economies

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Industrial Productivity Divergence and Input-Output Network Structures: Evidence from Japan 1973–2012

Alvaro Domínguez [1,*] and Carlos Mendez [2]

1 Graduate School of Economics, Nagoya University, Aichi 464-8601, Japan
2 Graduate School of International Development, Nagoya University, Aichi 464-8601, Japan; carlos@gsid.nagoya-u.ac.jp
* Correspondence: alvdom123@gmail.com or dominguez.alvaro@h.mbox.nagoya-u.ac.jp; Tel.: +81-052-789-4345

Received: 09 May 2019; Accepted: 25 May 2019; Published: 31 May 2019

Abstract: Since the early 1990s, there have been larger and increasing labor productivity differences across industries in Japan. More specifically, a clear pattern of sigma and beta divergence across industries is observed. To shed light on these stylized facts, we first evaluate the input–output structure of Japan through the lens of a community-detection algorithm from network theory. Results from this analysis suggest the existence of two input–output network structures: a densely-connected group of industries (a stationary community), whose members remain in it throughout the period; and a group of industries (a transitional community) whose members do not belong to this first group. Next, we re-evaluate the industrial divergence pattern of Japan in the context of each network structure. Results suggest that divergence is mostly driven by the transitional community. Interestingly, since 2007, a pattern of sigma convergence started to re-appear only in the stationary community. We conclude suggesting that industrial divergence and instability in community membership are not necessarily indicative of low productivity performance.

Keywords: communities; input-output networks; productivity; convergence analysis

1. Introduction

When analyzing the aggregate data of an economy regarding its growth performance, it is not possible to determine which sectors are leading this trend. By working with partitioned data, we can study the differences in productivity across groups while also obtaining some insights about different trends throughout the aforementioned sectors. By working with partitioned data, we aim to uncover important heterogeneous outcomes that could be masked when using wider data aggregations.

In this paper we first show that, since the early 1990s, there have been larger and increasing labor productivity differences across industries in Japan. This raises the question of whether there could be a group or cluster of industries whose productivity is behaving differently from that of the rest of the economy. Community detection algorithms from network science allow us to deal with these kind of issues through the partitioning of a network into smaller subsets. Fortunato and Hric (2016) define a community as a subnetwork whose nodes have a higher probability of being linked to other nodes in the subnetwork than to any of the remaining nodes of the network. In our paper, nodes represent industries and links between them constitute the trade that they perform. Input–output tables can be translated as directed weighted networks.[1]

[1] Directed networks can have a node connect to another without the latter necessarily connecting to the first. Weighted networks are those with weights in their links, which allows for asymmetric relationships.

By relying on input-output data from the Japanese Industrial Productivity Database of the Research Institute of Economy, Trade and Industry (RIETI), our interest in this paper is twofold: First, what kind of input–output network structures (industrial communities) characterize the Japanese economy? Second, to what extent is the productivity of the members of each network community converging?

Techniques to detect network communities have a long history. Girvan and Newman (2002) and Newman and Girvan (2004) proposed a simple yet powerful method to find these type of structures within networks, and since then the literature has grown enormously. More recently, other methods to detect communities such as Degree-corrected Stochastic Block Models (Karrer and Newman 2011) and the Louvain method (Blondel et al. 2008) were developed. Good surveys on these literatures are Fortunato (2010) and Fortunato and Hric (2016).

The analysis of economic structures and sectors dates back to the 1940s with the foundational analysis of Leontief (See for example Leontief (1944)). Even though the economic structure into sectors of an economy is related to a network, it is not the same as a social network. Both economic sectors and social networks can be graphed and understood through the use of nodes and links, but their interpretation is different. Social networks rest on behavior, incentives and relationships between the actors or agents under study; economic sectors build upon market and technological requirements and their structure is more stable.[2]

Although social networks play a traditional role in the literature, there is an emerging literature such as Acemoglu et al. (2012), Acemoglu et al. (2016) and Carvalho (2014) that in recent years use input–output data and networks to understand macro patterns and their fluctuations. Other authors as Kagawa et al. (2013) and Cerina et al. (2015) find network communities of industries in input-output tables by employing alternative community detection methods. Zhu et al. (2014) study the international trade network through a community detection algorithm and analyze the relationship between globalization and regionalization. del Río-Chanona et al. (2017) study the World Input Output Network, concentrating on the importance that countries or sectors have and find that these break into two groups: one group based on renewable resources and the other into non-renewable ones.

In order to detect clusters of industries in the Japanese economy, we employ the leading eigenvector algorithm for community detection developed by Newman (2006). This method consists in utilizing the leading eigenvalue and eigenvector of the modularity matrix to perform a spectral optimization of the modularity index, developed by Newman and Girvan (2004). An advantage that network portioning has is that when detecting clusters of industries, the limits between groups can be established based on measure such as the modularity index. The optimization performed by the modularity finds groups strongly connected by maximizing the connections of members inside the community while minimizing the connections between different groups. The problem is that this method can be computationally demanding. The method by Newman (2006) is computationally more efficient than other algorithms.

The first step of this procedure involves calculating the leading eigenvector of the modularity matrix and then partitioning the network into two. This is done in a way that the splitting maximizes the modularity index by relying on the leading eigenvector. This process is iterated and it re-partitions the network at each step until the modularity index is no longer positive. The resulting groups from these partitions consist on the communities that are detected.

Through this algorithm, we detect a stable community for the whole period under study. Because sometimes members of a community "leave" and/or "join" it in different years, it becomes difficult to derive results from communities in an intertemporal fashion due to a lack of consistency in their composition. Therefore, we proceed to define a different type of community, which we call the *stationary community*. It results from the intersection of members of a given community throughout

[2] We acknowledge and thank the insightful comments of an anonymous referee who helped improving this section.

the entire period. In other words, the stationary community consists only of members that remain "inside" the community for the entire period under study: 1973–2012. This allows us to examine only the industries that belong to a community and compare their performance with those of other communities or that belong to none at all. To the best of our knowledge, this has not been done before.

The community we obtain is composed of 44 out of 108 industries of the economy. These industries consist largely of globally non-tradable goods, such as local services. Although it is not clear-cut, by largely we mean that the ratio of services to non-services is higher in the stationary community. This is due to limitations that community detection algorithms sometimes have in avoiding the overlap of some communities. This is an ongoing research in the field of network science and is being worked upon (see for example Fortunato and Hric (2016) for further insights). We collect the remaining sectors of the economy into what we call the transitional community, the complement of the stationary community.

Given these two kinds of groups, we next evaluate to what extent the productivity of the members is converging. The study of economic convergence has been at the center of the modern literature on economic growth and development at least since the seminal work of Solow (1956). The empirical literature on economic convergence that started with the seminal work of Baumol (1986) has rapidly evolved in the last three decades.[3] Among the early pioneers, Barro and Sala-i Martin (1992a) studied convergence across countries, Barro and Sala-i Martin (1992b) focused on regional convergence, and Bernard and Jones (1996) focused on industries. Compared to cross-country convergence, regional and industrial convergence are more likely to be expected. This is because the regions and industries of a country are more likely to share common institutional and technological environments. Furthermore, labor mobility across regions and industries acts as a powerful force for convergence.

When applied to the whole economy, the classical convergence analysis of Barro and Sala-i Martin (1992a) suggests that Japan is characterized by two distinct productivity eras. On the one hand, the 1973–1990 period is characterized by a clear pattern of labor productivity convergence across industries; on the other, the 1990–2012 period is characterized by increasing productivity dispersion and a process of industrial divergence. When applied to the two kinds of network communities, the convergence analysis suggests that in more recent years, at least, overall divergence appears to be driven by the divergence patterns of the transitional community. Interestingly, since 2007, a pattern of convergence started to appear only in the stationary community.

The rest of the paper is organized as follows. Section 2 describes the methods and data. Section 3 presents some overall facts about productivity dispersion and industrial divergence in Japan. Section 4 shows the results of the convergence analysis for each network community. Finally, Section 5 offers some concluding remarks with suggestions for further research.

2. Methods and Data

2.1. Input-Output Network Analysis

In order to partition the input-output data into communities we made use of the modularity index, which is defined as:

$$Q = \frac{1}{4m} \sum_{ij} \left[A_{ij} - P_{ij} \right] \left(s_i s_j \right) \tag{1}$$

where m is the number of links in the network, A_{ij} is the adjacency matrix and $\left(s_i s_j\right)$ takes a value of 1 if i and j belong to the same group or a value of -1 otherwise. Additionally, we define $P_{ij} = \frac{k_i k_j}{2m}$, where k_i is the degree of node i. There are $2m$ link ends in the network so the probability that a node j is attached to one end of these is $\frac{k_j}{2m}$, and the expected number of links between nodes i and j is given by P_{ij}. The whole equation is divided by $4m$ so that it is normalized to the interval $[-1, 1]$.

[3] See the work of Abreu et al. (2005) and Islam (2003) for some comprehensive reviews of this literature.

We can rewrite (1) as:

$$Q = \frac{1}{4m}\mathbf{s}^T\mathbf{B}\mathbf{s} \tag{2}$$

Q is a measure of assortative mixing in the network.[4] Positive values imply assortativity while negative ones indicate disassortativity. The matrix **B** is a real symmetric matrix called the modularity matrix and it works in optimizing the modularity index, while the vector **s** represents an eigenvector of **B**. The modularity matrix is defined as:

$$B_{ij} = A_{ij} - P_{ij} = A_{ij} - \frac{k_i k_j}{2m}. \tag{3}$$

To obtain the maximum modularity, the vector **s** is utilized. This vector is set proportional to the eigenvector $\mathbf{u}_1$, which corresponds to the dominant eigenvalue of **B**. For this, a value of +1 is assigned to the *i*th elements of $\mathbf{u}_1$ having a non-negative value and a value of -1 is given otherwise. These two options represent the partition in which the node related to the *i*-th element will be placed. This process is iterated until the modularity is no longer positive, that is, there is no more positive assortativity.

2.2. Stationary and Transitional Communities

The method by Newman (2006) detects communities only for a network at a given time. Since we are working with many years (i.e., a network per year), the members of the communities may change throughout time. In other words, they could "enter" and "exit" a given community a number of times in the period under study. Therefore we need to define what a community is for the case of an intertemporal or evolving network. Ideally, members of a given community should remain in it for the period of time that we are interested in analyzing. We will call this type of community a *stationary community* which we define as:

$$SC_i = \bigcap_{t=0}^{n} C_{i,t}, \text{ with } C_{i,t} \text{ being community } i \text{ in year } t. \tag{4}$$

Equation (4) tells us that members that remain in the same community for every year under study, will form the stationary community. If even for a single year a member is not present, then it will not be considered a part of the stationary community and will be excluded from it. Nodes that do not belong to a stationary community are considered part of the *transitional community* or, in set-theoretical terms, the complement of the stationary communities. We note that the transitional community is not a community in the traditional definition, but simply a way for us to compare it with the stationary community.

2.3. Sigma and Beta Convergence Analysis

The work of Sala-i Martin (1996) highlights the importance of two classical summary measures of convergence: sigma and beta convergence. In the context of our paper, the former refers to the reduction of productivity dispersion across industries and the latter refers to the existence of catch-up effects (that is, the extent at which unproductive industries are catching up with the more productive ones). Furthermore, as shown by Furceri (2005), these two measures are closely related. To attain sigma convergence, beta convergence is a necessary condition, yet it is not a sufficient one.

More specifically, sigma convergence is commonly measured by either the standard deviation of the logarithm of the variable under study (labor productivity in the case of this paper) or by its coefficient of variation. In this paper, we use the former and define it as follows:

[4] Assortativity refers to the tendency of nodes in a network to connect with others with similar characteristics while dissasortativity implies the opposite case.

$$\sigma_t \equiv \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(log\,(x_{i,t}) - \overline{log(x_t)}\right)^2}, \tag{5}$$

where σ_t is the labor productivity dispersion across industries at time t, N is the number of industries in the sample, $x_{i,t}$ is the labor productivity of industry i at time t, and $\overline{log(x_t)}$ is the average of the natural logarithm of industrial labor productivity at time t.

Beta convergence in its simplest form[5] indicates the inverse relationship between the growth rate of a variable and its initial level. In this paper, we estimate this relationship as follows:

$$\frac{1}{t}\,log\left(\frac{x_{i,t}}{x_{i,0}}\right) = \alpha - \frac{\left(1-e^{-\beta t}\right)}{t}\,log\,x_{i,0} + u_t, \tag{6}$$

where the term in the right side of Equation (6) is the average annual growth rate of labor productivity in industry i, β is the speed of convergence, $x_{i,0}$ is the initial level of labor productivity, and u_t is a random disturbance.

2.4. Data

For our analysis we relied on the input–output tables of the Research Institute of Economy, Trade and Industry (RIETI). More specifically, we use the 2015 version of the Japanese Industrial Productivity Database (JIP Database 2015). Covering Japan's economy over the 1970–2012 period, this database contains information about 108 industries.[6] However, in order to construct a balanced panel dataset, the 1973–2012 period was evaluated. The labor productivity analysis was also based on this database. In particular, the series of gross real output and the number of workers were used to compute the labor indicator used in the paper.

Recent labor productivity studies have used the total number of work-hours to compute a more intensive measure of labor productivity. Thus, one could question the use of the number of workers in the computation of labor productivity. Yet, in our database, at least, it turns out to be that work-hours and the number of workers were highly correlated. For instance, the correlation coefficient between these two indicators was 0.98 and 0.99 in 1973 and 2012 respectively. Moreover, this high correlation has been stable over the entire 1973–2012 period. Thus, from an empirical standpoint, the selection of any of these indicators may not drastically affect the robustness of the results, particularly for the time trends.[7]

Since the community detection algorithm of Newman (2006) worked better with undirected and unweighted networks, we constructed networks with these characteristics from the Input-Output tables for each year we study. First, we symmetrized the data in the matrices. For this, we added each matrix with its transpose and we replaced with zeros the main diagonal of the matrices we obtained.[8] Finally, we replaced the positive entries in the matrices with ones and with zeros any entries that have negative values or zeros.

3. Some Stylized Facts: Productivity Dispersion and Divergence

Figures 1 and 2 document both the overall increase in labor productivity and the increase in its dispersion across industries. Panel (a) of each figure measures labor productivity as the ratio of

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5 The simplest form of beta convergence, also known as absolute beta convergence, is commonly used for the study of production units that share common technological and institutional environments.

6 For the labor productivity convergence analysis, however, 107 industries are considered. This is because there is no systematic data on the number of workers for the Housing industry (JIP code 72).

7 From a conceptual standpoint, however, using the number of work-hours allows for a more precise definition of labor productivity.

8 We do not take into account self-loops in the networks since communities are defined considering only linkages between different nodes.

industrial value-added (in millions of yen, 2000 prices) to the number of workers; panel (b), on the other hand, is based on the ratio of industrial gross output (in millions of yen, 2000 prices) to the number of workers. The increase in labor productivity dispersion is most noticeable and systematic in Figure 2b. In this figure, labor productivity is measured as the median gross output per worker and its dispersion is computed as the inter-quartile range (IQR).

Compared to the other three figures, Figure 2b is particularly more informative for the following two reasons. First, both the median and the IQR are less sensitive to extremely large or small values (outliers). Second, compared to value-added, gross output does not contain negative values. Positive values are required for the convergence analysis since it is based on the logarithm of output.

Figure 3 shows a U-shaped pattern that summarizes the convergence-divergence dynamics of industrial labor productivity in Japan. The dotted line indicates the actual evolution of the industrial dispersion. The solid line is a polynomial regression fit. Following previous studies on sigma convergence, the dispersion was measured as the standard deviation of the logarithm of output, which in this case is gross-output per worker. Given these measures, it was clear that most of the post-war history of industrial productivity in Japan was characterized by two distinct eras. On the one hand, as the dispersion decreased in the 1973–1990 period, there was a clear process of productivity convergence. On the other hand, as the dispersion increased in the 1990–2012 period, there was also a clear process of productivity divergence, which appears to be slowing down in more recent years.

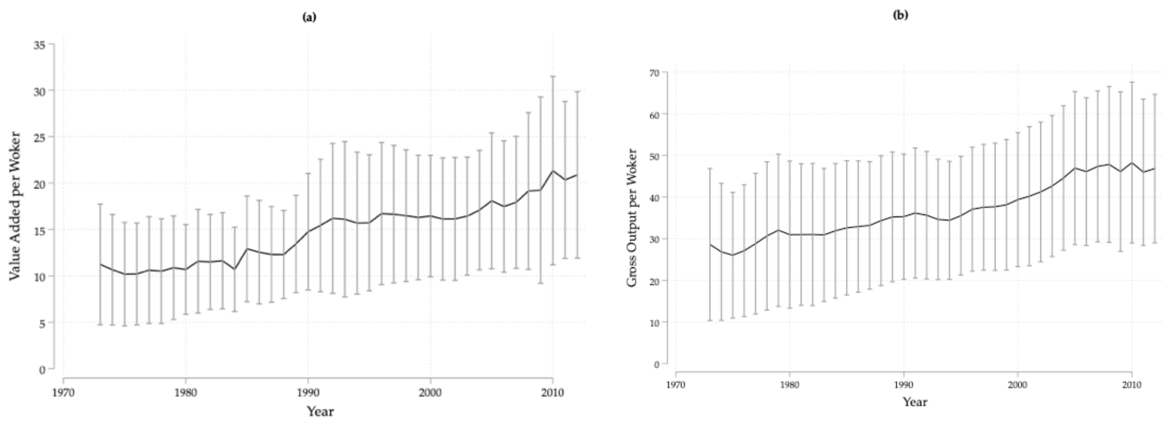

Figure 1. Mean labor productivity and dispersion (standard deviation).

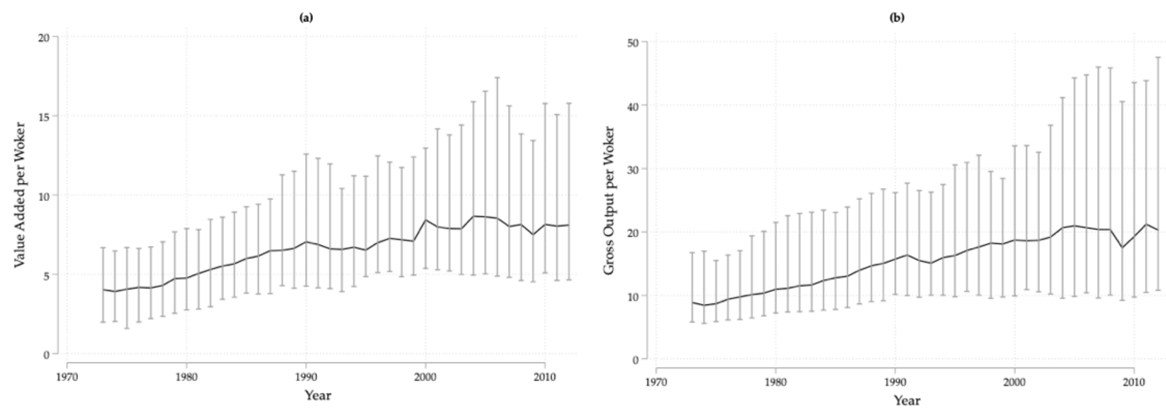

Figure 2. Median labor productivity and dispersion (inter-quartile range).

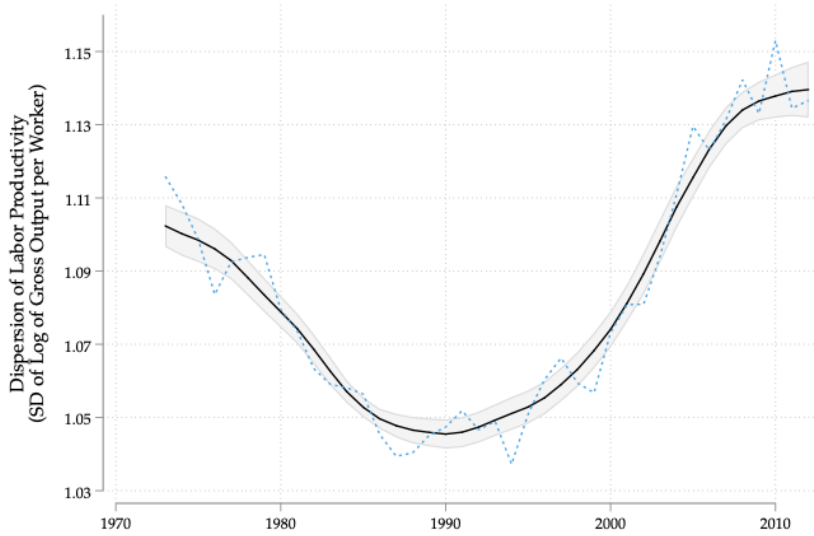

Figure 3. Sigma convergence and divergence.

Interestingly, the timing of the U-shaped pattern of labor productivity convergence/divergence matches closely with the Japanese asset price bubble's collapse of 1991 and its related economic stagnation of the 1990s and 2000s. Before the bubble's collapse, Japan achieved fast economic growth that allowed it to catch up with the most advanced economies of Europe and North America. Figure 3 provides some further insights about this catch-up process. Specifically, the fast economic growth of Japan appears to be associated with a reduction of labor productivity gaps across industries. After the bubble's collapse, however, overall economic growth in Japan stagnated. Moreover, the right-side of the U-shaped pattern of Figure 3, suggests that economic stagnation was accompanied with increasing productivity gaps across industries.

Consistent with the pattern of sigma convergence-divergence, Figure 4 also highlights the two distinct productivity eras of Japan by using the beta convergence approach. On the one hand, in the 1973–1990 period, the least productive industries have been catching up with the more productive ones. On the other, in the 1998–2012 period, this pattern is reversed. In other words, in more recent years, the least productive industries of Japan are not being able to catch up with the more productive ones.[9]

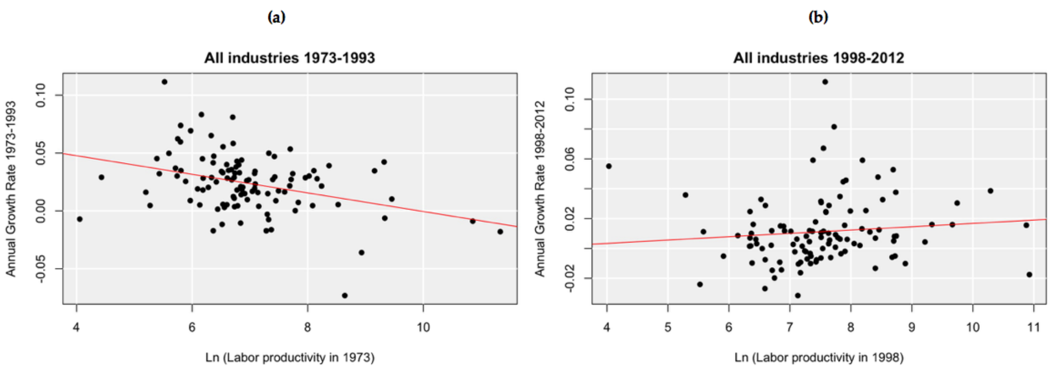

Figure 4. Beta convergence and divergence.

As previously noted, before its asset price bubble's collapse, Japan grew very fast and its industrial productivity gaps tended to decrease. In this context, panel (a) of Figure 4 shows that this decrease is

[9] There is an important statistical difference when comparing the regression lines of Figure 4. In panel (a) the relationship is statistically significant, whereas in panel (b) it is not. Indeed, when we estimate a linear relationship for the 1990–2012 period the regression line is actually flat.

explained in part by the faster productivity growth of the least productive industries. Among these industries,[10] the ones that experienced the fastest growth rates between 1973 and 1993 were electronic data processing machines (11 percent), household electrical appliances (7 percent), and semiconductor devices and circuits (6 percent).

In contrast, after the bubble's collapse, Japan stagnated and its industrial productivity gaps tended to increase. In this context, Panel (b) of Figure 4 shows that the this increase is explained in part by the negative productivity growth of the least productive industries. Among these industries, the ones that experienced the largest negative growth rates are waste disposal services (−3.1 percent), private and non-profit education services (−2.6 percent), and private and non-profit hygiene services (−2.4 percent).

4. Results and Discussion

We first partition the network formed from the input-output data and get a community that is made of 44 out of 108 industries. The result of this partition can be seen in Table A1 of Appendix A. The formation of this group of industries can be explained because its members have strong connections among themselves, while having weaker connections with the rest of the economy. This is the idea of a community. This stationary community turns out to be composed by a large number of service-related industries.[11] Among them, finance and real estate (construction, finance, insurance, and so forth), transportation and related services (railway, road transportation; and the like) and health and welfare-related services (medical, hygiene, education). Since the remaining sectors of the economy were not present in the stationary community, we gathered them in the transitional community. These are shown in Table A2 of Appendix A. These results are similar to those proposed by the Melitz model (Melitz 2003): the tradable goods sector tends to be more productive while the non-tradable one tends to be less productive.[12]

Figure 5 shows the structural differences of the two communities through the lens of both a standard centrality-and-dispersion analysis and the sigma convergence analysis. First, panel (a) and (b) present a simple analysis of centrality and dispersion similar to that of Figure 2. In terms of relative performance, the median labor productivity of the transitional community (panel b) has increased at a faster pace and, as a result, it ended up at a higher productivity level by the year 2012. These two panels also highlight the evolution of the productivity gaps within each community. Here again, the transitional community is particularly more interesting because the productivity gaps across industries (as measured by the interquartile range IQR) have drastically increased since the mid-1990s.

Panels (c) and (d) present the results of the partition through the lens of the sigma convergence approach. Both communities show a clear pattern of initial convergence (the dispersion decreases) followed by a period of divergence (the dispersion increases). The process of divergence in the transitional community (panel d), however, started earlier and appears to continue, although at a slower pace, in more recent years. In contrast, the stationary community appears to be starting a new wave of convergence since the year 2007.

Figure 6 shows the structural differences of the two communities through the lens of the beta convergence analysis. Similar to the sigma convergence results, both communities show a period of significant convergence followed by a period of lack of convergence. Furthermore, in the 1973–1993 period (panels a and c), the speed of beta convergence across industries in the stationary community is faster compared to that in the transitional community. In the 1993–2012 period, however, the slope

10 Based on panel (a) of Figure 4, relatively low productivity industries are those whose labor productivity was less than 6 in log terms. Although this threshold is arbitrary, its selection is just for illustration purposes.

11 As we noted in the introduction, community detection algorithms sometimes produce communities with some overlap. In our case this means that there may be some industries from the non-service sector present too. Ways to solve this type of issues are actively being researched in the field.

12 We tested and compared these results with the Louvain algorithm (Blondel et al. 2008) as a robustness check. The resulting communities obtained mostly coincide with those from the Newman (2006) algorithm we used.

of the regression lines (and the beta convergence coefficient) is not statistically different from zero in both communities.

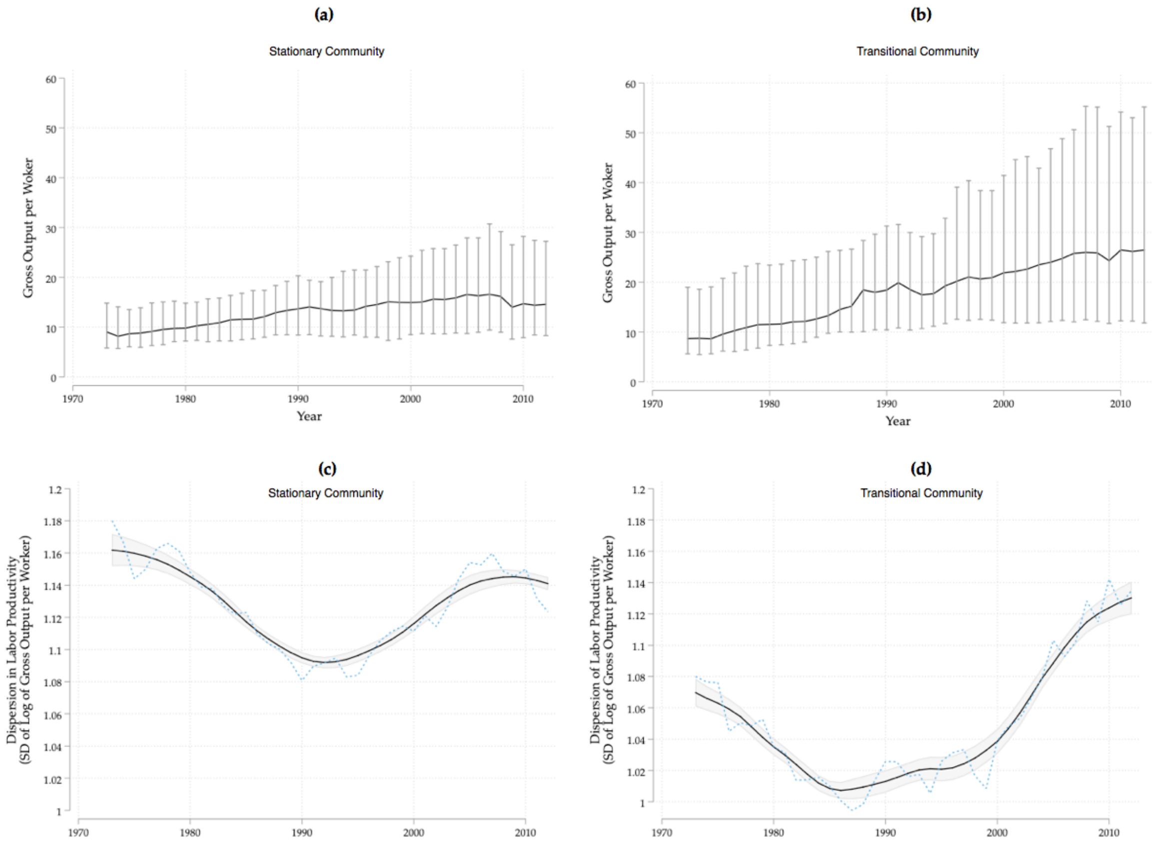

Figure 5. Sigma convergence approach: stationary and transitional communities.

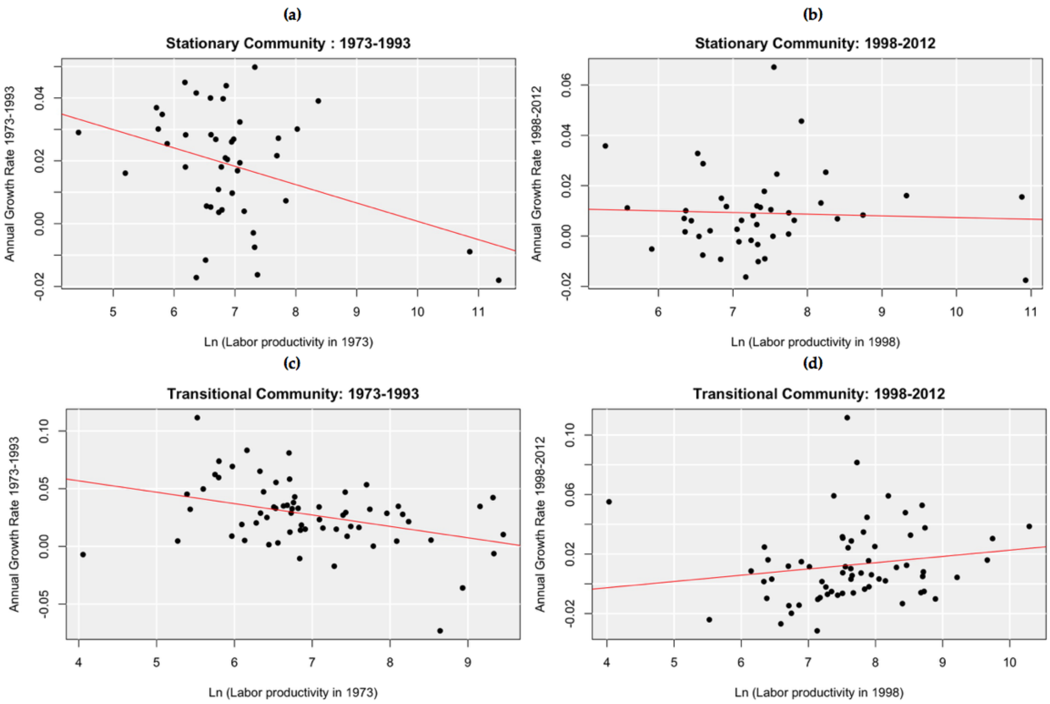

Figure 6. Beta convergence approach: stationary and transitional communities.

By focusing on the 1998–2012 sub-period, however, panels (b) and (d) of Figure 6 highlight an emerging difference between the two communities. If the slopes of the regression lines were to become statistically significant as new years are added to the analysis, then we could expect a significant pattern of beta convergence in the stationary community and a divergence pattern in the transitional community. These two processes, in turn, would reinforce the previously identified patterns of Figure 5, in which a new process of convergence may be appearing in the stationary community and a process of divergence may be continuing in the transitional community.

5. Conclusions

In this paper, we use input–output tables of Japan and analyze the productivity behavior of different community networks at the industry level. For this purpose, we implement the community detection algorithm of Newman (2006). Results from this analysis suggest the existence of two input-output network communities: a densely-connected group of industries (a stationary community), whose members remain in it throughout the period; and a group of industries (a transitional community) whose members do not belong to this first group. In terms of composition, the stationary community appears to be largely composed by service-related industries. Among them, finance and real estate, transportation and related services and health and welfare-related services.

Given these two kinds of network communities, we next evaluate to what extent the productivity of the members is converging. Results suggest that in more recent years, at least, industrial productivity divergence appears to be driven by the divergence patterns of the transitional community. Interestingly, since 2007, a pattern of convergence started to appear only in the stationary community. We also observe that productivity divergence and instability in community membership are not necessarily indicative of low economic performance. On average, divergent (and transitional) industries turn out to have a higher productivity level than their stationary counterparts. This finding could suggest that the members of the transitional community are diverging (or escaping) from a low-productivity equilibrium, while the members of the stationary community are converging towards one.

In the context of these findings, we could suggest at least two promising directions for further research. First, one could apply alternative community detection algorithms such as the Degree-corrected Stochastic Block Model (Karrer and Newman 2011) and the Louvain Method (Blondel et al. 2008). Second, the convergence analysis could be based on frameworks that emphasize both technological heterogeneity and transitional modeling. Among them, the work of Phillips and Sul (2007a) and Phillips and Sul (2007b) may prove useful. By extending this kind of research in any of these directions, one could test whether these alternative techniques produce relatively similar or contrasting results.

Author Contributions: Conceptualization, A.D. and C.M.; formal analysis, A.D. and C.M.; investigation, A.D. and C.M.; writing—original draft, A.D. and C.M.; writing—review and editing, A.D. and C.M.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Industries in the stationary community.

JIP 2015		
No.	**Industry No.**	**Industry Name**
1	1	Rice, wheat production
2	2	Miscellaneous crop farming
3	4	Agricultural services
4	5	Forestry

Table A1. *Cont.*

JIP 2015		
No.	**Industry No.**	**Industry Name**
5	11	Miscellaneous foods and related products
6	13	Beverages
7	15	Textile products
8	18	Pulp, paper, and coated and glazed paper
9	19	Paper products
10	21	Leather and leather products
11	22	Rubber products
12	27	Chemical fibers
13	28	Miscellaneous chemical products
14	30	Petroleum products
15	35	Miscellaneous ceramic, stone and clay products
16	41	Miscellaneous fabricated metal products
17	57	Precision machinery and equipment
18	58	Plastic products
19	59	Miscellaneous manufacturing industries
20	60	Construction
21	62	Electricity
22	64	Waterworks
23	67	Wholesale
24	68	Retail
25	69	Finance
26	70	Insurance
27	71	Real estate
28	72	Housing
29	73	Railway
30	74	Road transportation
31	75	Water transportation
32	77	Other transportation and packing
33	86	Rental of office equipment and goods
34	87	Automobile maintenance services
35	88	Other services for businesses
36	89	Entertainment
37	98	Education (public)
38	100	Medical (public)
39	101	Hygiene (public)
40	102	Social insurance and social welfare (public)
41	104	Medical (non-profit)
42	105	Social insurance and social welfare (non-profit)
43	107	Others (non-profit)
44	108	Activities not elsewhere classified

Table A2. Industries in the transitional community.

		JIP 2015
No.	**Industry No.**	**Industry Name**
1	3	Livestock and sericulture farming
2	6	Fisheries
3	7	Mining
4	8	Livestock products
5	9	Seafood products
6	10	Flour and grain mill products
7	12	Prepared animal foods and organic fertilizers
8	14	Tobacco
9	16	Lumber and wood products
10	17	Furniture and fixtures
11	20	Printing, plate making for printing and bookbinding
12	23	Chemical fertilizers
13	24	Basic inorganic chemicals
14	25	Basic organic chemicals
15	26	Organic chemicals
16	29	Pharmaceutical products
17	31	Coal products
18	32	Glass and its products
19	33	Cement and its products
20	34	Pottery
21	36	Pig iron and crude steel
22	37	Miscellaneous iron and steel
23	38	Smelting and refining of non-ferrous metals
24	39	Non-ferrous metal products
25	40	Fabricated constructional and architectural metal products
26	42	General industry machinery
27	43	Special industry machinery
28	44	Miscellaneous machinery
29	45	Office and service industry machines
30	46	Electrical generating, transmission, distribution and industrial apparatus
31	47	Household electric appliances
32	48	Electronic data processing machines, digital and analog computer equipment and accessories
33	49	Communication equipment
34	50	Electronic equipment and electric measuring instruments
35	51	Semiconductor devices and integrated circuits
36	52	Electronic parts
37	53	Miscellaneous electrical machinery equipment
38	54	Motor vehicles
39	55	Motor vehicle parts and accessories

Table A2. *Cont.*

	JIP 2015	
No.	**Industry No.**	**Industry Name**
40	56	Other transportation equipment
41	61	Civil engineering
42	63	Gas, heat supply
43	65	Water supply for industrial use
44	66	Waste disposal
45	76	Air transportation
46	78	Telegraph and telephone
47	79	Mail
48	80	Education (private and non-profit)
49	81	Research (private)
50	82	Medical (private)
51	83	Hygiene (private and non-profit)
52	84	Other public services
53	85	Advertising
54	90	Broadcasting
55	91	Information services and internet-based services
56	92	Publishing
57	93	Video picture, sound information, character information production and distribution
58	94	Eating and drinking places
59	95	Accommodation
60	96	Laundry, beauty and bath services
61	97	Other services for individuals
62	99	Research (public)
63	103	Public administration
64	106	Research (non-profit)

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