Who Works at the Interface in Knowledge Spillover Across Organizational Boundaries?

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Abstract To investigate the characteristics of engineers who act as an interface in transferring knowledge across national boundaries, I conducted an empirical analysis regarding the mobility of engineers in electrical manufacturing firms from Japan to South Korea. Statistical findings from negative binomial regressions show that the experience of working with foreign engineers facilitates knowledge spillover. In addition, the results show that interfirm knowledge transfer is more likely to occur when the engineers of the hiring firm work together with mobile engineers who (1) were focal members at their previous firm, (2) had a good connection with focal members, and (3) are young. This study suggests that engineers from external organizations are effective in knowledge transfer, especially if they are young, mobile engineers who were focal members at their previous firm and had a good connection with a focal member—and can act as an interface in transferring tacit knowledge.

Keywords Knowledge transfer · Mobile engineers · Interface · Network position

1 Introduction

It is crucial that innovation be both continuous and effective, particularly for R&D (Research and Development)-intensive firms because invention is vital to sustainable success in many business contexts [8, 19]. Invention is a risky process with a

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high probability of failure [41]; thus, a new invention may not yield the desired results [9]. However, although invention is risky, continuous invention is indispensable to the sustainable growth of a firm [19, 53].

It is difficult for many organizations to generate all knowledge internally; therefore, many firms rely on external sources, such as universities, suppliers, buyers, and competitors [51]. However, state-of-the-art technology that organizations wish to acquire is often tacit knowledge and embedded in individuals [37]. Transferring tacit knowledge through the mobility of individuals who possess it is an effective method for firms to gain knowledge [56, 62]. For example, the interfirm mobility of engineers played an important role in the rapid growth of the semiconductor industry in the United States [4, 21, 31]. As for Asian innovation, a successful strategy of hiring engineers from developed countries, such as the United States, was a key component in the acquisition of critical knowledge and rapid growth in South Korea [34, 52] and China [22, 23].

In this paper, I examine the mobility of engineers in the electrical manufacturing industry, specifically their mobility from Japanese companies to South Korean companies. I use patent data to trace the mobility of engineers and patent citation data to measure knowledge spillover. I then employ negative binomial regressions to investigate the characteristics of mobile engineers who act as an interface in transferring knowledge across national boundaries.

1.1 Theory and Hypotheses

Mobile engineers facilitate knowledge transfer. As mentioned above, invention is vital to sustainable success in many business contexts [8, 19]. Developing new ideas is particularly important in technology-intensive industries in terms of profitability [15] and cash flow [1]. However, it is difficult for most firms to generate all knowledge internally [51]. Therefore, firms often acquire external knowledge through alliances [43, 49], foreign direct investments [48], and rival firms in the region [5]. It is difficult to obtain state-of-the-art technology because firms do not willingly allow transfer to other rival firms [37]. State-of-the-art technologies are often tacit [62] and “sticky” [55] knowledge.

It is easy to transfer codified knowledge [38]; however, it is difficult to transfer tacit knowledge. A form of important knowledge that firms want to obtain is usually tacit and embedded in individuals [36]. The acquisition of embedded knowledge is difficult, except when individuals who have tacit knowledge move between firms [7, 51, 54]. Numerous studies have noted that the mobility of knowledgeable individuals leads to knowledge spillover, brain drain [27], and brain circulation [40, 47], affecting both recipient countries and sending countries [42, 46]. It has been noted that recipient countries can benefit from utilizing competent human resources to conduct research and development and from receiving knowledge transfer from overseas. On the other hand, sending countries have disadvantages, such as the loss of advanced knowledge and skills; however, it has been shown that there are also benefits, such as joint research with recipient countries and inflow of venture capital. Dosi [20] noted that hiring individuals from external firms is a way to transfer tacit knowledge because mobility enables firms to obtain external

knowledge without the approval of the rival firms [56, 62]. As for engineer mobility, Almeida and Kogut [4] found that patterns of engineer mobility influenced interregional and intraregional knowledge flow. Argote and Ingram [7] argued that engineer mobility is critical to knowledge transfer. Thus, engineer mobility can play an important role in transferring knowledge, which is tacit and sticky, to firms, regions, and countries [32, 55].

It is not easy to visualize knowledge flow. In previous studies, patent data were used to track the mobility of engineers [51], and patent citation data were used to trace interfirm knowledge flow [5, 6, 32]. Jaffe et al. [32] suggested using patent citation data as an indicator of knowledge spillover. Patent documents contain reference information about earlier patent documents. Such citations are evidence that knowledge has flowed from one cited patent to another and can be interpreted as knowledge spillover. Thus, these citations were used as an indicator of knowledge spillover in many subsequent studies.

Hypothesis 1 Mobile engineers facilitate interfirm knowledge flow.

Mobile engineer characteristics and knowledge spillover. Griliches [26] divides spillover into two types: one is related to exchanging objects and is called rent spillover, while the other occurs in the R&D process. Griliches [26] noted that knowledge spillover during R&D arises from the mobility of workers, information exchange at technology conferences, technical literature, such as papers and patents, reverse engineering, etc. Interfirm knowledge transfer provides opportunities to learn new knowledge and contributes to firm innovation. However, tacit and “sticky” knowledge is often difficult to spread [55, 60], although tacit knowledge can be transferred by mobile engineers [2, 51, 54].

Who works as an interface of knowledge spillover across organizational boundaries? Tsai [59] analyzed the intra-organizational network and found that network positions relate to absorptive capacity and a central network position is associated with innovation outcome. The focus of the network was on the ability of knowledge recipients. Certainly, the ability of the information recipient will influence information transfer. However, an important premise would be to know what kind of person possesses useful information to create information transfer and who can transfer it. In other words, I think that it is necessary to analyze the characteristics of individuals who are likely to generate information flow. It remains uncertain which transmitter characteristics facilitate interfirm knowledge transfer.

Network analysis. Previous knowledge-based studies have noted that social networks facilitate the transfer of knowledge and innovation (e.g., [36, 58]). Network position plays an important role in accessing new knowledge that is critical to creating new products and innovative ideas [59]. Different network positions mean different opportunities to access new knowledge because network position determines the individual’s ability to access new knowledge [17, 57]. Network analysis includes density, structural holes [14], centrality indicators, and so on. Density and structural holes are useful for analyzing the advantages of being embedded in neighbors and social structures, and the centrality indicator is used to evaluate and compare the importance of each vertex in the network. In this research, I focus on the importance of each engineer in the circulation of information;

therefore, I decided to use the centrality index. A central network position allows an individual to access new and important knowledge [59] because individuals who have numerous positive social connections can access new information and knowledge [35].

Centrality is one of the most studied concepts in social network analysis. Centrality can quantitatively measure the importance of an individual within a social network. The degree of centrality, betweenness, closeness, and eigenvector centrality are the four main measures of centrality. Degree centrality is defined as the number of links incident upon a node, or, in other words, the number of ties of a node [24]. Individuals with a high degree centrality are focal and popular actors in the network [33]. They have a high level of communication activity [24] and may act as a conduit for information exchange [18]. This argument leads to the following hypothesis:

Hypothesis 2a A mobile engineer who is a focal actor in the network facilitates knowledge spillover.

Closeness centrality measures depend on geodesic distance, which is the minimal length of an indirect path [13]. Closeness centrality can measure how long it will take information to spread to other individuals in the network [44]. Freeman [24] suggests that closeness centrality reflects the freedom of a node from the controlling actions of others and their capacity for independent action within the network. The following hypothesis is thus proposed:

Hypothesis 2b A mobile engineer who has freedom from controlling actions facilitates knowledge spillover.

Betweenness centrality reflects the intermediary location of a node along the indirect relationships linking other nodes [24]. It comprises conventional measures such as controlling information flow and the capacity to interrupt communication. An individual who has high betweenness centrality can control the amount and kind of information flowing between others [44]. Therefore, I posit the following hypothesis:

Hypothesis 2c A mobile engineer who can control the amount of information between others facilitates knowledge spillover.

Eigenvector centrality is a centrality index proposed by Bonacich [11]; it evaluates not only high-scoring nodes but also all nodes connected to high-scoring nodes. In short, connecting with a popular individual should add more to one's popularity [10]. Eigenvector centrality has become one of the standard measures of network analysis [10]. The reason for its popularity is that while the degree, betweenness, and closeness centralities are defined by binary relations using classically simple graphs [12], the eigenvector measures one's influence via those to whom one is connected [10]. This argument leads to the following hypothesis:

Hypothesis 2d A mobile engineer who connects with a popular individual facilitates knowledge spillover.

Demographic characteristics. An individual's demographic characteristics, such as age, gender, race, education, and work experience, influence one's attitudes and performance [29, 45]. The amount of work influences cognitive ability, knowledge, and skill base [29]. Hambrick and Mason [29] have suggested that individuals who have been in an organization for a long time have long experience and much firm-specific knowledge about finished products, markets, advanced technologies, and standard operating procedures. Thus, I posit the following hypothesis:

Hypothesis 3 A mobile engineer who has significant experience facilitates interfirm knowledge transfer.

1.2 Data and Methods

Data. In this study, I use US patent and patent citation data from the electrical manufacturing industry to test my hypotheses over a 30-year period (1985–2015). I focus on engineers who have moved within the electrical manufacturing industry from Japanese to South Korean firms and examine the characteristics of engineers who act as an interface in knowledge transfer from Japanese firms to South Korean firms. I focus on mobile engineers hired from Japanese firms because Japan is the technology leader in the Asian electronics industry and other Asian firms attempt to catch up to the Japanese firms by obtaining technology developed in Japan [25, 50]. Japan has been leading the world electronics industry since the 1980s, earlier than other Asian companies, while Korean and Chinese companies caught up with Japan in the 2000s (Fig. 1 in “Appendix”). In addition, previous research [25] has shown that the mobility of engineers from Japan to South Korea began to increase around 2000, which is consistent with the time when South Korean companies caught up with Japanese companies (Fig. 2 in “Appendix”). In addition, more than half of the engineers who moved from Japan to South Korea were from the top 8 companies in Japan, and approximately 80% belonged to companies with sales of 500 billion yen or more (Fig. 3 in “Appendix”). Based on these facts, it is clear that engineers with high technical capabilities from the early period who once belonged to Japanese companies often moved to South Korean firms. First, I found engineers who moved from Japanese to South Korean firms using inventors' names on patent bibliographic data filed by Japanese and South Korean electrical manufacturing firms. Next, I confirmed the identity of each engineer by checking their affiliation, IPC number, and filing date using the disambiguation method illustrated in Li et al.'s paper [39]. I found that a total of 385 engineers had moved from Japanese to South Korean firms. I then extracted the patents filed by South Korean engineers who worked with mobile engineers and found that 767 engineers had worked with mobile engineers from Japanese firms in South Korean firms. These data are based on 11,411 inventor-patent observations.

1.3 Dependent Variable

Knowledge transfer. The dependent variable, measured at the patent level, shows the extent of knowledge transfer from Japanese firms. I measured the dependent variable, knowledge transfer, by counting the number of patent citations referring to Japanese

patents in each hiring South Korean firm. An increase in this measure indicates an increase in the extent to which a hiring firm's patent builds on knowledge from external knowledge through the experience of working with a mobile engineer.

1.4 Independent Variables

Co-work experience. To examine co-work experience with foreign mobile engineers, I introduce a co-work experience dummy. It was coded as 1 if the engineer from the South Korean firm has experience working with a mobile engineer from a Japanese firm and 0 otherwise.

Mobile engineer characteristics. In this study, to examine who works as an interface in transferring knowledge across national boundaries, I measure the characteristics of engineers based on network position and work experience. Some social network indexes and work experience indexes measuring the mobile engineer's features are used as independent variables based on patent data.

I use social network indices of mobile engineers' characteristics by means of the patent data. I calculate the social network indices for each engineer in the company that hires them, and examine the structural positions in the network. NodeXL was used for the calculation of each centrality index.

Degree centrality is defined as the number of links incident upon a node, or, in other words, the number of ties in a node [24]. I examine the mobile engineer who worked with the engineer of the hiring firm and use degree centrality to measure how focal the mobile engineer was.

Closeness centrality measures depend on geodesic distance, which is the minimal length of an indirect path. I measure closeness centrality by determining how free the node is from control by others in the network.

The maximum theoretical value of betweenness centrality is given by $(n - 1)(n - 2)/2$ [13]. Betweenness centrality captures stress control and the capacity to interrupt communication. This variable indicates whether the individual works as a bridge or a conduit of information in the network.

A high eigenvector centrality score means that the node has connections with high-scoring nodes. Eigenvector centrality reflects the fact that individuals might profit from well-connected colleagues [61]. Eigenvector centrality measures the influence of a node in a network because being related to a node that has many relationships with other nodes implies an important position within the network. I use this variable to examine whether an engineer who is well connected with others is effective as an interface in transferring knowledge.

To measure the network position, work experience variables are used to capture the characteristics of mobile engineers. I measure the mobile engineer's career length by the number of years elapsed since the year in which the inventor in question filed his/her first patent application.

1.5 Control Variables

The strength of a hiring firm's technological absorptive capacity is measured as the total number of patent citations. An engineer's research productivity in the hiring

firm is measured as the total number of patents filed by the engineer in his/her firm. I examined the patent-filed year ranges of (1) earlier than 2005, (2) from 2006 to 2010, and (3) after 2010.

1.6 Methods

To test at the patent level, many studies have used Poisson regression [1, 30] or a negative binomial model [3, 16, 28] on patent citation counts. I tested both the Poisson and negative binomial models and determined which one fit best. In the null hypothesis, with the data following a Poisson distribution, the result of Chi square testing became significant, and the null hypothesis was rejected, which results in over-dispersion because it is assumed that the mean and distribution are equal in a Poisson model. However, distribution has, in fact, exceeded the mean. Therefore, I assumed that the dependent variable, firm inventiveness, followed a negative binomial distribution. The negative binomial model can be expressed as follows:

$$y = f(x|r, p) = \binom{r+x-1}{x} p^r q^x I_{(0,1,\dots)}(x).$$

The p indicates the probability of success in each trial, and q indicates the probability of failure. The r indicates the number of successes when performing independent Bernoulli trials with probability p , and x indicates a model of the number of failures until the specified number of successes occurs. The expected value and dispersion can be expressed as follows:

$$E(X) = r/p,$$

$$\text{var}(X) = \sigma^2 = r(1-p)/p^2.$$

There are two models with a negative binomial distribution. One uses distribution in the form of a quadratic function in a negative binomial distribution (NB2), and the other uses alignment function in a negative binomial distribution (NB1). I determined which model better fit the data. I conducted a log-likelihood test, AIC (Akaike Information Criterion) test, and BIC (Bayes Information Criterion) test. The results showed that NB2 is larger for a logarithm likelihood and smaller for AIC and BIC than NB2. As the NB1 model is considered more accurate statistically, I used the NB1 model in the analysis.

2 Results

Table 1 provides descriptive statistics and inter-correlations. Table 2 reports the negative binomial regression results. I estimated six models. Model 1 includes the co-work experience dummy and control variables. Model 2 includes the closeness centrality of the mobile engineer who worked with the hiring firm's engineer and control variables. Model 3 includes the closeness centrality of the mobile engineer who worked with the hiring firm's engineer and control variables. Model 4 includes

Table 1 Sample statistics and correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
Knowledge Transfer	3.04	5.26	1										
Joint experience dummy	0.67	0.47	0.04***	1									
Experience with long tenure	19.81	8.94	-0.01	0.00	1								
Mobility engineer with high degree centrality	4.01	3.64	0.04***	0.06***	0.51***	1							
Experience with high closeness centrality	13747.58	36809.04	-0.02	0.04***	0.37***	0.65***	1						
Experience with high betweenness centrality	0.08	0.24	-0.03***	-0.07***	-0.14***	-0.22***	-0.12***	1					
Experience with high eigenvector centrality	0.00	0.02	0.03***	0.01	0.00	0.00	-0.03***	0.05***	1				
#Of Japanese inventors	0.15	0.39	0.06***	0.28***	-0.07***	0.05***	0.05***	0.11***	0.02**	1			
#Of citations of patent	7.04	16.34	-0.05***	-0.22***	0.08***	0.02	0.06***	-0.03***	-0.01	-0.06***	1		
Productivity	17.67	25.60	0.00	0.20***	0.24***	0.09***	-0.10***	-0.14***	-0.05***	-0.19***	-0.01	1	
Year dummy	1.68	0.60	-0.06***	0.40***	-0.25***	-0.06***	0.04***	0.07***	-0.02*	0.01	-0.23***	-0.01	1

Table 2 Results of negative binomial regressions of knowledge spillover

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Co-work experience						
Co-work experience dummy (Hypothesis 1)	0.241*** (0.029)					
Mobile engineer characteristics						
Mobility engineer with high degree centrality (Hypothesis 2a)		0.013*** (0.004)				
Mobility engineer with high closeness (Hypothesis 2b)			−0.237*** (0.060)			
Mobility engineer with high betweenness (Hypothesis 2c)				−0.0000001 (0.000)		
Mobility engineer with high eigenvector (Hypothesis 2d)				2.244*** (0.567)		
Mobility engineer with long tenured (Hypothesis 3)						−0.004** (0.002)
Controls						
Year (Ref. –2005)						
2. (2006–2010)	−0.258*** (0.025)	0.208*** (0.031)	−0.198*** (0.031)	−0.205*** (0.031)	−0.204*** (0.031)	−0.227*** (0.032)
3. (2010–)	−0.406*** (0.049)	0.365*** (0.052)	−0.372*** (0.052)	−0.382*** (0.052)	−0.376*** (0.052)	−0.406*** (0.052)
Productivity	−0.001* (0.000)	−0.001* (0.000)	−0.001** (0.000)	−0.001 (0.000)	−0.001 (0.000)	−0.001 (0.000)
#Of Japanese inventors	0.079*** (0.030)	0.087*** (0.030)	0.107*** (0.030)	0.094*** (0.030)	0.093*** (0.030)	0.084*** (0.030)

Table 2 continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
#Of total citations	−0.009*** (0.001)	0.010*** (0.002)	−0.011*** (0.002)	−0.011*** (0.002)	−0.011*** (0.002)	−0.011*** (0.002)
Cons	1.168*** (0.026)	1.298*** (0.036)	1.362*** (0.034)	1.351*** (0.034)	1.341*** (0.034)	1.444*** (0.048)
LR chi2	276.890	128.480	131.480	114.750	127.420	120.180

$N = 11,411$

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the betweenness centrality of the mobile engineer who worked with the hiring firm's engineer and control variables. Model 5 includes the eigenvector centrality of the mobile engineer who worked with the engineer of the hiring firm and control variables. Model 6 includes the career length of the mobile engineer who worked with the hiring firm's engineer and control variables. Since each centrality index has a relatively strong correlation, a model is introduced in which variables are input one at a time to avoid multiple collinearity.

In Hypothesis 1, I proposed that the mobile engineer affects knowledge spillover across national boundaries. In Hypothesis 1, I expected that the experience of co-working with an engineer who moved from a foreign firm would facilitate knowledge transfer. The coefficient of the co-work experience dummy is positive and significant (at the 1% level) in Model 1. The results of Model 1 support Hypothesis 1.

In Hypothesis 2a, 2b, 2c, 2d, I examined which factors of the network position of mobile engineers would affect the transfer of knowledge across national boundaries. I expected that if an engineer in a hiring firm has a co-work experience with a mobile engineer from a technologically advanced country, the knowledge transfer would be facilitated. In Hypothesis 2a, I argued that a mobile engineer who was a focal actor in his/her previous firm will act as an interface in transferring knowledge to the new hiring firm. The coefficient of the degree centrality of a mobile engineer is positive and significant (at the 1% level) in Model 2. The results of Model 2 support Hypothesis 2a. In Hypothesis 2b, I proposed that the engineer who was free from the control of others in the network would facilitate knowledge spillover. The coefficient of the closeness centrality of a mobile engineer is negative and significant (at the 1% level) in Model 3. The result of Model 3 supports Hypothesis 2b. In Hypothesis 2c, I posited that a mobile engineer who controlled the flow of information among colleagues in his/her previous firm would facilitate knowledge spillover among inter-organizations. The coefficient of the interaction of the betweenness centrality of a mobile engineer is negative and non-significant in Model 4. Thus, the results of Model 4 do not support Hypothesis 2c. In Hypothesis 2d, I argued that a mobile engineer who was well connected with a focal actor in his/her previous firm will act as an interface in transferring knowledge to the new hiring firm. The coefficient of the eigenvector centrality of a mobile engineer is positive and significant (at the 1% level) in Model 5. The results of Model 5 support Hypothesis 2d.

In Hypothesis 3, I argued that if an engineer in a hiring firm has a co-work experience with a mobile engineer with long tenure in a technologically advanced country, knowledge transfer would be facilitated. The coefficient of the mobile engineer's career length is negative and significant (at the 1% level) in Model 6. Thus, the results of Model 6 do not support Hypothesis 3.

3 Discussion and Conclusions

In this study, I examined the relationship between a mobile engineer's characteristics and knowledge spillover between firms in technologically advanced and emerging countries from the perspective of inter-organizational labor mobility. I

investigated the role of engineers who moved from Japan to South Korea in transmitting knowledge and technology.

This analysis has yielded important insights regarding who acts as an interface in transferring knowledge across national boundaries. First, analysis of the network position of mobile engineers who work together in South Korean firms indicates that an engineer who was a focal actor in the network of his/her previous firm facilitates inter-organization knowledge transfer. A mobile engineer who was well connected with a focal engineer also facilitates transmitting knowledge. Generally, when attempting to acquire external information, knowledge, and skills, the spotlight is often on focal individuals, such as top engineers. However, results show that there is a high possibility that an engineer strongly connected with a focal engineer also contributes to knowledge transfer. This may apply not only when hiring foreign engineers but also when hiring researchers and employees. In other words, it suggests that not only a top researcher but a collaborative researcher can be a powerful candidate for transferring external knowledge and creating new knowledge. On the other hand, results also show that engineers not under the control of others in the network also contribute to knowledge transfer. This does not seem to contradict the fact that a person strongly connected with a focal engineer contributes to knowledge transfer. That is, results suggest that individuals who are widely and weakly connected to others in the network also contribute to knowledge transfer. As for the mobile engineer's work experience, long experience negatively affects transferring knowledge across national boundaries. In other words, younger engineers facilitate inter-organizational knowledge transfer. These findings dovetail reasonably well with the findings in Zellner's study [63].

My research has limitations that suggest directions for future research. First, I studied only a few industries. By adding more industries, experience in other companies may be more observable [1]. However, the electrical manufacturing industries I examined are representative of technology-intensive industries, and patents and inventions are important in this field. Therefore, I believe that these results can also be applied to other technology-intensive firms. As the evidence is considered more powerful when more industries are added, I believe that further investigation of other industries is important. Second, at this time, analyses of only Japan and South Korean firms were conducted. However, in terms of the relationship between innovation and mobility of engineers, it would be worthwhile to expand the scope of analysis to other nations. In this research, data on mobile engineers were extracted from hundreds of thousands of patent data and analyzed. The mobility of engineers to China and Taiwan has just begun to increase recently (Figs. 4, 5 in "Appendix"), so accumulating further data is necessary in analyzing knowledge transfer, and this could be my next research subject. Furthermore, in addition to moving knowledge workers from Japan to Asia, moving them to the United States and Europe, and moving them from those areas to Japan could also form the basis of future research.

My research shows that recruiting engineers from an external organization is effective for knowledge transfer. A mobile engineer who was a focal member, had a good connection with a focal member, or is young, will facilitate knowledge

transfer. I believe this information would be useful in deciding who will act as an interface of knowledge transfer across national boundaries.

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Appendix

See Figs. 1, 2, 3, 4, 5.

Fig. 1 Amount of sales. This graph shows the change in sales, with the scale in Japanese yen. *Simple lines* show Japanese companies, *dotted lines* show South Korean, Chinese, and Taiwanese companies

Fig. 2 Number of engineers who moved from Japan to South Korea. This *line graph* shows the transition by taking a 5-year average

Fig. 3 Affiliated company size of mobile engineers. This *graph* shows the size of the Japanese company to which the mobile engineer previously belonged

Fig. 4 Number of engineers who moved from Japan to China. This *line graph* shows the transition by taking a 5-year average

Fig. 5 Number of engineers who moved from Japan to Taiwan and Singapore. This *line graph* shows the transition by taking a 5-year average

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