Institute for Economic Studies, Keio University

Keio-IES Discussion Paper Series

Spatially Uneven Pace of Deindustrialization Within a Country

清田耕造

2022 年 7 月 22 日
DP2022-011
https://ies.keio.ac.jp/publications/18820/

Keio University

1858
CALAMVS GLADIO FORTIOR

Institute for Economic Studies, Keio University
2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan
ies-office@adst.keio.ac.jp
22 July, 2022

Spatially Uneven Pace of Deindustrialization Within a Country

清田耕造

IES Keio DP2022-011

2022 年 7 月 22 日

JEL Classification: F11, F14, R12

キーワード: 産業の空洞化;地域;新古典派貿易モデル;生産性;空間的相互依存

【要旨】

The declining share of manufacturing value-added, often referred to as "deindustrialization," is fast becoming a major concern for policymakers and academic researchers, especially in high-income countries. When compared with country-level analysis, however, regional-level analyses of deindustrialization within a country are limited. This paper empirically examines how and why the patterns of deindustrialization are uneven across regions within a country. The analysis builds upon the neoclassical trade model and uses regional-level data in Japan where both detailed output and input data are available at the regional and industry levels for both manufacturing and nonmanufacturing industries over the last four decades. One of the major findings is that the large variation in deindustrialization within a country is attributable to differences in productivity and price changes across regions. In contrast, the effect of the slowdown in capital accumulation, partly from the expansion of foreign direct investment or offshoring, commonly appears not in specific regions but across regions. The effect of spatial interdependence is also not only statistically significant but also nonnegligible in terms of its magnitude.

清田耕造

慶應義塾大学産業研究所

〒108-8345

東京都港区三田2-15-45

kiyota@keio.jp

謝辞：The author benefited from helpful comments on earlier drafts by Flora Bellone, Theresa Greaney, Takatoshi Ito, Yasusada Murata, Kentaro Nakajima, Toshihiro Okubo, Justin Pierce, Peter Schott, Nori Tarui, two anonymous referees, and seminar participants at Columbia University, Keio University, and the University of Hawai`i. The author gratefully acknowledges the financial support of the Japan Society for the Promotion of Science (JSPS) Grants-in-Aid (JP19H01475, JP19H00598, JP22H00063). The usual disclaimer applies.

Spatially Uneven Pace of Deindustrialization Within a Country*

Kozo Kiyota†

Keio University, RIETI, and TCER

July 22, 2022

Abstract

The declining share of manufacturing value-added, often referred to as "deindustrialization," is fast becoming a major concern for policymakers and academic researchers, especially in high-income countries. When compared with country-level analysis, however, regional-level analyses of deindustrialization within a country are limited. This paper empirically examines how and why the patterns of deindustrialization are uneven across regions within a country. The analysis builds upon the neoclassical trade model and uses regional-level data in Japan where both detailed output and input data are available at the regional and industry levels for both manufacturing and nonmanufacturing industries over the last four decades. One of the major findings is that the large variation in deindustrialization within a country is attributable to differences in productivity and price changes across regions. In contrast, the effect of the slowdown in capital accumulation, partly from the expansion of foreign direct investment or offshoring, commonly appears not in specific regions but across regions. The effect of spatial interdependence is also not only statistically significant but also nonnegligible in terms of its magnitude.

Key words: deindustrialization, region, neoclassical trade model, productivity, spatial interdependence

JEL classification codes: F11, F14, R12

---

*The author benefited from helpful comments on earlier drafts by Flora Bellone, Theresa Greaney, Takatoshi Ito, Yasusada Murata, Kentaro Nakajima, Toshihiro Okubo, Justin Pierce, Peter Schott, Nori Tarui, two anonymous referees, and seminar participants at Columbia University, Keio University, and the University of Hawai'i. The author gratefully acknowledges the financial support of the Japan Society for the Promotion of Science (JSPS) Grants-in-Aid (JP19H01475, JP19H00598, JP22H00063). The usual disclaimer applies.

†E-mail: kiyota@keio.jp

1 Introduction

The declining share of manufacturing value-added, often referred to as "deindustrialization," is fast becoming a major concern for policymakers and academic researchers (e.g., Rodrik, 2016; Bernard, Smeets, and Warzynski, 2017).[1] One reason for this is that "many observers and policy makers believe future economic hopes rest in important part on fostering new manufacturing industries" (Rodrik, 2016, p. 2). In this context, Redding (2002) and Nickell, Redding, and Swaffield (2008) examined the specialization dynamics of manufacturing production across countries. Redding (2002) found that factor endowments play an important role in the long-run patterns of specialization in Organisation for Economic Cooperation and Development (OECD) countries, while Nickell, Redding, and Swaffield (2008) concluded that the more rapid decline in the manufacturing share of gross domestic product (GDP) in the UK and the US than in Germany and Japan is explained by the patters of total factor productivity (TFP) and changes in the relative price of manufactured and nonmanufactured goods.

It is also a concern that manufacturing in some regions within a country decline more rapidly than in others, with recent studies suggesting that factor markets should be defined at the local rather than the national level. For example, Autor, Dorn, and Hanson (2013) argued that labor mobility across states is surprisingly low even in the US. Dix-Carneiro (2019) pointed out that the adjustment of capital across regions is also slow in Brazil because depreciation is low and new investments are gradually directed toward regions that are less affected by trade shocks. An important implication of these studies is that because factor adjustment across regions is slow, industrial structure could diversify across regions within a country and therefore the pace of deindustrialization may be uneven across regions.[2] This is important because regional heterogeneity could lead to unintended distributional consequences of various national policies, such as trade liberalization.

When compared to country-level analysis, the regional-level analysis of deindustrialization within a country remains limited. One reason is that to investigate deindustri-

[1]Deindustrialization is also represented by the declining share of manufacturing in employment. For example, see, Rodrik (2016).

[2]Bernard, Redding, and Schott (2013) found that factor price equalization does not hold across regions in the US. They also revealed that regional wage differentials are closely related to regional industrial structure.

alization (i.e., the declining share of manufacturing value-added), economists need not only information on manufacturing but also on nonmanufacturing to compute industry shares. In other words, the analysis of the patterns of manufacturing specialization across regions within a country is not necessarily able to directly address deindustrialization within a country. Nonetheless, some studies have addressed this issue. Redding and Vera-Martin (2006) examined the patterns of specialization for 45 regions in seven European countries; however, their regional classification is not sufficiently detailed to focus on a single country. Murakami (2015) and Dauth and Suedekum (2016) investigated the regional heterogeneity of deindustrialization in Japan and Germany, respectively. Murakami (2015) pointed out that migration and urbanization affected deindustrialization in Japan prior to 1970.[3] For their part, Dauth and Suedekum (2016) found that deindustrialization was driven by the increase in international trade.[4] While these studies present insightful results with significant contributions to the literature, their empirical analyses do not necessarily connect to the underlying theoretical models in the sense that the regression equations in Murakami (2015) and Dauth and Suedekum (2016) are not directly derived from theory.

This paper cements research gaps discussed above and also addresses these issues, focusing on Japan where both output and input data are available at detailed regional and industry levels for both manufacturing and non-manufacturing industries between 1972 and 2012.[5] Like other high-income countries, Japan has experienced shrinking manufacturing employment and falling manufacturing value-added as a share of total over the last four decades. Panel A in Figure 1 plots the level and share of manufacturing employment from 1972 to 2012. As shown, manufacturing employment peaked at well over 15 million workers in 1992 and then fell by nearly 35 percent over the next 20 years. Similarly, the share of manufacturing employment in total employment declined continuously over the same period, from 25.6 percent in 1972 to just 15.9 percent in 2012. Panel B in Figure 1 plots the level and share of manufacturing value-added (current prices) over the same period. As shown, manu-

[3]However, the migration rate in Japan declined after 1970, which is detailed in Section 2.3.

[4]In addition to these factors, some theoretical and simulation studies in new economic geography suggest that the decline in transportation costs could affect deindustrialization (e.g., Murata, 2008; Desmet and Rossi-Hansberg, 2014) or spatial inequality in incomes (e.g., Allen and Arkolakis, 2014). However, to the best of our knowledge, empirical studies have yet to confirm a clear relationship between these factors across regions within a country.

[5]Section 2 explains the data used in this paper in more detail.

facturing value-added peaked at 123.3 trillion yen in 1991, falling to only 86.5 trillion yen by 2012, while its total value-added share gradually declined from 35.5 percent in 1972 to just 20.8 percent in 2012.[6]

However, this deindustrialization pattern is not common across prefectures within Japan.[7] Figure 2 illustrates the share of manufacturing value-added in 1972 and 2012 by prefectures, which are sorted from left to right based on their manufacturing shares in 1972. If a percentage point decline is common across prefectures, the line exhibits a parallel downward shift. If the decline is proportional, the line depicts a smaller downward shift in the prefectures on the left and a larger downward shift in the prefectures on the right. Panel A of Figure 2 presents, however, neither of these patterns and the decline in the share of manufacturing value-added differs markedly across prefectures within the country. Consequently, even though Japanese manufacturing faces deindustrialization on average, there are a few prefectures in which the share of manufacturing value-added has increased. In other words, deindustrialization is spatially uneven within the country.

Panel B of Figure 2 presents this pattern on a map of Japan. Colors are based on the quartile of the changes in the share of manufacturing value-added, which corresponds to the vertical difference between 1972 and 2012 in Figure 2 for each prefecture (i.e., the change from 1972 to 2012 for each prefecture). A darker color indicates a larger decline. This figure shows that rapid deindustrialization is not randomly distributed across prefectures and is concentrated in two major metropolitan areas: Tokyo and Osaka. This also implies that deindustrialization may be spatially interdependent.[8]

Drawing on this background, this paper empirically examines how and why deindustrialization patterns can vary across regions within a country. Our theoretical and empirical approach is based on a series of works by Redding and colleagues (Redding, 2002; Redding and Vera-Martin, 2006; Nickel, Redding, and Swaffield, 2008) that analyzed cross-country specialization patterns according to neoclassical trade theory. An advantage of the use of a trade model is that it enables us to analyze the changes in the share of value-added across sectors simultaneously in a simple way. The contribution

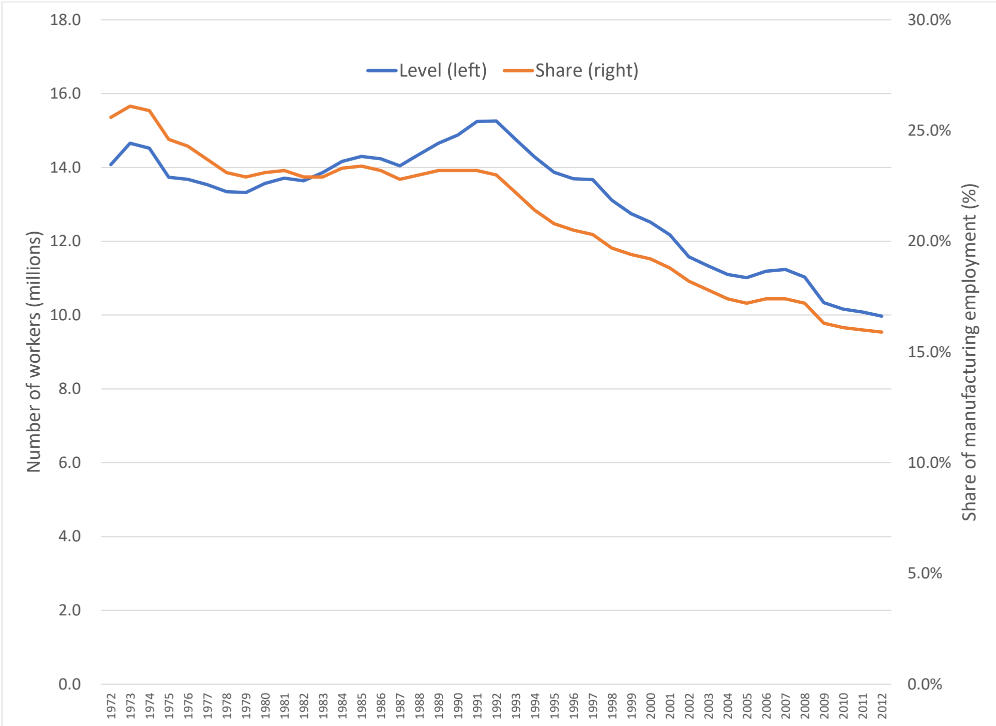
[6]The value-added per capita increased from 2.190 in 1972 to 9.591 in 2005 and then declined to 8.675 in 2012.

[7]Japan consists of 47 administrative regions. Each region is officially called a "prefecture." Hereafter, this paper freely interchanges the terms "region" and "prefecture."

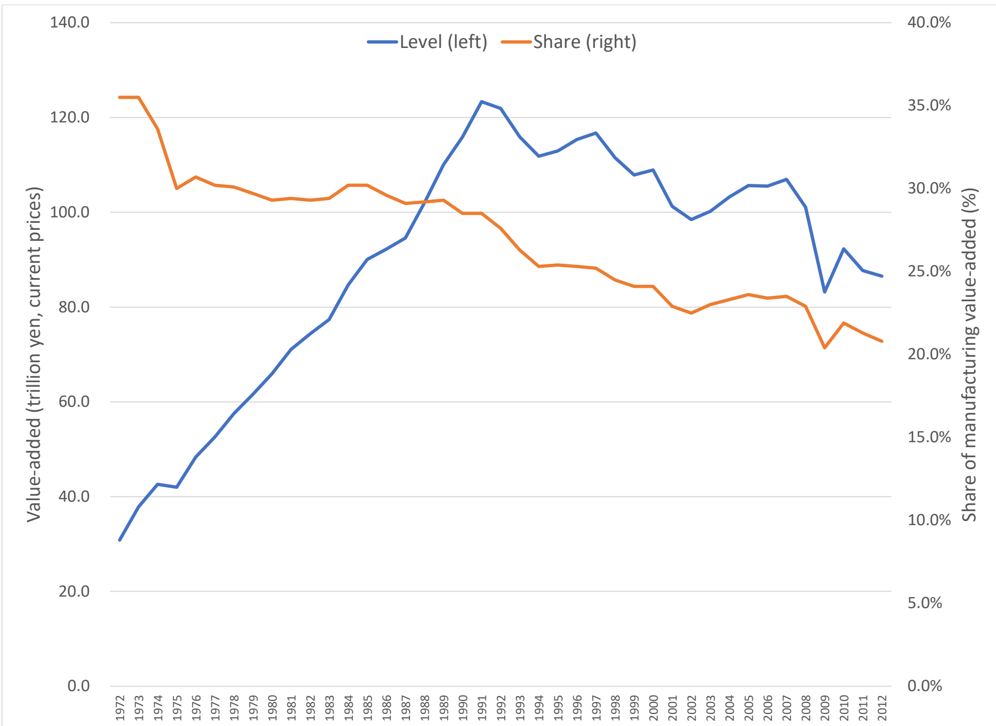
[8]Formal tests of spatial interdependence will be provided in Section 3.

Figure 1: Manufacturing Employment and Value-Added in Japan, 1972–2012

Panel A: Level and share of total employment



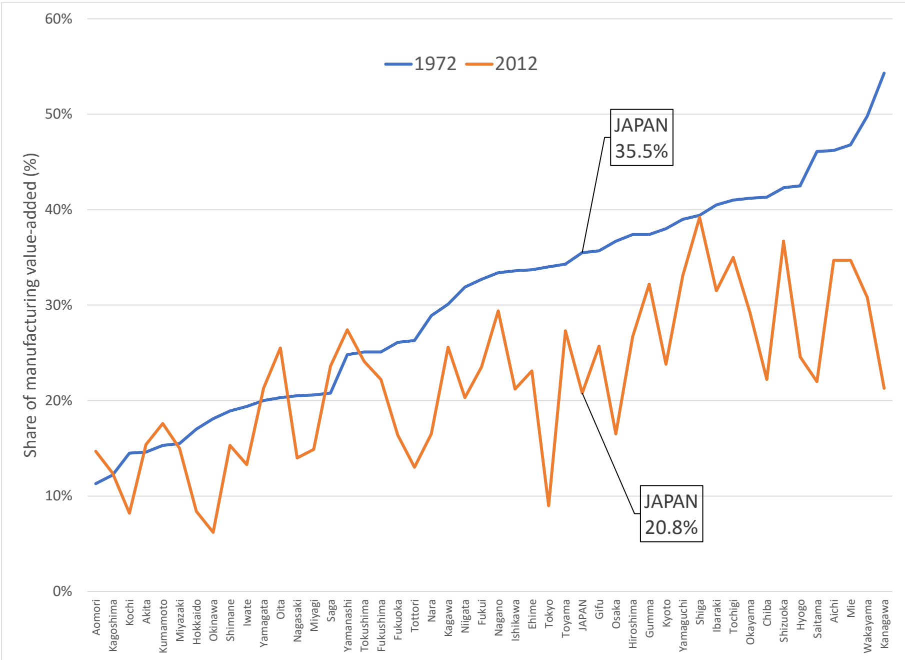
Panel B: Level and share of total value-added



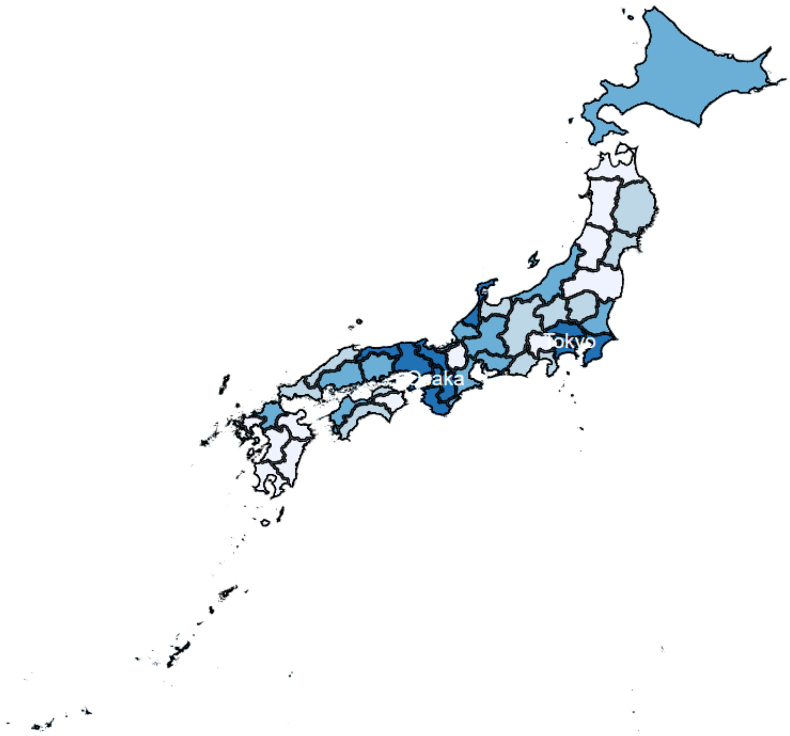
Notes: Manufacturing value-added based on current prices.
Source: Research Institute of Economy, Trade, and Industry (RIETI) (2017) R-JIP Database.

Figure 2: Share of Manufacturing Value-Added in 1991 and 2012 by Prefecture

Panel A: Share of manufacturing value-added



Panel B: Changes in the share of manufacturing value-added



Notes: In Panel A, JAPAN is the average of Japan. Manufacturing value-added is based on current prices. Colors relate to the quartile of the changes in the share of manufacturing GDP, with darker colors indicating larger declines. The Japanese map data are from https://gadm.org/.

Source: RIETI (2017) R-JIP Database.

of this study is twofold. First, the analysis considers the spatial interdependence of deindustrialization across regions using spatial econometric techniques and the framework of general equilibrium analysis. In this paper, spatial interdependence means the spatial correlation of production (e.g., through agglomeration externalities) and that of random shocks between prefectures.[9] Second, the paper quantifies the contribution of the factors that could potentially affect deindustrialization.

The major findings of this paper are threefold. First, the large variation in deindustrialization within a country is attributable to differences in productivity and price changes across prefectures. This suggests that prefectures with manufacturing industries that face sharp price declines and/or exhibit slower productivity growth are more likely to deindustrialize. Second, the effect of a slowdown in capital accumulation, partly because of the expansion of foreign direct investment (FDI) or offshoring, does not appear in individual prefectures, but is common across prefectures. Finally, the effect of spatial interdependence is not only statistically significant, but also nonnegligible in terms of magnitude.

The remainder of the paper is organized as follows. Section 2 explains the analytical framework, discussing the theoretical model, data, and econometric concerns. Section 3 presents the results of the baseline model and Section 3 discusses the results of alternative models. Drawing on these estimation results, Section 4 examines the economic magnitude of these results, the changes in industry composition within manufacturing, and the price changes. The final section summarizes the findings and presents their implications.

2 Analytical Framework

2.1 Theoretical background

Our theoretical framework follows Redding (2002) by drawing on the neoclassical theory of trade and production (Dixit and Norman, 1980). More specifically, the analysis focuses on production rather than trade. One of the advantages of this model is that

[9] In this paper, production is measured by the value-added (net output). Section 2.3 presents a formal definition.

it requires no assumptions about consumer preferences.[10] The analysis in this paper is thus consistent with a wider range of forms of consumer preferences, which affects the production structure through prices.[11]

Another advantage of neoclassical theory is that it enables us to analyze the changes in the share of value-added across sectors simultaneously in a simple manner.[12] More specifically, the theory allows us to identify the determinants of deindustrialization in the general equilibrium framework and derive an econometric specification with producer optimization. The theory translates the fall in manufacturing and the rise in the services sector into the contribution of relative prices, productivity, and factor endowments as follows.

Index regions by $z \in \{1, ..., Z\}$; industries by $j \in \{1, ..., N\}$; factors of production by $i \in \{1, ..., M\}$; and time t. Assume that production occurs under perfect competition and constant returns to scale.[13] Let y_{zjt} and v_{zjt} be the output and factor inputs of industry j in region z in year t. Assume that technology differences are represented by Hicks-neutral region–industry–time technology.[14]

In this setting, the revenue function takes the form $r(\varphi_{zt}p_{zt}, v_{zt})$, where φ_{zt} and p_{zt} are the vectors of the productivity parameter and relative prices of region z in year t; and v_{zt} is factor endowment in region z in year t. Assume that the revenue function is approximated as a translog form that provides an arbitrarily close local approximation

[10] Indeed, the central predictions of the Heckscher–Ohlin model are for producer equilibrium, as three of the Heckscher–Ohlin model's four key theorems (i.e., Rybczynski, Stolper–Samuelson, and factor price equalization) require no assumptions about consumer preferences.

[11] Recent studies have pointed out the importance of nonhomothetic preferences as a determinant of the sectoral composition in value-added. For example, see Matsuyama (2019).

[12] In recent years, studies such as Allen and Arkolakis (2014) have developed quantitative spatial models of trade. While their frameworks are precise and sophisticated, they are also complicated; therefore, they are not easy to implement. This paper attempts to present a simple alternative approach, although we acknowledge that the framework has several shortcomings.

[13] While these assumptions are restrictive, they are helpful when formulating a general equilibrium trade model. For example, see, Eaton–Kortum model (Eaton and Kortum, 2002) which develops a multi-country, multisector general equilibrium Ricardian model.

[14] The introduction of the productivity parameter allows us to control for Ricardian technology differences across regions. For details, see Morrow (2010).

to the true underlying revenue function:

$$\begin{aligned}\ln r(\varphi_{zt}p_{zt}, v_{zt}) &= \beta_{00} + \sum_j \beta_{0j} \ln \varphi_{zjt}p_{zjt} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln(\varphi_{zjt}p_{zjt}) \ln(\varphi_{zkt}p_{zkt}) \\ &+ \sum_i \delta_{0i} \ln v_{zit} + \frac{1}{2}\sum_i \sum_h \delta_{ih} \ln v_{zit} \ln v_{zht} \\ &+ \sum_j \sum_i \gamma_{ji} \ln(\varphi_{zjt}p_{zjt}) \ln(v_{zit}), \end{aligned} \tag{1}$$

where $j, k \in \{1, ..., N\}$ index industries and $i, h \in \{1, ..., M\}$ index factors. Assume further that the symmetry of the cross effects (i.e., $\beta_{jk} = \beta_{kj}$ and $\delta_{ih} = \delta_{ih}$ $\forall j, k, i, h$) and linear homogeneity of degree one in v and p (i.e., $\sum_j \beta_{0j} = 1, \sum_j \delta_{0j} = 1, \sum_j \beta_{jk} = 0, \sum_i \delta_{0j} = 0$, and $\sum_i \gamma_{ij} = 0$).

In the model, firms maximize profits, taking producer prices as given. Because under perfect competition, domestic producer prices equal foreign producer prices plus tariffs and transportation costs, producer prices include the effects of tariffs and transportation costs. Differentiating the revenue function with respect to the log of p_{zjt} and adding the error term ε_{zjt}, we obtain the following general equilibrium relationship between the share of industry j in region z's GDP in year t and relative prices, technology, and factor endowments:

$$\begin{aligned} s_{zjt} &\equiv \frac{p_{zjt}y_{zjt}(\varphi_{zt}p_{zt}, v_{zt})}{r(\varphi_{zt}p_{zt}, v_{zt})} + \varepsilon_{zjt} \\ &= \beta_{0j} + \sum_k \beta_{jk} \ln \varphi_{zkt}p_{zkt} + \sum_i \gamma_{ij} \ln v_{zit} + \varepsilon_{zjt}, \end{aligned} \tag{2}$$

where $\sum_j s_{zjt} = 1$.[15] Standard microeconomic theory suggests that the effect of own-sector price-productivity is positive (i.e., $\beta_{jj} > 0$) because it increases revenue. In contrast, the effect of other-sector price productivity is undetermined a priori because it depends upon the complementarity/substitutability between industries. Trade theory suggests that $\gamma_{ij} > 0$ if industry j is factor i-intensive. The magnitude of the coefficient cannot be determined a priori and thus clarified by the empirical analysis. In the matrix form, equation (2) is written as:

$$\mathbf{s}_{jt} = \beta_j \mathbf{X}_{jt} + \boldsymbol{\epsilon}_{jt}, \tag{3}$$

[15] For the derivation of equation (2), see Appendix A.

where $\mathbf{s}_{jt}$ is the GDP share of industry j in year t, and $\mathbf{X}_{jt}$ is a matrix of regressors including factor endowments. This equation is the basis of the regression analysis. Note that because $\sum_j s_{zjt} = 1$ and with parameter restrictions only $N - 1$ equations can be estimated.

2.2 Data

2.2.1 Source and classifications

Before discussing the econometric specification, we explain the data used in the analysis, being the 2017 Regional-level Japan Industrial Productivity (R-JIP) Database from 1972 to 2012.[16] This is a regional-level version of the Japan Industrial Productivity Database, which provides annual information on capital and labor inputs, as does the National Bureau of Economic Research manufacturing database. There are two notable features of this database. First, the information is available at the prefecture–industry level. Second, the data include both manufacturing and nonmanufacturing sectors in 47 administrative prefectures in Japan from 1970 to 2012 for 13 manufacturing industries and 10 nonmanufacturing industries.[17] The local market is defined using this prefecture classification.[18] Note that a "prefecture" in Japan corresponds to a "state" in the US. The sample period commences with the return of the Okinawa prefecture by the US to Japan in 1972.

Following Nickell, Redding, and Swaffield (2008), industries are aggregated into five sectors: Agriculture ($j = 1$), Manufacturing ($j = 2$), Other production ($j = 3$), Business services ($j = 4$), and Other services ($j = 5$).[19] Given that deindustrialization is concerned with the decline in the share of aggregate manufacturing in GDP, the manufacturing sector is considered as a whole, along with aggregates of the other major sectors. The Other production sector comprises mining, utilities, and construction. The services sector is divided into Business services and Other services because financial and business services are likely to be more tradable than other services, which may

[16] Available at https://www.rieti.go.jp/en/database/r-jip.html

[17] See Table B1 in Appendix B for the prefecture classification.

[18] The local market can be defined not only by the administrative classification but also by the commuting zone. However, "most of the workers work in the prefecture where they live" (Taniguchi, 2019, p. 3). Therefore, the definition of factor markets at the prefecture level may have some validity.

[19] See Table B2 in Appendix B for the industry classification. The original industry category is the "industry" while the aggregate industry category is the "sector."

lead to different price movement patterns between prefectures.

2.2.2 GDP shares

The model yields predictions for the share of the current value-added price of each sector in current price share of GDP. Hence, the current price share of GDP is the dependent variable. Table 1 presents the change in the share of sectoral GDP.[20] This table presents the arithmetic mean values across prefectures, showing that the average share of manufacturing value-added (Δs_2) declined in the period from 1972 to 2012. It is also interesting to note that all sectors except for Business services exhibit declining shares. The remaining variables are detailed in Section 3.

Table 1: Summary Statistics: Arithmetic Mean Change Across Prefectures, 1972–2012

	Mean	S.D.	Minimum	Maximum
Δs_1	-0.067	0.035	-0.137	-0.002
Δs_2	-0.083	0.081	-0.331	0.051
Δs_3	-0.040	0.026	-0.097	0.012
Δs_4	-0.006	0.011	-0.039	0.018
Δs_5	0.197	0.045	0.131	0.348
$\Delta \ln(\varphi_1 p_1)$	1.173	0.269	0.506	1.764
$\Delta \ln(\varphi_2 p_2)$	1.967	0.355	1.230	2.755
$\Delta \ln(\varphi_3 p_3)$	1.746	0.258	1.346	2.379
$\Delta \ln(\varphi_4 p_4)$	1.675	0.174	1.107	2.092
$\Delta \ln(\varphi_5 p_5)$	2.352	0.169	1.938	2.874
$\Delta \ln(K/L)$	1.604	0.237	1.058	2.094

Notes: Δs_j presents the changes in the share of sector j's GDP; $\Delta(\varphi_j p_j)$ indicates the changes in the log of the product of productivity and price of sector j; and $j = 1, 2, 3, 4, 5$ correspond to Agriculture, Manufacturing, Other production, Business services, and Other services, respectively.
Source: RIETI (2017) R-JIP Database.

2.2.3 Productivity

This paper measures productivity using a superlative index number measure of TFP (for example, see, Nishimura, Nakajima, and Kiyota, 2005) for the following reasons. First, it is derived under the neoclassical model's assumptions of constant returns to scale and perfect competition. It is thus consistent with the theoretical framework in this paper. Second, although much progress has been made on estimating production

[20] Summary statistics for the share of GDP and other variables are in Table B3 in Appendix B. Note that by definition, sectoral GDP includes sectoral exports while excluding sectoral imports. The analysis thus accounts for international trade. Note also that the changes in the share of manufacturing value-added in Table 1 is the arithmetic mean of the changes across prefectures. The change in Panel B in Figure 1 is the share of manufacturing value-added in Japan as a whole.

functions over the past decade (e.g., Dobbelaere and Kiyota, 2018; Gandhi, Navarro, and Rivers, 2020), that framework requires large cross-sectional variations (i.e., large sample sizes for a given time) and thus is usually unable to be applied to sector-level data (i.e., small sample).

Approximating constant returns to scale production technology with a translog functional form, this superlative index number evaluates productivity in each prefecture and year relative to a hypothetical average prefecture in the sector. Based on the availability of the data, we use real value-added for output Y, and capital K and labor L for inputs and set 2000 as the benchmark year (i.e., $\ln \varphi_{zjt} = 0$ if $t = 2000$). This means that TFP is measured relative to the hypothetical average prefecture in 2000. More detailed explanations are in Appendix C.

2.2.4 Output, factor inputs, and prices

Output is defined as real value-added. Prices are measured with value-added deflators. The deflator is an index of sector j in prefecture z in year t relative to their value in the same prefecture in 2000 (i.e., 2000 constant prices), and thus takes the value of one in 2000 in all prefectures. This deflator provides information on changes in nominal prices in a particular prefecture–sector over time. Although the deflator does not capture the level of prices across prefectures and sectors in 2000, the econometric specification captures the level of prices in 2000 using a prefecture–sector fixed effect as described below.

In the 2017 R-JIP Database, two factors are available at the prefecture–industry level: capital (K) and labor (L), which correspond to the inputs of the production function (equation (C1) in Appendix C) and the endowments (v_{zit}) in equation (2). Capital stock is defined as the net real capital stock, and the unit of measurement is one million Japanese yen (2000 constant prices). The capital stock primarily consists of machinery and buildings, but not land. Labor is measured by hours worked (i.e., number of workers multiplied by working hours per worker divided by 1,000).[21] All inputs were identified at the workplace.

Total cost is defined as $wL+rK$. The price of the capital (r) is the user cost of capital

[21] In the 2017 R-JIP Database, labor is not disaggregated by skills or tasks. For a detailed explanation, see Tokui, Makino, Fukao, Miyagawa, Arai, Arai, Inui, Kawasaki, Kodama, and Noguchi (2013).

that differs across industries but is identical across prefectures at the sector level. The price of labor (w) is the average wage at the prefecture–sector level. TFP is computed using the information on output, inputs, and prices (i.e., based on equation (C1) in Appendix C). Prefecture endowments are also computed by aggregating prefecture–sector capital and labor (hours worked) at the prefecture level. Before proceeding to the estimation, the next subsection discusses some of the econometric challenges.

One concern is the effects of Japanese outward FDI (or offshoring) on deindustrialization. Note that the expansion of FDI would lead to a decline in domestic capital stock (K_{zt}). In that sense, we consider the effects of FDI through the changes in capital stock. Another concern may be the effects of an aging and declining population, leading to a decline in the domestic labor force (L_{zt}). This analysis accounts for the effects of aging and a declining population through the changes in the labor force.

2.3 Econometric issues

2.3.1 Regression equations and estimation

There are four concerns in estimating equation (2). First, equation (2) forms a system of $N-1$ equations reflecting the general equilibrium relationship between variables. Noting the cross-equation symmetry constraints, the error terms across equations may be contemporaneously correlated; therefore, it is necessary to use a systems estimator. To address this issue, we select Zellner's method for seemingly unrelated regression (SUR) equations, because of the following reasons. The one is that SUR can consider the correlation of error terms in the system of equations. The other is that it enables us to impose constraints on the parameters between the equations in a simple way. No other estimation method appears to address these concerns simultaneously.[22] Owing to the parameter restrictions, we drop Other services from the estimation.

Second, as discussed earlier, deindustrialization may also be spatially interdependent. For example, suppose that an automobile company locates in one prefecture with automotive parts provided by other firms located in either the same or neighboring prefectures through vertical linkages. If production of the automobile company declines for some reason (e.g., the global financial crisis), the production of parts in other pre-

[22] SUR is often used in estimating the system of equations. For example, see, Cicerone, McCann, and Venhorst (2020).

fectures may also decline through backward linkages. In that case, deindustrialization between prefectures will indicate positive correlation. In contrast, some manufacturing activities in one prefecture may move to another neighboring prefecture to avoid high land prices. Then, deindustrialization between prefectures will show a negative correlation. Moreover, unobserved shocks may be correlated because of geographical proximity. However, such spatial interdependence is not captured in the theoretical model in this paper.

To address the issue of spatial interdependence while simplifying the theoretical framework, we employ spatial econometric techniques. Indeed, such spatial econometric issues are not new in the literature on international trade.[23] The value-added in this study is to extend the analysis by introducing spatial econometric techniques and SUR simultaneously, which is novel in the trade literature.

Note that there are several forms of spatial dependence. For example, spatial correlation can be controlled for by including the spatial lag of the dependent variable as an additional independent variable when some part of the total variation in deindustrialization would be explained by each prefecture's dependence on its neighbors. Alternatively, spatial lag can be included as an error term when the error of an observation affects the error of its neighbors. More generally, spatial lags can be included as both an independent variable and as an error term. For the choice of spatial form, we employ the Lagrange multiplier test proposed by Mur, López, and Herrera (2010).[24]

Third, the initial industrial structure attributable to various factors, such as infrastructure and policies following WWII, may also affect the results. Noting that the initial sectoral structure is constant throughout the period, we control for this effect by introducing a prefecture–sector fixed effect, α_{zj}. This fixed effect also captures the time-invariant prefecture–sector effects such as hysteresis.[25]

Finally, both factor prices and TFP are potentially endogenous because they may be correlated with unobserved demand and/or supply shocks. In addition, factors

[23] For example, see, Baldwin and Jaimovich (2012) for the analysis of free trade agreements.

[24] Another popular test for spatial autocorrelation is Moran's I test which investigates the correlations of a variable among nearby locations in space. However, as pointed out by Bivand, Millo, and Piras (2021), Moran's I provides no guidance in choosing between alternative models (e.g., a model with a spatial autoregressive term or spatial errors). Therefore, we employ the Lagrange multiplier test rather than Moran's I test.

[25] While the prefecture–sector fixed effect controls for the time-invariant (e.g., initial) structure between sectors, it does not control for the time-invariant structure within each sector. We address this in Section 4.2.

are mobile across prefectures. Therefore, the demand-side effect may lead to reverse causality between the sectoral share of GDP and factor endowments. However, unlike country–industry-level data, it is not easy to find valid instruments at the prefecture–sector level for both nonmanufacturing and manufacturing over the period.[26] Even if we could find some valid instruments, it is difficult to combine the instrumental variable approach with SUR and spatial interdependence simultaneously because the SUR itself is "structural" in the sense that it forms a system of equations that reflect the general equilibrium relationships between variables. While we acknowledge the importance of endogeneity, we place more weight on the general equilibrium as well as spatial aspects given the difficulty in identifying appropriate instruments and the growing importance of general equilibrium (e.g., Allen and Arkolakis, 2014).

Fortunately, labor mobility across prefectures is not high in Japan. This alleviates some concern about the demand-side effects. Nevertheless, there remains a concern about the effects of unobserved demand and/or supply shocks, which we control for by introducing a sector–period fixed effect, $\alpha_{j\tau}$, where the period is defined as the 5-year interval (i.e., $\tau = 1972$–1976, 1977–1981, etc.).[27]

Note that even though the use of a year fixed effect is ideal, it is equivalent to including the average GDP share of sector j across all prefectures (Klemm and Van Parys, 2012). If the regression equation includes both a year fixed effect (i.e., simple mean GDP share) and a spatial autoregressive term (i.e., weighted mean GDP share) simultaneously, they will be highly correlated. Therefore, it would be difficult to identify the true impact of each variable.[28] To address this, we follow Olney (2013) and use a 5-year fixed effect to control for trends in the data while avoiding the issues associated with including a year fixed effect. Also note that for each observation, the sum of the dependent variables (the value-added shares) over all equations always equal one. Together with the parameter restrictions, if there are N sector equations, only $N - 1$ are linearly independent. In other words, the coefficients of the N-th sector can be computed from the coefficients of the other $N - 1$ sectors. We thus estimate the system of equations

[26] For example, Nickell, Redding, and Swaffield (2008) utilized variables such as the share of government expenditure, the share of imported intermediate inputs, and tariffs as instruments. However, these are available at the country level but not at the prefecture level.

[27] Section 3.4 re-estimates the model with alternative fixed effects to evaluate the robustness of the results.

[28] For details, see Elhorst (2010).

after dropping one sector (Other services) from the estimation.[29]

Let the spatial weighting matrix be W, that is, a $Z \times Z$ positive symmetric and nonstochastic matrix with element $w_{zz'}$:[30]

$$w_{zz'} = \begin{cases} 1 & \text{if regions } z \text{ and } z' \text{ are contiguous;} \\ 0 & \text{if regions } z \text{ and } z' \text{ are not contiguous.} \end{cases} \tag{4}$$

Because the analysis is based on five sectors ($N = 5$) and two factors ($M = 2$: capital K and labor L), with parameter restrictions (i.e., $\sum_j \beta_{jk} = 0$ and $\sum_i \gamma_{ij} = 0$), we estimate the following system of equations:

$$\begin{aligned}
s_{1zt} &= \beta_{01} + \sum_{k=1}^{4} \beta_{1k} \ln \frac{\varphi_{kzt} p_{kzt}}{\varphi_{5zt} p_{5zt}} + \gamma_1 \ln \frac{K_{zt}}{L_{zt}} + \lambda_1 \left(\sum_m w_{zm} s_{jmt} \right) + \alpha_{1z} + \alpha_{1\tau} + u_{1zt} \\
s_{2zt} &= \beta_{02} + \sum_{k=1}^{4} \beta_{2k} \ln \frac{\varphi_{kzt} p_{kzt}}{\varphi_{5zt} p_{5zt}} + \gamma_2 \ln \frac{K_{zt}}{L_{zt}} + \lambda_2 \left(\sum_m w_{zm} s_{jmt} \right) + \alpha_{2z} + \alpha_{2\tau} + u_{2zt} \\
s_{3zt} &= \beta_{03} + \sum_{k=1}^{4} \beta_{3k} \ln \frac{\varphi_{kzt} p_{kzt}}{\varphi_{5zt} p_{5zt}} + \gamma_3 \ln \frac{K_{zt}}{L_{zt}} + \lambda_3 \left(\sum_m w_{zm} s_{jmt} \right) + \alpha_{3z} + \alpha_{3\tau} + u_{3zt} \\
s_{4zt} &= \beta_{04} + \sum_{k=1}^{4} \beta_{4k} \ln \frac{\varphi_{kzt} p_{kzt}}{\varphi_{5zt} p_{5zt}} + \gamma_4 \ln \frac{K_{zt}}{L_{zt}} + \lambda_4 \left(\sum_m w_{zm} s_{jmt} \right) + \alpha_{4z} + \alpha_{4\tau} + u_{4zt},
\end{aligned} \tag{5}$$

where $\beta_{jk} = \beta_{kj}$; $\sum_m w_{zm} s_{jmt}$ is the spatial autoregressive term and α_{jz} is the prefecture–sector fixed effect. In matrix form, equation (5) is written as:[31]

$$\mathbf{s}_{jt} = \beta_j \mathbf{X}_{jt} + \lambda_j \mathbf{W} \mathbf{s}_{jt} + \mathbf{u}_{jt} \quad \text{and} \quad \mathbf{u}_{jt} = \rho_j \mathbf{W} \mathbf{u}_{jt} + \boldsymbol{\epsilon}_{jt}. \tag{6}$$

The signs of λ_j and ρ_j are undetermined a priori because they depend upon the structure of spatial interdependence.

For each sector j, the variables are obtained at the prefecture-year level (z and t) and thus these subscripts are suppressed in matrix form. Note that the SUR considers the correlation of error terms between industries for a given prefecture, whereas the spatial

[29]Strictly speaking, the spatial terms do not face parameter restrictions. We also re-estimate the system of equations by dropping Other production instead of Other services as a robustness check and find that the signs and levels of significance of the coefficients are generally the same as those of the main results.

[30]By convention, $w_{zz} = 0$ for the diagonal elements.

[31]In matrix form, the model with a spatial autoregressive term is written as $\mathbf{s}_{jt} = \beta_j \mathbf{X}_{jt} + \lambda_j \mathbf{W} \mathbf{s}_{jt} + \boldsymbol{\epsilon}_{jt}$; and the model with spatial errors is written as: $\mathbf{s}_{jt} = \beta_j \mathbf{X}_{jt} + \mathbf{u}_{jt}$ and $\mathbf{u}_{jt} = \rho_j \mathbf{W} \mathbf{u}_{jt} + \boldsymbol{\epsilon}_{jt}$.

interdependence accounts for the correlation of the dependent variable and error term between prefectures for a given industry. The SUR and spatial interdependence thus focus on correlation across different dimensions.

Also note that theoretically, it is also possible to include spatial lags for the regressors (i.e., $\mathbf{WX}_{jt}$). However, it would be technically difficult to estimate this model because of the fixed effects (i.e., number of year and region dummies). We thus focus on the spatial autoregressive term and spatial errors.[32]

2.3.2 Spatial weighting matrix

The spatial weighting matrix is constructed on whether prefectures have a common border or are connected by bridges or by tunnels if there are seas between them.[33] The spatial weighting matrix is assumed to be the same across equations and time periods. As is common, we use a row-standardized weighting matrix where it is normalized so that each row sums to unity.

As an alternative, the weighting matrix could be constructed using information on distance rather than contiguity. However, because the capital of the prefecture is not necessarily the center of economic activity in the prefecture, it remains controversial how to measure the distance between prefectures. To check the robustness of the results, Section 4 utilizes an alternative weighting matrix using information on highways and railways.

2.3.3 Notes on factor mobility and factor prices

A concern is whether the neoclassical trade model is applicable to regional analysis because factor mobility is higher within a country than between countries. However, the model does not make any assumptions about factor mobility. Indeed, equation (2) and thus equation (5) hold irrespective of factor mobility (Redding and Vera-Martin, 2006). Nevertheless, factor mobility changes the interpretation of these relationships. On the one hand, when factors are geographically immobile, exogenous changes in factor endowments lead to endogenous changes in production structure. Therefore, the

[32] This in turn implies that the analysis addresses the spatial correlation of deindustrialization itself. The spatial interdependence through regressors (e.g., productivity spillovers between prefectures) is beyond the scope of the analysis.

[33] We use data for bridges or tunnels from 2000 and most were constructed before 1990. The number of neighboring prefectures is presented in Figure B1.

general equilibrium relationship between production structure and factor endowments should be interpreted in supply-side terms. On the other hand, when factors are geographically mobile, an exogenous change in demand and therefore production causes factors to move endogenously across regions, which is a demand-side interpretation. The equation could then reflect both demand- and supply-side effects.

In Japan at least, labor mobility is low. Fujita, Mori, Henderson, and Kanemoto (2004) pointed out that the three largest metropolitan areas (i.e., Tokyo, Osaka, and Nagoya) experienced a high rate of net migration until 1970 with a peak early in the 1960s. Kiyota (2012) also showed that annual migration across prefectures was about one percent between 1995 and 2000, which is mostly the same as the migration rates of some OECD countries, such as Switzerland.[34] The demand-side effect does not seem to be so serious in the case of Japan.[35] Note also that factor endowment is measured by the ratio rather than the absolute value. The effect of capital and labor movement will be mitigated if both capital and labor move from one prefecture to another prefecture simultaneously.

In addition, the use of regional data allows us to mitigate some problems from use of cross-country data. For example, both measurement error and policy differences are likely to be much smaller across prefectures within a country than across countries. A similar argument can be applied to institutional differences in the labor market. Indeed, several empirical tests of the trade model, such as Kiyota (2012), utilized prefectural data within a country, as does this analysis.

In contrast, the disparities in factor prices across prefectures are much smaller within a country than between countries. Even so, Kiyota (2012) confirmed large wage disparities, even among prefectures, in Japan. For example, the wage rate in Kanagawa is twice as high as the wage rate in Aomori. It is also important to note that in the neoclassical trade model, any differences in wages across prefectures should be reflected in differences in relative factor abundance if the skill composition is the same across prefectures.[36]

[34] As a result, average manufacturing wages vary across prefectures. The average manufacturing wage rate in Kanagawa prefecture was twice as much as that in Aomori prefecture.

[35] Section 3.4 employs an alternative period in the sample when labor mobility was low.

[36] Section 3.4 employs alternative measure of labor input to control for the differences in skill composition across prefectures.

3 Results

3.1 Descriptive analysis

Before proceeding to the regression results, this subsection examines the changes in the independent variables. Panel A in Figure 3 presents the log of average prefecture prices by sector from 1972 to 2012, which suggest an inverse U-shape for all sectors after peaking in the mid-1990s. However, the Manufacturing price declines more rapidly than that for the other sectors. As a result, the Manufacturing price in 2012 was smaller than that in 1972. Panel B in Figure 3 presents the log of TFP from 1972 to 2012 by sector. As shown, productivity increased over the period in all sectors. However, the productivity of Manufacturing grew more rapidly than the other sectors. Because the positive effects of productivity growth offset the negative effects of prices, the changes in the price–productivity term ($\Delta \ln(\varphi_2 p_2)$) is greater in the Manufacturing sector than the other sectors except for Other services, as presented in Table 1.

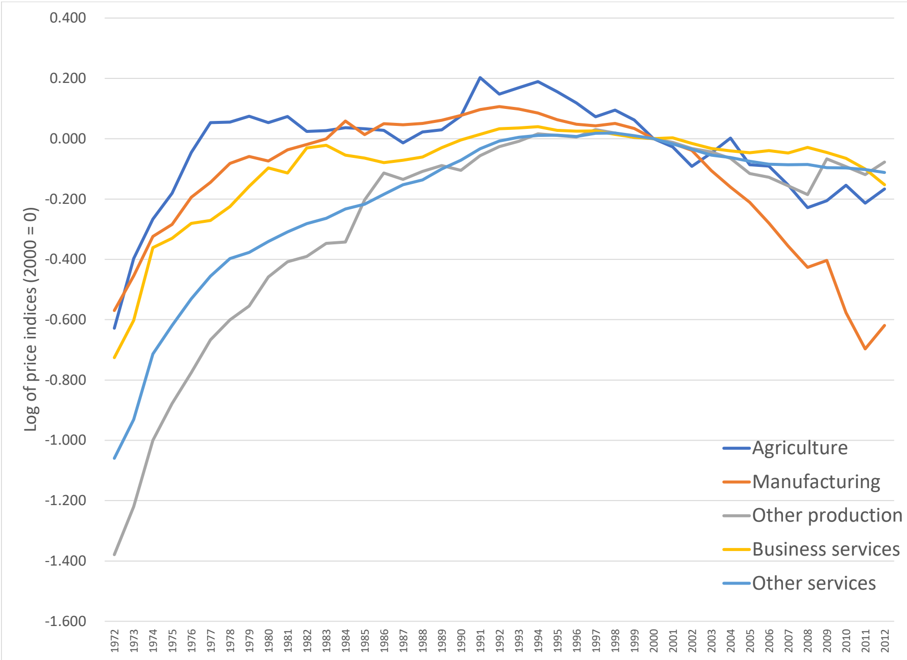
Panel A in Figure 4 plots the average prefecture capital–labor ratio and the average labor input between 1972 and 2012. We highlight three main observations. First, the capital–labor ratio grew steadily over the period. Second, labor inputs declined after the early 1990s. Finally, despite this decline in labor inputs, the growth of the capital–labor ratio slowed from 2000. The dashed line in this figure indicates the linear trend of the capital–labor ratio using the data from 1972 to 2000. After 2000, the actual capital–labor ratio is below the trend line. Moreover, the gap between the actual and trend lines increased from 2000 to 2012. This slowdown of capital accumulation may be attributable to the expansion of FDI and/or declining opportunities for investment given the aging and declining population in Japan.[37] While these are important issues, more detailed analyses are needed to explain them, which is beyond the scope of this paper.

Panel B in Figure 4 presents a scatterplot of the changes in the share of value-added and those for the Manufacturing price, Manufacturing TFP, and prefecture capital–labor ratio from 1972 to 2012. The sectoral share of value-added is computed by each prefecture. The results suggest a negative relationship with the changes in the Manu-

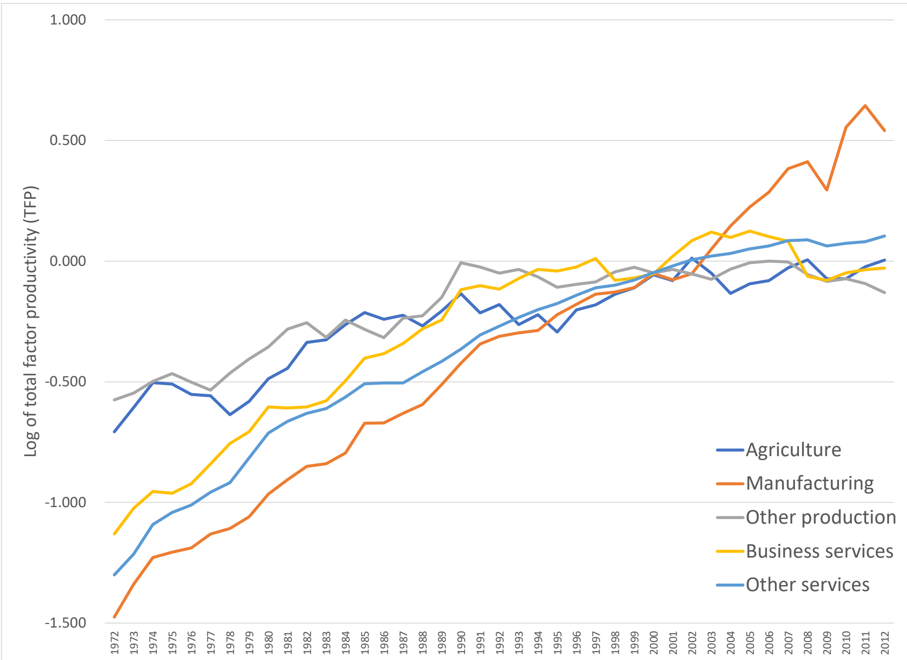
[37] Japan's outward FDI stock rapidly increased after 2000. In 2015, it was 1,167 billion dollars, which is more than five times greater than in 2000 (251 billion dollars). For more details, see Greaney and Kiyota (2020, Table A2).

Figure 3: Changes in Sectoral Prices and Productivity, 1972–2014

Panel A: Changes in sectoral prices (value-added deflator)



Panel B: Changes in TFP



Notes: For Panel A, the figure presents the log of sectoral price deflators, and the price is measured relative to the price in 2000 ($\ln P = 0$ for 2000). For Panel B, TFP is measured relative to the geometric mean for the prefecture in 2000.

Source: Author's estimation using RIETI (2017) R-JIP Database.

Table 2: Lagrange Multiplier Test for the Existence of a Spatial Effect

Alternative hypothesis	Null hypothesis No spatial effects $(\mathbf{s}_{jt} = \beta_j \mathbf{X}_{jt} + \boldsymbol{\epsilon}_{jt})$
Spatial autoregressive term $(\mathbf{s}_{jt} = \beta_j \mathbf{X}_{jt} + \lambda_j \mathbf{W} \mathbf{s}_{jt} + \boldsymbol{\epsilon}_{jt})$	97.5 (0.000)
Spatial errors $(\mathbf{s}_{jt} = \beta_j \mathbf{X}_{jt} + \mathbf{u}_{jt}$ & $\mathbf{u}_{jt} = \rho_j \mathbf{W} \mathbf{u}_{jt} + \boldsymbol{\epsilon}_{jt})$	113.3 (0.000)
Spatial autoregressive term & spatial errors $(\mathbf{s}_{jt} = \beta_j \mathbf{X}_{jt} + \lambda_j \mathbf{W} \mathbf{s}_{jt} + \mathbf{u}_{jt}$ & $\mathbf{u}_{jt} = \rho_j \mathbf{W} \mathbf{u}_{jt} + \boldsymbol{\epsilon}_{jt})$	189.2 (0.000)

Notes: Figure in parentheses is the p-value.
Source: Author's estimation based on the RIETI (2017) R-JIP Database.

facturing price but a positive relationship with the growth of Manufacturing TFP and the prefecture capital–labor ratio. While only indicative, these suggest that these variables might play an important role in explaining the spatial unevenness of deindustrialization. The following subsection investigates this point further using the spatial econometric analysis.

3.2 Model selection

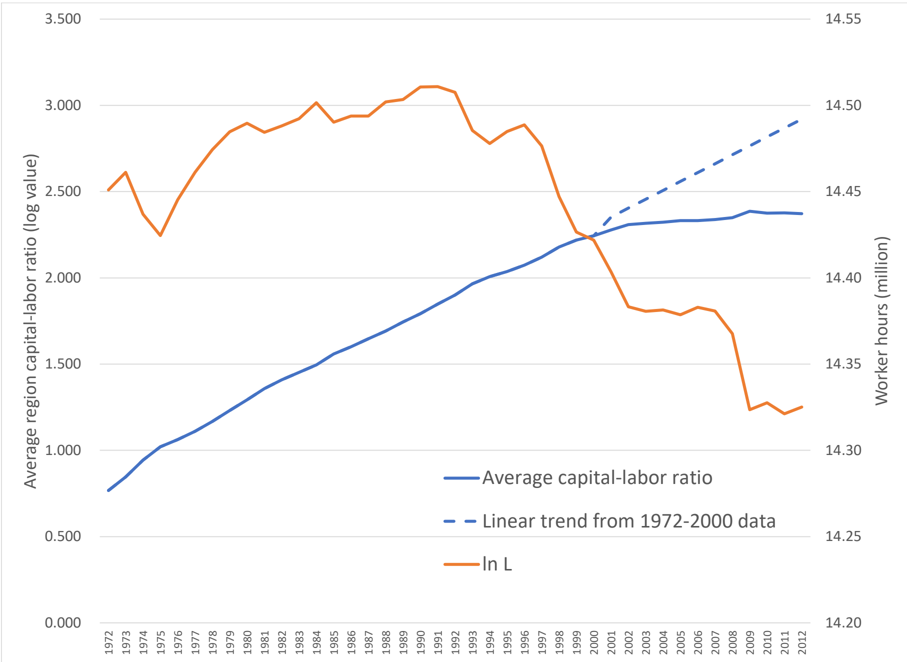
Before proceeding to the spatial regressions, it is important to check whether there is any spatial correlation. Note that there are several spatial models available. To address this issue, we employ the Lagrange multiplier test, as mentioned in Section 2.3. The choice of model depends on the following two steps. First, we compare the spatial models with an autoregressive term and/or spatial errors with that without the spatial effect.[38] Table 2 presents the results of the Lagrange multiplier test. The null hypothesis is that the model without spatial effect is valid. The alternative hypothesis is that one or more of 1) the model with an autoregressive term, 2) the model with spatial error, and 3) the model with both autoregressive term and spatial error are valid. Table 2 indicates that the model without spatial error is rejected at the 1 percent level in all the alternatives. This result suggests the existence of a statistically significant spatial effect.

Next, we examine which spatial model is more appropriate. To inform this, we conduct a Lagrange multiplier test where the null hypothesis is that each model (either the

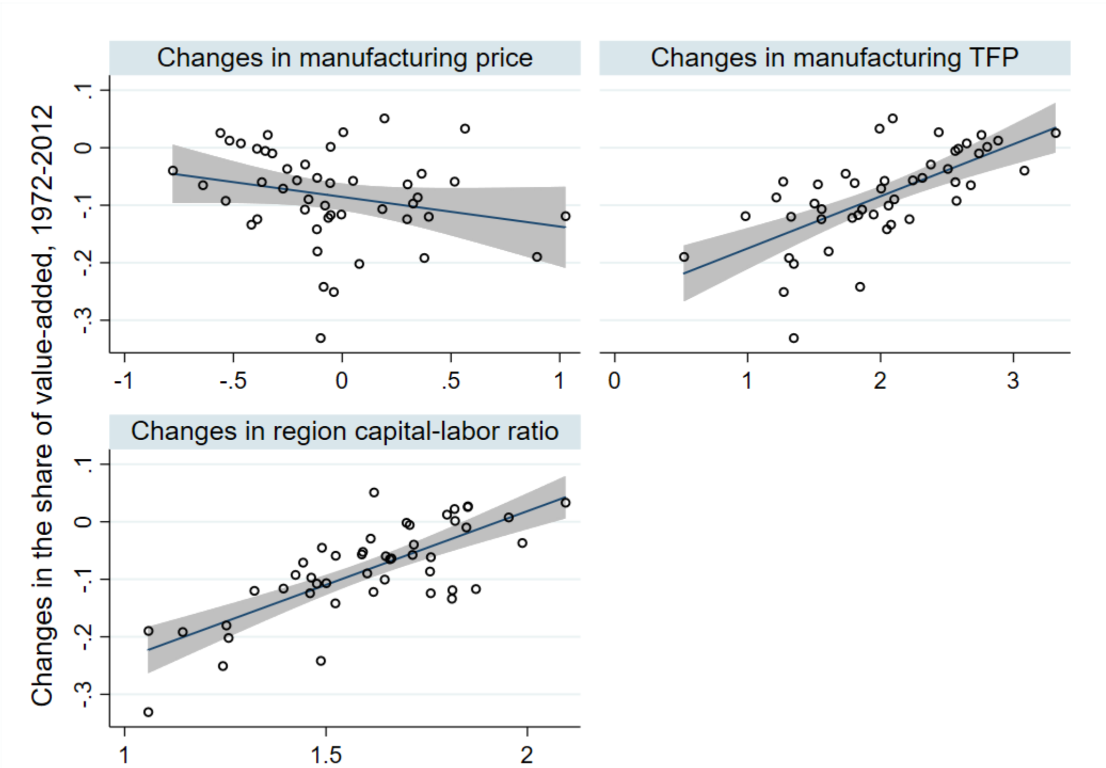
[38]The tests and estimations in this paper use the R-package `spsur` (version 1.0.0.4) developed by Ana Angulo, Fernando A. López, Roman Minguez, and Jesus Mur.

Figure 4: Changes in the Share of Value-Added and the Capital–Labor Ratio, 1972–2012

Panel A: Changes in prefecture capital–labor ratio



Panel B: Changes in the share of manufacturing value-added and key independent variables, 1972–2012



Notes: The sectoral share of value-added is computed for each prefecture. The solid line denotes the fitted value from ordinary least squares estimation. Gray areas denote 95 percent confidence intervals.

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

Table 3: Lagrange Multiplier Test for Model Selection

	Null hypothesis	
	No spatial autoregressive term & spatial errors	Spatial autoregressive term & no spatial errors
Alternative hypothesis		
Spatial autoregressive term & spatial errors	98.4 (0.000)	123.9 (0.000)

Notes: Figure in parentheses is the p-value.
Source: Author's estimation based on the RIETI (2017) R-JIP Database.

model with spatial errors but without spatial autoregressive term or the model with spatial autoregressive term but without spatial errors) is valid while the alternative hypothesis is that the model with both the spatial autoregressive term and spatial errors is valid. Table 3 presents the results. Table 3 shows that both models reject the null hypothesis. This supports the model with both a spatial autoregressive term and spatial errors. Based on these test results, a model with a spatial autoregressive term and spatial errors becomes the baseline model.

3.3 Main results

Table 4 presents the estimation results of the SUR model with spatial effects. We highlight four main findings. First, the Breusch–Pagan test statistic indicates that the null hypothesis that the error terms across equations are contemporaneously uncorrelated is rejected. This suggests that a system of equations should be estimated that accounts for the correlation of the error terms across equations. Second, the coefficients on the spatial autoregressive term are significant in Agriculture and Business services while the spatial error is significant in Agriculture, Manufacturing, and Business services. These significantly positive spatial errors suggest that the unobserved sector-year shocks are correlated locally rather than uniformly across prefectures in Japan.[39] This confirms the importance of spatial interdependence in explaining deindustrialization, which is hitherto unknown in the existing literature such as Redding (2002) and Nickell, Redding, and Swaffield (2008).

[39]This are known as "correlated effects" (Elhorst, 2010). In the context of our analysis, correlated effects imply that the neighboring prefectures face similar environments and thus common unobserved shocks.

Table 4: Regression Results: SUR With Spatial Effects

	Agriculture	Manufacturing	Other production	Business services
Relative productivity & price				
Agriculture	0.012***			
($\ln(\varphi_1 p_1/\varphi_5 p_5)$)	(0.002)			
Manufacturing	-0.019***	0.172***		
($\ln(\varphi_2 p_2/\varphi_5 p_5)$)	(0.001)	(0.003)		
Other production	0.006***	-0.028***	0.089***	
($\ln(\varphi_3 p_3/\varphi_5 p_5)$)	(0.001)	(0.001)	(0.001)	
Business services	-0.003***	-0.013***	-0.009***	0.056***
($\ln(\varphi_4 p_4/\varphi_5 p_5)$)	(0.001)	(0.001)	(0.001)	(0.001)
Relative endowment	-0.078***	0.067***	0.013***	0.007***
($\ln(K/L)$)	(0.002)	(0.004)	(0.002)	(0.001)
Spatial autoregressive term	-0.266***	-0.017	0.022	-0.235***
($\mathbf{W}\mathrm{s}$)	(0.025)	(0.018)	(0.024)	(0.022)
Spatial errors	0.315***	0.321***	0.042	0.404***
($\mathbf{Wu}$)	(0.031)	(0.027)	(0.037)	(0.028)
Number of observations	1972			
R-squared	0.943	0.976	0.950	0.966
Log-likelihood	27431.9			
Breusch-Pagan statistic	837.4***			

Notes: Figures in parentheses are standard errors. ***, **, and * denote the significance level at 1, 5, and 10 percent, respectively.

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

Third, the effects of own-sector price-productivity are significantly positive in all sectors. This suggests that increases in the own-sector price relative to the other sector or the growth of productivity lead to the increases in the sector's value-added share. This is consistent with the economic priors: that is, own-sector prices and productivity have typically significantly positive effects on the share of sectoral GDP. Fourth, although the effect of factor endowment varies across sectors, there are some similarities. For instance, even though the prefecture capital–labor ratio has positive effects in Manufacturing, Other production, and Business services, it has negative effects in Agriculture. These suggest that both Manufacturing and Business services are capital-intensive sectors whereas Agriculture and Other production are labor-intensive sectors.

Because both the own-sector price and endowment display significant coefficients that conform to their expected signs, the neoclassical model well explains the uneven pace of deindustrialization across prefectures within Japan. While the analysis could identify the possible factors in explaining the regional unevenness of deindustrialization, it does not identify the relative importance of each factor. The following section addresses this along with some other specification issues.

Note that the analysis in this paper is positive rather than normative. It thus is unable to evaluate whether deindustrialization itself is desirable or not. Nevertheless, if rapid deindustrialization involves large adjustment costs, the welfare gains from deindustrialization will decline. In that case, the results suggest that policies to mitigate rapid price changes or to facilitate factor movements across sectors may be helpful to accommodate the deindustrialization process.

3.4 Alternative models

In addition to the baseline model, we estimate the following alternative models to address various concerns:

1. A model without spatial effects
2. A model with alternative fixed effects
3. A model without fixed effects
4. A model with an alternative weighting matrix

5. A model with an alternative measure of labor input

6. A model with an alternative sample period

This subsection briefly summarizes the concerns and results. More detailed results are presented in Appendix D.

The first concern is how the results change if the analysis ignores the spatial effect. To respond to this question, we estimate the system of equations assuming no spatial effects. The results indicate that all the estimated coefficients, except for the coefficients on the spatial terms that are excluded from the regression, provide the same signs and significance levels (Table D1).

However, the magnitudes are slightly different. For example, for Manufacturing, the coefficient for the prefecture capital–labor ratio declines from the baseline model to the model without spatial effects. This suggests that the coefficients on these variables will be underestimated if spatial effects are not considered.

The second concern is that the use of a sector–5-year fixed effect may not be sufficient to control for the movement of labor or unobserved demand and/or supply shocks more generally. However, it is difficult to include both a year fixed effect and a spatial autoregressive term simultaneously (see Section 2.3). To check the sensitivity of the results while avoiding multicollinearity, we specify a 2-year fixed effect instead of 5-year fixed effect, which allows us to account for short-term unobserved economic shocks. The results indicate that the sign and significance level of the coefficients show little difference from those for the baseline results (Table D2). This reassures us about the robustness of our results when the analysis considers short-term demand and/or supply shocks.

The third concern is whether the results change when the analysis excludes prefecture–sector and sector–5-year fixed effects. To address this concern, we re-estimate the system of equations after removing these fixed effects. The estimation results indicate that some of the coefficients have different signs from those of the baseline model (Table D3). These suggest the importance of controlling for unobserved prefecture–sector and sector–period fixed effects.

The fourth concern is whether the weighting matrix employed in the baseline analysis is appropriate. In the baseline analysis, the spatial weighting matrix is constructed, based on whether the prefectures are contiguous. In Japan, all prefectures are connected by roads if they have common borders. Nevertheless, the existence of a road connection does not necessarily infer large transactions between these prefectures because some prefectures are connected by only minor roads.

For example, Nagano prefecture, which is surrounded by mountains, is contiguous with eight other prefectures, the most of any prefecture. However, three of these prefectures are connected by neither highways nor railways, just ordinary roads. It may thus be difficult to imagine that Nagano prefecture is equally interdependent with its eight neighboring prefectures. To address issue, we use an alternative weighting matrix, defining contiguity only when prefectures are directly connected by highways or railways.

The results indicate that while the spatial effects become insignificant for Business services, the sign and significance levels are the same for all sectors (Table D4). Moreover, the estimated coefficients are almost the same as those of the baseline results for Manufacturing, except for the coefficients of spatial terms. The results are thus robust even when contiguity is defined as highway and railway connections.

The fifth concern lies in the measurement of the labor input in the baseline analysis. Although the baseline analysis does not consider differences in skill composition between prefectures, deindustrialization may also be affected by skill abundance. As discussed, labor is not disaggregated by skills in the 2017 R-JIP Database. To crudely consider the differences in skill composition across prefectures, we use total wages rather than work hours at the prefecture level as the measure of labor endowment. Hsieh and Klenow (2009) also employ this approach to consider the differences in hours worked and human capital. The data on total wages by prefecture are also available in the 2017 R-JIP Database.

The estimation results using the alternative measure of labor input indicate that the estimated coefficients are again mostly the same as those of the baseline results for Manufacturing (Table D5). One notable difference is that the coefficient for the spatial autoregressive term becomes significantly positive. This suggests that the effect of spatial interdependence is more evident given skill difference in the labor input. Otherwise, the baseline results are mostly robust.

The final issue is the effect of labor mobility. Although the size of migration declined after 1970, Fujita, Mori, Henderson, and Kanemoto (2004) found that the Tokyo metropolitan area experienced a high rate of net migration around the mid-1980s. The estimation results thus may be affected by labor mobility. Unfortunately, it is difficult to control for the effect of factor mobility in this framework. As a compromise, we estimate the model, focusing only on the latter half of the sample period (i.e., between 1992 and 2012) when labor mobility was lower than the first half of the sample period.

From the estimation results (Table D6), we can see that the estimated coefficients are almost the same as those of the baseline results for Manufacturing. A notable difference is that the coefficient for the spatial autoregressive term is now significant. The effect of spatial interdependence is thus more evident in the more recent period.

In this regard, the data may not reflect current fast-changing realities because the sample period in the 2017 R-JIP Database ends in 2012. The latest version of the 2021 R-JIP Database was released in March 2022 (RIETI, 2022).[40] The 2021 R-JIP Database was substantially revised from the previous version (i.e., 2017 R-JIP Database). For example, the sample period of 2021 R-JIP Database is 1994–2018, which is significantly shorter than the sample period of the previous version (i.e., 1972–2012 in the 2017 R-JIP Database). The changes in the share of manufacturing value-added were also small after 2012 in Japan (on average, 21.6 percent in 2012 to 23.0 percent in 2018).

Because the 2021 R-JIP Database is not directly comparable to the 2017 R-JIP Database given the changes in the data compilation, the data cannot be extended from 1972–2012 to 1972–2018. Accordingly, given our focus is the long-run (over four decades) changes in manufacturing, we present the results using the 2021 R-JIP Database as a further robustness check.

The estimation results (Table D7) indicate that the estimated coefficients are generally the same as those of the baseline results for Manufacturing. However, there are two notable differences. First, the coefficient for the capital–labor ratio is insignificant for manufacturing. As confirmed in Panel A in Figure 4, capital accumulation in Japan slowed after 2000. This may suggest that with the growth of other countries like China, Japan is losing its earlier comparative advantage in capital-intensive sectors. Second, like the results using the alternative measure of labor input, the coefficient of the spa-

[40] Unlike the country-level JIP Database, the regional-level JIP Database is not updated as frequently. For details, see https://www.rieti.go.jp/en/database/r-jip.html

tial autoregressive term become significantly negative. This implies that the effect of spatial interdependence becomes more important recently. However, the main finding of the analysis is unchanged, even when we focus on a more recent period.

4 Discussion

4.1 Economic magnitude

The estimation results confirm the statistically significant effects of spatial interdependence. Another important question is how large the spatial effects are because statistically significant results do not necessarily infer economically significant results. Note that based on the estimated coefficients, the regression equation is written as:

$$\begin{aligned} s_{jzt} &= \hat{\beta}_{0j} + \sum_k \hat{\beta}_{jk} \ln \frac{\varphi_{kzt} p_{kt}}{\varphi_{5zt} p_{5zt}} + \hat{\gamma}_j \ln \frac{K_{zt}}{L_{zt}} \\ &\quad + \hat{\lambda}_j \left(\sum_m w_{zm} s_{jmt} \right) + \hat{\alpha}_{jz} + \hat{\alpha}_{j\mathcal{T}} + \hat{\rho} u_{jzt} + \varepsilon_{jzt}. \end{aligned} \tag{7}$$

The second term can be decomposed into the price and productivity terms. Taking the difference between $t = 0$ and $t = T$, it is possible to decompose the changes into the share of manufacturing GDP to the effects of prices, productivity, and endowments as well as the spatial effect:[41]

$$\begin{aligned} \Delta s_{jzT} &= \underbrace{\sum_k \hat{\beta}_{jk} \Delta \ln \frac{\varphi_{kzT}}{\varphi_{5zT}}}_{\text{Productivity effect}} + \underbrace{\sum_k \hat{\beta}_{jk} \Delta \ln \frac{p_{kzT}}{p_{5zT}}}_{\text{Price effect}} \\ &\quad + \underbrace{\hat{\gamma}_j \Delta \ln(K_{zT}/L_{zT})}_{\text{Endowment effect}} + \underbrace{\Delta \hat{\alpha}_{j\mathcal{T}}}_{\text{Period effect}} + \underbrace{\hat{\lambda} \Delta W s_{jzT} + \hat{\rho} \Delta u_{jzT}}_{\text{Spatial effect}} + \underbrace{\Delta \varepsilon_{jzt}}_{\text{Error}}, \end{aligned} \tag{8}$$

where Δ is the difference between $t = 0$ and $t = T$. In this exercise, we focus on the changes between 1972 and 2012. The estimated coefficients are based on the main results in Table 4. Note that as mentioned in footnote 10, any effects of preferences including nonhomothetic preferences will appear through relative prices because the model does not make any assumptions on consumer preferences.

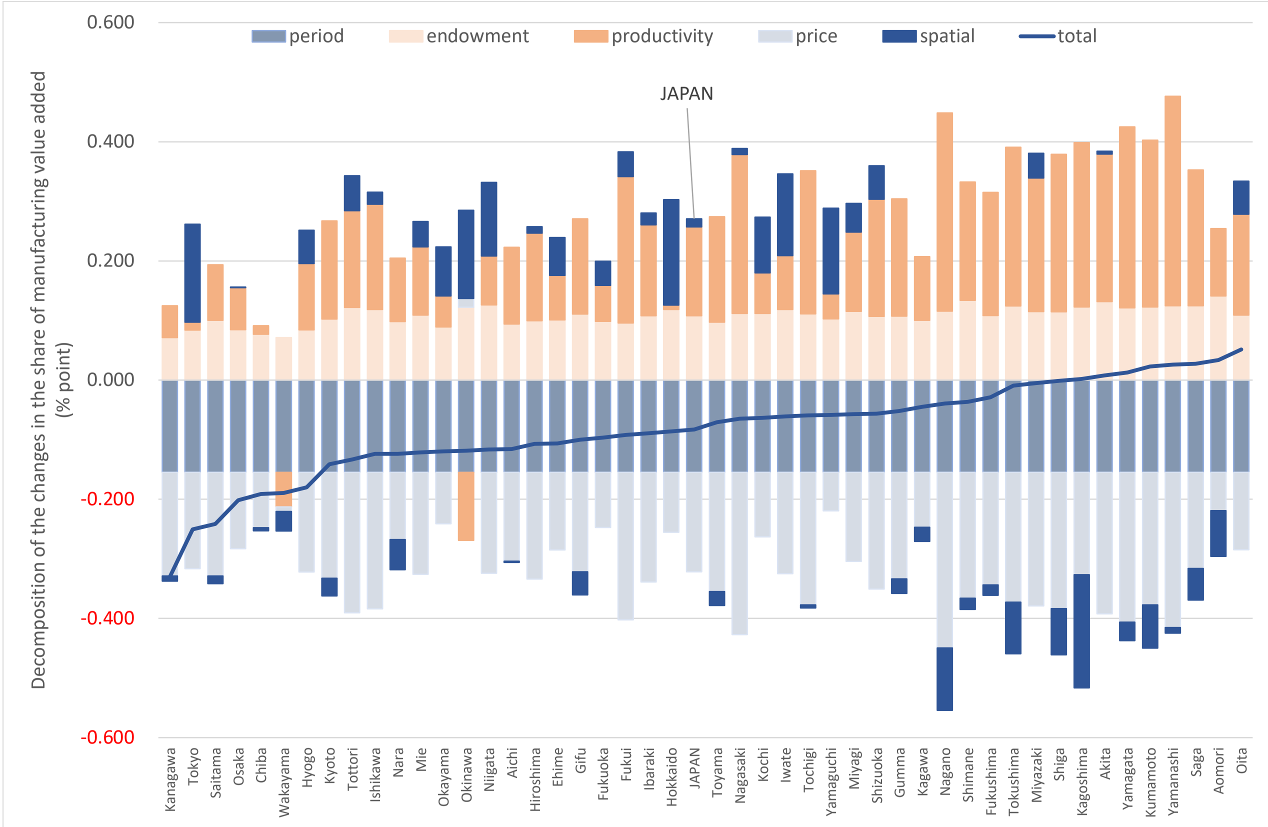
Figure 5 presents the decomposition results of equation (8) for manufacturing in

[41] Other studies employ a similar decomposition exercise. For example, see, Harrison and McMillan (2011) and Kambayashi and Kiyota (2015).

Japan as a whole and by prefecture. For ease of explanation, we suppress the changes in the error term. The major findings are threefold. First, in Japan as a whole (i.e., JAPAN in Figure 5), the negative price and period effects outweigh the positive effects of productivity and endowment. In particular, the negative contribution of price is large. As a result, the share of Manufacturing GDP declined. The large negative period effect suggests the importance of unobserved period-specific factors, such as demand and/or supply shocks.

Second, at the prefecture level, the price and productivity effects exhibit larger variations than the endowment and period effects. This suggests that the contribution of these effects varies across prefectures. This in turn implies that the large variation in deindustrialization within a country is attributable to differences in productivity and price changes across prefectures. In contrast, the effect of the slowdown in capital accumulation (Panel A in Figure 4), at least partly from the expansion of FDI or offshoring, appears not in specific prefectures but is common to all prefectures. Note that the variation in the changes in productivity and price across prefectures arises from the differences in the composition of industry within manufacturing. Prefectures with industries that face sharp price declines and/or exhibit slow productivity growth are more likely to deindustrialize. The following subsection discusses this in more detail.

Figure 5: Changes in the Share of Manufacturing Value-Added by Prefecture: Decomposition by Contribution



Notes: JAPAN is the prefecture average for Japan. Manufacturing value-added is based on current prices.

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

30

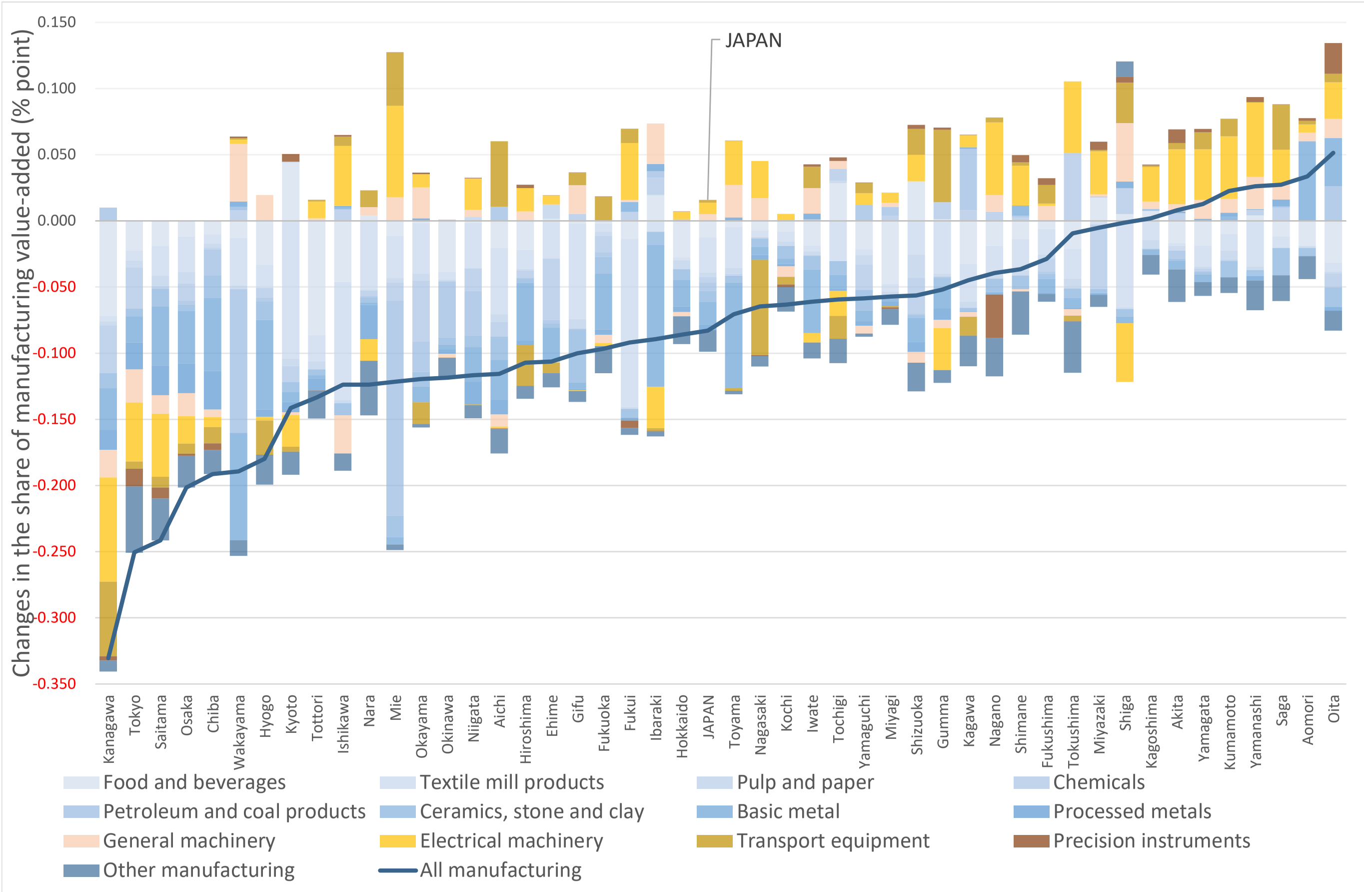
Finally, the effect of spatial interdependence also matters. At first sight, the average spatial effect looks small in Japan as a whole. However, this is because the prefecture-level positive and negative effects offset each other. Indeed, the spatial effect has both large positive and negative effects in some prefectures. This suggests that the deindustrialization of a particular prefecture could also affect neighboring prefectures. It is important to note that the spatial effect here is measured at the prefecture level. Therefore, even though our analysis captures the spatial interdependence across prefectures, it cannot capture the spatial interdependence within a prefecture across cities or towns. The spatial effect may then be more important in a detailed geographic classification.

4.2 Do the changes in industry composition within Manufacturing matter?

In this paper, we focus on the changes in the share of manufacturing value-added as a whole. A concern may then be that the changes in productivity and prices reflect the changes in the composition of industries within the Manufacturing sector rather than changes in the productivity and prices themselves because the Manufacturing sector includes 13 industries in the R-JIP Database.

Figure 6 presents the changes in the share of manufacturing value-added by prefecture. The solid line is the total changes in the Manufacturing sector, which equals the vertical difference between 1972 and 2012 in Figure 2 for each prefecture. The prefectures are sorted from left to right, based on the changes in the total share of the Manufacturing sector from 1972 to 2012.

Figure 6: Changes in the Share of Manufacturing Value-Added by Prefecture: Decomposition by Industry



Notes: JAPAN is the prefecture average for Japan. Manufacturing value-added is based on current prices.
Source: Author's estimation based on the RIETI (2017) R-JIP Database.

32

There are two notable findings in Figure 6. First, for Japan as a whole (i.e., JAPAN in Figure 6), the value-added share declined in all manufacturing industries except for machinery industries (i.e., General machinery, Electrical machinery, Transport equipment, and Precision instruments). This suggests that the declining share of value-added is a trend common to almost all manufacturing industries in Japan. Second, although it is not easy to identify a common pattern across prefectures, changes in industry structure suggest that the changes in aggregate productivity and prices are from the changes in the composition of industries rather than the changes in productivity and prices themselves.

To address this further, we apply the alternative decomposition exercise developed by Foster, Haltiwanger, and Krizan (2001). Let Z be the Manufacturing productivity or price aggregated from more detailed manufacturing industries. Denote each detailed manufacturing industry as f. Define the productivity or price at the aggregate manufacturing level as:

$$\ln Z_t \equiv \sum_f v_{ft} \ln z_{ft}, \tag{9}$$

where v_{ft} is the share of value-added industry f at year t and z_{ft} is either productivity or price of industry f at year t. Following Foster, Haltiwanger, and Krizan (2001), decompose the aggregate growth of the Manufacturing variable from $t-1$ to t, $\ln Z_t - \ln Z_{t-1}$, as follows:

$$\begin{aligned} \ln Z_t - \ln Z_{t-1} \quad \simeq \quad & \underbrace{\sum_f v_{f,t-1} \Delta \ln z_{ft}}_{\text{Within effect}} \\ & + \underbrace{\sum_f \Delta v_{ft} \left(\ln z_{f,t-1} - \overline{\ln z_{t-1}} \right)}_{\text{Between effect}} + \underbrace{\sum_f \Delta v_{it} \Delta \ln z_{ft}}_{\text{Covariance effect}}, \end{aligned} \tag{10}$$

where Δ is the difference between year $t-1$ and year t. An upper bar denotes the arithmetic average.

This decomposition consists of three parts. The first term is a within-industry component based on changes in each industry, weighted by the value-added share in year $t-1$. Because this reflects the change within each industry, it is called the "within effect." The second term represents a between-industry component that reflects changing value-added shares, weighted by the deviation of each industry in year $t-1$ from the average. An increase in the value-added share contributes positively to the between-industry component only when the industry has higher productivity or price than average in year $t-1$. This is a "between effect" because it reflects the reallocation of resources between industries. The final term represents a covariance term and is the "covariance effect." This term makes a positive contribution if industries that increased productivity or price were more likely to do so by generating additional value-added. If the changes in aggregate manufacturing are driven by changes in the composition of industries, a large contribution of the between effect is expected.

Table 5 presents the decomposition results. We highlight two main findings. First, productivity growth is primarily from the within effect. This implies that the changes in industry composition do not have a significant effect on the growth of aggregate manufacturing productivity. Second, in contrast, the changes in the price of aggregate manufacturing are mainly from the covariance effect, not the between effect. This suggests that the changes in industry composition within manufacturing alone cannot be the main source of changes in the aggregate manufacturing price. In other words, not only the changes in industry composition but also those in prices affect the changes in the aggregate manufacturing price.

Table 5: Decomposition of the Effects for Manufacturing: Industry Composition

	Total change	Within effect	Between effect	Covariance effect
TFP	1.779	1.648	-0.115	0.247
Price	-0.065	0.012	0.070	-0.147

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

4.3 Where does this price change come from?

The previous subsections showed that the negative contribution of price is large and that the changes in industry composition within manufacturing alone cannot be the main source of changes in the aggregate manufacturing price. One may then ask why the price effect is so large. While identifying the source of the declining price itself is a major concern in Japan, for which more detailed analysis is required, this subsection briefly discusses several reasons implied by both the findings of this study and previous studies.

There are at least five possibilities. The first is transportation costs because they have continuously declined over time (Anderson and van Wincoop, 2004). What is puzzling, however, is that the sectoral prices changed nonmonotonically over the period. The changes in the sectoral prices indicated an inverse U-shape (Figure 3), which does not correspond to the continuous decline in transportation costs. Accordingly, although the change in transportation costs could be one of the factors, there seems to be more important ones.

The second is the effect of technology growth, which enables firms to reduce their marginal costs. If technology growth is more rapid in manufacturing than other sectors, this may result in the decline of relative manufacturing prices. However, our analysis has already considered the effect of technology growth by introducing TFP into the regression analysis. Therefore, the effect of technology growth on relative price seems to be, if anything, marginal.

The third possible reason is the effect of deflation. Following the second half of the 1990s, Japan suffered a period of prolonged deflation, in which the consumer price index has declined in general (Watanabe and Watanabe, 2018). Thus, one may argue that the declining manufacturing price is attributable to deflation. However, the analysis covers the period between 1972 and 2012, which includes not only a deflation period but also an inflation period. Indeed, among five sectors in the analysis, only the Manufacturing sector experienced a decline in price over the period between 1972 and 2012 (Table B3). More importantly, the manufacturing price is measured as the price relative to that in Other services. In that sense, the key question may be why the price of manufacturing declines more rapidly than in Other services. Although deflation can explain the decline in *absolute price* of manufacturing (i.e., p_{2zt}), it does not necessary explain the decline in the *relative price* of manufacturing (i.e., p_{2zt}/p_{5zt}).

The fourth reason is the effect of imports from low-wage countries that produce less-expensive goods than high-wage countries.[42] The domestic manufacturing price may also decline as imports from low-wage countries expand. Noting that imports affect tradable goods only, it is plausible that the decline in the relative price of manu-

[42] In this sense, one may be concerned about the effects of the decline in export prices because Japanese terms of trade (i.e., the ratio of export to import prices) declined over the period. However, this is attributable to the increases in import prices rather than a decline in export prices, where the increases in import prices are attributable to a rise in the price of the natural resources (e.g., oil). Therefore, the effects of the decline in export prices do not seem to be a strong reason.

facturing can be attributed to increasing imports from low-wage countries. Besides, the decline in the aggregate manufacturing price started in the mid-1990s (Figure 3), which coincides with the establishment of the World Trade Organization. Indeed, Zeng and Zhao (2010) developed a theoretical model showing that globalization causes deindustrialization.[43] Dauth and Suedekum (2016) found that deindustrialization was driven by increases in international trade. Our results are also consistent with their findings. However, Broda and Weinstein (2010) found that the effect of Chinese exports on Japanese prices was small between 1992 and 2005. Their analysis can be improved because they address a shorter period than in this analysis and focus only on imports from China. In sum, the effects of imports on domestic price remain ambiguous. More detailed analysis is needed.

The fifth reason is the declining markup. Several studies have pointed out the declining markup of Japanese firms. For example, Kiyota, Nakajima, and Nishimura (2009) concluded that the average markup of Japanese firms declined from the 1970s and 1980s to the 1990s. Similarly, Kiyota (2018) showed that the markup of Japanese manufacturing firms declined between 1995 and 2012 based on study by Dobbelaere and Kiyota (2018). A more recent study by Nakamura and Ohashi (2019) also indicated a slight decline in the markup of Japanese manufacturing firms from 2001 to 2016. Because the analysis in this paper relies on neoclassical trade theory, price does not include markup. However, the actual data may include markup. The declining relative price of manufacturing may thus be attributable to the declining markup of Japanese firms due to, for example, increasing competition among firms.

In sum, the decline in markup of Japanese manufacturing firms is one of the possible reasons explaining the large negative price effect on deindustrialization. Increasing imports from low-wage countries is another possible reason. In contrast, other factors such as technology growth, deflation, and the changes in transportation costs do not seem to be strong reasons. However, more detailed analysis is needed to explain why the relative price of manufacturing has declined so rapidly.

[43] Their model is based on a new economic geography model while our empirical framework is based on a neoclassical trade model. Although the results are consistent with the implications of their model, we do not necessarily test the empirical validity of their model.

5 Concluding Remarks

The declining share of manufacturing value-added, often called "deindustrialization," is becoming a major concern for policymakers as well as academic researchers, especially in high-income countries. Compared with country-level analysis, however, the regional-level analysis of deindustrialization within a country remains limited. Against this background, this paper empirically examines how and why deindustrialization patterns vary across regions within a country. Our theoretical and empirical approach is based on a series of studies by Redding and colleagues (Redding, 2002; Redding and Vera-Martin, 2006; Nickel, Redding, and Swaffield, 2008), which analyzed cross-country specialization patterns, building upon neoclassical trade theory. The contribution of this study is to: 1) consider the spatial interdependence of deindustrialization across regions using spatial econometric techniques and 2) quantify the contribution of those factors that could affect deindustrialization.

Focusing on regions in Japan over the last four decades, we found that the large variation of deindustrialization within a country is attributable to differences in productivity and price changes across prefectures. This implies that prefectures with manufacturing industries that face sharp price declines and/or exhibit slow productivity growth are more likely to deindustrialize. In contrast, it appears that the effect of the slowdown of capital accumulation, partly caused by the expansion of FDI or offshoring, is common to all prefectures rather than to specific prefectures. The effect of spatial interdependence is not only statistically significant but also nonnegligible in terms of its magnitude. This confirms the importance of the spatial interdependence in explaining deindustrialization, which is unknown in the existing literature such as Redding (2002) and Nickell, Redding, and Swaffield (2008). Another important finding is that the changes in aggregate manufacturing productivity and price cannot be attributable to the change in industry composition within manufacturing alone. Such price changes in manufacturing may come from several factors such as increasing competition from low-wage countries and declining markups. However, more detailed analysis is needed to explain why the relative price of manufacturing has declined rapidly.

These findings also have an important policy implication in that the decline in the manufacturing share can be mitigated by productivity growth, as the largest variation in deindustrialization is attributable to differences in productivity and price changes. It is important to note that productivity is measured at the sector level rather than at the firm level. This is important as sectoral productivity growth is not only achievable through the productivity growth of firms, but also through the entry of more productive firms and the exit of less productive firms (Nishimura, Nakajima, and Kiyota, 2005). Even though deindustrialization itself is inevitable for advanced countries, it is important for policymakers to recognize that its shock can be accommodated by the turnover of firms along with the productivity growth of existing firms.

This study also has some limitations. First, the main contributions of this study are empirical, and we acknowledge that the paper lacks theoretical innovation. Second, the analysis does not address potential endogeneity because of technical difficulty in developing a SUR including a spatial effect. Nonetheless, this paper contributes majorly to the literature by introducing a new technique and presenting new findings.

Before closing, we point out several remaining research challenges. First, addressing the potential endogeneity in the SUR with the spatial effect is an important issue. To do so, more advanced econometric techniques are required. Second, another interesting research avenue would be to investigate the sources of the price effects in greater detail. Identifying the sources of these price changes will have useful implications for policymakers as well as academic researchers. Finally, it is important to investigate adjustment mechanisms in more detail at the micro level using, for example, establishment-level data.[44] The construction of establishment-level panel data covering both manufacturing and nonmanufacturing industries would enable us to address this and other concerns in future research.

References

Allen, Treb and Costas Arkolakis (2014) "Trade and the Topography of the Spatial Economy," *Quarterly Journal of Economics*, 129(3): 1085–1139.

Anderson, James E. and Eric van Wincoop (2004) "Trade Costs," *Journal of Economic Literature*, 42(3): 691–751.

[44] In this context, Fort, Pierce, and Schott (2018) decomposed the decline in US manufacturing employment into decline caused by the exit of plants and decline caused by the contraction of continuing plants.

Autor, David H., David Dorn, and Gordon H. Hanson (2013) "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103(6): 2121–2168.

Baldwin, Richard and Dany Jaimovich (2012) "Are Free Trade Agreements Contagious?" *Journal of International Economics*, 88(1): 1–16.

Bernard, Andrew B., Valerie Smeets, and Frederic Warzynski (2017) "Rethinking Deindustrialization," *Economic Policy*, 32(89): 5–38.

Bernard, Andrew B., Stephen J. Redding, and Peter K. Schott (2013) "Testing for Factor Price Equality with Unobserved Differences in Factor Quality or Productivity," *American Economic Journal: Microeconomics*, 5(2): 135–163.

Bivand, Roger, Giovanni Millo, and Gianfranco Piras (2021) "A Review of Software for Spatial Econometrics in R," *Mathematics*, 9: 1276.

Broda, Christian and David E. Weinstein (2010) "Exporting Deflation? Chinese Exports and Japanese Prices," in Robert C. Feenstra and Shang-Jin Wei (eds.) *China's Growing Role in World Trade*, Chicago, IL: University of Chicago Press and National Bureau of Economic Research, 203–227.

Cicerone, Gloria, Philip McCann, and Viktor A. Venhorst (2020) "Promoting Regional Growth and Innovation: Relatedness, Revealed Comparative Advantage and the Product Space," *Journal of Economic Geography*, 20(1): 293–316.

Dauth, Wolfgang and Jens Suedekum (2016) "Globalization and Local Profiles of Economic Growth and Industrial Change," *Journal of Economic Geography*, 16(5): 1007–1034.

Desmet, Klaus and Esteban Ross-Hansberg (2014) "Spatial Development," *American Economic Review*, 104(4): 1211-1243.

Dix-Carneiro, Rafael (2019) "Trade and Labor Market Adjustment: Recent Evidence from Brazil," in Luís A.V. Catão and Maurice Obstfeld (eds.), *Meeting Globalization's Challenges*, Princeton, NJ: Princeton University Press.

Dobbelaere, Sabien and Kozo Kiyota (2018) “Labor Market Imperfections, Markups and Productivity in Multinationals and Exporters,” *Labour Economics*, 53: 198–212.

Eaton, Jonathan and Samuel Kortum (2002) “Technology, Geography, and Trade,” *Econometrica*, 70(5): 1741–1779.

Elhorst, Paul J. (2010) “Spatial Panel Data Models,” in Manfred M. Fischer and Arthur Getis (eds.), *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications*, Springer.

Fort, Teresa C., Justin R. Pierce, and Peter K. Schott (2018) “New Perspectives on the Decline of US Manufacturing Employment,” *Journal of Economic Perspectives*, 32(2): 47–72.

Foster, Lucia, John C. Haltiwanger, and C.J. Krizan (2001) “Aggregate Productivity Growth: Lessons from Microeconomic Evidence,” in Charles R. Hulten, Edwin R. Dean, and Michael J. Harper (eds.), *New Developments in Productivity Analysis*, Chicago, IL: University of Chicago Press, 303–372.

Fujita, Masahisa, Tomoya Mori, J. Vernon Henderson, and Yoshitsugu Kanemoto (2004) “Spatial Distribution of Economic Activities in Japan and China,” J. Vernon Henderson and Jacque F. Thisse (eds.), *Handbook of Regional and Urban Economics, Volume 4*, 2911–2977.

Gandhi, Amit, Salvador Navarro, and David A. Rivers (2020) “On the Identification of Gross Output Production Functions,” *Journal of Political Economy*, 128(8): 2973–3016.

Greaney, Theresa M. and Kozo Kiyota (2020) “Japan’s Outward FDI Potential,” *Journal of the Japanese and International Economies*, 57: 101073.

Harrison, Ann and Margaret McMillan (2011) “Offshoring Jobs? Multinationals and U.S. Manufacturing Employment,” *Review of Economics and Statistics*, 93(3): 857–875.

Hsieh, Chang-Tai and Peter J. Klenow (2009) “Misallocation and Manufacturing TFP in China and India,” *Quarterly Journal of Economics*, 124(4): 1403–1448.

Kambayashi, Ryo and Kozo Kiyota (2015) "Disemployment Caused by Foreign Direct Investment? Multinationals and Japanese Employment," *Review of World Economics*, 151(3): 433–460.

Kiyota, Kozo (2012) "A Many-cone World?" *Journal of International Economics*, 86(2): 345–354.

Kiyota, Kozo (2018) "Labor Market Imperfections, Markups and Productivity in Multinationals and Exporters: Non-Technical Summary," Research Institute of Economy, Trade, and Industry (RIETI) Website:

(https://www.rieti.go.jp/jp/publications/nts/18e033.html). (In Japanese)

Kiyota, Kozo, Takanobu Nakajima and Kiyohiko G. Nishimura (2009) "Measurement of the Market Power of Firms: The Japanese Case in the 1990s," *Industrial and Corporate Change*, 18(3): 381–414.

Klemm, Alexander and Stefan Van Parys (2012) "Empirical Evidence on the Effects of Tax Incentives," *International Tax and Public Finance*, 19(3): 393–423.

Matsuyama, Kiminori (2019) "Engel's Law in the Global Economy: Demand-Induced Patterns of Structural Change, Innovation, and Trade," *Econometrica*, 87(2): 497–528.

Morrow, Peter M. (2010) "Ricardian–Heckscher–Ohlin Comparative Advantage: Theory and Evidence," *Journal of International Economics*, 82(2): 137–151.

Mur, Jesús, Fernando López, and Marcos Herrera (2010) "Testing for Spatial Effects in Seemingly Unrelated Regressions," *Spatial Economic Analysis*, 5(4): 399–440.

Murakami, Naoki (2015) "Changes in Japanese Industrial Structure and Urbanization: Evidence from Prefectural Data," *Journal of the Asia Pacific Economy*, 20(3): 385–403.

Murata, Yasusada (2008) "Engel's Law, Petty's Law, and Agglomeration," *Journal of Development Economics*, 87(1): 161–177.

Nakamura, Tsuyoshi and Hiroshi Ohashi (2019) "Linkage of Markups through Transaction," RIETI Discussion Paper Series, 19-E-107, Research Institute of Economy, Trade and Industry (RIETI).

Nickell, Stephen, Stephen Redding, and Joanna Swaffield (2008) "The Uneven Pace of Deindustrialisation in the OECD," *The World Economy*, 31(9): 1154–1184.

Nishimura, Kiyohiko G., Takanobu Nakajima, and Kozo Kiyota (2005) "Does the Natural Selection Mechanism Still Work in Severe Recessions? - Examination of the Japanese Economy in the 1990s," *Journal of Economic Behavior and Organization*, 58(1): 53–78.

Olney, William W. (2013) "A Race to the Bottom? Employment Protection and Foreign Direct Investment," *Journal of International Economics*, 91(2): 191–203.

Redding, Stephen (2002) "Specialization Dynamics," *Journal of International Economics*, 58(2): 299–334.

Redding, Stephen and Mercedes Vera-Martin (2006) "Factor Endowments and Production in European Regions," *Review of World Economics*, 142(1): 1–32.

Rodrik, Dani (2016) "Premature Deindustrialization," *Journal of Economic Growth*, 21(1): 1–33.

Taniguchi, Mina (2019) "The Effect of an Increase in Imports from China on Local Labor Markets in Japan," *Journal of the Japanese and International Economies*, 51: 1–18.

Tokui, Joji, Tatsuji Makino, Kyoji Fukao, Tsutomu Miyagawa, Nobuyuki Arai, Sonoe Arai, Tomohiko Inui, Kazuyasu Kawasaki, Naomi Kodama, and Naohiro Noguchi (2013) "Compilation of the Regional-Level Japan Industrial Productivity Database," RIETI Discussion Paper Series, 13-J-037, Research Institute of Economy, Trade and Industry (RIETI). (In Japanese)

Tokui, Joji and Tatsuji Makino (2022) "Estimation Method and Analysis of R-JIP Database 2021," RIETI Discussion Paper Series, 22-J-007, Research Institute of Economy, Trade and Industry (RIETI). (In Japanese)

Watanabe, Kota and Tsutomu Watanabe (2018) "Why Has Japan Failed to Escape from Deflation?" *Asian Economic Policy Review*, 13: 23–41.

Zeng, Dao-Zhi and Laixun Zhao (2010) "Globalization, Interregional and International Inequalities," *Journal of Urban Economics*, 67(3): 352–361.

A Derivation of equation (2)

This appendix explains the derivation of equation (2) from equation (1). To simplify the notation, denote revenue function as $r = \sum_j p_j y_j$. We drop the subscript z and t for ease of exposition. Taking the log of revenue and differentiating it with respect to the log of price i, we have:

$$\frac{d \ln r}{d \ln p_j} = \frac{dr}{r} \frac{p_j}{dp_j} = \frac{p_j}{r} \frac{dr}{dp_j} = \frac{p_j}{r} y_j = \frac{p_j y_j}{r} = s_j, \tag{A1}$$

where s_j is the revenue share of industry j, which corresponds to the left-hand-side of equation (2).

To further simplify the notation, drop productivity term φ for the moment, and rewrite the revenue function as:

$$\begin{aligned} r &= \beta_{00} + \sum_j \beta_{0j} x_j + \frac{1}{2} \sum_j \sum_k \beta_{jk} x_j x_k \\ &\quad + \sum_i \delta_{0i} z_i + \frac{1}{2} \sum_i \sum_h \delta_{ih} z_i z_h + \sum_j \sum_i \gamma_{ji} x_j z_i, \end{aligned} \tag{A2}$$

where $x_j = \ln p_j$ and $z_h = \ln v_i$. Differentiating the revenue function with respect to x_j ($=$ the log of p_j), the intercept β_{00} and the first and the second terms in the second line in equation (A2) disappear because these terms do not have x_j. Also note that

- Second term:

$$\sum_j \beta_{0j} x_j = \beta_{01} x_1 + \beta_{02} x_2 + ... + \beta_{0j} x_j. \tag{A3}$$

  From $d \ln r / d \ln x_j$, the second term $= \beta_{0j}$.

- Third term:

$$\frac{1}{2} \sum_j \sum_k \beta_{jk} x_j x_k = \frac{1}{2} \left(\beta_{1j} x_1 x_j + \beta_{2j} x_2 x_j + ... + \beta_{j1} x_j x_1 + ... + \beta_{jk} x_j x_k + ... \right).$$

  Because $\beta_{jk} = \beta_{kj}$, from $d \ln r / d \ln x_j$, the third term becomes:

$$\frac{1}{2} \left(2\beta_{j1} x_1 + 2\beta_{j2} x_2 + ... + 2\beta_{jk} x_k + ... \right) = \sum_k \beta_{jk} x_k. \tag{A4}$$

- Last term:

$$\sum_j \sum_i \gamma_{ji} x_j z_i = \gamma_{11} x_1 z_1 + ... + \gamma_{1i} x_1 z_i + ... + \gamma_{j1} x_j z_1 + ... + \gamma_{ji} x_j z_i + ... \tag{A5}$$

  From $d \ln r / d \ln x_j$, the last term becomes:

$$\gamma_{j1} z_1 + ... + \gamma_{ji} z_i + ... = \sum_i \gamma_{ji} z_i. \tag{A6}$$

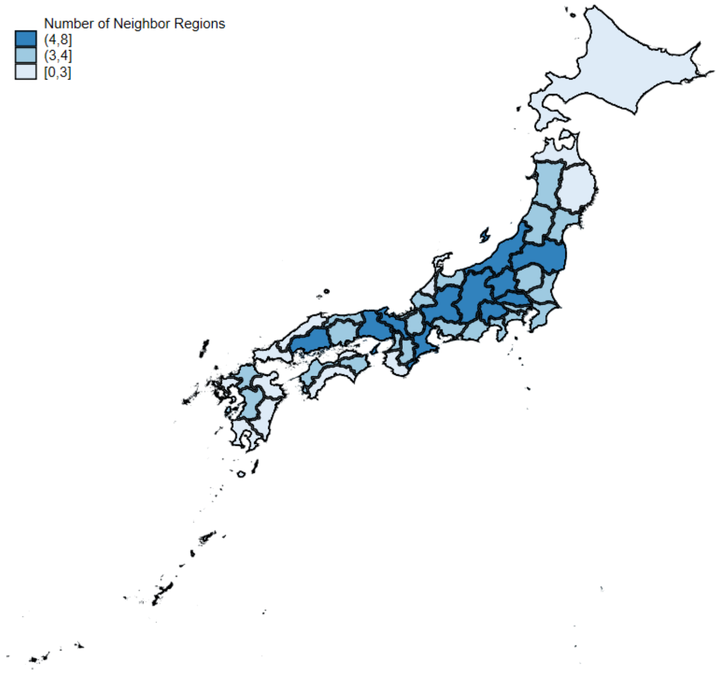
From equation (A1) and these three terms, we have:

$$s_j = \beta_{0j} + \sum_k \beta_{jk} x_k + \sum_i \gamma_{ji} z_i. \tag{A7}$$

Return the productivity term and subscripts z and t into this equation. Add an error term. Then equation (2) can be derived from equation (1).

B Data Appendix

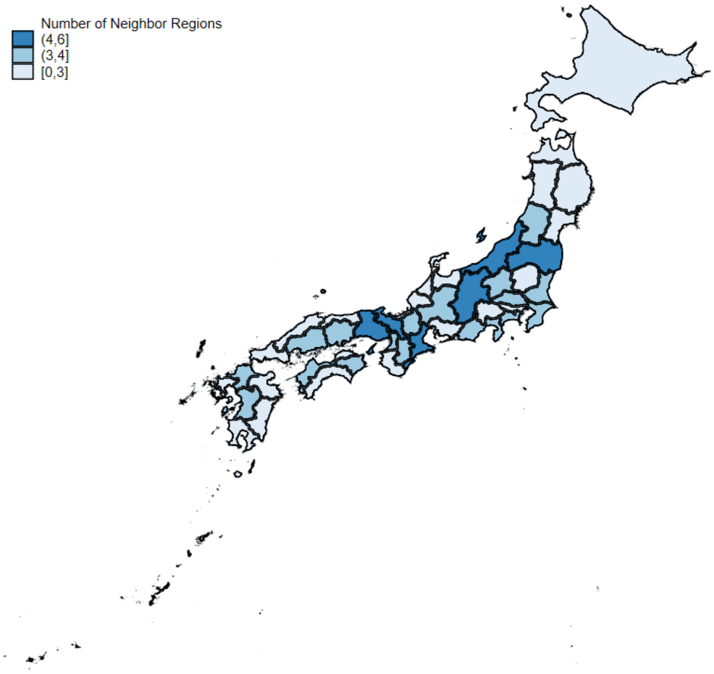
Figure B1: Number of Prefectures With Common Borders



Notes: If two regions have a common border or are connected by bridges or tunnels, they are counted. Colors are based on the number of neighboring regions. A darker color indicates a region with a larger number of common borders. The Japanese map data are from https://gadm.org/.

Source: RIETI (2017) R-JIP Database.

Figure B2: Number of Prefectures With Common Borders: Alternative Definition



Notes: Prefectures are regarded as having common borders only when they are connected by highways or railways. For other notes and sources, see Table B2.

Table B1: Industry Classification

Number	Industry	Sector
1	Agriculture, forestry, and fisheries	Agriculture
2	Mining	Other production
3	Food and beverages	Manufacturing
4	Textile mill products	Manufacturing
5	Pulp and paper	Manufacturing
6	Chemicals	Manufacturing
7	Petroleum and coal products	Manufacturing
8	Ceramics, stone and clay	Manufacturing
9	Basic metal	Manufacturing
10	Processed metals	Manufacturing
11	General machinery	Manufacturing
12	Electrical machinery	Manufacturing
13	Transport equipment	Manufacturing
14	Precision instruments	Manufacturing
15	Other manufacturing	Manufacturing
16	Construction	Other production
17	Electricity, gas and water utilities	Other production
18	Wholesale and retail trade	Other services
19	Finance and insurance	Business services
20	Real estate	Business services
21	Transport and communications	Other services
22	Non-government other services	Other services
23	Government other services	Other services

Source: RIETI (2017) R-JIP Database.

Table B2: Prefecture Classification

Number	Prefecture name	Number	Prefecture name
1	Hokkaido	25	Shiga
2	Aomori	26	Kyoto
3	Iwate	27	Osaka
4	Miyagi	28	Hyogo
5	Akita	29	Nara
6	Yamagata	30	Wakayama
7	Fukushima	31	Tottori
8	Ibaraki	32	Shimane
9	Tochigi	33	Okayama
10	Gunma	34	Hiroshima
11	Saitama	35	Yamaguchi
12	Chiba	36	Tokushima
13	Tokyo	37	Kagawa
14	Kanagawa	38	Ehime
15	Niigata	39	Kochi
16	Toyama	40	Fukuoka
17	Ishikawa	41	Saga
18	Fukui	42	Nagasaki
19	Yamanashi	43	Kumamoto
20	Nagano	44	Oita
21	Gifu	45	Miyazaki
22	Shizuoka	46	Kagoshima
23	Aichi	47	Okinawa
24	Mie		

Source: RIETI (2017) R-JIP Database.

Table B3: Summary Statistics: Average of Levels Across Prefectures by Year

Agriculture		1972	1982	1992	2002	2012	Δ 1972-2012
Value-added share	s	0.092	0.056	0.038	0.028	0.025	-0.067
Log of price	$\ln P$	-0.628	0.024	0.148	-0.092	-0.167	0.461
Log of productivity	$\ln \varphi$	-0.052	-0.054	-0.055	-0.057	-0.057	-0.005
Manufacturing		1972	1982	1992	2002	2012	Δ 1972-2012
Value-added share	s	0.305	0.268	0.274	0.234	0.222	-0.083
Log of price	$\ln P$	-0.569	-0.019	0.106	-0.039	-0.619	-0.049
Log of productivity	$\ln \varphi$	-0.060	-0.057	-0.053	-0.051	-0.050	0.010
Other production		1972	1982	1992	2002	2012	Δ 1972-2012
Value-added share	s	0.139	0.146	0.146	0.123	0.099	-0.040
Log of price	$\ln P$	-1.379	-0.390	-0.026	-0.033	-0.078	1.301
Log of productivity	$\ln \varphi$	-0.052	-0.052	-0.051	-0.048	-0.047	0.005
Business services		1972	1982	1992	2002	2012	Δ 1972-2012
Value-added share	s	0.065	0.069	0.068	0.070	0.058	-0.006
Log of price	$\ln P$	-0.726	-0.031	0.033	-0.015	-0.152	0.574
Log of productivity	$\ln \varphi$	-0.060	-0.051	-0.055	-0.051	-0.052	0.008
Other services		1972	1982	1992	2002	2012	Δ 1972-2012
Value-added share	s	0.400	0.461	0.473	0.545	0.596	0.197
Log of price	$\ln P$	-1.060	-0.281	-0.008	-0.035	-0.112	0.947
Log of productivity	$\ln \varphi$	-0.052	-0.047	-0.048	-0.047	-0.047	0.004
Region level endowment		1972	1982	1992	2002	2012	Δ 1972-2012
Log of capital stock	$\ln K$	15.218	15.897	16.408	16.692	16.697	1.478
Log of labor	$\ln L$	14.451	14.488	14.508	14.383	14.325	-0.126
Log of capital–labor ratio	$\ln K/L$	0.767	1.409	1.900	2.308	2.371	1.604

Note: Δ 1972–2012 indicates the difference in each variable from 1972 to 2012.
Source: Simple average across regions for price and productivity. Author's calculation, based on the RIETI (2017) R-JIP Database.

C Measurement of TFP

Approximating constant returns to scale production technology with a translog functional form, this superlative index number evaluates productivity in each prefecture and year relative to a hypothetical average prefecture in the sector. Let Y, L, K denote the real value-added, labor input (hours worked), and real capital stock, respectively. Denoting the geometric mean of the variables as an upper bar, this relative TFP is written as follows:

$$\begin{aligned} \ln \varphi_{zjt} &= \ln \frac{Y_{zjt}}{\bar{Y}_{jt}} - \sigma_{zjt} \ln \frac{L_{zjt}}{\bar{L}_{jt}} - (1-\sigma_{zjt}) \ln \frac{K_{zjt}}{\bar{K}_{jt}} \\ &\quad + \ln \frac{\bar{Y}_{jt}}{\bar{Y}_{j0}} - \bar{\sigma}_{jt} \ln \frac{\bar{L}_{jt}}{\bar{L}_{j0}} - (1-\bar{\sigma}_{jt}) \ln \frac{\bar{K}_{jt}}{\bar{K}_{j0}}, \end{aligned} \tag{C1}$$

where $\sigma_{zjt} = 1/2 \cdot (c_{zjt} + \bar{c}_{jt})$ is the average of labor share in total cost in prefecture z (c_{zjt}) and the arithmetic mean labor share ($\bar{c}_{jt}$); $\bar{\sigma}_{jt} = 1/2 \cdot (\bar{c}_{jt} + \bar{c}_{j0})$. Note that, for a given year t, the productivity of sector j in prefecture z is measured relative to the (geometric) average productivity of sector j in all prefectures in Japan in year 0. Thus, if the estimated productivity of sector j in prefecture z is greater (smaller) than zero, its productivity is greater (smaller) than the average productivity of sector j in Japan in the benchmark year. We set 2000 as the benchmark year (i.e., $\ln \varphi_{zjt} = 0$ if $t = 2000$). This means that TFP is measured relative to the hypothetical average prefecture in 2000. We set 2000 as the benchmark year (i.e., $\ln \varphi_{zjt} = 0$ if $t = 2000$). This means that TFP is measured relative to the hypothetical average prefecture in 2000.

D Alternative Models

D.1 Alternative specifications

The baseline results in Section 3.3 indicate the statistically significant effect of spatial interdependence. However, one may be interested in how the results change if the analysis ignores the spatial effects. To respond, we estimate the system of equations assuming no spatial effects. Table D1 provides the results. The results are like those of the baseline model. The Breusch–Pagan test statistic indicates that the null hypothesis that error terms across equations are contemporaneously uncorrelated is rejected. All the estimated coefficients, except for the coefficients on spatial terms that are excluded from the regression, yield the same signs and significance levels.

Table D1: Regression Results: SUR With No Spatial Effects

	Agriculture	Manufacturing	Other production	Business services
Relative productivity & price				
Agriculture	0.012***			
($\ln(\varphi_1 p_1/\varphi_5 p_5)$)	(0.002)			
Manufacturing	-0.021***	0.179***		
($\ln(\varphi_2 p_2/\varphi_5 p_5)$)	(0.002)	(0.003)		
Other production	0.006***	-0.029***	0.089***	
($\ln(\varphi_3 p_3/\varphi_5 p_5)$)	(0.001)	(0.001)	(0.001)	
Business services	-0.003***	-0.015***	-0.008***	0.055***
($\ln(\varphi_4 p_4/\varphi_5 p_5)$)	(0.001)	(0.001)	(0.001)	(0.001)
Relative endowment	-0.073***	0.046***	0.014***	0.007***
($\ln(K/L)$)	(0.002)	(0.003)	(0.002)	(0.001)
Spatial autoregressive term	n.a.	n.a.	n.a.	n.a.
($\mathbf{Ws}$)				
Spatial errors	n.a.	n.a.	n.a.	n.a.
($\mathbf{Wu}$)				
Number of observations	1972			
R-squared	0.936	0.973	0.950	0.961
Log-likelihood	27281.7			
Breusch-Pagan statistic	910.2***			

Notes: Figures in parentheses are standard errors. ***, **, and * denote the significance level at 1, 5, and 10 percent, respectively.

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

However, the magnitudes are slightly different. For example, for Manufacturing, the coefficient on the prefecture capital–labor ratio (i.e., $\ln(K/L)$) declines from 0.067 in the baseline model to 0.046 in the model without spatial effects. Given that these coefficients have small standard errors, these results suggest that the coefficients on these variables will be underestimated if spatial effects are not considered.

One may then argue that the use of the sector–5-year fixed effect may not be sufficient to control for the movement of labor or for unobserved demand and/or supply shocks more generally. However, it is difficult to include both a year fixed effect and a spatial autoregressive term simultaneously (see Section 2.3). To check the sensitivity of the results while avoiding multicollinearity, we use a sector–2-year fixed effect instead of sector–5-year fixed effect, which allows us to account for short-term unobserved economic shocks. Table D2 presents the results. The results indicate that the sign and significance level of the coefficients present little difference from those in the baseline results. This reassures the robustness of the results even when the analysis considers the short-term demand and/or supply shocks.

Table D2: Regression Results: SUR With Sector–2-Year Fixed Effect

	Agriculture	Manufacturing	Other production	Business services
Relative productivity & price				
Agriculture	0.015***			
($\ln(\varphi_1 p_1/\varphi_5 p_5)$)	(0.002)			
Manufacturing	-0.026***	0.176***		
($\ln(\varphi_2 p_2/\varphi_5 p_5)$)	(0.002)	(0.003)		
Other production	0.006***	-0.027***	0.088***	
($\ln(\varphi_3 p_3/\varphi_5 p_5)$)	(0.001)	(0.001)	(0.001)	
Business services	-0.003***	-0.012***	-0.010***	0.054***
($\ln(\varphi_4 p_4/\varphi_5 p_5)$)	(0.001)	(0.001)	(0.001)	(0.001)
Relative endowment	-0.072***	0.080***	0.005**	0.004***
($\ln(K/L)$)	(0.003)	(0.004)	(0.002)	(0.001)
Spatial autoregressive term	-0.277***	0.018	-0.013	-0.238***
($\mathbf{Ws}$)	(0.032)	(0.017)	(0.023)	(0.024)
Spatial errors	0.217***	0.071**	-0.088**	0.362***
($\mathbf{Wu}$)	(0.037)	(0.030)	(0.037)	(0.030)
Number of observations	7708			
R-squared	0.935	0.977	0.954	0.966
Log-likelihood	27533.3			
Breusch-Pagan statistic	851.6***			

Notes: Figures in parentheses are standard errors. ***, **, and * denote the significance level at 1, 5, and 10 percent, respectively.

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

In this context, one may also ask how the results change when the analysis excludes prefecture–sector and sector–5-year fixed effects. To address this, we estimate the system of equations after dropping these fixed effects (i.e., α_{zj}, $\alpha_{j\tau}$). Table D3 indicates the estimation results, which are different from the baseline results. For example, for Manufacturing, the coefficient on the prefecture capital–labor ratio (i.e., $\ln(K/L)$) turns negative. This implies that the Japanese manufacturing sector is labor-intensive, which is not easy to explain. Moreover, the coefficient on the own-sector price-productivity term (i.e., $\ln(\varphi_2 p_2/\varphi_5 p_5)$) increases from 0.172 to 0.221. The results suggest the importance of controlling for the unobserved prefecture–sector and sector–period fixed effects.

Table D3: Regression Results: SUR With Spatial Effects/No Fixed Effects

	Agriculture	Manufacturing	Other production	Business services
Relative productivity & price				
Agriculture	0.032***			
($\ln(\varphi_1 p_1/\varphi_5 p_5)$)	(0.001)			
Manufacturing	-0.021***	0.221***		
($\ln(\varphi_2 p_2/\varphi_5 p_5)$)	(0.001)	(0.002)		
Other production	0.009***	-0.040***	0.105***	
($\ln(\varphi_3 p_3/\varphi_5 p_5)$)	(0.001)	(0.001)	(0.001)	
Business services	-0.013***	-0.020***	-0.010***	0.073***
($\ln(\varphi_4 p_4/\varphi_5 p_5)$)	(0.000)	(0.000)	(0.001)	(0.001)
Relative endowment	-0.026***	-0.032***	0.012***	0.007***
($\ln(K/L)$)	(0.001)	(0.002)	(0.001)	(0.001)
Spatial autoregressive term	-0.043***	0.043***	0.016	-0.183***
($\mathbf{W}s$)	(0.016)	(0.011)	(0.010)	(0.009)
Spatial errors	0.108***	0.079***	0.345***	0.621***
($\mathbf{Wu}$)	(0.030)	(0.027)	(0.025)	(0.017)
Number of observations	1972			
R-squared	0.827	0.847	0.872	0.876
Log-likelihood	22305.9			
Breusch-Pagan statistic	678.7***			

Notes: Figures in parentheses are standard errors. ***, **, and * denote the significance level at 1, 5, and 10 percent, respectively.

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

D.2 Alternative weighting matrix

In the baseline analysis, the spatial weighting matrix is constructed based on whether prefectures are contiguous or not. In Japan, all prefectures are connected by roads to each other if the prefectures have common borders. Nevertheless, the existence of a road connection does not necessarily imply large transactions between these prefectures because some prefectures are connected only by minor roads.

For example, Nagano prefecture, which is surrounded by mountains, is contiguous with eight other prefectures, the most of any prefecture. However, among these eight prefectures, three are connected by neither highways nor railways, just ordinary roads. It thus may be difficult to imagine that the Nagano prefecture is equally interdependent with its prefectures. To address this, we employ an alternative weighting matrix, defining contiguity only when the prefectures are directly connected by highways or railways.

Table D4 presents the estimation results. Although the spatial effects are insignificant for Business services, the sign and significance levels for other variables are the same for all sectors. Moreover, the estimated coefficients are the same as those of the baseline results for Manufacturing. The results are thus robust even when contiguity is defined as highway and railway connections.

Table D4: Regression Results: SUR With Alternative Weighting Matrix

	Agriculture	Manufacturing	Other production	Business services
Relative productivity & price				
Agriculture	0.012***			
($\ln(\varphi_1 p_1/\varphi_5 p_5)$)	(0.002)			
Manufacturing	-0.019***	0.172***		
($\ln(\varphi_2 p_2/\varphi_5 p_5)$)	(0.001)	(0.003)		
Other production	0.006***	-0.028***	0.089***	
($\ln(\varphi_3 p_3/\varphi_5 p_5)$)	(0.001)	(0.001)	(0.001)	
Business services	-0.003***	-0.013***	-0.009***	0.056***
($\ln(\varphi_4 p_4/\varphi_5 p_5)$)	(0.001)	(0.001)	(0.001)	(0.001)
Relative endowment	-0.077***	0.066***	0.013***	0.007***
($\ln(K/L)$)	(0.002)	(0.004)	(0.002)	(0.001)
Spatial autoregressive term	-0.227***	-0.021	0.016	-0.228***
($\mathbf{W}\mathbf{s}$)	(0.025)	(0.018)	(0.023)	(0.021)
Spatial errors	0.253***	0.275***	0.041	0.378***
($\mathbf{W}\mathbf{u}$)	(0.032)	(0.027)	(0.035)	(0.028)
Number of observations		1972		
R-squared	0.942	0.975	0.950	0.966
Log-likelihood		27406.3		
Breusch-Pagan statistic		838.0***		

Notes: Figures in parentheses are standard errors. ***, **, and * denote the significance level at 1, 5, and 10 percent, respectively.

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

D.3 Alternative measure of labor input

The baseline analysis does not consider the differences in skill composition between prefectures. However, deindustrialization may also be affected by skill abundance. As mentioned, however, labor is not disaggregated by skills in the R-JIP Database. To crudely reflect the differences in skill composition across prefectures, we use total wages rather than work hours at the prefecture-level as the measure of labor endowment. Hsieh and Klenow (2009) also employ this approach to consider the differences in hours worked and human capital. The data on total wages by prefecture are also available in the R-JIP Database.

Table D5 provides the estimation results using the alternative measure of labor input. The estimated coefficients are mostly the same as those of the baseline results for Manufacturing. One notable difference is that the coefficient of the spatial autoregressive term is now significantly positive. This suggests that the effect of spatial interdependence is more evident if skill differences in the labor input are considered. Otherwise, the baseline results are mostly robust.

Table D5: Regression Results: SUR With Alternative Measure of Labor Input

	Agriculture	Manufacturing	Other production	Business services
Relative productivity & price				
Agriculture	0.019***			
$(\ln(\varphi_1 p_1/\varphi_5 p_5))$	(0.002)			
Manufacturing	-0.024***	0.176***		
$(\ln(\varphi_2 p_2/\varphi_5 p_5))$	(0.001)	(0.003)		
Other production	0.003***	-0.027***	0.088***	
$(\ln(\varphi_3 p_3/\varphi_5 p_5))$	(0.001)	(0.001)	(0.002)	
Business services	-0.003***	-0.012***	-0.009***	0.053***
$(\ln(\varphi_4 p_4/\varphi_5 p_5))$	(0.001)	(0.001)	(0.001)	(0.001)
Relative endowment	-0.052***	0.067***	-0.002	0.002**
$(\ln(K/L))$	(0.003)	(0.004)	(0.002)	(0.001)
Spatial autoregressive term	-0.506***	-0.036**	0.038	-0.274***
$(\mathbf{Ws})$	(0.026)	(0.017)	(0.024)	(0.023)
Spatial errors	0.584***	0.277***	0.027	0.451***
$(\mathbf{Wu})$	(0.022)	(0.027)	(0.037)	(0.027)
Number of observations	1972			
R-squared	0.936	0.975	0.948	0.966
Log-likelihood	27124.9			
Breusch-Pagan statistic	790.8***			

Notes: Figures in parentheses are standard errors. ***, **, and * denote the significance level at 1, 5, and 10 percent, respectively.

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

D.4 Alternative sample period

Fujita, Mori, Henderson, and Kanemoto (2004) pointed out that the three largest metropolitan areas (i.e., Tokyo, Osaka, and Nagoya) experienced a high rate of net migration until 1970 with the peak early in the 1960s.[45] Although our baseline analysis covers the

[45] Nagoya is located in Aichi prefecture.

period from 1972, Fujita, Mori, Henderson, and Kanemoto (2004) also indicated that the Tokyo metropolitan area experienced a high rate of net migration around the mid-1980s. The estimation results may thus be affected by labor mobility. Unfortunately, however, it is difficult to control for the effect of factor mobility in our framework. As a compromise, we re-estimate the model focusing only on the latter half of the sample period (i.e., between 1992 and 2012) when labor mobility was lower.

The estimation results are presented in Table D6. From the estimation results, the estimated coefficients are mostly the same as those of the baseline results for Manufacturing. A notable difference is that the coefficient of the spatial autoregressive term is now significant. Accordingly, the effect of spatial interdependence is more evident in the recent period.

Table D6: Regression Results: SUR With Alternative Sample Period, 1992–2012

	Agriculture	Manufacturing	Other production	Business services
Relative productivity & price				
Agriculture	0.025***			
$(\ln(\varphi_1 p_1/\varphi_5 p_5))$	(0.001)			
Manufacturing	-0.010***	0.136***		
$(\ln(\varphi_2 p_2/\varphi_5 p_5))$	(0.001)	(0.003)		
Other production	-0.001	-0.024***	0.087***	
$(\ln(\varphi_3 p_3/\varphi_5 p_5))$	(0.001)	(0.002)	(0.002)	
Business services	-0.003***	-0.010***	-0.007***	0.049***
$(\ln(\varphi_4 p_4/\varphi_5 p_5))$	(0.001)	(0.001)	(0.001)	(0.001)
Relative endowment	-0.016***	0.035***	-0.012***	0.010***
$(\ln(K/L))$	(0.001)	(0.005)	(0.003)	(0.001)
Spatial autoregressive term	-0.070**	0.074**	-0.007	-0.098***
$(\mathbf{W}s)$	(0.035)	(0.033)	(0.031)	(0.032)
Spatial errors	0.228***	0.391***	0.201***	0.171***
$(\mathbf{Wu})$	(0.048)	(0.041)	(0.047)	(0.048)
Number of observations	987			
R-squared	0.986	0.991	0.969	0.986
Log-likelihood	16459.5			
Breusch-Pagan statistic	138.6***			

Notes: Figures in parentheses are standard errors. ***, **, and * denote the significance level at 1, 5, and 10 percent, respectively.

Source: Author's estimation based on the RIETI (2017) R-JIP Database.

In this context, one may be further concerned that the data do not reflect current fast-changing realities because the data used in this paper, the 2017 R-JIP Database, ended in 2012. The latest version of the 2021 R-JIP Database was released in March 2022.[46] The 2021 R-JIP Database was substantially revised from the previous version (i.e., 2017 R-JIP Database). For example, the sample period of 2021 R-JIP Database is 1994–2018, which is significantly shorter than the sample period of the previous version (i.e., 1972–2012 in the 2017 R-JIP Database). The changes in the share of manufacturing value-added were small after 2012 in Japan: on average, from 21.6 percent in 2012 to 23.0 percent in 2018.

[46] Unlike the country-level JIP Database, regional-level JIP Database is not frequently updated. For more detail, see https://www.rieti.go.jp/en/database/r-jip.html

Because the 2021 R-JIP Database is not directly comparable to the 2017 R-JIP Database given the changes in the data compilation method, the data cannot be extended from 1972–2012 to 1972–2018. As our focus is the long-run (over four decade) changes in manufacturing, we present the results of the 2021 R-JIP Database as another robustness check.

Table D7 provide the estimation results. As shown, the estimated coefficients are the same as those of the baseline results for Manufacturing. However, there are two notable differences. First, the coefficient for the capital–labor ratio is insignificant for manufacturing. As confirmed in Panel A in Figure 4, capital accumulation in Japan slowed after 2000. This result may suggest that with the growth of other countries like China, Japan is moving from a capital-abundant to a capital-scarce country in the global economy. Second, like the results of alternative measure of labor input, the coefficient for the spatial autoregressive term turns significantly negative. This implies that the effect of spatial interdependence becomes more important in the recent period. However, the main message of the analysis is mostly unchanged even when we focus on the more recent period.

Table D7: Regression Results: SUR With Alternative Sample Period, 1994–2018

	Agriculture	Manufacturing	Other production	Business services
Relative productivity & price				
Manufacturing	0.016***			
$(\ln(\varphi_2 p_2/\varphi_1 p_1))$	(0.001)			
Other production	-0.005***	0.150***		
$(\ln(\varphi_3 p_3/\varphi_1 p_1))$	(0.001)	(0.003)		
Business services	-0.002***	-0.022***	0.076***	
$(\ln(\varphi_4 p_4/\varphi_1 p_1))$	(0.001)	(0.002)	(0.002)	
Other services	-0.002***	-0.016***	-0.025***	0.048***
$(\ln(\varphi_5 p_5/\varphi_1 p_1))$	(0.001)	(0.001)	(0.003)	(0.001)
Relative endowment	-0.004***	0.009	-0.016***	0.001
$(\ln(K/L))$	(0.001)	(0.006)	(0.004)	(0.001)
Spatial autoregressive term	-0.346***	-0.078**	-0.037	-0.086***
$(\mathbf{Ws})$	(0.040)	(0.032)	(0.035)	(0.032)
Spatial errors	0.658***	0.246***	0.153***	0.360***
$(\mathbf{Wu})$	(0.028)	(0.042)	(0.047)	(0.039)
Number of observations		1175		
R-squared	0.981	0.987	0.935	0.973
Log-likelihood		18577.2		
Breusch-Pagan statistic		308.4***		

Notes: Figures in parentheses are standard errors. ***, **, and * denote the significance level at 1, 5, and 10 percent, respectively.

Source: Author's estimation based on the RIETI (2022) R-JIP Database.