i=1, \ \ldots, \ n, \ j=1, \ \ldots, \ m. \tag{1}$$

In other words, the *outdegree index* of sector i measures sector i's weight as a 'supplier' of intermediate goods in the entire economy during a period of time. The collection of each sector's *outdegree indices* is called the *outdegree sequence* of the whole economy.

By contrast, sector j's *indegree index* is the sum of the share of sector j's intermediate input in all sectors' total intermediate output, including sector j itself. Equation (2) is the definition of *indegree index* of column sector j:

$$\sum_{i=1}^{n}\left(p_{ij} / \sum\nolimits_{j=1}^{m} p_{ij}\right) \ for \ i=1, \ \ldots, \ n, \ j=1, \ \ldots, \ m. \tag{2}$$

In other words, the *indegree index* of sector i measures sector i's weight as a 'demander' of intermediate goods in the entire economy for a period of time. The collection of each sector's *indegree indices* is called the *indegree* *sequence*.

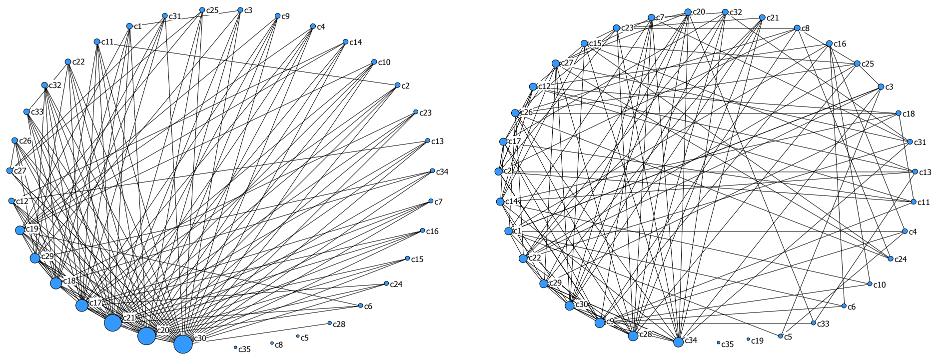
By calculating each sector's *outdegree* and *indegree index* from a country's input-output matrix, I can obtain an *outdegree/indegree sequence* of this economy for a corresponding period. I define this *outdegree sequence* as $N_{outdegree} = \{a_1, a_2, \ldots, a_n\}$, where the $a_1, a_2, \ldots, a_n$ are the *outdegree indices* corresponding to each row sector *n*, and $N_{indegree} = \{b_1, b_2, \ldots, b_m\}$, where the $b_1, b_2, \ldots, b_m$ are the *indegree indices* corresponding to each column sector *m.* For example, the $N_{outdegree} = \{a, b, c, d, e\}$ for matrix *A* in figure 1 is {2.08, 1.08, 0.58, 0.25, 0}, which indicates that the first sector *a* in figure 1 has the highest weight as a supplier, and the $N_{indegree} = \{a, b, c, d, e\}$ of matrix *A* is {0, 0.25, 0.58, 1.08, 2.08}, indicating that the last sector *e* in figure 1 has the highest weight as a demander. Therefore, by calculating the *outdegree* and *indegree sequences* according to equation (1) and (2), I can separate the effect of industrial network into the 'supply side' and 'demand side'. The *outdegree sequence* could help us focus on the supply-side effect and the *indegree sequence* on the demand-side effect. In brief, important suppliers or demanders should have more power to shock the input-output network, and my *outdegree* and *indegree sequences* should be able to measure the structure of network.

2.2. Industrial Network Structures in the Real World

Industrial networks are observable in the real world by visualizing the sector transactions revealed in the input-output matrix. The directed graph with vertices and directed edges gives us clues as to how commodities are transported among sectors. For example, a directed edge from vertex 1 to vertex 2 indicates that sector 1 supplies commodities to sector 2, and vice versa. If there are relatively even numbers of connecting edges among all sectors, or equivalently speaking, the more 'even' the structure is, the network is the case where each sector relies equally on any others. In this case, the law of large numbers applies. In other words, the more even the net is, the more rapidly the industrial shocks can average out. By contrast,

Figure 2 Industrial Network of Two Extreme Cases in 2009

Luxembourg China



Notes: Each vertex corresponds to a sector in the National Input-Output table in current prices for 2009. Each sector's industry name is in Appendix. For every input transaction above 5% of the total input of a sector, a directed link from sector C1 to sector C2 means that sector C1 supplies inputs to sector C2, for example.

Sources: WIOD database, National Input-Output Tables, April 2012 release.

if the connecting edges are concentrated in a few sectors, the industrial network becomes unstable. Therefore, the estimation of the network effect on the aggregate fluctuations may be conducted by studying the structure of each country's input-output connection at the first stage.

Figure 2 represents the two extreme cases in the real world corresponding to the industrial network derived from the China and Luxembourg input-output matrices in 2009. The network structure for China in figures 2 is more close to the 'even' network. On the contrary, the edges in the graph for Luxembourg are obviously more concentrated on a small group of sectors, such as c30 and c20.[1] The sizes of circle dots in figure 2 represent how many edges connected with the dots (sectors). Bigger dot has more outdegree and indegree numbers in the system.

I further attempt to measure the structures of the networks observed in figures 2 by using the concepts of a *degree sequence* introduced above. The standard deviation in *degree sequence* measures the variations among *degree*

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[1] Please refer Appendix for the names of sector c30 and c20.

indices of all sectors in the input-output matrix during a period of time, and the *degree index* shows the 'gravity' of a sector as an intermediate supplier (in the case of the *outdegree index*) or demander (in the case of the *indegree index*). Therefore, the standard deviation of each *degree sequence* should reveal information about whether the economy belongs to a supplier-dominant and/or demander-dominant economy. The higher that the standard deviation of the *outdegree sequence* of an economy is, the higher the few sectors' share of output in all sectors' inputs is in the use of intermediate goods, and the more likely it is that the economy belongs to the supplier-dominant case. By contrast, the higher the standard deviation of the *indegree sequence* of an economy is, the higher the few sectors' share of inputs in all sectors' outputs is in the use of intermediate goods, and the more likely it is that the economy belongs to the demander-dominant case. Therefore, the standard deviation of the *degree sequence* becomes one of the possible measurements for the structures of the industrial networks.

2.3. The Measurement of the Industrial Network Structure

Since we need to capture the distribution of the *degree sequences*, the standard deviation of the *degree sequence* is one possible estimator for measuring the network structure. Another estimator is to borrow the idea of a power law distribution. Acemoglu *et al*. (2012) declared that the empirical counter-cumulative distribution functions of *outdegree indices* on a log-log scale possess the property of a power law distribution as in equation (3).

$$P(Z > z) \sim Cz^{-\beta}, \;\; C,\; z,\; \beta > 0, \tag{3}$$

where β is the tail index in which case lower values of β represent heavier tails and higher variances of the *degree sequence*.

In this paper, I simplify the method of Acemoglu *et al*. (2012) by using the modified log-log rank-size regression proposed by Gabaix and Ibragimov

(2011) to estimate the unbiased tail index of β, which is in equation (4).

$$\log\left(t-\frac{1}{2}\right)=a-beta*\log\hat{Z}_{(t)}, \tag{4}$$

where t is the rank of the observation of *degree indices*, and $\hat{Z}_{(t)}$ is the observed t-th value, or the size of a sector's *degree index*, in the ordered *degree sequence* of $\hat{Z}_{(1)} \geq \cdots \geq \hat{Z}_{(n)}$. I assume that the observed *degree indices* are from a population satisfying the power law distribution as in equation (3).[2] Therefore, by using equation (4), I can get beta as my estimate of the unbiased tail index of β for both *outdegree* and *indegree sequences*.

However, Clauset *et al*. (2009) found that the power law for some empirical phenomena applies only for values greater than a certain minimum level. In other words, only the tails of these distributions follow a power law. For tail index estimation, Acemoglu *et al*. (2012) used the top 20% largest *degree index* values in *outdegree sequence*. In this paper, because my database consists of cross-country data, I cannot obtain as many *degree index* observations as did Acemoglu *et al*. (2012). Therefore, I expand the range of the tail to the top 30% largest values[3] in my *outdegree* and *indegree sequences* to estimate the unbiased tail index, β.

I also use the coefficient of variation to measure the network structures. The coefficient of variation is the ratio of the standard deviation to the mean of my *outdegree* or *indegree sequences*, and it is an alternative estimator for measuring the degrees of variations of *outdegree and indegree sequences* on a cross-country scale under the constraint of limited observed *degree indices*.

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[2] Clauset *et al*. (2009) provided a statistical framework for discerning and quantifying power-law behavior in empirical data. In this paper, I skip these processes in order to more directly focus on the effect of industrial network on aggregate fluctuation.

[3] For outdegree beta estimation, I use $\hat{Z}_{(t)}$, t =1 to 18 as the tail in equation (4). For indegree beta estimation, I use $\hat{Z}_{(t)}$, t =1 to 11 as the tail.

Table 1 presents the measurements of the structures of industrial networks of 37 countries[4] in the average of 1995-2010.[5] I calculate the values for 37 countries. The countries, including developed and developing, are sorted increasingly by the standard deviation respectively. According to these measurements in table 1, I can easily check the correlation coefficients between each pair of three estimators for network structure.

Table 2 presents the results of the correlation check for three estimators. I can find that, for both *outdegree* or *indegree sequences*, the correlation coefficients between the standard deviation and coefficient of variation are over 0.9 with the correct sign, which means that the possible distortion of standard deviation by the means of my collected *outdegree* and *indegree indices* is not serious. In addition, the correlation coefficients between beta and the other two estimators are still highly correlated with the correct sign. For the *indegree sequence*, the correlation coefficient between the standard deviation and beta is not as high as for the other two pairs, but is also highly negatively correlated. Table 2 shows that, for the purpose of measuring the network structure, the three estimators I use in my paper are sufficiently coordinated with each other. In this paper, I use the additional estimators of standard deviation and coefficient of variation to remedy the disadvantage of fewer observed degree indices when I use the unbiased tail index, β.

Therefore, I use the log-log rank-size regression estimate of the beta in equation (4), the standard deviation of the *degree sequence*, and the coefficient of variation of the *degree sequence* as the estimators for measuring network structure. The relationship between the industrial network

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[4] These countries are Australia (AUS), Austria (AUT), Belgium (BEL), Bulgaria (BGR), Brazil (BRA), Canada (CAN), China (CHN), the Czech Republic (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany (GER), Greece (GRC), Hungary (HUN), Indonesia (IDN), India (IND), Ireland (IRL), Italy (ITA), Japan (JPN), Korea, Republic of (KOR), Lithuania (LTU), Luxembourg (LUX), Mexico (MEX), the Netherlands (NLD), Poland (POL), Portugal (PRT), Romania (ROM), Russia (RUS), Spain (SPN), the Slovak Republic (SVK), Slovenia (SVN), Sweden (SWE), Turkey (TUR), Taiwan (TWN), the United Kingdom (UK), and the United States (USA).

[5] The data are obtained from the WIOD database, National Supply and Use Tables, April 2012 release. For the contents, sources and methods used in compiling the World Input-Output Database, please refer Timmer (2012).

Table 1 The Measurements of Network Structures of 37 Countries

Outdegree Sequence Estimators				Indegree Sequence Estimators			
	Standard Deviation	Coefficient of Variation	*beta* (top 30%)		Standard Deviation	Coefficient of Variation	*beta* (top 30%)
CHN	0.529	0.849	3.000	AUT	0.926	0.569	4.556
JPN	0.560	0.873	2.305	ROM	0.944	0.619	2.816
CZE	0.565	0.883	2.665	PRT	0.950	0.577	4.171
POL	0.577	0.900	2.508	POL	0.953	0.582	3.651
ROM	0.578	0.900	2.760	ITA	0.954	0.569	3.577
AUS	0.585	0.911	2.494	SVN	0.958	0.572	4.013
ITA	0.594	0.927	2.315	BRA	1.004	0.721	2.674
KOR	0.595	0.927	2.480	TUR	1.006	0.614	3.020
EST	0.607	0.946	2.278	EST	1.036	0.636	3.199
SVK	0.609	0.952	2.278	GER	1.060	0.632	3.926
FIN	0.609	0.953	2.265	CHN	1.066	0.706	2.743
SVN	0.618	0.965	2.498	KOR	1.070	0.674	2.725
AUT	0.620	0.967	2.154	JPN	1.075	0.677	4.000
SPN	0.629	0.982	2.543	HUN	1.083	0.646	3.471
HUN	0.630	0.982	2.298	DNK	1.084	0.646	2.728
IRL	0.642	1.001	2.166	FIN	1.088	0.648	3.531
DNK	0.648	1.012	2.167	CZE	1.091	0.639	3.606
TUR	0.651	1.024	2.126	FRA	1.095	0.655	3.042
LTU	0.657	1.026	1.930	UK	1.098	0.654	3.819
BGR	0.661	1.031	2.102	SVK	1.103	0.661	4.573
UK	0.661	1.033	2.159	NLD	1.124	0.670	3.363
GRC	0.666	1.038	2.030	BGR	1.133	0.688	3.279
GER	0.669	1.045	1.897	SWE	1.141	0.692	5.176
PRT	0.673	1.049	2.049	SPN	1.149	0.697	2.649
CAN	0.676	1.053	1.820	RUS	1.167	0.763	3.229
IDN	0.677	1.088	2.280	BEL	1.174	0.717	2.873
SWE	0.695	1.089	1.892	IDN	1.234	0.933	2.044
MEX	0.702	1.094	2.131	AUS	1.248	0.774	2.189
USA	0.709	1.108	1.969	MEX	1.271	0.815	1.987
IND	0.719	1.121	1.427	CAN	1.307	0.838	2.056
FRA	0.725	1.131	1.970	LTU	1.315	0.785	2.539
RUS	0.725	1.130	1.956	GRC	1.348	0.804	2.873
TWN	0.739	1.153	1.691	TWN	1.358	0.824	2.341
BRA	0.740	1.153	1.901	IRL	1.374	0.838	2.027
BEL	0.789	1.230	1.651	IND	1.460	0.903	2.182
NLD	0.789	1.231	1.784	USA	1.485	0.871	2.630
LUX	0.849	1.406	1.736	LUX	1.628	1.012	1.984

Note: Countries are sorted in ascending order by Standard Deviation. The measurements are 1995-2010 averages by author's own estimation.

Source: WIOD database, National Supply and Use Tables, April 2012 release.

Table 2 Correlation Coefficients of the Measurements of 37 Countries' Network Structures

	Outdegree Sequence Estimators		Indegree Sequence Estimators	
	beta (top 30%)	Coefficient of Variation	*beta* (top 30%)	Coefficient of Variation
Standard Deviation	–0.845	0.993	–0.629	0.931
Beta (top 30%)		–0.809		–0.722

Source: WIOD database, National Supply and Use Tables, April 2012 release.

and aggregate fluctuations on the cross-country scale could be further investigated to empirically test the hypothesis that the industrial network affects aggregate fluctuations.

Before starting the regression analysis, there is still one more question that needs to be solved. The estimators for measuring the industrial network structure actually captures the structure during a period of time and, logically speaking, the aggregate fluctuations should exactly correspond to this period of time. However, in practice this is impossible since most of the official input-output tables are not continuous. Even if I am able to access the yearly input-output tables, such as the WIOD database, the industrial network structure should reflect continuous instead of discrete stages. In cross-sectional data analyses, I can use the time span covering the collectable data period, but in the panel data model, choosing the time span to calculate my aggregate fluctuations should be an important issue in the regression analysis in this paper.

In panel data regressions, I refer Comin and Mulani (2006) to calculate the volatility of growth rates of GDP per capita, y_t, as the standard deviation of a five-year rolling window as in equation (5):

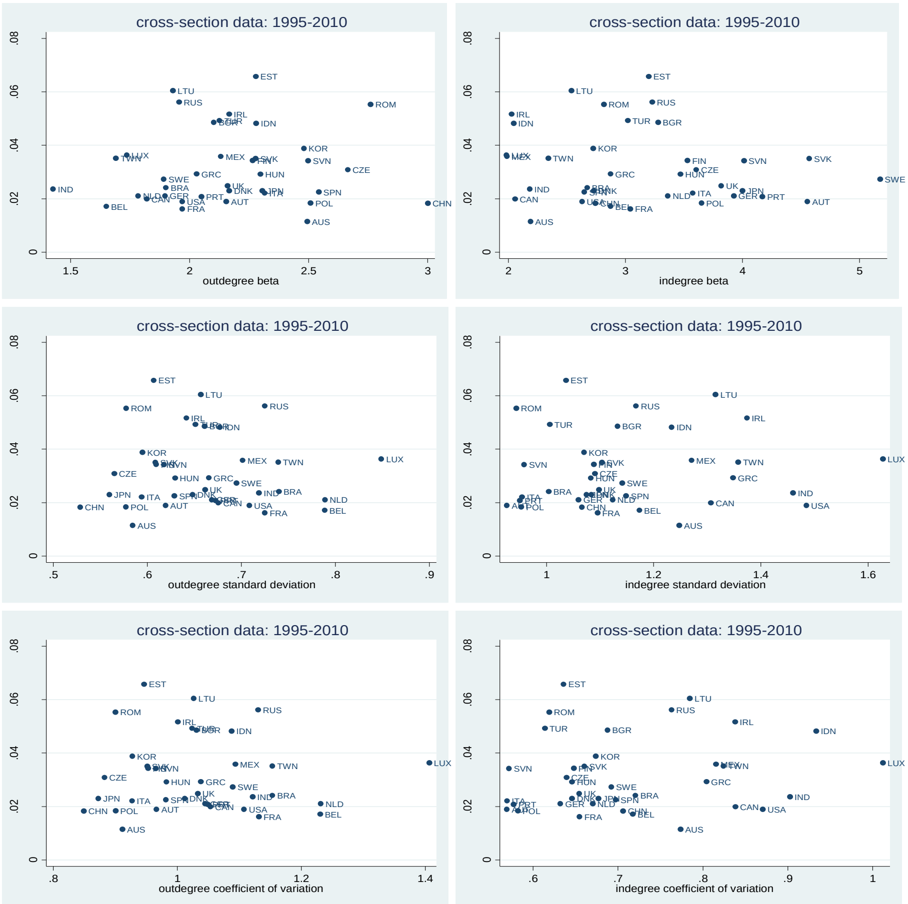
$$\sigma(y_t) = \sqrt{\frac{\sum_{\tau=t+2}^{t-2}(y_\tau - \bar{y}_\tau)^2}{5}}, \tag{5}$$

where $\bar{y}_\tau$ is the average of y_τ between t–2 and t+2.

2.4. A First Look at the Relationship between the Industrial Network Structure and GDP Fluctuations

I check the relationship between the industrial network structure and GDP fluctuations by using cross-sectional data. Three estimators of the industrial network structure are employed in order to depict this relationship. Figure 3

Figure 3 Relationship between GDP Fluctuations and Network Structure



Sources: WIOD database, National Supply and Use Tables, April 2012 release. World Development Indicators.

presents the scatter plots of real GDP per capita volatility and measurements of industrial network structure, estimated by three estimators, beta, standard deviation and coefficient of variation in 37 countries. Each point in the scatter plot represents each country's position in the quadrant composed by GDP fluctuations and the network structure measurements.

According to my theoretical framework, the higher the standard deviation and coefficient of variation of *degree sequence* is, the more concentrated the share of the intermediate transaction is in a few sectors and the more unstable the economy is. Therefore, the higher values of the standard deviation and coefficient of variation should correspond with a higher volatility of GDP. The pattern of the scatter plot consisting of 37 points in the panels of the standard deviation and coefficient of variation in figure 3 roughly exhibits a belt with a positive slope. By contrast, by using the estimator of the beta, the pattern of the 37 points roughly shows a belt with a negative slope, which is consistent with my theoretical prediction that lower values of the beta estimate represent heavier tails and more unstable economy. In the following regression tests, I am going to use these estimators to find the empirical evidences of the industrial network effect on GDP fluctuations with other control variables.

3. EMPIRICAL METHODOLOGY AND DATA

3.1. Studies on Aggregate Volatility and Its Source

A series of studies, such as McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), and Stock and Watson (2002), had investigated the trends in volatilities of macroeconomic variables and the causes, such as technological change and policy improvement. However, these studies lay emphasis on the long-term volatility trends instead of sources of volatility. Comin and Mulani (2006) studied the diverging trends in the volatility of the growth rate of sales at the aggregate and firm level, and proposed a possible explanation by arguing that the decline in macro volatility in the U.S. economy may be caused by the symmetric nature of the diverging trends at the micro level, but the study lacked empirical evidence.

Ramey and Ramey (1995) investigated the relationship between output growth and volatility, and found robust empirical evidence to the effect that countries with higher GDP volatility experience lower growth. In addition, they also found a negative impact of government-spending volatility on output growth. Head (1995) used the regression models to study the dependence between country size and other business cycle statistics, such as the volatility of the GDP growth rate, aggregate consumption and gross capital formation on a cross-country scale. Head (1995) argued that the higher output volatility in smaller countries could have contributed to their greater openness because of their susceptibility to shocks from other countries. Karras and Song (1996) further studied the relationship between OECD countries' output volatility and a series of sources of business cycles, such as the money supply, government size, openness, exchange rate flexibility, and price flexibility. Since then, many studies, such as Sutherland (1996), Kraay and Ventura (2002), Kose *et al*. (2003), Wolf (2004), Kose *et al*. (2006), and Cavallo and Frankel (2008), focused on economic size, fiscal policy, trade and financial linkages, financial development, human capital, and other controls as a variety of sources of aggregate volatility.

In addition, a group of studies had provided another source of aggregate volatility. Easterly and Levine (2003), Mobarak (2005), and Acemoglu *et al*. (2003) suggested that institutional causes, such as democracy, institutions, and policies, could affect aggregate volatility and growth. Mobarak (2005) suggested the fractionalization index of the agriculture, industry, and services shares of GDP have a significantly negative effect on aggregate volatility. The most similar attempt with my work is Carvalho and Gabaix (2013), this paper show that microeconomic shocks have significant explanatory power for the macroeconomic volatility.

In this paper, I focus on finding the empirical evidence of industrial network effect on macroeconomic volatility, and have categorized the sources of aggregate volatility revealed in the literature into three groups. The social and economic endowment group includes the variables of population, initial GDP, human capital, and the indicator of democracy. The trade and financial development group includes standard deviation of trade openness, real exchange rate overvaluation, and M2 (% of GDP). The monetary and fiscal policy group includes government consumption (% of GDP), the inflation rate, and standard deviation of investment (% of GDP).

The summary statistics, expected signs and data sources of all variables are presented in table 3. I now turn to checking the meanings and expected effects of my control variables in the literature. Population is a proxy for the size of the economy, Head (1995) expected that a larger economy is more immune to external shocks. Therefore, the expected effect on volatility is negative. Initial GDP is a proxy for the level of economic development. Acemoglu and Zilibotti (1997) found evidence of a negative relationship between initial income and aggregate volatility, indicating that richer countries are more stable in terms of economic growth. School enrollment in primary schools (as a gross percentage), human capital, serves as a proxy of the stock of human capital, and Mobarak (2005) and Wolf (2004) expected that it is negatively related to GDP volatility. An indicator of democracy, polity, serves as a proxy for political stability, and Mobarak (2005) expected that it is negatively related to GDP volatility.

In the trade and financial development group, standard deviation of trade openness (% of GDP) serves as a proxy for variation of trade openness, where Mendoza (1995), Head (1995), and Kose *et al*. (2003) expected that a higher volatility of trade openness appears to be linked to a higher volatility of output. Real exchange rate overvaluation, overvaluation, serves as a proxy for the extent to which the exchange rate is overvalued on average. Easterly and Levine (2003) expected that extreme overvaluation usually indicates that the government has kept the official exchange rate at a high level, which may result in high inflation and output instability. Therefore, the expected effect of overvaluation on volatility is positive. M2 (% of

GDP) is proxy for financial development or financial deepening. The literature suggests that financial development could be responsible for reducing output volatility. Weak financial development or financial intermediation may give rise to economic volatility.[6)]

Within the group of monetary and fiscal policy variables, government size (% of GDP) serves as a proxy for government consumption. Gali (1994) documented a robust negative correlation between government size and GDP volatility since Rodrik (1998) argued that traditionally the government plays a risk-reducing role when the economy suffers an external shock. The inflation rate is a proxy for the consistency of monetary and fiscal policies. Easterly and Levine (2003) argued that long-lasting fiscal imbalance may lead to debt monetization and a higher inflation rate and further affect economic stability. Yoon (2006) found that inflation is procyclical in movement with the real growth of output during the Korean War and the two Oil Shock periods by using Korean data. Therefore, the expected effect of the inflation rate on volatility is positive.

In this paper, I introduce a new variable to control for the volatility of GDP in the group of monetary and fiscal policy variables, namely, standard deviation of investment share (% of GDP).[7)] Mobarak (2005) used the gross domestic investment share as the control variable for explaining GDP growth and obtained a significant and positive result, meaning that a higher level of investment brings about higher GDP growth. In my model, I believe that the volatility of the investment share should also exhibit a positive relationship with the volatility of the growth of GDP. In other words, there is a procyclical movement between GDP growth and the investment share, because the economy is likely to suffer from an unstable stock of investment, and reliable monetary and fiscal policies may help to stabilize the investment stock. Table 3 shows the variables and statistical summary in my models according to above studies on aggregate volatility.

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6) Please refer Acemoglu *et al*. (2003), Kose *et al*. (2003), Wolf (2004), and Denizer *et al*. (2002).

7) The standard deviation of total investment (% of GDP) is based on a five-year rolling window of level values.

Table 3 Data Summary

Variables	Variable Description	Mean (a) (Std. Dev.)	Source	Expected Effect on Volatility
Dependent Variable				
GDP Volatility	Std. Dev. of growth rates of PPP converted GDP per capita at 2005 international $	0.03 (0.01)	World Development Indicators (WDI)	
Consumption Volatility	Std. Dev. of growth rates of final consumption expenditure per capita at constant price, 2005.	0.03 (0.02)	WDI	
Investment Volatility	Std. Dev. of growth rates of gross capital formation per capita at constant price, 2005.	0.12 (0.07)	WDI	
Trade Volatility	Std. Dev. of growth rates of total trade per capita at constant price, 2005.	0.08 (0.03)	WDI	
Network Structure Measurement				
Outdegree Beta	Beta Estimates of Tail of *Outdegree Sequence*	2.15 (0.33)	World Input-Output Database (WIOD)	–
Outdegree s.d.	Standard Deviation of *Outdegree Sequence*	0.66 (0.07)	WIOD	+
Outdegree c.v.	Coefficient of Variation of *Outdegree Sequence*	1.03 (0.12)	WIOD	+
Indegree Beta	Beta Estimates of Tail of *Indegree Sequence*	3.12 (0.81)	WIOD	–
Indegree s.d.	Standard Deviation of *Indegree Sequence*	1.15 (0.17)	WIOD	+
Indegree c.v.	Coefficient of Variation of *Indegree Sequence*	0.71 (0.11)	WIOD	+
Social and Economic Endowment				
Population	Population (in billions)	0.11 (0.27)	Penn World Table Version 7.1 (PWT)	–
Initial GDP	GDP per capita in 1995, PPP (constant 2005 price of international $)	0.02 (0.01)	WDI	–
Human Capital	School Enrollment, Primary (% gross)	104.2 (8.38)	WDI	–

Variables	Variable Description	Mean (a) (Std. Dev.)	Source	Expected Effect on Volatility
Polity	Indicator of Democracy: + 10 (full democracy) to –10 (full autocracy)	8.67 (3.03)	Polity IV Project	–
Trade and Financial Development				
Std. Dev. of Trade Openness	Std. Dev. of Trade Openness (% of GDP)	13.16 (8.71)	PWT	+
Overvaluation	Real Exchange Rate Overvaluation (b)	0.54 (0.46)	WDI	+
M2 Share	M2 (% of GDP)	106.4 (100.8)	WDI	-
Monetary and Fiscal Policy				
Government Size	Government Consumption (% of GDP)	7.88 (2.67)	PWT	-
Inflation	Inflation Rate: Consumer Prices (annual %)	8.75 (15.54)	WDI	+
Std. Dev. of Investment Share	Std. Dev. of Total Investment (% of GDP)	2.81 (1.59)	IMF	+

Notes: (a) Mean and Std. Dev. of data for 37 countries cover the period from 1995 to 2010.
(b) Real exchange rate overvaluation is (domestic CPI) / (exchange rate of domestic currency per dollar*US CPI) for each year. See Dollar (1992).
Source: Author's own Summary.

3.2. The Regression Model for Analyzing the Sources of GDP Volatility and Data

For the purpose of this paper, I focus my analysis on the component of GDP volatility that is explained by the industrial network, which is measured by three estimators derived from each country's *outdegree and indegree sequences*. Specifically, I propose a regression model with my main explanatory variable and other control variables as shown in equation (6):

$$\sigma(y)_{it} = \alpha_i + \delta \times network\ effect_{it} + V_{it}' \times \gamma + \varepsilon_{it}, \qquad (6)$$

where $\sigma(y)_{it}$ is the standard deviation of the growth rate of real GDP per capita, *network effect*$_{it}$ is the main explanatory variable, which is the measurements of industrial network structure, V_{it} is vector of the other control variables that contain sources of GDP volatility, α_i is an unobservable individual-specific component that cannot be explained by *network effect*$_{it}$ and V_{it}, and ε_{it} is an idiosyncratic error.

In practice, I conduct different models that regress the standard deviation of the growth rates of real GDP per capita on the main explanatory variable, *network effect*$_{it}$ and a set of control variables. The robustness check will be conducted by different regression models. According to the theories in section 2, the coefficient of *network effect*$_{it}$ should be significantly negative for the estimators of beta and positive for the other two estimators.

4. EMPIRICAL RESULTS OF INDUSTRIAL NETWORK EFFECTS ON AGGREGATE FLUCTUATIONS

In this section, I use both cross-sectional and panel data models to test the effects of network on GDP fluctuations. I also use other aggregate variables, such as volatilities of investment, consumption and total trade amount to examine whether the industrial network has different effects on these macroeconomic fluctuations, and discuss the implications.

4.1. Empirical Results and Robustness

Table 4 presents the cross-sectional empirical results of beta estimate (*beta*), standard deviation (*s.d.*) and coefficient of variation (*c.v.*) for *outdegree* and *indegree network-effect* variables. I find that the network effects of the three *outdegree* variables (*beta*, *s.d.*, and *c.v.*) and two *indegree* variables (*s.d.* and *c.v.*) are significant with the correct signs. The cross-sectional empirical results show that the network effects indeed exist. Table 5 shows the results of the panel data models with fixed effects. I also test three *outdegree* and *indegree network-effect* variables and get the significant results except for the *outdegree* variables in Model 2 and 3. In my

Table 4 The Empirical Results of Cross-sectional Regressions

Dependent Variable: Standard Deviations of Growth Rates of PPP-converted GDP per Capita at 2005 Constant Prices, Average for 1995-2010

Variables	Expected Effect on Volatility	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Outdegree Network Effect/beta	–	–.0109* (.0065)					
Outdegree Network Effect/s.d.	+		.0456* (.0269)				
Outdegree Network Effect/c.v.	+			.0293* (.0167)			
Indegree Network Effect/beta	–				–.0027 (.0021)		
Indegree Network Effect/s.d.	+					.0232** (.0107)	
Indegree Network Effect/c.v.	+						.0334** (.0163)
Social and Economic Endowment							
Population	–	–.0354*** (.0079)	–.0321*** (.0072)	–.0322*** (.0071)	–.0320*** (.0076)	–.0358*** (.0079)	–.0339*** (.0078)
Initial GDP	–	–.7087* (.3719)	–.7286* (.3728)	–.7269* (.3705)	–.7224* (.4145)	–.8075** (.3660)	–.7887** (.3717)
Human Capital	–	–.00035 (.0002)	–.00041 (.00025)	–.00042 (.00026)	–.00032 (.00022)	–.0002 (.0002)	–.00032 (.00021)
Polity	–	–.0022** (.0009)	–.0017** (.0007)	–.0017** (.0007)	–.0013* (.0006)	–.0017*** (.0006)	–.0014** (.0006)
Trade and Financial Development							
Std. Dev. of Trade Openness	+	.0001 (.0002)	.00005 (.0002)	.00004 (.0002)	.00007 (.0002)	.0001 (.0002)	.0001 (.0002)
Overvaluation	+	–.0019 (.0033)	–.0013 (.0036)	–.0014 (.0036)	–.0013 (.0039)	–.0017 (.0032)	.0025 (.0032)
M2 Share	+	.00002 (.00002)	.00002 (.00002)	.00002 (.00003)	.00003 (.00002)	.00002 (.00002)	.00002 (.00002)
Monetary and Fiscal Policy							
Government Size	–	–.0009 (.0007)	–.0008 (.0007)	–.0008 (.0007)	–.0005 (.0006)	–.0007 (.0007)	–.0007 (.0007)
Inflation	+	–.00002 (.0002)	–.00002 (.0002)	.00003 (.0002)	.00003 (.0002)	.00004 (.0002)	.00005 (.00018)
Std. Dev. of Investment Share	+	.0039** (.0020)	.0040* (.0021)	.0040* (.0021)	.00323 (.00205)	.0028 (.0021)	.0026 (.0022)

Notes: *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors in parentheses are heteroskedasticity robust.

Source: Author's own estimation.

Table 5 The Empirical Results of Panel Regressions: Fixed-effects Estimates

Dependent Variable: Standard Deviations of Five-year Rolling Windows (*t*–2~*t*+2) of Growth Rates of PPP-converted GDP per Capita at 2005 Constant Prices

Variables	Expected Effect on Volatility	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Outdegree Network Effect/beta	–	–.0068* (.0039)					
Outdegree Network Effect/s.d.	+		.0449 (.0316)				
Outdegree Network Effect/c.v.	+			.0290 (.0198)			
Indegree Network Effect/beta	–				–.0024* (.0014)		
Indegree Network Effect/s.d.	+					.0299** (.0134)	
Indegree Network Effect/c.v.	+						.0466** (.0216)
Social and Economic Endowment							
Population	–	–.0069 (.0447)	–.0154 (.0401)	–.0153 (.0399)	–.0305 (.0457)	–.0536 (.0524)	–.0517 (.0507)
Human Capital	–	–.00056*** (.0002)	–.0006*** (.0002)	–.0006*** (.0002)	–.0005*** (.00018)	–.00056*** (.00019)	–.00055*** (.00018)
Polity	–	–.0019*** (.00045)	–.0019*** (.00047)	–.0019*** (.0004)	–.0019*** (.0004)	–.0019*** (.00046)	–.0019*** (.00046)
Trade and Financial Development							
Std. Dev. of Trade Openness	+	.00078** (.00035)	.00077** (.00035)	.00076** (.00035)	.0008** (.00035)	.00079** (.00035)	.0008** (.00036)
Overvaluation	+	.0035* (.00189)	.0028 (.0018)	.0028 (.0018)	.0029 (.002)	.0032 (.00196)	.0032 (.00197)
M2 Share	–	–.00003 (.00003)	–.00004 (.00003)	–.00004 (.00003)	–.00004 (.00003)	–.00004 (.00003)	–.00004 (.00003)
Monetary and Fiscal Policy							
Government Size	–	–.0013 (.00084)	–.0015* (.00078)	–.0015* (.00078)	–.00125 (.0008)	–.00148* (.0008)	–.0015* (.00077)
Inflation	+	.00004*** (7.27e-06)	.00004*** (7.30e-06)	.00004*** (7.21e-06)	.000036*** (8.46e-06)	.00004*** (8.22e-06)	.00004*** (7.87e-06)
Std. Dev. of Investment Share	+	.0051*** (.00093)	.0051*** (.0009)	.0051*** (.0009)	.0052*** (.00098)	.0054*** (.00096)	.0054*** (.00097)
Year Effect		yes	yes	yes	yes	yes	yes

Notes: *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors in parentheses are cluster-robust.

Source: Author's own estimation.

panel data models, I use year dummy variables from 1996 to 2010 to eliminate the disturbance due to the aggregate shocks during certain periods. In other words, by using the year-effect dummy variables in panel data models, I eliminate the systematic shocks, such as the 2007-2008 financial crises, and more directly test the network effects on aggregate fluctuations.

For all models in table 4, the control variables of *population*, *initial GDP* and *polity* are significant and have consistent signs with the literature's predictions, but *human capital* is not significant. In table 5, *human capital* and *polity* become significant with correct signs, but *population* becomes insignificant. This result implies the argument that some of social and endowment variables have better performances by using the cross-sectional data model than by using the panel data model.

For the group of trade and financial development variables in table 4, all models show that none of these variables is significant. However, in table 5, *std. dev. of trade openness*[8)] in Model 1-6 and *overvaluation* in Model 1 are significant with correct sign. It implies that the volatility of trade openness share and real exchange rate *overvaluation* affect GDP fluctuations more significantly in the short term (within 5 years) than in the long term (10 years or more) since panel data models measure the effects on a short-term scale. The relationship between volatilities of trade openness share and GDP is procyclical in all models of table 5, which is consistent with the literature's prediction. However, the *M*2 *share* (% of GDP) has no significant effect on GDP volatility for both cross-sectional and panel data models.

For monetary and fiscal policy variables in table 4, only *std. dev. of investment share* in Model 1-3 has significant effect on GDP volatility with correct sign. However, in table 5, all monetary and fiscal policy variables are significant with correct signs except the *government size* in Model 1 and 4. The empirical results in table 5 show that the procyclical co-movements between GDP volatility and both *inflation* and *std. dev. of investment share* variables indeed exist on a short-term scale.

[8)] The standard deviation of trade openness (% of GDP) is based on a five-year rolling window of the level values.

Table 6 presents the results of random-effects panel data models. The empirical results show that the network effects are significant except for the *c.v.* variable in Model 6. The test results of network effect between the fixed- and random-effect models implies that whether α_i is an individual-specific residual or not would change the significant levels of some of the network effect variables, such as *outdegree s.d.*, *outdegree c.v.* and *indegree c.v.* However, for *outdegree beta*, *indegree beta* and *indegree s.d.*, the results are consistent between fixed-effect and random-effect models.

In order to detect the short-term variation effects by using the panel data, I use standard deviations of five-year rolling windows of growth rates of GDP per capita as my dependent variable, $\sigma(y)_{it}$.[9] However, this procedure would create correlation between $\sigma(y)_{it}$ and its preceding period, such as $\sigma(y)_{it-1}$. One of the solutions to fix this distortion is to use the dynamic panel regression. In this paper, I use the Arellano and Bond estimator provided by Stata and use moment conditions in which lags of the dependent variable and first differences of the exogenous variables are instruments for the first-differenced equation. I use three lags of the dependent variable to correct the overlapping interference. Table 7 shows that the coefficients of the *network-effect* variables are significant with the correct sign except for Model 1 and 4. The *outdegree and indegree network effects* are significant with correct sign for the variables of s.d. and c.v., but for beta the test results are not consistent comparing to the results in table 5 and 6. The variables of outdegree and indegree beta become insignificant in table 7, but the coefficient signs of these variables are consistent.

As I have mentioned in section 2, the constraint of limited observed *outdegree* and *indegree indices* on a cross-country scale is the main reason of using three estimators for measuring industrial network structure. My panel data models show that the empirical results of fixed-effect, random-effect and dynamic panel regressions are not entirely consistent among *s.d.*, *c.v.*, and *beta* variable. The data constraint indeed weakens test robustness of network effects on GDP fluctuations. However, my empirical results in

[9] Please refer the equation (5) in section 2.3.

Table 6 The Empirical Results of Panel Regressions: Random-effects Estimates

Variables	Expected Effect on Volatility	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent Variable: Standard Deviations of Five-year Rolling Windows (*t*–2~*t*+2) of Growth Rates of PPP-converted GDP per Capita at 2005 Constant Prices							
Outdegree Network Effect/beta	–	–.008** (.0034)					
Outdegree Network Effect/s.d.	+		.0421* (.0236)				
Outdegree Network Effect/c.v.	+			.0267* (.0148)			
Indegree Network Effect/beta	–				–.00199* (.0011)		
Indegree Network Effect/s.d.	+					.0156* (.0096)	
Indegree Network Effect/c.v.	+						.0245 (.0164)
Social and Economic Endowment							
Population	–	–.0124* (.0068)	–.0105 (.0071)	–.0108 (.0072)	–.0135 (.0091)	–.0153* (.0086)	–.0154* (.0089)
Human Capital	–	–.00037** (.00017)	–.00044** (.00018)	–.00044** (.0002)	–.00036*** (.00018)	–.00035* (.0002)	–.00038** (.0002)
Polity	–	–.0019*** (.0004)	–.0018*** (.0004)	–.0018*** (.0004)	–.0017*** (.0004)	–.0019*** (.0004)	–.0018*** (.0004)
Trade and Financial Development							
Std. Dev. of Trade Openness	+	.0007** (.0003)	.0007** (.0003)	.0007** (.0003)	.00076** (.00032)	.0007** (.0003)	.0007** (.0003)
Overvaluation	+	.0017 (.0015)	.0013 (.0016)	.0013 (.0017)	.0020 (.0018)	.002 (.0017)	.0022 (.0017)
M2 Share	–	–.00003** (.00001)	–.000037** (.00001)	–.00004** (.00001)	–.00003** (.00001)	–.00004** (.00001)	–.00004** (.00001)
Monetary and Fiscal Policy							
Government Size	–	–.00097* (.00057)	–.0011* (.00056)	–.001* (.0005)	–.00093* (.00054)	–.001* (.0006)	–.001* (.0005)
Inflation	+	.00004*** (8.21e-06)	.00004*** (7.90e-06)	.00004*** (7.84e-06)	.00003*** (8.95e-06)	.00004*** (8.61e-06)	.00004*** (8.33e-06)
Std. Dev. of Investment Share	+	.0053*** (.0009)	.0054*** (.0009)	.005*** (.0009)	.0054*** (.0009)	.0055*** (.00092)	.0055*** (.0009)
Year Effect		yes	yes	yes	yes	yes	yes

Notes: *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors in parentheses are cluster-robust.

Source: Author's own estimation.

Table 7 The Empirical Results of Dynamic Panel Regressions

Dependent Variable: Standard Deviations of Five-year Rolling Windows (*t*–2~*t*+2) of Growth Rates of PPP-converted GDP per Capita at 2005 Constant Prices

Variables	Expected Effect on Volatility	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Outdegree Network Effect/beta	–	–.00063 (.0031)					
Outdegree Network Effect/s.d.	+		$.0744^{**}$ (.0299)				
Outdegree Network Effect/c.v.	+			$.0472^{**}$ (.019)			
Indegree Network Effect/beta	–				–.0015 (.0010)		
Indegree Network Effect/s.d.	+					$.0344^{**}$ (.0151)	
Indegree Network Effect/c.v.	+						$.0604^{**}$ (.0235)
Lag 1 of dep. var.		$.5629^{***}$ (.0591)	$.5193^{***}$ (.0654)	$.5195^{***}$ (.0655)	$.5579^{***}$ (.0581)	$.5263^{***}$ (.0555)	$.5174^{***}$ (.0564)
Lag 2 of dep. var.		$–.0663^{**}$ (.0278)	$–.0853^{***}$ (.0325)	$–.0851^{***}$ (.0325)	$–.0676^{**}$ (.0276)	$–.0646^{**}$ (.0304)	$–.0612^{**}$ (.0306)
Lag 3 of dep. var.		–.0547 (.0508)	–.0565 (.0495)	–.0569 (.0495)	$–.0570^{**}$ (.0515)	$–.0506^{*}$ (.0477)	–.0513 (.0472)
Social and Economic Endowment							
Population	–	.0888 (.0577)	.0512 (.0554)	.0525 (.0550)	.0705 (.0613)	–.0049 (.0892)	–.0154 (.0921)
Human Capital	–	$–.0004^{*}$ (.0002)	$–.00043^{**}$ (.0002)	$–.00044^{**}$ (.0002)	$–.0004^{*}$ (.0002)	$–.00039^{*}$ (.0002)	$–.0004^{*}$ (.0002)
Polity	–	$–.0065^{***}$ (.002)	$–.0063^{***}$ (.0018)	$–.0063^{***}$ (.0018)	$–.0066^{***}$ (.0021)	$–.0064^{***}$ (.002)	$–.0064^{***}$ (.002)
Trade and Financial Development							
Std. dev. of Openness Share	+	$.00046^{**}$ (.0002)	$.00045^{**}$ (.0002)	$.00045^{**}$ (.0002)	$.00047^{**}$ (.0002)	$.00054^{**}$ (.0002)	$.00055^{**}$ (.0002)
Overvaluation	+	.003 (.0032)	.0026 (.0031)	.0026 (.0031)	.0027 (.0032)	.0023 (.0031)	.0023 (.0031)
M2 Share		.00001 (.00006)	8.99e-06 (.00006)	9.11e-06 (.00006)	.000015 (.00006)	.00001 (.00006)	.00001 (.00006)
Monetary and Fiscal Policy							
Government Size	–	–.0016 (.0013)	$–.002^{*}$ (.0012)	$–.002^{*}$ (.0012)	–.0017 (.00126)	–.002 (.0013)	$–.0022^{*}$ (.0013)
Inflation	+	.00003 (.0002)	.00007 (.0002)	.00007 (.0002)	.00002 (.0002)	.00003 (.0002)	.00003 (.00026)
Std. Dev. of Investment Share	+	.00022 (.0012)	.0003 (.0011)	.0003 (.0011)	.00025 (.0012)	.00043 (.0012)	.0004 (.0011)
Year Effect		yes	yes	yes	yes	yes	yes

Notes: *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively. All coefficients are estimated by the Arellano-Bond method with robust standard errors.

Source: Author’s own estimation.

table 5, 6, and 7 do not show that the direction of network effect contradicts the theoretical predictions. Thus, I still have confidence to conclude that the industrial *outdegree* and *indegree network effects* on GDP fluctuations empirically exist even though we have the disadvantage of data constraint.

To sum up, after controlling a wide range of explanatory variables, the industrial network effects on GDP volatility indeed exist according to the results of cross-sectional and panel data models. Furthermore, as mentioned in section 2, the supply-side and demand-side network effects may work independently. That is, the *outdegree* and *indegree sequences* should reveal information about how the economy will react depending on whether its network is supplier-dominant or demander-dominant. I am going to deal with this issue in the following section.

4.2. Further Issues about Industrial Network Effects

I have shown that the effects of industrial network on GDP volatility indeed exist according to my empirical evidence by using a wide range of control variables. In this section, I further investigate how the network affects volatilities of different macroeconomic variables. Kose *et al*. (2003) and Wolf (2004) used volatilities of output, consumption, and income as dependent variables to examine the effects of control variables on macroeconomic fluctuations. In my paper, I use the seemingly unrelated regression (SUR) models including four dependent variables to enlarge my empirical findings, since single-equation models with different macroeconomic fluctuations, such as output, consumption, and investment, as dependent variables would not be efficient when the error terms among equations are highly correlative.[10)]

Table 8-10 present the results of the SUR models with four dependent variables, namely, GDP volatility, consumption volatility, investment

[10)] I have also used the multivariate regression models for the same set of independent variables and dependent variables with SUR models. The comparison of results between multivariate regression and SUR models indeed confirm that the error terms are not independent between equations.

volatility, and trade volatility.[11] Table 8 presents the empirical results in variables of *beta* estimator and other control variables. Table 9 presents the results in *s.d.* and others. Table 10 presents the results in *c.v.* and others. The test results of cross-equation constraints for the network effect difference between GDP volatility and one of the other three dependent variables are also reported. I set up the null hypothesis that the network effects on GDP volatility and any other aggregate volatility are equal.

The empirical results of SUR models indeed show that the supply-side and demand-side network effects have different influence on different aggregate volatility. First, I still get consistent results about network effect on the GDP volatility in SUR models comparing to my cross-sectional data models in table 4. The network effects of three network-effect variables (*beta*, *s.d.*, and *c.v.*) for both outdegree and indegree are all significant with the correct signs in table 8-10. Second, the demand-side, not supply-side, network effects on the final consumption volatility are all significant with correct sign in table 8-10. In addition, the test results of cross-equation constraints show that the coefficients of *indegree network-effect* variables are higher in the equation with consumption volatility as dependent variable than in the equation with GDP volatility as dependent variable. This implies that the *indegree network effect* on final consumption is stronger than the effect on GDP.

Third, both demand-side and supply-side network effects on the investment volatility are significant with correct sign in table 8-10 except the Model 7 in table 8. Furthermore, the test results of cross-equation constraints show that the network effects, for both demand-side and supply-side, on investment are much stronger than the network effects on GDP. In table 9 and 10, the coefficients of both *indegree* and *outdegree network-effect* variables are averagely five-times higher in the equation with investment volatility as dependent variable than in the equation with GDP volatility as dependent variable. Fourth, only the demand-side network effects on the trade volatility are significant with correct sign in the model 8 of table 9 and 10. However, the test results of cross-equation constraints show

[11] For the data summary about these four dependent variables, please refer table 3.

Table 8 Aggregate Volatilities and Network Effect for SUR Models: Beta Estimate

	Predicted Sign	Outdegree				Indegree			
		(1) GDP Volatility	(2) Consumption Volatility	(3) Investment Volatility	(4) Trade Volatility	(5) GDP Volatility	(6) Consumption Volatility	(7) Investment Volatility	(8) Trade Volatility
Beta Estimate	–	–.0111** (.0049)	–.0110 (.0071)	–.0577*** (.0175)	–.0011 (.0073)	–.0032* (.0017)	–.0080*** (.0023)	–.0103 (.0066)	–.0026 (.0026)
Control Variable:									
Population	–	–.0326*** (.0088)	–.0323** (.0129)	–.1263*** (.0314)	–.0305** (.0131)	–.0295*** (.0088)	–.0325*** (.0114)	–.1067*** (.0337)	–.0262** (.0128)
Initial GDP	–	–.8537*** (.2780)	–1.041** (.4129)	–3.691*** (.9226)	–.9033** (.4362)	–.7995*** (.2858)	–.9513*** (.3729)	–3.428*** (1.023)	–.8938** (.4435)
Human Capital	–	–.0004** (.00018)	–.00041 (.00026)	–.0024*** (.0006)	–.0002 (.0002)	–.00033* (.00018)	–.00037 (.00023)	–.0021*** (.0007)	–.0001 (.0003)
Polity	–	–.0021*** (.0008)	–.0017 (.0011)	–.0055** (.0028)	–.0024** (.0012)	–.0011* (.0007)	–.0007 (.0009)	–.0006 (.0026)	–.0014 (.0010)
Std. dev. of Trade Openness		.0002 (.00018)	.0004 (.00028)	.0002 (.0007)		.0002 (.00018)	.00043* (.00025)	–.00002 (.00076)	
Overvaluation		.0021 (.0037)	.0024 (.0053)	–.0019 (.0131)	–.0038 (.0055)	.0015 (.0038)	.0019 (.0048)	–.0048 (.0144)	–.0042 (.0056)
M2 Share		.00002 (.00002)	6.35e-06 (.00003)	.0001 (.00008)	.00003 (.00003)	.00003 (.00002)	–8.25e-07 (.00003)	.00016* (.00009)	.00004 (.00003)
Government Size	–	–.0009 (.0007)	–.0004 (.001)	.0017 (.0025)	.0002 (.001)	–.0005 (.0007)	.0002 (.0009)	.0031 (.0028)	.0005 (.001)
Inflation	+	.00006 (.0001)	.0002 (.0001)	.0018*** (.0004)	.0003 (.0002)	.00009 (.0001)	.00023* (.00015)	.002*** (.0004)	.0003* (.00018)
Std. dev. of Investment Share	+	.0021** (.001)	.0018 (.0016)		.0094*** (.0021)	.0019* (.0009)	.0010 (.0014)		.0088*** (.0021)

		Predicted Sign	Outdegree				Indegree			
			(1) GDP Volatility	(2) Consumption Volatility	(3) Investment Volatility	(4) Trade Volatility	(5) GDP Volatility	(6) Consumption Volatility	(7) Investment Volatility	(8) Trade Volatility
Tests of Cross-equation Constraints	$H_{0:}$(1)*beta* = (2)*beta*			(0.9817) Not Reject				(0.0029) Reject		
	$H_{0:}$(1)*beta* = (3)*beta*				(0.0013) Reject				(0.1928) Not Reject	
	$H_{0:}$(1)*beta* = (4)*beta*					(0.9896) Not Reject				(0.8257) Not Reject

Notes: 1) *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors in parentheses are heteroskedasticity robust. 2) *P*-values are in parentheses for testing cross-equation constraints.
Source: Author's own estimation.

Table 9 Aggregate Volatilities and Network Effect for SUR Models: Standard Deviation

	Predicted Sign	Outdegree				Indegree			
		(1) GDP Volatility	(2) Consumption Volatility	(3) Investment Volatility	(4) Trade Volatility	(5) GDP Volatility	(6) Consumption Volatility	(7) Investment Volatility	(8) Trade Volatility
Standard Deviation (s.d.)	+	.0433* (.0228)	.0446 (.0330)	.2346*** (.0824)	.0184 (.0353)	.0254*** (.0093)	.0419*** (.0126)	.1191*** (.0318)	.0258* (.0142)
Control Variables:									
Population	–	–.0287*** (.0086)	–.0285** (.0125)	–.1071*** (.0313)	–.0247* (.0128)	–.0342*** (.0087)	–.0384*** (.0118)	–.1321*** (.0306)	–.0313** (.0128)
Initial GDP	–	–.8730*** (.2810)	–1.058** (.4144)	–3.818*** (.9499)	–.9161** (.4469)	–.8566*** (.2746)	–1.071*** (.3837)	–3.658*** (.8928)	–.9740** (.4369)
Human Capital	–	–.00045** (.00019)	–.00046* (.00028)	–.0027*** (.0007)	–.0001 (.0003)	–.0002 (.00017)	–.0002 (.0002)	–.0016*** (.0006)	–.00004 (.0002)
Polity	–	–.0015** (.0007)	–.0012 (.0010)	–.0026 (.0025)	–.0016 (.0011)	–.0016** (.0007)	–.00158* (.0009)	–.0029 (.0023)	–.0019* (.0010)
Std. Dev. of Trade Openness		.00019 (.00018)	.0003 (.0003)	–.00007 (.0007)		.0002 (.00018)	.0004 (.0002)	6.15e-06 (.0007)	
Overvaluation		.0016 (.0037)	.0019 (.0053)	–.0046 (.0136)	–.0041 (.0057)	.0019 (.0036)	.0025 (.0049)	–.0029 (.0127)	–.0039 (.0054)
M2 Share		.00002 (.00002)	3.98e-06 (.00003)	.00012 (.00008)	.00004 (.00003)	.00002 (.00002)	–.00001 (.00003)	.0001 (.00008)	.00003 (.00003)
Government Size	–	–.0008 (.0007)	–.0003 (.001)	.0022 (.0026)	.0003 (.001)	–.0008 (.0007)	–.0003 (.0009)	.0022 (.0024)	.0003 (.001)
Inflation	+	.00006 (.0001)	.0002 (.00017)	.0018*** (.0004)	.0003* (.00018)	.00008 (.0001)	.0002 (.0001)	.0019*** (.0003)	.00032* (.00017)
Std. Dev. of Investment Share	+	.0021** (.001)	.0018 (.0016)		.0091*** (.0021)	.00198** (.00098)	.0014 (.0016)		.0086*** (.0021)

	Predicted Sign	Outdegree				Indegree			
		(1) GDP Volatility	(2) Consumption Volatility	(3) Investment Volatility	(4) Trade Volatility	(5) GDP Volatility	(6) Consumption Volatility	(7) Investment Volatility	(8) Trade Volatility
Tests of Cross-equation Constraints	$H_{0:}$ (1)*beta* = (2)*beta*		(0.9555) Not Reject				(0.0865) Reject		
	$H_{0:}$ (1)*beta* = (3)*beta*			(0.0051) Reject				(0.0003) Reject	
	$H_{0:}$ (1)*beta* = (4)*beta*				(0.4674) Not Reject				(0.9763) Not Reject

Notes: 1) *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors in parentheses are heteroskedasticity robust. 2) *P*-values are in parentheses for testing cross-equation constraints.

Source: Author's own estimation.

Table 10 Aggregate Volatilities and Network Effect for SUR Models: Coefficient of Variation

	Predicted Sign	Outdegree				Indegree			
		(1) GDP Volatility	(2) Consumption Volatility	(3) Investment Volatility	(4) Trade Volatility	(5) GDP Volatility	(6) Consumption Volatility	(7) Investment Volatility	(8) Trade Volatility
Coefficient of Variation (c.v.)	+	.0279** (.0142)	.0286 (.0206)	.1499*** (.0513)	.0140 (.0220)	.0372*** (.0137)	.0618*** (.0187)	.1567*** (.0480)	.0404* (.0206)
Control Variables:									
Population	–	–.0288*** (.0086)	–.0286** (.0125)	–.1077*** (.0312)	–.0249* (.0129)	–.0324*** (.0086)	–.0353*** (.0117)	–.1212*** (.0311)	–.0303** (.0125)
Initial GDP	–	–.8711*** (.2803)	–1.056** (.4139)	–3.809*** (.9446)	–.9100** (.4463)	–.8292*** (.2755)	–1.032*** (.3835)	–3.481*** (.9263)	–.9783** (.4335)
Human Capital	–	–.00045** (.00019)	–.00046* (.00028)	–.0027*** (.0007)	–.0002 (.0003)	–.00033* (.00018)	–.0003 (.0002)	–.0020*** (.0006)	–.0001 (.0003)
Polity	–	–.0015** (.0007)	–.0011 (.0010)	–.0024 (.0025)	–.0016 (.0011)	–.0014** (.0007)	–.0011 (.0009)	–.0016 (.0024)	–.0016 (.0010)
Std. Dev. of Trade Openness		.00018 (.00018)	.00034 (.00027)	–.0001 (.0007)		.0002 (.0002)	.00045* (.00026)	.0001 (.0007)	
Overvaluation		.0016 (.0037)	.0020 (.0053)	–.0044 (.0134)	–.0041 (.0056)	.0028 (.0037)	.0040 (.0049)	–.0007 (.0132)	–.0030 (.0054)
M2 Share		.00002 (.00002)	7.91e-07 (.00003)	.0001 (.00008)	.00003 (.00003)	.00002 (.00002)	–.00001 (.00003)	.00009 (.00008)	.00003 (.00003)
Government Size	–	–.0008 (.0007)	–.0003 (.001)	.0024 (.0026)	.0003 (.0011)	–.0007 (.0007)	–.00019 (.00095)	.0026 (.0025)	.0005 (.001)
Inflation	+	.00005 (.0001)	.0002 (.00017)	.0018*** (.0004)	.0003* (.00018)	.00008 (.0001)	.0002 (.0001)	.0019*** (.0003)	.00033* (.00017)
Std. Dev. of Investment Share	+	.0021** (.001)	.0018 (.0016)		.0092*** (.0021)	.00188* (.00098)	.0012 (.0016)		.0083*** (.0021)

	Predicted Sign	Outdegree				Indegree			
		(1) GDP Volatility	(2) Consumption Volatility	(3) Investment Volatility	(4) Trade Volatility	(5) GDP Volatility	(6) Consumption Volatility	(7) Investment Volatility	(8) Trade Volatility
Tests of Cross-equation Constraints	$H_{0:}$ (1)*beta* = (2)*beta*		(0.9639) Not Reject				(0.0844) Reject		
	$H_{0:}$ (1)*beta* = (3)*beta*			(0.0041) Reject				(0.0025) Reject	
	$H_{0:}$ (1)*beta* = (4)*beta*				(0.5182) Not Reject				(0.8749) Not Reject

Notes: 1) *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Standard errors in parentheses are heteroskedasticity robust. 2) *P*-values are in parentheses for testing cross-equation constraints.

Source: Author's own estimation.

that the demand-side network effects on trade volatility and on GDP volatility are not different.

The further development of theoretic framework for my empirical results in these SUR models is still needed. However, I can still highlight two of empirical findings in this section. The first finding is the significantly stronger impact of industrial network shock on investment volatility, for both indegree and outdegree. Corresponding with the theoretic framework I have discussed in section 2, the channel of how the network affects aggregate fluctuations is based on the input-output relationship in the process of supplying and consuming intermediate goods among sectors. According to my findings, the volatility of aggregate investment driven by intermediate-good interaction among sectors would be stronger than the GDP volatility. The reasonable economic implication for this may be that the micro-level shocks at intermediate-good interaction, which spread throughout the network by the definition, affect aggregate investment activities more directly than the consequent intermediate- and final-good production activities. Since the value of GDP is the sum of the gross values added in all stages of production, including final-good production, network effect on GDP volatility through intermediate-good interaction is the indirect effect in other words. Therefore, the impact of idiosyncratic shocks on GDP volatility is less than the impact of idiosyncratic shocks on investment volatility.

The second finding I would highlight is that only demand-side network effect on the final consumption volatility is significant with correct sign. And this effect on consumption volatility is statistically stronger than the effect on GDP volatility. The interesting thing is that final consumption volatility has no direct connection with intermediate-good interaction since the components of final consumption are all final goods according to the input-output methodology. Therefore, it is coherent with my theoretic framework that there is no significant supply-side network effect on the final consumption volatility. However, for demand-side network effect on consumption volatility, the theoretic framework cannot explain my empirical findings. The situation is the same for demand-side network effect on trade volatility.

By calculating the *outdegree* and *indegree sequences* according to equation (1) and (2) in section 2, I can separate the effect of industrial network into the 'supply side' and 'demand side'. According to my empirical findings about the demand-side network effect on consumption and trade volatility in table 8-10, it seems to show that demand-side idiosyncratic shocks through intermediate-good interactions have 'indirect' influence on final-good aggregate volatility, but supply-side idiosyncratic shocks do not. We still need more specific theoretic framework to prove above inference in the following studies about the issue of industrial network effect on different kinds of aggregate fluctuations.

5. CONCLUSIONS

The empirical studies in this paper have confirmed that the industrial network can affect aggregate fluctuations. In checking the robustness of my empirical evidence, the cross-sectional data models for 37 countries and the panel data models for 37 countries from 1995 to 2010 show that the significant control variables have consistent signs with the literature's predictions, and the coefficient sign of my three-network effect variables, namely, the beta, standard deviation, and coefficient of variation for both *outdegree* and *indegree sequences*, are consistent with my theoretical predictions and significant in most of my cross-sectional and panel data models. I have confidence to conclude that the industrial *outdegree* and *indegree network effects* on GDP fluctuations exist and are robust.

There are two additional findings regarding the effects of industrial network on aggregate fluctuations according to my SUR model results. First, both industrial supply-side and demand-side network effects on investment volatility are significantly stronger than the effects on GDP volatility. The reasonable economic implication for this would be that the micro-level shocks through intermediate-good interactions, which form the network by the definition, affect investment activities more directly than the consequent intermediate- and final-good production activities, since the value of GDP is the sum of the gross values added in all stages of production, including final and intermediate goods production. Therefore, the network effect on GDP volatility is significantly less than the network effect on investment volatility.

Second, only demand-side network effect on the final consumption volatility is significant with correct sign. And the demand-side network effect on final consumption volatility is statistically stronger than the demand-side network effect on GDP volatility. The interesting thing is that final consumption volatility has no direct connection with intermediate-good interaction since the components of consumption are all final goods. Therefore, it seems to show that demand-side network has 'indirect' effect on final-good aggregate volatility, but supply-side network does not. We still need more specific theoretic framework to prove above inference in the following studies.

In summary, there are still many puzzles regarding the details of how micro-level shocks spread throughout the whole economy due to the network effect. For example, since I have found the evidences that the effect of input-output network shocks on investment volatility is stronger than on GDP volatility, and only demand-side network shocks affect consumption volatility, what is the mechanism of network shock propagation in different kinds of aggregate fluctuations? More theoretic studies are obviously needed in the future to shed more light regarding the industrial network effect on aggregate fluctuations.

APPENDIX

Table A1 Sector Industry Names

Sector Codes	Industry Names
c1	Agriculture, Hunting, Forestry, and Fishing
c2	Mining and Quarrying
c3	Food, Beverages, and Tobacco
c4	Textiles and Textile Products
c5	Leather, Leather, and Footwear
c6	Wood and Products of Wood and Cork
c7	Pulp, Paper, Paper, Printing, and Publishing
c8	Coke, Refined Petroleum, and Nuclear Fuel
c9	Chemicals and Chemical Products
c10	Rubber and Plastics
c11	Other Non-Metallic Minerals
c12	Basic Metals and Fabricated Metal
c13	Machinery, Nec.
c14	Electrical and Optical Equipment
c15	Transport Equipment
c16	Manufacturing, Nec.; Recycling
c17	Electricity, Gas, and Water Supply
c18	Construction
c19	Sale, Maintenance and Repair of Motor Vehicles, and Motorcycles; Retail Sale of Fuel
c20	Wholesale Trade and Commission Trade, Except for Motor Vehicles and Motorcycles
c21	Retail Trade, Except for Motor Vehicles and Motorcycles; Repair of Household Goods
c22	Hotels and Restaurants
c23	Inland Transport
c24	Water Transport
c25	Air Transport
c26	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
c27	Post and Telecommunications
c28	Financial Intermediation
c29	Real Estate Activities
c30	Renting of M&Eq and Other Business Activities
c31	Public Admin and Defense; Compulsory Social Security
c32	Education
c33	Health and Social Work
c34	Other Community, Social and Personal Services
c35	Private Households with Employed Persons

Source: WIOD database, April 2012 release.

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