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博　士　論　文

平成 30 年 12 月

神戸大学大学院経済学研究科

経済学専攻

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（空間的相互作用に関する３つの実証論文）

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Chapter 1
Introduction

1.1 Spatial Interactions: Backgrounds and Approaches

Recently, interest in spatial data or urban and regional data in economics is notably increasing (Martin, 1999; Combes, et al., 2008; and Proost and Thisse, 2017). This increase in interest becomes more visible in the empirical research when considering spatial interactions.

We employ three approaches to cope with spatial interactions in this doctoral dissertation:

a) Empirics of spatial economy using spatial econometrics;
b) Policy evaluation using interactive-effects model;
c) Using spatial econometrics for time series data.

Utilizing these three approaches, our main purpose of this study is to develop empirical methodologies to treat spatial interactions contained in spatial data or urban and regional data with higher accuracy and a solid theoretical foundation. For this purpose, we apply the latest econometric methods and our originally constructed economic model to analyze spatially interacted data through the following processes:

a) Constructing a spatial economic model based on Redding and Venables (2004);
b) Using the interactive-effects model by Bai (2009) for DID and newly proposed Spatial Error-DID;
c) Utilizing the Spatial GAS (Generalized Autoregressive Score) model proposed by Blasques et al. (2016).

1.2 Motivation and Abstract for Chapter 2

Since Marshall (1890), external economies have become a key factor in agglomeration economies. Marshall describe three types of external economies for the formation of clusters: i) specialized inputs with low unit cost, ii) access to a large labor market pool that allows good matching, and iii) ideas derived from face-to-face communication.

One of the reasons for spatial inequality is from natural endowments, or "first nature," such as vast and flat plains, abundant natural resources, easy access to efficient ports, and stable climate. However, this does not substantiate a comprehensive explanation for the spatial inequality of modern economic activities. Agglomeration force, or "second nature," leads to spatial unevenness of economic activity, and inequality is fiercer than expected from the imbalance of natural endowments. New economic geography (hereafter NEG) attempts to explain distributions of economic activities and optimization behaviors of players, consumers, firms, landlords, and other related parties to establish an equilibrium.

Fujita (1988), Krugman (1991), and Venables (1996) are pioneers of NEG; these studies led to the collaborative work, *The Spatial Economy: Cities, Regions, and International Trade* by Fujita, Krugman, and Venables (1999). Their basic theories mainly shed light on the manufacturing and traditional sector, agriculture. However, modern economies—especially developed countries' economies—demonstrate dense agglomeration of service sectors or functions in large cities (Ottaviano and Thisse, 2004; Duranton and Puga, 2005).

With increasing importance of the Knowledge-Intensive Business Service (KIBS) sector in Japan, we observe dense agglomerations of KIBS in large cities such as Tokyo and Osaka. Such urban features of KIBS stem from the fact that the main customers for KIBS are corporate headquarters (HQs), and KIBS's main input is highly skilled labor.

To analyze the market structure of KIBS, we propose a monopolistic competition model. We follow the model of Redding and Venables (2004). Under free entry market competition, higher wages attract laborers who work for KIBS.

A few empirical investigations of KIBS firms' location in economic geography literature are found (Jacobs et al. 2014; Meliciani and Savona, 2015; Klaesson and Norman, 2015). Additionally, all of these empirical studies are based on ad-hoc reduced form equations, they are not explicitly derived from theoretical economic geography models.

In spite of the increasing importance of KIBS in developed countries, there are no theory-based empirical studies that identify agglomeration factor of KIBS. To the best of our knowledge, ours is the first study to estimate the agglomeration forces of KIBS derived from the spatial economic model setting.

Based on spatial economic theory, we test the hypothesis that better "market access" and "supply access" are causal factors in KIBS agglomeration. Our results

indicate that market access (the agglomeration of HQs and KIBS) and supply access (the share of highly skilled labor) have statistically significant positive effects on the share of KIBS in municipalities. However, the magnitude of the agglomeration of HQs and KIBS is pretty low from our empirics. On the one hand, the effect of the share of highly skilled labor and that for the neighbors in municipalities is strongly supported. In addition, although the magnitude is low, the effect of the knowledge agglomeration is also confirmed.

It implies that better access to highly skilled labor strengthen supply access and KIBS firms will be even more inclined to establish locations in those municipalities. Additionally, the agglomeration of HQs and KIBS and knowledge agglomeration also attracts KIBS firms.

1.3 Motivation and Abstract for Chapter 3

Estimation of causal effects is problematic in econometrics (Angrist and Pischke, 2008), empirics of economic geography (Combes, et al., 2008), and geographical data (Gibbons and Overman, 2012). One of the best methods is “causal inference” (Baum-Snow and Ferreira, 2015).

After Rubin's study (1974), a causal inference of program evaluation policy has developed in the field of statistics. Research in economics did not clearly take causal inference into consideration until the rigorous work of Joshua Angrist and Guido Imbens in the early 90’s (Angrist and Imbens, 1991; Angrist, 1991, 1992; Imbens and Angrist, 1994). After two decades, we have seen many empirical works in economics related to analysis of causal effects (Imbens and Wooldridge, 2011).

We establish a “treatment group” that is treated by a policy or program and a “control group” that does not. Under the experimental situation, we only have to compare the outcome of treatment group and control group to evaluate causal effect.

However, in many cases, economic data is not derived from pure experimentation. Hence, in many economic empirics, simple comparisons of the outcome of treatment group and control group does not lead to the evaluation of causal effect. There are covariates that affect the outcome of both groups. If we can observe both the outcome data of the treatment group and those of the control group after the execution of policy or program—the simple comparison of both outcomes indicate causality. However, this is not possible in many cases.

Consequently, we establish counterfactuals and compare the outcome data of

treatment and control groups after the period of some policy. This is the average treatment effect on the treated (ATT). Exception is established by randomized controlled trial (RCT). If RCT is possible, comparing the outcome of the treatment and control groups lead to reasonable causal inference. Similar to the RCT, under the situation of natural experiment, causal inference is straightforward. We have seminal papers in economic geography empirics, e.g. Redding and Sturm (2008) on the case of German division, and Nakajima (2008) on the case of the economic separation of Japan and Korea after World War II. Both papers compare population growth in treatment and control regions.

Non-experimental research designs suggest sophisticated causal inference methods such as difference-in-differences (DID, Snow, 1855), regression discontinuity (Thistlethwaite and Campbell, 1960), propensity score matching (PSM, Rosenbaum and Rubin, 1983), and partial identification (Manski, 1989, 1990). Traditional methods of causal inference in econometrics include control variables or IV methods.

Flourishing studies of policy or program evaluation are seen in the field of education and labor because plausible counterfactuals are obtainable. Investigations on the causal inference of regional policies using program evaluation have recently been developing in the field of microeconomics (Blundell and Costa-Dias, 2009; Imbens and Wooldridge, 2011).

Interestingly, in the field of urban and regional economics, more and more studies are focusing on sophisticated causal inference methods. Baum-Snow and Ferreira (2015) investigate the prevalence of empirical methods in the *Journal of Urban Economics*. Their definition of sophisticated causal inference methods includes DID, Randomization, and Matching. Percentage of the three methods in published papers in the *Journal of Urban Economics* is 0% in 1990, 4% in 2000, and 16% in 2010.

Compared with the field of education and labor, the field of urban and regional economics has difficulty in conducting causal inference. Policies or programs designated for urban, regional units are called place-based policies.[1] Place-based

[1] Different nomenclature is used for policies or programs designated for urban, regional units; place-based policy (or programs) (Harger and Ross, 2016; Ahlfeldt, et al., 2017; Givord, et al., 2018), regional policy (Gobillon and Magnac, 2016), spatially targeted programs (Wang, 2013), preferential regional policy programs (Schminke and Biesebroeck, 2013), and area-based programs (Accetturo and Blasio, 2012). Hereafter, we refer to place-based policy when discussing policies or programs implemented in urban, regional units.

policies are designated for deprived areas and are aimed to revitalize certain disadvantaged local economic activities: growth of population, residents, employment, and small enterprises' activity. Therefore, in place-based policies, the implementation of policy or program is far from random, and the treated area is correlated with the policy or program. In other words, the determination process of policy or program is largely dependent on the local economic situation.

Therefore, it is difficult to establish effective controlled regional units. Also, it is difficult to appropriately evaluate causality in place-based policies. One solution that may be more efficient for this is to estimate synthetic controls (Alberto, et al., 2010). A more elaborate strategy includes applying Bai's (2009) method, which controls for unobservable factors in DID as proposed by Kim and Oka (2014) and Gobillon and Magnac (2016) combined with PSM.

There are some papers that focus on place-based policies and evaluate them with sophisticated causal inference. All of these studies that use DID or related methods focus on empowerment of enterprise or economic zone (Papke, 1994; Neumark and Kolko, 2010; Accetturo and Blasio, 2012; Freedman, 2013; Wang, 2013; Schminke and Biesebroeck, 2013; Kline and Moretti, 2014; Gobillon and Magnac, 2016; Harger and Ross, 2016; Ahlfeldt, et al., 2017; and Givord, et al., 2018).[2]

Rapid population growth in large cities in Japan was seen from the mid 50's to 60's. This led to the enactment of the "Act concerning the Industry Restriction" (hereafter AIR) which mainly restricted manufacturing activity to avoid congestion and environmental problems in large cities. The AIR targeted central areas of the Metropolitan area (central Metro) and the central area of the Kinki region (central Kinki).

At that time, the economy of central Kinki was more dependent on manufacturing than central Metro. Therefore, the AIR is said to have a greater negative impact on central Kinki than central Metro. We conduct causal inference on this place-based policy to assess whether such an over-restriction took effect.

There are no studies to confirm the causal effects of AIR using causal inference, to the best of our knowledge. Higher accuracy is expected when employing Bai's (2009) method with DID combined with PSM for our causal inference. We also

[2] Another mode of policy or program evaluation in the field of urban and regional economics is assessing infrastructure effects, e.g. Bernard, et al. (2015), Inoue, et al. (2017) (high-speed (Shinkansen) train line), and Michaels (2008) (highway).

propose “Spatial Error-DID” (SE-DID) model.

Our results support this view: AIR hampered economic growth of central Kinki. Without Bai’s model, empirical results indicate that central Metro is also hampered by the AIR. Additionally, the results of the Monte Carlo simulation support the results from the estimation using Bai’s model and our proposed SE-DID model. Our analysis finds that the AIR mitigated the economic growth of central Kinki.

1.4 Motivation and Abstract for Chapter 4

In the field of empirics in macroeconomics, many studies focus on spatial interaction. Some countries' economic situations or business conditions affect some other countries' economic conditions. The most traditional and successful method is the gravity model (Tinbergen, 1962). Another elaborate method is spatial econometrics (Anselin, 1988; LeSage and Pace, 2009).

With decreasing transport costs, business cycle synchronization seems to be increasing, and the economic turmoil of one country tends to affect the economies of other countries more seriously. In such circumstances, we estimate business cycle synchronization of the Asia-Pacific region and Euro Area.

We apply the spatial generalized autoregressive score (Spatial GAS) method to measure business cycle synchronization. Spatial GAS was proposed by Blasques et al. (2016). This mode of estimation became possible using GAS model. This study would be the first that applied a time-varying spatial parameter in measuring business cycle synchronization.

The GAS models has been applied successfully in many areas, including modeling time-varying dependence structures. The GAS models was proposed by Creal, et al. (2008, DP) (Revised paper is Creal, et al., 2012). At the same time, Harvey and Chakravarty (2008) also developed a score driven model—the Beta-t-(E) GARCH model. This model is a special case of the GAS model.

Likelihood evaluation is straightforward in GAS modeling. The GAS model is score-based. After applying the GAS model and using maximum likelihood estimation, time-varying spatial parameter estimation is feasible.

Business cycle synchronization is defined as a time-varying common indicator. Using Spatial GAS, we can estimate the time-varying spatial parameter. The spatial parameter corresponds to the degree of business cycle synchronization in the examined context.

As a result, when the spatial parameter exhibited a high value, geographically and economically closer countries' business cycles will be synchronized. Estimated business cycle synchronization indicators show positive high values in periods of economic turmoil, such as the Asian crisis of 1997, the collapse of the dot-com bubble (or internet bubble), the European sovereign debt crisis, and the collapse of the Lehman Brothers in 2008.

Our findings indicate that when common business cycle movements show serious economic shocks, business cycle synchronization exhibits high values. When economic shocks occur and business cycle volatility drastically increases, business cycle synchronization will be inflated similarly. In addition, business cycle synchronization is related to the degree of economic integration to some extent.

With the recent increase in economic integration, exogenous shocks increased geographically and economically closer countries' business cycle synchronization to each other, and such shocks cause economic instability.

Chapter 2
Firm Agglomeration in Knowledge Intensive Business Service Sectors

2.1 Introduction

In the last few decades, the business service sector has expanded enormously in economically developed economies, including Japan (Ministry of Economy, Trade and Industry 2002, OECD 2005a). The business service sector has become important for Japanese economic performance (Ministry of Economy, Trade and Industry 2017).

One prominent feature of business service activity is its high knowledge intensity. The OECD (2005b) classifies post and telecommunications, finance and insurance, business activities (not including real estate), education, and health as a knowledge-intensive business services (KIBS) at the two-digit ISIC/NACE level. Miles et al. (1995), who used the term KIBS originally, defined KIBS as

1. Relying heavily upon professional knowledge
2. Being themselves primary sources of information and knowledge, using their knowledge to produce intermediary services for their clients' production processes
3. Having competitive importance and supplied primarily to business.

Based on those earlier studies and the industrial classification used in the "*Economic Census*" of the Statistics Bureau, Ministry of Internal Affairs and Communications (MIC), our definition of KIBS corresponds to the following.

F: Finance and insurance

IT: Information services, Services incidental to the internet, Content industries, producing video picture information, sound information, character information production and distribution

P: Professional services, for which qualifications are needed, Professional services, providing design services and business consultants, Advertising

T: Technical services, such as commodity inspection and non-destructive testing services, engineering and architectural services, and mechanical

design services

Following Miles et al. (1995), over the last few decades, the concentration, activity, and evolution of KIBS have garnered growing attention from numerous authors: Den Hertog (2000), Muller and Zenker (2001), Keeble and Nachum (2002), Wood (2002), Miles (2006), Koch and Stahlecker (2006), Wood (2006), Freel (2006), Doloreux and Muller (2007), Shearmur and Doloreux (2008), Johansson and Klaesson (2011), Doloreux and Shearmur (2012), Jacobs et al. (2014), Meliciani and Savona (2015), and Klaesson and Norman (2015).

The products of KIBS are characterized as intermediate supplier services rather than final goods for consumption. They supply services that are provided mainly to the other sectors. Additionally, KIBS is characterized as a knowledge-intensive sector. Therefore, the main customers for this sector are some pivotal corporate functions including headquarters (HQs). These customers tend to be agglomerated in larger cities (Fukui and Matsushita, 2018). Whereas KIBS demands highly skilled labor as input, highly skilled workers tend to reside in larger cities (Glaeser, 1999; Kox and Rubalcaba, 2007a, 2007b; Karlsson et al., 2009; and Schricke et al., 2012).

For instance, 37.9% of the KIBS labor force is in the 23 wards of Tokyo and Osaka city, the share of employees working for HQs in the 23 wards of Tokyo and Osaka city throughout Japan is approximately 10% (*"Economic Census for Business Activity 2012"* (*Keizai sensasu katsudo chousa*, Statistics Bureau, MIC, hereafter *ECBA2012*)). Additionally, the 23 wards of Tokyo and Osaka city have approximately 12% of all university graduates of all of Japan (*"National Census 2010"* from Statistics Bureau, MIC). That importance notwithstanding, the surface area of the 23 wards of Tokyo and Osaka city accounts for only about 0.2% of the entirety of Japan.

To analyze the KIBS market structure, we propose a monopolistic competition model. KIBS produce a wide variety of differentiated services demanded by HQs which produce homogeneous HQ services using a wide variety of services produced by KIBS as input. In addition, KIBS rely on highly skilled workers.

In a competitive market with free entry, higher wages attract laborers who work to provide KIBS. In fact, according to *ECBA2012*, 359,326 enterprises provide KIBS, whereas the total number of enterprises in KIBS with fewer than five employees is 203,179, with the share of 56.5%. Therefore, the market can be regarded as competitive, due to a large degree of small firms.

As a salient feature of KIBS, firms tend to locate in core cities such as Tokyo and Osaka, rather than in periphery cities. This agglomeration tendency is particularly

stronger for KIBS than for other sectors such as manufacturing or retail sales. Therefore, KIBS is an important driving force of the economy in large cities (Ottaviano and Thisse, 2004; Proost and Thisse, 2017). This paper is designed to elucidate the causes of KIBS agglomeration.

Industrial agglomeration is a main subject of economic geography (e.g., Fujita et al. 1999; Fujita and Thisse, 2002). Larger cities tend to show agglomeration of firms and facilities because higher market potential or market accessibility associated with larger cities generates scale economies, thereby enabling firms to obtain greater profits.

A Few empirical investigations of the location of KIBS firms can be found in the urban economics and economic geography literature. Jacobs et al. (2014) test the relations between location of birth of KIBS and multinational enterprises (MNEs). Meliciani and Savona (2015) examine the determinants of specialization of business service across EU-27. Klaesson and Norman (2015) explore the relation between spatial distribution and the growth of KIBS and market potential.

It is unsatisfactory, however, that all of these empirical studies are based on ad-hoc reduced-form equations, but are not derived explicitly from a theoretical model of spatial economics. For instance, although Klaesson and Norman (2015) use market potential calculated using the size of the economy in the region as an explanatory variable, if one considers the actual situation, then the market potential for KIBS should be based explicitly on the distribution of demand: agglomeration of HQs. Johansson and Klaesson (2011) present an empirical model that uses the demand function and pricing equation under the setting of increasing returns to scale. In spite of their explicit reference to the spatial economics theory, their analytical model is not derived from a clear description of the structural form.

Davis and Henderson (2008) and Strauss-Kahn and Vives (2009) examine the determinant factors affecting HQ location choice. Business services are used as one important factor to ascertain the HQ location. However, our study analyzes causality in the opposite direction: the demand by HQs to induce the location of KIBS firms.

From a theoretical perspective, Duranton and Puga (2005) explain the relations between trade cost and urban specialization in HQs and business services. They conclude that if the transmission cost of headquarter services is sufficiently low, then firms locate their headquarters away from their production plants and closer to other business service firms. This result is attributable to low intra-firm operating costs between HQs and the production site, while locating HQs proximate to concentrated business services in the city. Nevertheless, no empirical investigation has used this theoretical form.

In spite of the increasing importance of KIBS in economically developed countries, no research in the relevant literature describes a theory-based empirical study conducted to identify the agglomeration factor of KIBS. In fact, ours is the first study to estimate the agglomeration forces of KIBS derived from the spatial economic model setting.

As described herein, we seek the determinants of agglomeration of KIBS using data for Japan. Given that large cities such as Tokyo and Osaka represent the driving force of the Japanese economy and given that they maintain great agglomerations of KIBS, investigating how KIBS agglomeration is created in the Japanese economy is important.

The remainder of the paper proceeds as follows. Following the Introduction, Section 2 outlines the related literature. Section 3 presents basic information related to the KIBS, HQs, and highly skilled laborers' agglomerations in Japan. Section 4 presents an explanation of the theoretical founding of our analysis. Section 5 presents a description of the empirical model and the data used in our estimation. Section 6 provides results and discussion. Section 7 presents conclusions.

2.2 Related literature

Several empirical studies have been conducted based on the theoretical background of economic geography. Redding and Venables (2004) are the first to suggest a structural framework of market access. They find the relation between per-capita income and distance to markets and supply access. The wage equation *à la* Fujita et al. (1999) plays a central role in their analysis. Hanson (2005) states that a strong relation exists between wages and market access across U.S. counties. Head and Mayer (2004, 2006) examine the link between the wage equation and market potential. Related to these, with increasing returns to scale and transport costs, some studies test the existence of home market effects (Davis and Weinstein, 1996, 1999, 2003).

Building on Helpman's research (1998), Redding and Sturm (2008) derive theoretically that the population increases with greater market access. They use the division of Germany after World War II as a natural experiment to examine the role played by market access. Amiti and Cameron (2007) estimate agglomeration benefits attributable to market access effects for firms in Indonesia. Hering and Poncet (2010) explain that individual wage differences arise from the geography of market access of Chinese cities. Another line of study based upon a natural experiment is that of Nakajima (2008) for Japan.

Several researchers examine the sectoral concentration of KIBS based on economic geography. Jacobs et al. (2014) test the relations between the location of birth of KIBS and multinational enterprises (MNEs) in Amsterdam in the Netherlands. After they assume the profit function of a firm, they conclude that KIBS tend to locate close to MNEs due to agglomeration externalities. Although they point out that HQs of MNEs are important for KIBS-birth, for the roles HQs play such as "command and control activities" and "concentrations of human capital and knowledge spillover," their inspection is not comprehensive: they only specifically examine MNEs. Meliciani and Savona (2015) examine the determinants of specialization of business service across EU-27 using explanatory factors such as agglomeration economy, intermediate demand, and innovation in services. They treat the manufacturing sector and neighboring business services as intensive users of business services and treat information and communication technologies (ICTs) as an important determinant factor for specialization in business services. Klaesson and Norman (2015) explore the relation between spatial distribution and growth of KIBS and market potential in Sweden. The market potential of their paper is measured as in the total number of jobs in area. They find positive relations between the growth of KIBS and market potential.

2.3 Agglomerations of KIBS firms, HQs, and highly skilled laborers

Although using municipal unit data, we scrutinize maps of prefectural level data here because, if the data are mapped at the municipal level, then agglomeration is unclear because of large differences of land area on a municipal level. For instance, Kita ward of Osaka city is small compared with larger municipalities such as Ishikawa city. Therefore, if all of these municipalities are mapped, then each municipality is indiscernible in some cases.

Figure 2.1 presents the names of the prefectures in Japan, whereas Figure 2.2 presents the share of the number of employees in KIBS in prefecture throughout Japan, from *ECBA2012*. Here one can see the strong agglomeration of KIBS employees in Tokyo, Osaka, Aichi, and Kanagawa: large cities. Hokkaido, Chiba, Saitama, Shizuoka, Hyogo, and Fukuoka also exhibit agglomeration.

Figure 2.3 maps the share of the number of employees in HQs in all prefectures of Japan from the "*Economic Census for Business Frame 2009"* (*Keizai sensasu kiso chousa*, hereafter *ECBF2009*) from Statistics Bureau, MIC. Maps from Figure 2.2 and Figure 2.3 show very similar patterns of agglomeration. Agglomeration of HQ employees

in Tokyo, Osaka, Aichi, and Kanagawa are prominent. Hokkaido, Chiba, Saitama, Shizuoka, Hyogo, Hiroshima, and Fukuoka also show agglomeration. From these maps, one can ascertain that KIBS and HQs are strongly agglomerated in large cities.

Figure 2.4 presents share of the number of highly skilled laborers in prefectures throughout Japan from the "*National Census 2010*" from Statistics Bureau, MIC. We define a highly skilled laborer as a worker who graduated from college or graduate school. From this map, the tendency appears to be slightly different from those presented in Figures 2.2 and 2.3. In addition to Tokyo, Osaka, Aichi, and Kanagawa, strong agglomeration is apparent in Saitama, Chiba, and Hyogo. Therefore, although highly skilled labor is concentrated in large cities such as Tokyo or Osaka, it also extends outward to surrounding prefectures. Hokkaido, Shizuoka, Hiroshima, and Fukuoka also show agglomeration.

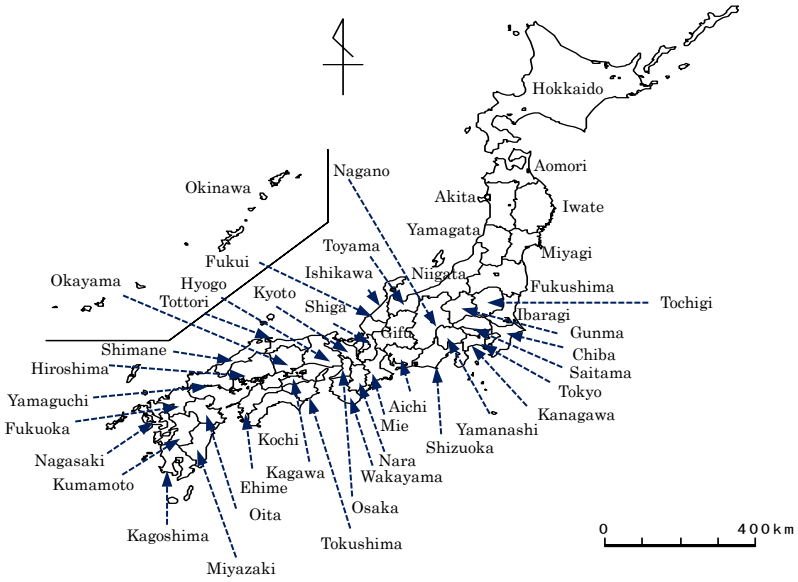

Figure 2.1 Names of Japanese prefectures

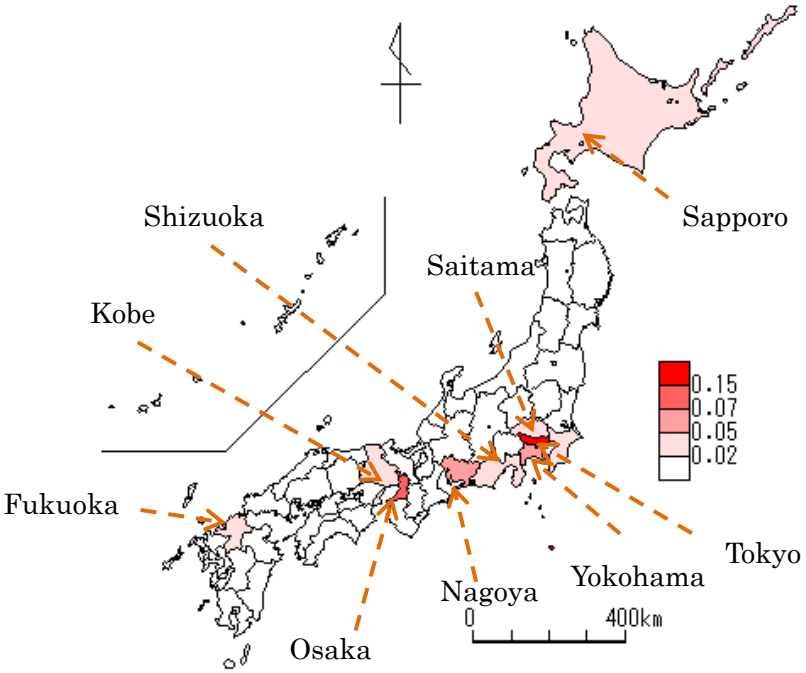

Figure 2.2 Share of employees in KIBS in prefecture for all Japan in 2012

Note: Names of major (larger) cities. City names are not necessarily equivalent to the names of the related prefectures. Source: "*Economic Census for Business Activity 2012"*, Statistics Bureau, Ministry of Internal Affairs and Communications. The more densely shaded regions indicate higher shares. The highest point of the scale shows a share of 0.15 or more, the second highest point shows a share of 0.07 or more to less than 0.15, the third highest point shows a share of 0.05 or more to less than 0.07, and the fourth highest point shows a share of 0.02 or more to less than 0.05.

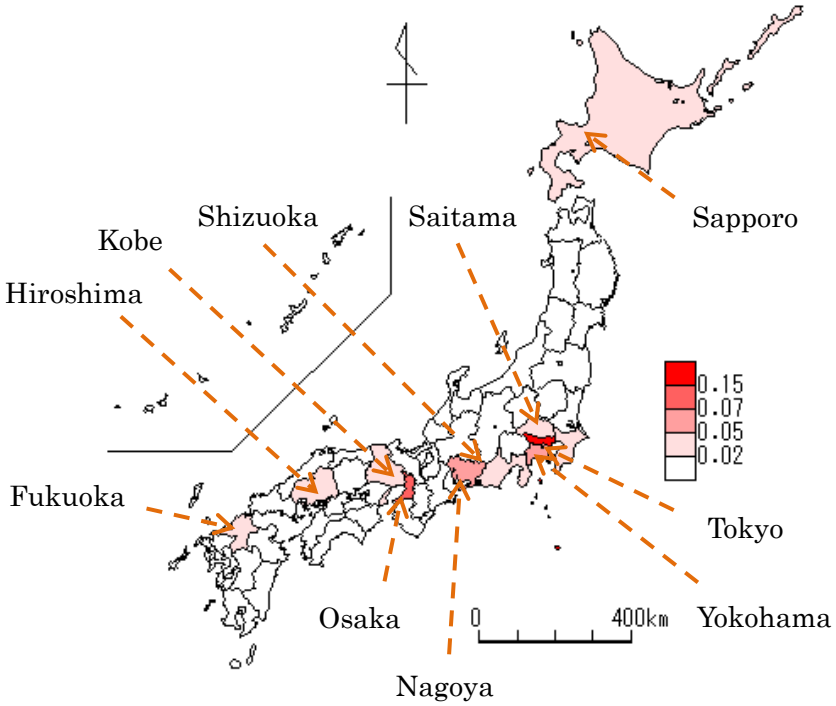

Figure 2.3 Share of employees in HQs in prefectures for all Japan in 2009

Note: Names of major (larger) cities. City names are not necessarily equivalent to the names of the related prefectures. Source: "*Economic Census for Business Frame 2009*", Statistics Bureau, Ministry of Internal Affairs and Communications. The more densely shaded regions show higher share. The highest point of the scale shows a share of 0.15 or more, the second highest point shows a share of 0.07 or more to less than 0.15, the third highest point shows a share of 0.05 or more to less than 0.07, and the fourth highest point shows a share of 0.02 or more to less than 0.05.

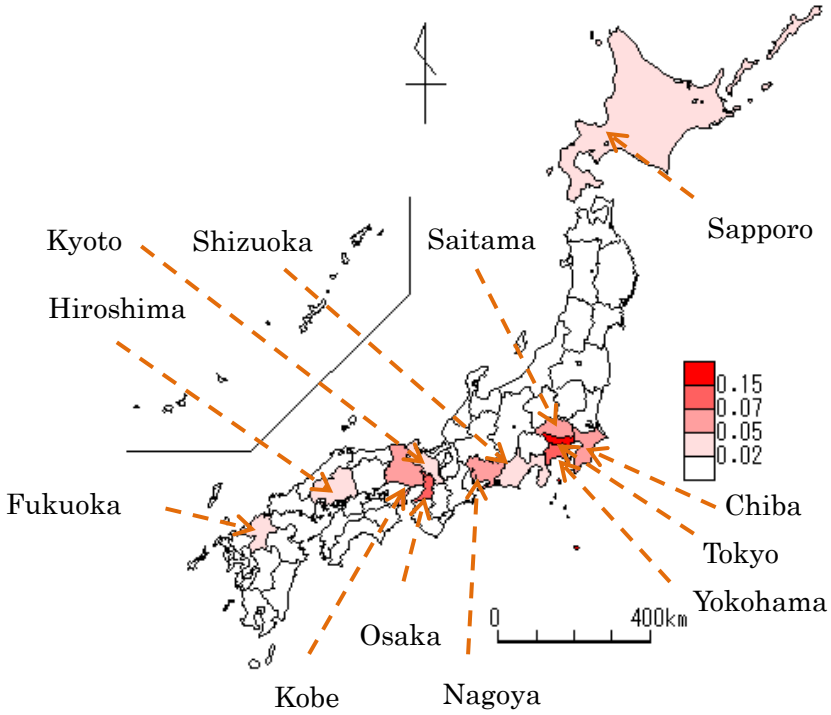

Figure 2.4 Share of the number of highly skilled laborers in prefecture for all of Japan in 2010

Note: Names of major (larger) cities. City names are not necessarily equivalent to the names of the related prefectures. Source: "*National Census 2010*", Statistics Bureau, Ministry of Internal Affairs and Communications. The more densely shaded regions indicate higher shares. The highest point in the scale shows a share of 0.15 or more, the second highest point shows a share of 0.07 or more to less than 0.15, the third highest point shows a share of 0.05 or more to less than 0.07, and the fourth highest point shows a share of 0.02 or more to less than 0.05.

2.4 Theoretical background

In this section, to derive our estimable specification form, we follow the model presented by Redding and Venables (2004), which is built on the spatial economic theory *à la* Fujita et al. (1999).

The economy consists of two sectors, HQs (sector H) and KIBS (sector K) and there are $i, j = 1, \cdots, R$ cities.

First, we describe the demand side of the economy. H sector in city j has the production function in producing homogeneous HQ services represented as

$$H_j = \left[\sum_i^R \int_0^{n_i} k_{ij}(z)^{\frac{\sigma-1}{\sigma}} dz\right]^{\frac{\sigma}{\sigma-1}} = \left[\sum_i^R n_i k_{ij}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \qquad (2.1)$$

where $k(z)$ denotes the varieties of KIBS services with $z \in [0, n_i]$, n_i represents the range of varieties produced in city i, and $\sigma > 1$ stands for the constant elasticity of substitution. The second equality holds because all services produced in city i behave in a symmetric way. The price index for these HQs to purchase all variety of KIBS is defined as

$$P_j = \left[\sum_i^R \int_0^{n_i} p_{ij}(z)^{1-\sigma} dz\right]^{\frac{1}{1-\sigma}} = \left[\sum_i^R n_i {p_{ij}}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \qquad (2.2)$$

where $p_{ij}(z)$ denotes the price of variety z produced in city i and sold in city j. z can be dropped by assuming symmetry.

Using Shephard's lemma to the KIBS service price index, demand for a KIBS service in city j produced in city i is

$$k_{ij} = {p_{ij}}^{-\sigma} E_j {P_j}^{(\sigma-1)}, \qquad (2.3)$$

where $E_j = H_j q_j + \int_0^{n_j} k_j(z) p_j(z) dz$ represents the total expenditure on KIBS and HQs in city j and q_j expresses the price for the HQ service.

The profit function of a sector *K* firm in city i is

$$\pi_i = \sum_j^R p_{ij} k_{ij} - P_i^{\alpha} w_i^{\beta} c \sum_j^R k_{ij} T_{ij} - P_i^{\alpha} w_i^{\beta} F, \qquad (2.4)$$

where c represents a composite of KIBS and skilled labor required for one unit of *K* production, whereas fixed input is F and $P_i^{\alpha} w_i^{\beta}$ gives a unit price of the composite input. Each KIBS firm employs all varieties of KIBS as input with price index P and highly skilled labor with wage w, subject to input shares α and β, where $\alpha + \beta = 1$. For this study, $T_{ij} > 1$ represents the iceberg type transport cost and $T_{ij} - 1$ denotes the proportion of loss of service output produced in city i to arrive in city j. This

expression implies that $k_{ij}T_{ij}$ amount of service must be produced to sell a service to city j that is produced in city i. Consequently, $\sum_j^R k_{ij}T_{ij}$ represents the total output of a sector *K* firm at city i to attend to demand from all regions.

The price for each city where the service product is sold is $p_{ij} = p_i T_{ij}$. With profit maximization, the f.o.b. price p_i has a constant markup as

$$p_i = \frac{\sigma}{\sigma - 1} \times unit\ cost, \qquad (2.5)$$

where $unit\ cost = P_i^{\alpha} w_i^{\beta} c$. Substituting equation (2.5) in (2.4), the profit of sector *K* in each city i becomes

$$\pi_i = \frac{p_i}{\sigma}\left[\sum_j^R k_{ij}T_{ij} - (\sigma - 1)F\right]. \qquad (2.6)$$

The free entry market equilibrium requires that $\pi_i = 0$. It follows from equation (2.6) that

$$\bar{k} = \sum_j^R k_{ij}T_{ij} = (\sigma - 1)F, \qquad (2.7)$$

where $\bar{k}$ represents equilibrium output of a sector *K* firm that is constant irrespective of the market size. Substituting the demand equation (2.3) to $\sum_j^R k_{ij}T_{ij}$, then using equation (2.5), the equation becomes

$$\bar{k}\left[\left(\frac{\sigma}{\sigma - 1}\right) P_i^{\alpha} w_i^{\beta} c\right]^{\sigma} = \sum_j^R E_j P_j^{(\sigma-1)} T_{ij}^{(1-\sigma)}. \qquad (2.8)$$

Solving the equation (2.8) for w_i, the equation is rewritten as

$$w_i^{\beta\sigma} = \left(\frac{\sigma}{\sigma-1}\right)^{-\sigma} c^{-\sigma}\bar{k}^{-1}P_i^{-\alpha\sigma}\sum_j^R E_j P_j^{(\sigma-1)} T_{ij}^{(1-\sigma)},$$

$$w_i = constant \times P_i^{-\frac{\alpha\sigma}{\beta\sigma}}\left[\sum_j^R E_j P_j^{(\sigma-1)} T_{ij}^{(1-\sigma)}\right]^{\frac{1}{\beta\sigma}}, \qquad (2.9)$$

where $constant = \left(\frac{\sigma}{\sigma-1}\right)^{-1/\beta} c^{-1/\beta}\bar{k}^{-1/\beta\sigma}$. This is the wage equation (Fujita et al., 1999). The right hand side (RHS) of the equation shows the "market access": the summation of market capacities under consideration of transport cost. The left hand side (LHS) of the equation is the wage at which each firm in city i can pay with zero profit.

We now turn to the supply side, where access to supply is measured as ${n_i p_{ij}}^{1-\sigma}$, where n_i signifies the number of firms, and where ${p_{ij}}^{(1-\sigma)}$ stands for the price in which the trade cost is included.

From the demand equation (2.3), total service sold from city i to city j is

$$n_i p_i k_{ij} = n_i {p_i}^{1-\sigma} {T_{ij}}^{(1-\sigma)}\left(q_j H_j + \int_0^{n_j} k_j(z)p_j(z)dz\right){P_j}^{(\sigma-1)}. \qquad (2.10)$$

This equation represents transaction between cities. The RHS of equation (2.10) gives both the market capacity $m_j \equiv \left(q_j H_j + \int_0^{n_j} k_j(z)p_j(z)dz\right){P_j}^{(\sigma-1)}$ and the supply capacity $s_i \equiv n_i {p_i}^{1-\sigma}$ associated with trade cost ${T_{ij}}^{(1-\sigma)}$ between cities. Here, m_j denotes the capacity of total sales in city j, which expresses the amount that the services sector *K* in city i can sell. Here, s_i represents the capacity of production, which consists of the number of firms n_i and service price in sector *K* in city i.

Using $p_{ij} = p_i T_{ij}$, the price index becomes

$$P_j = \left[\sum_i^R n_i \left(p_i T_{ij}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = \left[\sum_i^R s_i \, {T_{ij}}^{(1-\sigma)}\right]^{\frac{1}{1-\sigma}}. \qquad (2.11)$$

The price index shows how severe the competition is in city j.

From equation (2.10), the market access of each city i and the supply access of

each city j is defined as

$$MA_i \equiv \sum_j^R \left(q_j H_j + \int_0^{n_j} k_j(z) p_j(z) dz \right) P_j^{(\sigma-1)} T_{ij}^{(1-\sigma)}, \qquad (2.12)$$

$$SA_i \equiv \sum_j^R n_i p_i^{(1-\sigma)} T_{ij}^{(1-\sigma)}. \qquad (2.13)$$

In those expressions, MA_i signifies market access, which is the distance-weighted sum of the market capacities of all partner cities. Also SA_i denotes supply access, which is the distance-weighted sum of supplier capacities of all partner cities.

Finally, from equations (2.9), (2.10), (2.11), (2.12) and (2.13), we have the estimable function of

$$w_i = constant \times P_i^{-\alpha\sigma/\beta\sigma} \left[\sum_j^R \left(q_j H_j + \int_0^{n_j} k_j(z) p_j(z) dz \right) P_j^{(\sigma-1)} T_{ij}^{(1-\sigma)} \right]^{1/\beta\sigma}$$

$$= constant \times SA_j^{\alpha\sigma/\beta\sigma(\sigma-1)} MA_i^{1/\beta\sigma}, \qquad (2.14)$$

where $constant$ is the same as that in equation (2.9).

Parameters are $\sigma > 1, \alpha < 1, \beta < 1$. Therefore, the following are true.

- High demand $\left(q_j H_j + \int_0^{n_j} k_j(z) p_j(z) dz\right)$ in city j leads to high market access.
- If the price index P_j increases, then sector *K* in city i can sell much more of their services. This improvement corresponds to increased market access.
- Reduction in transport cost leads to increased market access.
- An increase in the number of firms n_i and a decline of the price $p_{ij}^{(1-\sigma)}$ increase the supply access.
- Increased supply access reduces the price index, so the cost reduction in KIBS leads to reduced service production cost in city i (from equation (2.11)).
- Similarly, reduction in transport costs will lead to an increase in supply access.

Market access expresses the benefit of proximity to a large market. Supply access indicates the benefit of proximity to suppliers. All in all, the higher the market access and higher the supply access, the higher a wage payment can be afforded.

2.5 Data description and econometric model

2.5.1 Data description

The logarithm of equation (2.14) will be

$$\ln w_i = constant + \left[\frac{1}{\beta\sigma}\right]\ln MA_i + \left[\frac{\alpha\sigma}{\beta\sigma(\sigma-1)}\right]\ln SA_i. \quad (2.15)$$

When defining parameters as $b_1 \equiv \left[\frac{1}{\beta\sigma}\right], b_2 \equiv \left[\frac{\alpha\sigma}{\beta\sigma(\sigma-1)}\right]$, this formation will be estimable.

We use a municipal unit of data for Japan for estimation because the inspection of spatial interaction is appropriate in such a small unit of aggregated data. Because wage data of KIBS are not available in municipal units, we substitute wages with share of the number of KIBS employees in municipalities for all of Japan. This substitution is plausible because it is more profitable for firms to locate in city i, which has a higher wage. The KIBS share corresponds to location probability, in a sense.

As defined by Nakajima (2008), we replace "market access" MA_i with "market potential": MP_i. We follow Head and Mayer (2004) and use Harris (1954) type market potential in municipality i: MP_i. Here, MP_i is derived as

$$MP_i = \sum_{i}^{R} \frac{Y_j}{d_{ij}}, \qquad i \neq j, \qquad (2.16)$$

where Y_j denotes the size of the economy of the other municipality j and d_{ij} expresses the distance from municipalities i to j. Distance is calculated according to the Euclidean distance between municipalities i and j.[3] We use the number of the employees of HQs plus KIBS in municipalities for Y_j. For that reason, the variable is expressed as $MP(HQs + KIBS)_i$.

On the supply side, we replace "supply access" SA_i with the share of highly

[3] Define longitude and latitude of municipality 1 for x_1, y_1, longitude and latitude of municipality 2 for x_2, y_2, and calculate the Euclidean distance as $d = 6378.137 \times \cos^{-1}(siny_1 siny_2 + cosy_1 cosy_2 \cos(x_2 - x_1))$. Longitude and latitude are computed using a "Geocoding Service" provided by the Center for Spatial Information Science of The University of Tokyo. When we input the names of municipalities, "Geocoding Service" returns the longitude and latitude of city offices of the municipalities. Therefore, we use these data.

skilled labor: $Lshare_i$. This share is calculated as the share of the number of highly skilled laborers in municipality i of the number of highly skilled laborers throughout Japan. We also use $WLshare_i$ to capture the neighboring effects of share of highly skilled laborers. Highly skilled labor in the neighboring municipality affects the KIBS wage in own municipality. W is $R \times R$ spatial weight matrix, where R represents the number of municipalities. Diagonal elements of W are set to 0; off-diagonal elements are the inverse distance of 1,000 km unit between cities i and j. This connection effect is thought to have distance decay so the off-diagonal elements of W can be expressed as a gravity-like model, following Anselin (2002), as

$$w_{ij} = \frac{1}{dist_{ij}^2}, \qquad i \neq j,$$

where $dist_{ij}$ expresses the distance between municipalities i and j. As a convention, each row of W is normalized to 1.

For the KIBS share, we use *ECBA2012* for the data of KIBS employees in municipalities. The KIBS share of municipality i is calculated as the share of the number of employees of KIBS in municipality i to the number of employees of KIBS for all of Japan. The numbers of HQ employees and KIBS employees are taken from *ECBF2009* for calculating market potential. As a proxy for highly skilled labor, the population of university graduates is taken from the "*National Census 2010*" from Statistics Bureau, MIC.

We use some controls for municipalities. Population density ($POPdense_i$) is a proxy for congestion. This setting of the proxy is in line with a procedure used in an earlier study: Jacobs et al. (2014) state that population density represents crowding effects. For calculation of the population density, the population is taken from "*Basic Resident Register (Jyumin-kihon-daicho) 2010*" from Statistics Bureau, MIC. The land area of municipalities is from "*Statistical reports on the land area by prefectures and municipalities in Japan* (*Zenkoku-todoufuken-sikutyoson-betsu-mennski-no-shirabe*)" from the Geospatial Information Authority of Japan.

Second, the number of enterprises (ent_i) is used because KIBS also sell their services to the other sector, irrespective of HQs and KIBS. Third, the manufacturing share of municipalities ($manu\ share_i$) is used because municipalities with high manufacturing shares show different activities for KIBS locations. For instance, Aichi prefecture is known to have high inclination of manufacturing, with many HQs related to

manufacturing. However, KIBS activity is lower than in other large cities such as Tokyo, Osaka, or Kanagawa (Fukui and Matsushita, 2018). The number of enterprises and the manufacturing share based on the number of manufacturing employees in municipalities to the number of employees of the total sector in municipalities are from *ECBA2012*.

In addition to these, we use the cross term $Knowledge_i = Lshare_i \times POPdense_i$ and $WKnowledge_i$ to capture knowledge agglomeration in the municipalities. Population density is a proxy to the degree of urbanization. Therefore, if the share of highly skilled labor and population density is simultaneously high, then the concentration of highly skilled labor is apparent in large cities so knowledge spillover occurs and agglomeration of knowledge is strong in that municipality. We conduct an alternative estimation using $Knowledge_i$ and $WKnowledge_i$ instead of using $Lshare_i$ and $WLshare_i$.

For cross-section, 1877 municipalities are used. The data pertain to private sectors (excluding public sector). *ECBA2012* and *ECBF2009* are exhaustive surveys about Japanese establishments and enterprises. Single-unit enterprises are excluded: we use only data of head office of multi-unit enterprises, for HQs because single-unit enterprises are presumed to demand KIBS in different way compared with head office of multi-unit enterprises. Demand for KIBS of head office of multi-unit enterprises is presumed to be more knowledge-intensive than for single-unit enterprises.

Descriptive statistics are presented in Table 2.1. The maximum and minimum values of *KIBS share* are 0.063 and 0.000, respectively. The *market potential of HQs and KIBS* ranges from 5,907 to 849,875. The mean of *share of highly skilled labor* shows low value (0.001). *Knowledge agglomeration* ranges from 0 to 186, and the standard deviation is relatively high. The maximum value of *Population density* is 20,712, and the minimum value of *Population density* is 1.508. *Number of enterprises* ranges from 70 to 952,499, and the standard deviation is relatively high. *Manufacturing share* ranges from 0 to 0.678.

Table 2.1 Descriptive statistics for variables used in estimation for the agglomeration of KIBS

	Mean	Standard deviation	Median	Max	Min
KIBS share	0.001	0.003	0.000	0.063	0.000
Market potential of HQs and KIBS	63471	68277	44512	849875	5907
Share of highly skilled labor	0.001	0.001	0.000	0.013	0.000
Knowledge agglomeration	2.649	10.01	0.036	186	0.000
Population density	1524	3129	251	20712	1.508
Number of enterprises	29731	59128	10868	952499	70
Manufacturing share	0.206	0.122	0.192	0.678	0.000

Note: *KIBS share* is the share of the number of KIBS employees in municipalities, *Market potential of HQs and KIBS* is market potential in municipality i which is defined in equation (2.16) using the number of employee of HQs plus KIBS in municipalities and distances between municipality i and j, *Share of highly skilled labor* is the share of the number of highly skilled laborers in municipality i to the number of highly skilled laborers throughout Japan, *Population density* is the population density in municipality i, *Knowledge agglomeration* is *Share of highly skilled labor* × *Population density*. Also, *Number of enterprises* denotes the number of enterprises, and *Manufacturing share* stands for the manufacturing share based on the number of employees of manufacturing in municipalities to the number of employees of all sectors in municipalities.

2.5.2 Econometric model

Our specification in estimating agglomeration of KIBS is using the Spatial Error model (SEM). Meliciani and Savona (2015) use the Spatial Durbin model (SDM) for the estimation of business service specialization. Actually, SDM is a general model that encompasses SEM or a Spatial Autoregressive model (SAR) (LeSage and Pace, 2009). In our spatial regression, spatial dependence for the independent variable and dependent variable are already included in specifications. These are market potentials of KIBS and HQs: $MP(HQs + KIBS)_i$ and the spatial lag of highly skilled labor share: $WLshare_i$. Therefore, in our case, spatial dependence between municipality i and j is summarized in the error term. Unobserved spatial dependence might appear in the error term. For instance, knowledge spillover or office supply in neighboring regions is conceivably unobserved spatial dependence. These variables are not available.

Specification for the estimation is

$$KIBSshare_i = constant + b_1 \ln MP(HQs + KIBS)_i + b_2\, Lshare_i + b_3 WLshare_i + \gamma_1 \ln POPdense_i + \gamma_2 \ln ent_i + \gamma_3 manushare_i + u_i,$$

$$u_i = \lambda W u_i + e_i, \quad (2.17)$$

where the $KIBSshare_i$ is the share of the number of KIBS employees in municipalities, $\ln MP(HQs + KIBS)_i$ is the log of market potential in municipality i, which is defined in equation (2.16) using the number of the employees of HQs plus KIBS in municipalities and distances between municipality i and j. Also, $Lshare_i$ is the share of the number of highly skilled laborers in municipality i to the number of highly skilled laborers throughout the whole of Japan, $WLshare_i$ represents the weighted sum of $Lshare_i$ using $R \times R$ spatial weight matrix W, $\ln POPdense_i$ signifies log of population density in municipality i, $\ln ent_i$ denotes the log of the number of enterprises, $manushare_i$ expresses the manufacturing share based on the number of employees of manufacturing in municipalities to the number of employees of the total sector in municipalities, u_i is the error component, λ is a spatial parameter associated with the spatial weight matrix, and e_i is the idiosyncratic error term.

An alternative specification is

$$\begin{aligned} KIBSshare_i = constant &+ b_1 \ln MP(HQs + KIBS)_i + b_2 \ln Knowledge_i \\ &+ b_3 W \ln Knowledge_i + \gamma_1 \ln POPdense_i + \gamma_2 \ln ent_i \\ &+ \gamma_3 manushare_i + u_i, \\ u_i = \lambda W u_i + e_i, \quad (2.18) \end{aligned}$$

where $\ln Knowledge_i$ is the log of $Lshare_i \times POPdense_i$ and $W \ln Knowledge_i$ is the weighted sum of $\ln Knowledge_i$ using the $R \times R$ spatial weight matrix W.

Correlation coefficients are presented in Table 2.2. High correlation coefficients (over 0.6) are apparent between *KIBS share* and *Market potential of HQs and KIBS* (0.658), *KIBS share* and *Number of enterprises* (0.865), *Market potential of HQs and KIBS* and $W \times$ *share of highly skilled labor* (0.819), *Market potential of HQs and KIBS* and $W \times$ *Knowledge agglomeration* (0.896), *Market potential of HQs and KIBS* and *Population density* (0.788), *Market potential of HQs and KIBS* and *Number of enterprises* (0.664), *Share of highly skilled labor* and $W \times$ *share of highly skilled labor* (0.667), *Share of highly skilled labor* and *Knowledge agglomeration* (0.790), *Share of highly skilled labor* and $W \times$ *Knowledge agglomeration* (0.650), *Share of highly skilled labor* and *Number of enterprises* (0.684), *Knowledge agglomeration* and $W \times$ *Knowledge agglomeration* (0.803), *Knowledge agglomeration* and *Population density* (0.740), and $W \times$ *Knowledge agglomeration* and *Population density* (0.813). Negative correlations

are seen among *Manufacturing share* and all other variables.

Consequently, one can expect positive causality among our examined variables: *KIBS share*, *Market potential of HQs and KIBS*, *Share of highly skilled labor*, $W \times$ *share of highly skilled labor*, *Knowledge agglomeration*, and $W \times$ *Knowledge agglomeration*. Here, estimation is conducted via the generalized moments (GM) estimator presented by Kelejian and Prucha (1999).

Table 2.2 Correlation coefficients for variables used in estimation for the agglomeration of KIBS

	KIBSshare	Market potential of HQs and KIBS	Share of highly skilled labor	W × share of highly skilled labor	Knowledge agglomeration	W × Knowledge agglomeration	Population density	Number of enterprises
Market potential of HQs and KIBS	0.658							
Share of highly skilled labor	0.342	0.544						
W × share of highly skilled labor	0.370	0.819	0.667					
Knowledge agglomeration	0.337	0.677	0.790	0.695				
W × knowledge agglomeration	0.463	0.896	0.650	0.923	0.803			
Population density	0.351	0.788	0.599	0.765	0.740	0.813		
Number of enterprises	0.865	0.664	0.684	0.504	0.503	0.547	0.490	
Manufacturing share	-0.149	-0.092	-0.218	-0.123	-0.198	-0.185	-0.210	-0.167

Note: *KIBS share* is the share of the number of KIBS employees in municipalities, *Market potential of HQs and KIBS* is market potential in municipality i which is defined in equation (2.16) using the number of employee of HQs plus KIBS in municipalities and distances between municipality i and j, *Share of highly skilled labor* is the share of the number of highly skilled laborers in municipality i to the number of highly skilled laborers throughout Japan, $W \times$ *Share of highly skilled labor* is the weighted sum of *Share of highly skilled labor* using the $R \times R$ spatial weight matrix W, *Population density* is the population density in municipality i, *Knowledge agglomeration* is *Share of highly skilled labor* × *Population density*, and $W \times$ *Knowledge agglomeration* is the weighted sum of *Knowledge agglomeration* using $R \times R$ spatial weight matrix W. Also, *Number of enterprises* denotes the number of enterprises, and *Manufacturing share* stands for the manufacturing share based on the number of employees of manufacturing in municipalities to the number of employees of all sectors in municipalities.

2.6 Results and discussion

This section presents our estimation results. Results are arranged in Table 2.3. In Specification (1), only structural variables are employed.

Our parameters of concern under GM estimation are all positive and significant. If the *Market potential of HQs plus KIBS* increases 1%, then the *KIBS share* increases by 0.000005 points. The magnitude is extremely low. However, if the *highly skilled labor*

share increases 1 point, then the *KIBS share* increases by 0.462 points. If the *highly skilled labor share* of neighboring municipalities increases 1 point, then the *KIBS share* increases by 0.668 points.

In (2) we consider all explanatory variables (excluding $\ln Knowledge_i$ and $W \ln Knowledge_i$). For this estimation, all the control variables are plausible. Estimation yields positive and significant values for the *Number of enterprises*, but negative and significant values for the *Population density* and the *Manufacturing share*. The magnitude for *Market potential of HQs plus KIBS* increases. *Highly skilled labor share* is not significant here, but the *Weighted highly skilled labor share* is positive and significant.

For alternative specifications (3) and (4), a similar tendency is apparent for concerned parameters, but the magnitude for highly skilled labor share decreases in (4). In specification (3), *highly skilled labor share* is not significant.

In specifications from (1)–(4), all spatial parameters are positive and significant. For that reason, unobserved spatial dependence might exist, e.g., knowledge spillover, among nearer municipalities.

Considering specifications (5)–(8), we next examine *Knowledge agglomerations*. In (5), concerned parameters are significant and positive for *Market potential of HQs plus KIBS* and for *Knowledge agglomeration*, but they are not significant for *Weighted knowledge agglomeration.* If the *Market potential of HQs plus KIBS* increases 1%, then the *KIBS share* increases by 0.000005 points. If *Knowledge agglomeration* increases 1%, then the *KIBS share* increases by 0.00001 points. The magnitudes for both variables are very low.

Specification (6) incorporates all control variables and all results are plausible. Alternative specification (7) shows non-significance for *Knowledge agglomeration* and *Weighted knowledge agglomeration.* Specification (8) shows a similar tendency to that of (6). All the estimated spatial parameters are positive and significant again.

The results support our model. If the agglomeration of HQs and KIBS is strong in municipalities, then the market access will be high. If easy access to highly skilled labor increases, then supply access will increase in kind. Therefore, KIBS will be located in those municipalities. However, the magnitude of the agglomeration of HQs and KIBS is relatively low from our empirics. On the one hand, the effect of highly skilled labor share and that of the neighbors in municipalities is strongly supported.

Table 2.3 Estimation results of the agglomeration forces of KIBS

	GM(1)	GM(2)	GM(3)	GM(4)
Market potential of HQs and KIBS (log)	0.0005 ***	0.001 ***	0.0005 ***	0.001 ***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Share of highly skilled labor	0.462 ***	0.058	0.083	0.157 *
	(0.073)	(0.083)	(0.084)	(0.082)
W × share of highly skilled labor	0.668 ***	0.808 ***	0.520 ***	1.010 ***
	(0.220)	(0.220)	(0.220)	(0.219)
Knowledge agglomeration (log)				
W × knowledge agglomeration (log)				
Population density (log)		-0.0004 ***		-0.0004 ***
		(0.000)		(0.0001)
Number of enterprises (log)		0.0006 ***	0.0004 ***	0.0005 ***
		(0.0001)	(0.0000)	(0.0001)
Manufacturing share		-0.003 ***	-0.003 ***	
		(0.0005)	(0.0005)	
Intercept	-0.006 ***	-0.011 ***	-0.008 ***	-0.010 ***
	(0.001)	(0.002)	(0.001)	(0.002)
Lambda	0.264 **	0.264 **	0.269 **	0.270 **

	GM(5)	GM(6)	GM(7)	GM(8)
Market potential of HQs and KIBS (log)	0.0005 ***	0.0008 ***	0.0005 ***	0.0006 ***
	(0.000)	(0.0002)	(0.0002)	(0.0002)
Share of highly skilled labor				
W × share of highly skilled labor				
Knowledge agglomeration (log)	0.001 ***	0.0003 **	0.00005	0.0005 ***
	(0.000)	(0.0001)	(0.0001)	(0.0001)
W × knowledge agglomeration (log)	0.0002	0.0005 **	0.0003	0.0006 ***
	(0.000)	(0.0002)	(0.0002)	(0.0002)
Population density (log)		-0.0004 ***		-0.0005 ***
		(0.0001)		(0.0001)
Number of enterprises (log)		0.0006 ***	0.0004 ***	0.0006 ***
		(0.0001)	(0.00005)	(0.0001)
Manufacturing share		-0.002 ***	-0.003 ***	
		(0.001)	(0.001)	
Intercept	-0.005 ***	-0.011 ***	-0.009 ***	-0.009 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Lambda	0.268 **	0.263 **	0.276 **	0.264 **

Note: Parentheses show the standard error. The number of observations is 1877. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. “Lambda” corresponds to the spatial parameter in equations (2.17) and (2.18).

2.7 Conclusion

With the increasing importance of the knowledge-intensive business service sector (KIBS) in Japan, one can observe dense agglomerations of KIBS in large cities such as Tokyo and Osaka. We attempt to identify the cause for dense agglomeration of

KIBS. We take “market access” and “supply access” (Redding and Venables, 2004) as causes for agglomeration in KIBS because higher market access and higher supply access make higher wage payments for KIBS affordable. No study—building on spatial economic theory—has specifically examined the agglomeration force of KIBS.

We estimate several regression equations using Japanese municipal unit data. We use the KIBS share as the independent variable. The market potential for HQs and KIBS is used as a proxy for market access. Also, the population of university graduates is used as a proxy for supply access, highly skilled labor. Additionally, we use a cross term, the product of highly skilled labor share and population density, to express knowledge agglomeration in the municipalities.

We propose our monopolistic competition model for describing the agglomeration force of KIBS built on Redding and Venables (2004). A reduced form, based on the structural form, is driven. We conduct estimation for the whole KIBS sector.

Results obtained using GM method by Kelejian and Prucha (1999) demonstrate that all the related parameters are estimated with positive and significant values. The results support our model. If the agglomeration of HQs and KIBS is strong in municipalities, then the market access will be high. If easy access to the highly skilled labor increases, then supply access will be high. Therefore, KIBS will be located in those municipalities. However, the magnitude of the agglomeration of HQs and KIBS is pretty low from our empirics. On the one hand, the effect of the share of highly skilled labor and that for the neighbors in municipalities is strongly supported. In addition, although the magnitude is low, the effect of the knowledge agglomeration is also confirmed.

It implies that better access to highly skilled labor strengthen supply access and KIBS firms will be even more inclined to establish locations in those municipalities. Additionally, the agglomeration of HQs and KIBS and knowledge agglomeration also attracts KIBS firms.

Chapter 3
Did the Act concerning the Industry Restriction Hamper Economic Growth?

3.1 Introduction

Rapid population growth occurred in large cities in Japan in the mid-1950s to the 1960s. During 1955–1960, the Tokyo metropolitan area population increased from approximately 7 million to 8.3 million, whereas the population of Osaka city increased from approximately 2.6 million to 3 million (National Census). These increases in these two main economic areas in Japan are attributable to a population influx from other areas (National Land Development Council, 2001). In addition to this, Japan experienced high economic growth from the mid-1950s until the mid-1970s, which led to the concentration of industries into large cities. According to such rapid growth of population and high economic growth, large cities such as Tokyo and Osaka and their surrounding areas became overcrowded; environmental problems ensued. At the same time, under a national policy of geographically well-balanced national development, the "Comprehensive National Development Plan" was set in 1962 and was enforced until 2000.

These changes led to the enactment of the law called the "Act concerning the Industry Restriction" (hereafter AIR). The AIR restricted new construction of factories and universities and expansion of existing factories and universities in congested areas. Policymakers judged the cause for the rapid population growth as newly constructed and expanded factories and universities.

Targeted areas of the AIR were the central area of the Metropolitan area including Tokyo (hereafter central Metro) and the central area of the Kinki region including Osaka (hereafter central Kinki).[4,5] Therefore, the AIR is a kind of "place-based policy," by which the policy execution is limited to some area (place). The AIR comprised

[4] The Metropolitan area for purposes of this paper includes Saitama, Chiba, Tokyo, and Kanagawa prefectures.
[5] The Kinki region for purposes of this paper includes Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama prefectures.

two specific laws: the "Act concerning the Industry Restriction in the Built-up Area of the National Capital Region" (enacted in 1959, hereafter AIR in Metro) and the "Act concerning the Industry Restriction in the Built-up Areas of the Kinki Region" (enacted in 1964, hereafter AIR in Kinki)

At that time, the economy of central Kinki was more highly dependent on the manufacturing sector when compared with central Metro. Because no data are available to assess the respective sectoral shares of economic activity for covering areas of central Kinki and central Metro, we substitute central Kinki and central Metro, respectively, for Osaka prefecture and Tokyo Metropolis. Using nominal GDP from "*Annual Report on Prefectural Accounts (Kenmin Keizai Keisan)*" by the Cabinet Office, the share of the manufacturing sector in Osaka was 42% in Tokyo was 35% in 1958: the year before the enactment of AIR in Metro. Through the 1980s and the 1990s, central Metro has enjoyed centralization of service, finance, and information technology (IT) and communication sectors because of the transformation in the industrial structure in Japan: from manufacturing to tertiary industries. Using nominal GDP, again, the share of the sum of service, finance, and transportation and communications sectors in Osaka were 26% in 1985 and 36% in 1999, whereas the share of the sum of service, finance, and transportation and communications sectors in Tokyo were 34% in 1985 and 46% in 1999.[6]

Therefore, until the repeal of the AIR in 2002, the AIR was believed to exert a stronger negative effect on central Kinki than on central Metro because the AIR mainly restricted manufacturing activity. The AIR was suspected to be overly restrictive. For the over-restricted period, restricted areas in central Kinki might have experienced lower growth than expected (Kakumu and Fukushige, 2003; Hatta, 2008).

Actually, the economy of central Kinki is more deprived than that of central Metro. Fukui (2014) argues that the share of nominal GDP of Osaka prefecture compared to all of Japan was 10.2% in 1970, but it declined to 7.3% in 2010. By comparison, the share of nominal GDP of Tokyo metropolis compared to all of Japan was 17.1% in 1970 and increased to 18.4% in 2010. Many possible factors can account for this deterioration of economy in Osaka (or in Kinki as in Fukui, 2014); a main reason is probably the AIR.[7] Therefore, closer inspection of the effects of AIR is expected to be important for regional economic policy.

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[6] IT and communication sectors are included in the transportation and communications sector.

[7] Another important possibility is high-speed bullet trains, Shinkansen, which commenced operations in 1964. Shinkansen trains pass mainly between Tokyo and Osaka. However, the verification of this causality is expected in future work.

As described herein, we investigate whether legal restrictions hampered the growth of the restricted areas or not, especially in central Kinki. To implement regional program evaluation for verifying the AIR effects, we set a treatment group (restricted area) and a control group (unrestricted area) to conduct causal inference. Treatment in this paper is repeal of the law.

To verify the causal inference of place-based policies (Neumark and Simpson, 2014), a program evaluation method has been developed in the field of microeconomics (Blundell and Costa-Dias, 2009; Imbens and Wooldridge, 2011).

A usual and familiar ways of identifying the effect of these programs is using the difference-in-differences (DID). However, spatial dependence or cross-sectional dependence is strongly suspected in place-based policies. Under spatial dependence or cross-sectional dependence, unobserved heterogeneity exists. Unobserved heterogeneity is comprised of many economic or social factors vary across regions and time. Moreover, because these factors evolve in a complicated way, the standard DID cannot capture such an unobservable factor.

Bai (2009) proposes “interactive-effects model” or “linear factor model” for panel data. Bai’s model is useful for our empirics. A few studies have specifically examined regional program evaluation using interactive effect model constructed on DID (Hsiao et al., 2012; Kim and Oka, 2014; Gobillon and Magnac, 2016; and Givord et al., 2018). Nevertheless, no studies have explored the Japanese regional policy evaluation by using an interactive effect model.

We also propose “Spatial Error-DID” (hereafter SE-DID) which controls unobserved spatial dependence using a spatial weight matrix instead of factors in Bai’s model. We include a spatial weight matrix for the error term and depict the spatial autoregressive structure in the error term.

Only Kakumu and Fukushige (2003) investigate whether the AIR is overregulating the restricted area or not, to our knowledge. They use a production function to assess the respective productivities of restricted and unrestricted areas before repeal of the law (2002). They conclude that the laws led to overregulation. However, they do not investigate causality. They merely compare productivity before treatment in 2002, so that the conclusion is provisional. Unless we consider those examining the importance in assessing the influence of the law: AIR, we find only a few studies addressing this issue.

The importance of this study is twofold. Although great doubt persists about the obstruction of the growth of larger cities, especially for central Kinki, because of the law,

the influence of the AIR has received less attention in the literature. Moreover, the accuracy of place-based policy evaluation is important for regional policy making, although no study has examined the Japanese regional policies by using a more elaborate ways—an interactive effect model.

The paper is organized as follows. Section 2 proposes a quick review of the literature on place-based policy evaluation. Section 3 provides an explanation of AIR. Section 4 is a brief discussion of causal inference and place-based policy. Section 5 presents steps for causal inference. Section 6 proposes an empirical strategy and data description. Section 7 explains empirical results and discussion, followed by Section 8, which presents conclusion.

3.2 Literature review of place-based policy evaluation

Many recent studies have evaluated the effects of policies that are specific to the regional units. Papke (1994) analyzes the effect of the Indiana, U.S. Enterprise Zone (EZ) program on local employment and investment. Using DID, positive effects are found. Hanson (2009) assesses the effects of the federal EZ on employment and poverty; IV estimation shows no effect of the program. Neumark and Kolko (2010) specifically examine California's EZ program with establishment level data: no effects are detected. Accetturo and Blasio (2012) evaluate the effectiveness of government sponsored programs. Using a difference-in-differences with propensity score matching, their results show that the program has no effect on economic growth.

Freedman (2013) explores the effects of a Texas EZ program using regression discontinuity. A positive effect is verified. Wang (2013) investigates the effect of Special Economic Zones in China and finds that the program increases foreign direct investment. Schminke and Biesebroeck (2013) evaluate the program effectiveness of Economic and Technological Development Zones (ETDZ) in China. Results demonstrate that firms located in ETDZ achieve much higher export values. Kline and Moretti (2014) assess the long-run effects of a development program in the U.S.: the Tennessee Valley Authority (TVA). They find that the TVA led to growth in agricultural employment, and agricultural employment growth fell after the scaling down of programs while manufacturing employment continued to grow.

Harger and Ross (2016) examine the effects of a New Market Tax Credit on business activity. They find an increase in retail employment. Ahlfeldt et al. (2017) assess the effects of a revitalization policy which was implemented in Berlin, Germany because

of the partition between West and East Germany until 1989. Results show that the policy reduced the buildings to poor conditions. Givord et al. (2018) use Bai's method to investigate the French "Enterprise Zone" (EZ) initiative implemented in 1997. Long-term estimates suggest that this program is not effective for sustaining economic development. Conclusions are diverse depending on the period to be evaluated or the method to be used for estimation.

Program evaluation in this paper is slightly different from many research papers that have presented investigations in this area. Usual place-based policies are that a law or system is implemented for some period to improve some aspect of economic activity. For example, an economic zone initiative is implemented in revitalizing distressed areas for improvement of business location. However, we interpret a law repeal as an implementation of policy. This is the treatment under place-based policy for our case. Actually, law repeal was intended to avoid over-restriction for the restricted area because the original purpose of the law was presumably accomplished. Our study casts new light on evaluation of place-based policy.

3.3 About the Act concerning the Industry Restriction

The AIR in Metro and Kinki restricted new construction and expansion of factories. With these restrictions, the law was aimed at improving urban congestion and environmental problems by preventing population influx from the other areas.

Specifically examining AIR in Kinki, restricted areas are the greater part of Osaka city, approximately half of Amagasaki city, part of Kyoto city, Kobe city, Ashiya city, Nishinomiya city, Sakai city, Higashiosaka city, and Moriguchi city. The total area was approximately 461 square kilometers (Figure 3.1).

The size of factories is restricted to 1,000 square meters at most.[8] The classroom size for university and technical colleges is restricted to 1,500 square meters at most. The classroom size for technical school and schools of various kinds is restricted to 800 square meters at most. Construction of factories or classrooms larger than these restrictions is fundamentally prohibited under AIR.

A noteworthy exception is that if the new construction or expansion is judged not to accelerate the expansion of population, then the prefectural governor or mayor of designated city can approve new construction or expansion of factories or classrooms

[8] The factory size restriction in Higashiosaka and Amagasaki city, where are the agglomerated areas of small and medium sized enterprises was relaxed to 1,500 square meters.

greater than the restriction.[9] However, approval was granted under the AIR valid period in Kinki only for 14 factories and one university.[10]

After 1965, the population of urban areas in Kinki (only Osaka, Hyogo, and Kyoto city) decreased from 5.74 million in 1965 to 5.49 million in 1995 (National Census). The share of enterprises of the manufacturing sector in the whole economy in Japan decreased from 15.8% in 1966 to 11.1% in 1999. The enrollment in universities and colleges showed a downward trend from 810 thousand at its peak in 1993 (National Land Development Council, 2001). From such a transition of economic background, both AIR in Metro and AIR in Kinki were repealed in July 2002.

[9] For new construction or expansion of a factory over 3,000 square meters or university, irrespective of square measure, approval is needed from the Minister of Land, Infrastructure and Transport.
[10] Approval in Metro was only 27 for factories and 9 for universities.

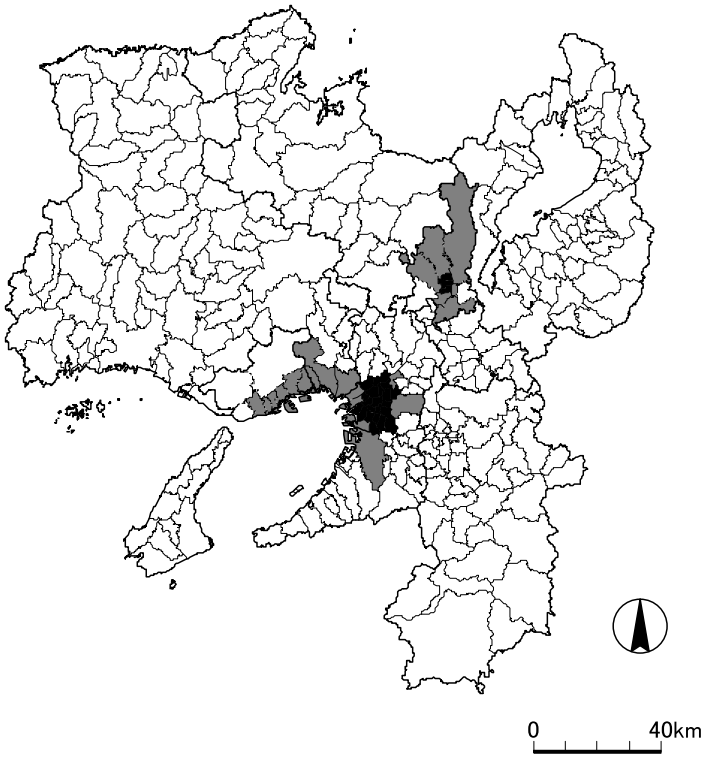

Figure 3.1 Map of the area restricted by Act concerning the Industry Restriction in Kinki

Note: Dark areas are fully restricted; pale areas are partially restricted municipalities. Classification of municipalities was done in 2001. Kinki is Shiga, Kyoto, Osaka, Hyogo, and Wakayama prefectures, but we exclude Wakayama prefecture from the map. The fully restricted area is Kamigyou-ku, Nakagyo-ku, and Shimogyo-ku of Kyoto city, Miyakojima-ku, Fukushima-ku, Nishi-ku, Minato-ku, Taisyo-ku, Tennouji-ku, Naniwa-ku, Higashi-yodogawa-ku, Higashinari-ku, Ikuno-ku, Asahi-ku, Jyoutou-ku, Abeno-ku, Sumiyoshi-ku, Higashi-sumiyoshi-ku, Nishinari-ku, Yodogawa-ku, Tsurumi-ku, Hirano-ku, Kita-ku, and Chuoku of Osaka city. Partially restricted areas are Kita-ku, Sakyo-ku, Higashiyama-ku, Minami-ku, Ukyo-ku, and Fushimi-ku of Kyoto city, Konohana-ku, Nishiyodogawa-ku, and Suminoe-ku of Osaka city, Higashinada-ku, Nada-ku, Hyogo-ku, Nagata-ku, Suma-ku, and Chuo-ku of Kobe city, Sakai, Moriguchi, Higashiosaka, Amagasaki, Nishinomiya, and Ashiya cities.

3.4 Causal inference and place-based policy

For program evaluation, we call the “treatment group” that group which takes treatment of the policy or program and designate the “control group” as that group which does not take treatment of a policy or program.

In many empirics in economics, a simple comparison of the outcomes of the treatment and control groups does not lead to accurate evaluation of a causal effect. Some covariates affect the outcomes of both groups. If one can observe both outcome data of treated for treatment group and outcome data of untreated for treatment group after the execution of policy or program, then a simple comparison of both outcomes corresponds to a causal effect. Nevertheless, this is not possible in many cases. Consequently, we make a counterfactuals, which corresponds to the outcome data of untreated for the treatment group after the execution of policy or program. Then we compare the real outcome data for the treated group and counterfactual after the period of policy execution. This is a so-called average treatment effect on the treated (ATT).

Flourishing studies of policy or program evaluation can be found in the fields of education and labor because a plausible counterfactuals is obtainable with random assignment. Compared with the fields of education and labor, the field of urban and regional economics presents some difficulty in conducting causal inference because of rare random assignment. In accordance with related literature, we designate “place-based policy” as related to policies or programs implemented for urban or regional unit.

Place-based policies are designated mainly for deprived areas and are aimed to revitalize these disadvantaged local economic activities such as growth of population, residents, employment, and small enterprises’ activity. Therefore, for place-based policy, a policy or program is far from a random assignment, in which the treated area is correlated with a policy or program. In other words, the determination process of policy or program is strongly dependent on the local economic situation. Accordingly, it is difficult to find a useful controlled regional units. Also, it is difficult to appropriately evaluate causality in place-based policies.

DID combined with propensity score matching (PSM, Rosenbaum and Rubin, 1983) is a useful ways of evaluation of place-based policy. Nevertheless, using standard DID for identifying the causal effects of these programs might lead to some bias. Unbiased estimation using DID requires the assumption of a common trend before the treatment, although the estimated value under a place-based policy tends to be affected by unobserved economic variations, which leads to a biased estimation of DID.

To be more specific, spatial dependence or cross-sectional dependence is strongly suspected in urban or regional outcomes. Under the spatial dependence or cross-sectional dependence, unobserved heterogeneity exists. However, unobserved heterogeneity comprises many economic or social factors that vary across regions and time. Moreover, because these factors evolve in complicated ways, the standard DID

cannot capture such an unobservable phenomenon.

As a solution to this difficulty, Bai (2009) proposes a more elaborate mode of using an interactive effect model or linear factor models for panel data that describe the complicated unobservable. Applying Bai's model for DID (Kim and Oka, 2014; Gobillon and Magnac, 2016) is useful for our empirics. Actually, a pivotal part of Bai's estimator relies on a factor model, factor and factor loadings capture the complicated unobservable of the urban or regional economies. It is particularly interesting that using Monte Carlo simulation, Kim and Oka (2014) and Gobillon and Magnac (2016) show that standard DID leads to biased estimation compared with the interactive effect model when interactive effects or factors are included in DGP.

We use Bai's (2009) method combined with PSM (Gobillon and Magnac, 2016; Givord et al., 2018) for our empirics. We also propose SE-DID combined with PSM. SE-DID controls unobserved spatial dependence using a spatial weight matrix instead of factors in Bai's model.

3.5 Setup for causal inference

Here we describe the setup for causal inference used for this paper. Following Gobillon and Magnac (2016), the average effect of the treatment on the treated (ATT) is discerned as

$$ATT = [y_{it}(1) - y_{it}(0)|D_i = 1], \quad t \geq T_D, \qquad (3.1)$$

where $i = 1, 2, \cdots, N$ is an index of cross-sectional units, $t = 1, 2, \cdots, T$ represents the time index of observations, $D_i \in \{0, 1\}$ is a dummy variable for treatment, and $y_{it}(d)$ is the outcome for the $d = 1$ treatment group and the $d = 0$ control group. Treatment is executed on date $T_D < T$.

Cross-sectional units $i = 1, 2, \cdots, N_1$ are assigned to the treatment group; the other units $i = N_1 + 1, N_1 + 2, \cdots, N$ are assigned to the control group. ATT is also written as

$$ATT = \mathrm{E}[y_{it}(1)|D_i = 1] - \mathrm{E}[y_{it}(0)|D_i = 1], \quad t \geq T_D. \qquad (3.2)$$

The first term of the RHS of the equation is observed after the period of treatment, although the second term is not observable after the period of treatment. This is indeed

"counterfactual."

Under the equal trend, we can write standard DID setting as

$$E\left[y_{it}(0) - y_{i,T_D-1}(0)\middle|D_i = 1\right] = E\left[y_{it}(0) - y_{i,T_D-1}(0)\middle|D_i = 0\right].\ \ t \geq T_D. \qquad (3.3)$$

Then, the counterfactual is rewritten as

$$\mathrm{E}[y_{it}(0)|D_i = 1] = E\left[y_{it}(0) - y_{i,T_D-1}(0)\middle|D_i = 0\right] + E\left[y_{i,T_D-1}(0)\middle|D_i = 1\right].$$
$$t \geq T_D. \qquad (3.4)$$

When there is no treatment, one can specify the outcome in the following equation as

$$y_{it}(0) = x'_{it}\beta + \lambda_i^* + \delta_t + \varepsilon_{it}, \qquad (3.5)$$

where x_{it} is $1 \times K$ covariates, λ_i^* denotes a fixed effect of cross-sectional unit, δ_t stands for a time fixed effect, and ε_{it} is an idiosyncratic term.

Now we introduce the interactive fixed effect term as

$$y_{it}(0) = x'_{it}\beta + f_t'\lambda_i + \varepsilon_{it}, \qquad (3.6)$$

where λ_i is $L \times 1$ factor loadings, f_t is $L \times 1$ factors, and ε_{it} is the idiosyncratic term. Restriction of the linear formation $f_t'\lambda_i = \lambda_i^* + \delta_t$ leads to a two-way model as given by equation (3.5). Consequently, the term $f_t'\lambda_i$ is a general expression to cope with complicated unobservable.

In the case of treatment, the corresponding specification becomes

$$y_{it}(1) = \alpha_{it} + x'_{it}\beta + f'_t\lambda_i + \varepsilon_{it}, \qquad (3.7)$$

where α_{it} is a treatment effect or causal effect. The whole observable outcome is

$$y_{it} = y_{it}(0)(1 - I_t D_i) + y_{it}(1) I_t D_i, \qquad (3.8)$$

where I_t is time indicator of treatment and D_i is an individual indicator of treatment.

Using (3.6) and (3.7), the above expression can be rewritten as

$$y_{it} = \alpha_{it} I_t D_i + x'_{it}\beta + f'_t \lambda_i + \varepsilon_{it}. \qquad (3.9)$$

We can reformulate the equation as

$$y_{it} = \alpha_t I_t D_i + x'_{it}\beta + f'_t \lambda_i + \varepsilon_{it} + (\alpha_{it} - \alpha_t) I_t D_i. \qquad (3.10)$$

Conditioned on "Assumption 3" in Gobillon and Magnac (2016, p.540),

$$\forall t \geq T_D, \quad \alpha_t = \alpha,$$

the estimable equation becomes,

$$y_{it} = \alpha I_t D_i + x'_{it}\beta + f'_t \lambda_i + \varepsilon_{it}. \qquad (3.11)$$

We consider multiple L factors for f_t in this model.

Writing the model in vector as

$$\boldsymbol{y}_i = \alpha \boldsymbol{I}' \boldsymbol{D}_i + \boldsymbol{X}_i \beta + \boldsymbol{F}' \lambda_i + \boldsymbol{\varepsilon}_i, \qquad (3.12)$$

where $\boldsymbol{y}_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{iT} \end{bmatrix}, \boldsymbol{I}' = \begin{bmatrix} I'_1 \\ I'_2 \\ \vdots \\ I'_T \end{bmatrix}, \boldsymbol{D}_i = \begin{bmatrix} D_{i1} \\ D_{i2} \\ \vdots \\ D_{iT} \end{bmatrix}, \boldsymbol{X}_i = \begin{bmatrix} X_{i1} \\ X_{i2} \\ \vdots \\ X_{iT} \end{bmatrix}, \boldsymbol{F}' = \begin{bmatrix} F'_1 \\ F'_2 \\ \vdots \\ F'_T \end{bmatrix}, \boldsymbol{\varepsilon}_i = \begin{bmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \vdots \\ \varepsilon_{iT} \end{bmatrix}.$

Factor $\boldsymbol{F}$ has a dimension L. We can rewrite the model using matrix form as

$$\boldsymbol{y} = \alpha \boldsymbol{I}' \boldsymbol{D} + \boldsymbol{F}\boldsymbol{\Lambda}' + \boldsymbol{\varepsilon}, \qquad (3.13)$$

where $\boldsymbol{y} = (\boldsymbol{y}_1, \boldsymbol{y}_2, \cdots, \boldsymbol{y}_N)$, $\boldsymbol{\Lambda} = (\lambda_1, \lambda_2, \cdots, \lambda_N)'$, $and\ \boldsymbol{\varepsilon} = (\boldsymbol{\varepsilon}_1, \boldsymbol{\varepsilon}_2, \cdots, \boldsymbol{\varepsilon}_N)$. because of $\boldsymbol{F}\boldsymbol{\Lambda}' = \boldsymbol{F}\boldsymbol{A}\boldsymbol{A}^{-1}\boldsymbol{\Lambda}$, where $\boldsymbol{A}\boldsymbol{A}^{-1}$ is an $L \times L$ matrix, the possible solution for this is $L \times L$. Identification is possible with the L^2 restriction shown below.

Normalization, as

$$\frac{\boldsymbol{F}'\boldsymbol{F}}{\boldsymbol{T}} = \boldsymbol{I}, \quad (3.14)$$

leads to restriction of $L(L+1)/2$. Another $L(L-1)/2$ is from

$$\boldsymbol{\Lambda}'\boldsymbol{\Lambda} = diagonal. \quad (3.15)$$

Total restriction will be $\frac{L(L+1)+L(L-1)}{2} = L^2$. These steps are commonly taken for identification of the factor model.

3.6 Empirical strategy and data

3.6.1 Strategy for matching

The significant and positive parameter for α in equation (3.11) implies that the economic performance is suppressed under the AIR executed period. Therefore, our hypothesis that AIR hampers economic growth is supported.

In our empirical implementation, central Kinki (the restricted area by AIR): the central part of Osaka and Kyoto and the bay area of Hyogo (Fig. 3.1) are set as treatment group. As we mentioned earlier, it is difficult to find a control group or to make a counterfactual in place-based policy. Nevertheless, we follow Gobillon and Magnac (2016) and Givord et al. (2018): PSM is used to find control groups (municipalities). We use the nearest neighbor one-to-one PSM.

For unbiased causal inference, first of all, we omit the AIR in Metro for candidate for controls because these areas are also affected by the AIR. Secondly, to avoid possible interaction because of the AIR, we exclude the surrounding area of the AIR. In place-based policy, some policy which acts on some city possibly strongly affects nearer cities. If a nearer city is selected for controls, it might lead to a biased inference. Thirdly, we exclude partially restricted municipalities by AIR for preventing mixed up causal inference. We also exclude 2011 because a strong earthquake (The Great East Japan Earthquake) occurred at that time, disturbing the economic activity.

Targeted areas of the AIR are the same as the “Urbanized Area” designated by the “Kinki Region Development Act” and the “National Capital Region Development Act.” These two laws also define “Suburban Consolidation Zone,” where surrounding areas of “Urbanized Area.” Therefore, we exclude the “Suburban Consolidation Zone.” This is in line with the study by Accetturo and Blasio (2012), which set a control area as a different region from the treated areas so that estimation might be less exposed to a

spillover of policy implementation.

Because AIR targeted large population areas, we choose municipalities with a large population as a candidate for control group under PSM method. Regarding a candidate for a control group, municipalities are chosen from currently (as of 2018) designated "Government-ordinance-designated Cities," "Core Cities," and "Special Cities," because these municipalities are designated by government mainly according to population criteria. The population criterion for "Government-ordinance-designated Cities" is 500 thousand, "Core Cities" is 300 thousand, and "Special Cities" is 200 thousand. [11,12,13]

For comparison, we also apply causal inference for central Metro.[14]

3.6.2 Data description

Data are extracted from "*Census of Manufacture* (*Kogyo Toukei*)" (by Ministry of Economy, Trade and Industry) for the dependent variable (the number of the enterprises in the manufacturing sector) and for the control variable (the number of the enterprises in the transportation and machinery equipment sector). In addition, we extract nominal GDP data from "*Annual Report on Prefectural Accounts (Kenmin Keizai Keisan)*" (by Cabinet Office) as a control variable.[15]

The bean sprout, publication, and newspaper sectors are excluded from *Census of Manufacture* from 2002. Therefore, we exclude food-manufacturing industries and publication, printing, and allied industries from the number of enterprises in the manufacturing sector.[16]

The data are those of 1996–2015. We set the starting period to 1996 because, in 1995, the area was affected by a huge earthquake, the Great Hanshin-Awaji Earthquake, so that a marked decrease of the number of manufacturing enterprises was apparent in

[11] Names of municipalities are in the appendix.
[12] We exclude Naha city because Naha is distant from the other municipalities. Moreover, they seem to follow different economic trends from those of the other municipalities.
[13] Because the system of special cities was abolished on 2015, requirements of population criteria for the core cities were relaxed to 200 thousand.
[14] Data for central Metro is constructed in the same way as that of central Kinki.
[15] The reason we only use the number of enterprises for outcome variable is that the data for the other variables, for instance, shipment value, in "*Census of Manufacture*" for the municipals where only one or two enterprises located are to be concealed. This leads to difficulties in adjustment for municipal mergers, which we conduct in making the panel dataset.
[16] Data for municipalities at the sector level is not available. Only the industrial classifications of food and publication, printing, and allied industries are available.

Hyogo prefecture, in which the area restricted by AIR was included at that time.[17,18] The other area of AIR in central Kinki (Osaka and Kyoto) might also have been affected by this earthquake to a greater or lesser extent.

Data are annual. We take growth rate for each variable so that the total period T is 18 and the treatment year T_D is 7 because the law was repealed on July 2002. We regard 2003 as a treatment year.

We use a one-year lag variable of nominal GDP growth rate to control the economic trend or structural changes. Available GDP data are only those for the prefectural level. Therefore, we apply these data for the municipalities' corresponding prefectures. Transportation and machinery equipment sectors' share of the whole sector in municipality is also used for the control. In the 2000s, the automotive industry shows a great increase in the Japanese manufacturing industry.

3.6.3 Spatial Error-DID

An interactive effect model is written also as

$$y_{it} = \alpha I_t D_i + u_{it},$$
$$u_{it} = f'_t \lambda_i + \varepsilon_{it}. \qquad (3.16)$$

The interactive model deals with unknown term u_{it}. This term contains time-varying factor f_t, cross-sectional varying factor loadings λ_i, and idiosyncratic term ε_{it}.

Another way of depicting the unknown term u_{it} is to use a spatial weight matrix (SWM). Introducing a spatial model in DID is called "spatial DID." Spatial DID is proposed by Delgado and Florax (2015) as

$$y_{it} = \alpha_1 I_t D_i + \alpha_2 \sum_{j=1}^{N} w_{ij} I_t D_i + u_{it},$$

where $\sum_{j=1}^{N} w_{ij}$ is SWM.[19] However, application of spatial DID by Delgado and Florax

[17] The earthquake mainly affected Suma, Nagata, Hyogo, Chuo, Nada, and Higashinada wards and Ashiya and Nishinomiya cities. These municipalities are all in the restricted area.
[18] However, Hyogo prefecture is already excluded because all of the restricted municipalities in Hyogo were partially restricted.
[19] They focus on the violation of the stable unit treatment value assumption (SUTVA) (Rubin, 1978, 1990). If there exists a spatial interaction in outcomes (or treatment effects), then the SUTVA is violated.

(2015) is not straightforward in our case. Our concern is on unobserved heterogeneity and control of it.

We propose Spatial Error-DID (SE-DID). Using SWM, the equation became

$$y_{it} = \alpha I_t D_i + u_{it},$$
$$u_{it} = \rho \sum_{j=1}^{N} w_{ij}\, u_{it} + \nu_{it}. \qquad (3.17)$$

We use SWM with off diagonal elements w_{ij} to the model. The diagonal is set to zero. Here, w_{ij} describes the spatial interaction between region i and j, $\sum_{j=1}^{N} w_{ij}$ accompanies a spatial parameter ρ, and ν_{it} is an idiosyncratic term. As a convention, spatial weight matrix $\sum_{j=1}^{N} w_{ij}$ is row-normalized.

Case et al. (1993) propose the SWM from economic similarity using

$$w_{ij}^{e} = \frac{1}{|z_i - z_j|}, \qquad (3.18)$$

where z_i, z_j is the economic variable in region i and j.

Meanwhile, the inverse distance measure is

$$w_{ij}^{d} = \frac{1}{dist_{ij}^{2}}, \; i \neq j. \qquad (3.19)$$

We multiply them so that the spatial weight matrix will be $W_n = W_n^d \circ W_n^e$, where $\sum_{j=1}^{N} w_{ij} = W_n$ i.e. $w_{ij} = w_{ij}^e w_{ij}^d$ for each element of SWM W_n.

We use log of the shipment value of the manufacturing sector in each municipality in 2001 from the "*Census of Manufacture*" (by Ministry of Economy, Trade and Industry) for economic variable z.

We also conduct standard DID for comparison. Every method depends on PSM. Additionally, for every method, the data-differentiated and cross-sectional fixed effects μ_i and time fixed effects δ_t are used. Therefore, specification for Bai's method with DID is

$$\Delta y_{it} = \alpha I_t D_i + \Delta x'_{it}\beta + f'_t \lambda_i + \mu_i + \delta_t + \varepsilon_{it}. \qquad (3.20),$$

The specification for SE-DID is

$$\Delta y_{it} = \alpha I_t D_i + \Delta x'_{it}\beta + \mu_i + \delta_t + \rho \sum_{j=1}^{N} w_{ij}\, u_{it} + \varepsilon_{it}. \qquad (3.21),$$

The standard DID is

$$\Delta y_{it} = \alpha I_t D_i + \Delta x'_{it}\beta + \mu_i + \delta_t + \varepsilon_{it}. \qquad (3.22).$$

3.6.4 Monte Carlo simulation

We conduct a Monte Carlo simulation to examine the performance of Bai's model, SE-DID, and standard DID. We consider both factors and spatial dependence in the error term; therefore, DGP is,

$$y_{it} = \alpha I_t D_i + u_{it},$$
$$u_{it} = \rho \sum_{j=1}^{N} w_{ij}\, u_{it} + f_t' \lambda_i + \varepsilon_{it}. \qquad (3.23)$$

We follow the data used in empirics for central Kinki: N=23 for the treatment group, N=107 for the control group (before PSM), $T = 18$, and $T_D = 7$. The sample size is 130×18=2340.

Referring to Gobillon and Magnac (2016), we set the number of replications to 1,000. Each shock, ε_{it} is $i.i.d.$ and $\varepsilon_{it} \sim \mathrm{N}(0,1)$. The number of factor is set to 3. The value of factors f_t and factor loadings λ_i follow uniform distribution with a parameter range of 0 to 1. The treatment effect is fixed at $\alpha = 0.3$. The spatial parameter ρ is fixed at 0.5.

Results are shown in Table 3.1. SE-DID exhibits the most unbiased performance when we compare the mean. However, from the median perspective, Bai's DID is the most unbiased. Standard DID reports biased estimation compared to SE-DID and Bai's DID. From the results here, SE-DID and Bai's DID are useful when the error term contains spatial interactions.

Table 3.1 Results of the Monte Carlo simulation comparing Bai's method with DID, SE-DID, and standard DID

	Bai's DID	SE-DID	DID
mean	0.292	0.297	0.292
median	0.303	0.296	0.291
standard error	0.274	0.357	0.344

Note: Bai's DID refers to DID using interactive effects by Bai (2009), SE-DID refers to spatial error DID, and DID refers to standard DID.

3.7 Empirical results and discussion

3.7.1 Propensity score matching

For central Kinki, we have 23 municipalities for the candidate treatment group and 107 municipalities for the candidate control group. For central Metro, 29 municipalities are taken for the candidate treatment group, and 107 municipalities are taken for the candidate control group.

Data used for the PSM are the share of the number of employees in the service sector plus the finance sector among all sectors in municipalities (from "*Establishment and Enterprise* 2001" by Statistics Bureau, Ministry of Internal Affairs and Communications (MIC)) and the growth rate of the number of employees in the service sector plus the finance sector during 1996–2001 (from "*Establishment and Enterprise* 1996" by Statistics Bureau, MIC).

This is from the perspective of the instrumental variable. We choose covariate, which is meant to be uncorrelated with the outcome—manufacturing activity. If one uses data related to manufacturing activity, then the allocation of the control group might be exposed to bias in our case.

We present our PSM results for Central Kinki only in Figure 3.2. This is meant to show common support, so the matching is acceptable here.

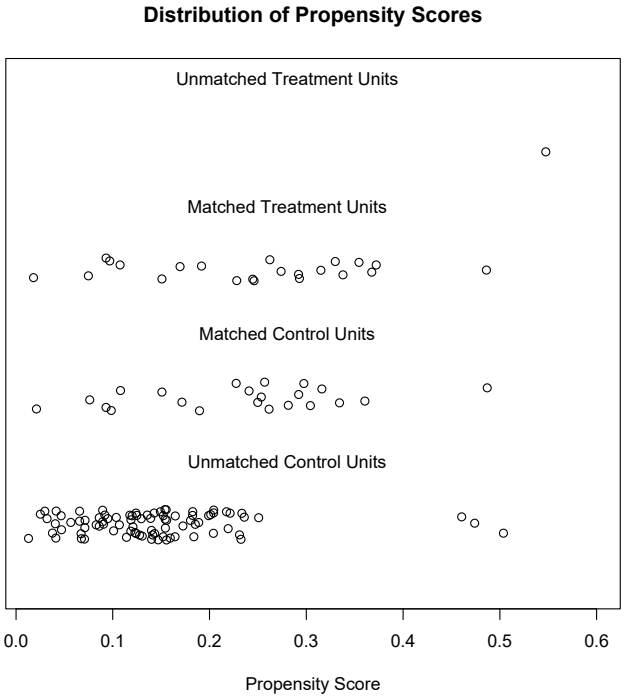

Figure 3.2 Results of propensity score matching for central Kinki using one-to-one nearest neighbor matching

Note: One-to-one nearest neighbor matching is conducted. Data used for the PSM are the share of the number of employees in the service sector plus the finance sector among all sectors in the examined municipalities (from "Establishment and Enterprise 2001" by Statistics Bureau, MIC) and the growth rate of the number of employees in the service sector plus the finance sector during 1996–2001 in the examined municipalities (from "Establishment and Enterprise 1996" by Statistics Bureau, MIC). We use "MatchIt" package in R.

As a result, from propensity score matching, we have 22 treated municipalities and 22 control municipalities for central Kinki and 21 treated municipalities and 21 control municipalities for central Metro.

3.7.2 Results of causal inference

After controlling for unobservable heterogeneity, if the outcome in treated municipalities becomes significant and large after the treatment compared with counterfactual, then one could infer that the AIR suppress the economic activity in restricted area through the law's applicability period. Then one might conclude that there exists a causal effect (or treatment effect) and that the law hampers economic growth. We judge this causality to ascertain the estimated value of α in equations (3.21)–(3.23).

Results of causal inference of the repeal of AIR in central Kinki and central Metro using DID with Bai's method with PSM are shown in Tables 3.2 and 3.3.[20] Numbers of factors are 1–3. As a result, for the number of factor 1, the estimated value of α are significant and positive in Kinki. However, for the number of factor 2 and 3, the results are not significant. Whereas all of the results are not significant for the Metro.

Although the result is dependent on the number of factors, interpretation of this result indicates that the restricted area in Kinki shows steady trends in manufacturing activity compared with the unrestricted area (designated as control) after repeal of AIR. Therefore, AIR surely hampers economic growth in Kinki. However, the lack of effects in the Metro indicate no causality between the repeal of AIR and manufacturing activity.

With or without control variables, the results are robust for the number of factor 1. The GDP growth rate in Kinki's estimation is significant and positive for factors 1 and 2. The share of the transportation and machinery sector is also significant and positive for all number of factors. However, when we drop GDP growth rate, the share of transportation and machinery sector is only significant and positive for the number of factor 2.

SE-DID is conducted via the generalized moments (GM) estimator presented by Kelejian and Prucha (1999). For the results of SE-DID with PSM, in Tables 3.4 and 3.5, we detect causal effects for all specification. Also, all estimated spatial parameters (*Rho*) are significant. This result supports the necessity of controlling unobserved spatial dependencies. In this case, not just central Kinki, but central Metro also demonstrates causal effects. From the results of SE-DID, both the activities of manufacturing in central Kinki and central Metro are affected by the repeal of AIR. Standard DID in Tables 3.6 and 3.7 denote similar results from those found for SE-DID.

[20] Iterations are conducted for 100 times for our estimation.

Table 3.2 Results of causal inference of repeal of Act concerning the Industry Restriction in central Kinki using Bai's method with propensity score matching

	the number of factors		
	1	2	3
Treatment effect	0.02 ***	0.004	-0.002
	0.006	(0.008)	(0.007)
GDP growth rate			
Share of transportation and machinery			
Treatment effect	0.022 ***	0.005	-0.001
	(0.006)	(0.008)	(0.007)
GDP growth rate	0.489 ***	0.266 *	0.213 *
	(0.119)	(0.137)	(0.129)
Share of transportation and machinery	0.023 **	0.019 **	0.022 ***
	(0.009)	(0.008)	(0.008)
Treatment effect	0.021 ***	0.005	-0.002
	(0.006)	(0.008)	(0.007)
GDP growth rate			
Share of transportation and machinery	0.018	0.023 *	0.016
	(0.015)	(0.013)	(0.012)
Treatment effect	0.021 ***	0.004	-0.002
	(0.006)	(0.008)	(0.007)
GDP growth rate	0.497 ***	0.280 **	0.244 *
	(0.120)	(0.137)	(0.129)
Share of transportation and machinery			

Note: Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Total number of periods is 18, number of periods before treatment is 6. The total number of observations for cross-sectional units is 44 (22 treated, 22 control). The treatment group is selected with propensity score matching from the central part of Osaka and Kyoto. The control group is selected with propensity score matching from candidate municipalities. The outcome variable is the number of the enterprises. The data source is the "*Census of Manufacture* (*Kogyo Toukei*)" for 1996–2015 (by Ministry of Economy, Trade and Industry).

Table 3.3 Results of the causal inference of repeal of Act concerning the Industry Restriction in central Metro using Bai's method with propensity score matching

	the number of factors		
	1	2	3
Treatment effect	-0.001	0.000	-0.002
	(0.009)	(0.008)	(0.007)
GDP growth rate			
Share of transportation and machinery			
Treatment effect	-0.001	0.000	-0.002
	(0.009)	(0.008)	(0.007)
GDP growth rate	-0.132	0.087	0.047
	(0.162)	(0.147)	(0.126)
Share of transportation and machinery	-0.027 ***	-0.033 ***	-0.002
	(0.010)	(0.009)	(0.009)
Treatment effect	-0.002	-0.002	-0.002
	(0.009)	(0.007)	(0.007)
GDP growth rate			
Share of transportation and machinery	-0.027 ***	-0.002	-0.002
	(0.010)	(0.008)	(0.008)
Treatment effect	-0.001	0.000	-0.002
	(0.009)	(0.008)	(0.007)
GDP growth rate	-0.131	0.031	0.046
	(0.163)	(0.148)	(0.126)
Share of transportation and machinery			

Note: Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Total number of periods is 18, number of periods before treatment is 6. Total number of observations for cross-sectional units is 42 (21 treated, 21 control). The treatment group is selected with propensity score matching from central part of Tokyo and Kanagawa. The control group is selected with propensity score matching from candidate municipalities. The outcome variable is the number of the enterprises. The data source is the "*Census of Manufacture* (*Kogyo Toukei*)" for 1996–2015 (by Ministry of Economy, Trade and Industry).

Table 3.4 Results of the causal inference of repeal of Act concerning the Industry Restriction in central Kinki using Spatial Error-DID with propensity score matching

	(1)	(2)	(3)	(4)
Treatment effect	0.022 ***	0.023 ***	0.022 ***	0.022 ***
	(0.007)	(0.007)	(0.007)	(0.007)
GDP growth rate		0.407 ***		0.413 ***
		(0.135)		(0.135)
Share of transportation and machinery		0.021 **	0.021 **	
		(0.010)	(0.010)	
Intersept	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Rho	-0.019 ***	-0.012 ***	-0.018 ***	-0.012 ***

Note: Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Total number of periods is 18, number of periods before treatment is 6. The total number of observations for cross-sectional unit is 44 (22 treated, 22 control). The treatment group is selected with propensity score matching from the central part of Osaka and Kyoto. The control group is selected with propensity score matching from candidate municipalities. The outcome variable is the number of the enterprises. The data source is the "*Census of Manufacture* (*Kogyo Toukei*)" for 1996–2015 (by Ministry of Economy, Trade and Industry).

Table 3.5 Results of the causal inference of repeal of Act concerning the Industry Restriction in central Metro using Spatial Error-DID with propensity score matching

	(1)	(2)	(3)	(4)
Treatment effect	0.028 ***	0.028 ***	0.028 ***	0.028 ***
	(0.010)	(0.010)	(0.010)	(0.010)
GDP growth rate		-0.226		-0.226
		(0.204)		(0.204)
Share of transportation and machinery		-0.001	-0.001	
		(0.012)	(0.012)	
Intersept	0.000	0.00013	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Rho	0.004 ***	0.002 ***	0.004 ***	0.002 ***

Note: Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Total number of periods is 18, number of periods before treatment is 6. The total number of observations for cross-sectional units is 42 (21 treated, 21 control). The treatment group is selected with propensity score matching from the central part of Tokyo and Kanagawa. The control group is selected with propensity score matching from candidate municipalities. The outcome variable is the number of the enterprises. The data source is the "*Census of Manufacture* (*Kogyo Toukei*)" for 1996–2015 (by Ministry of Economy, Trade and Industry).

Table 3.6 Results of the causal inference of repeal of Act concerning the Industry Restriction in central Kinki using standard DID with propensity score matching

	(1)	(2)	(3)	(4)
Treatment effect	0.019 ***	0.021 ***	0.020 ***	0.021 ***
	(0.007)	(0.007)	(0.007)	(0.007)
GDP growth rate		0.421 ***		0.427 ***
		(0.136)		(0.137)
Share of transportation and machinery		0.021 **	0.021 **	
		(0.010)	(0.010)	
Intersept	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)

Note: Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Total number of periods is 18, number of periods before treatment is 6. The total number of observations for cross-sectional units is 44 (22 treated, 22 control). The treatment group is selected with propensity score matching from the central part of Osaka and Kyoto. The control group is selected with propensity score matching from candidate municipalities. The outcome variable is the number of the enterprises. The data source is the "*Census of Manufacture* (*Kogyo Toukei*)" for 1996–2015 (by Ministry of Economy, Trade and Industry).

Table 3.7 Results of the causal inference of repeal of Act concerning the Industry Restriction in central Metro using standard DID with propensity score matching

	(1)	(2)	(3)	(4)
Treatment effect	0.027 ***	0.028 ***	0.027 ***	0.028 ***
	(0.010)	(0.010)	(0.010)	(0.010)
GDP growth rate		-0.228		-0.228
		(0.204)		(0.204)
Share of transportation and machinery		-0.001	-0.001	
		(0.013)	(0.013)	
Intersept	0.000	0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)

Note: Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Total number of periods is 18, number of periods before treatment is 6. The total number of observations for cross-sectional units is 42 (21 treated, 21 control). The treatment group is selected with propensity score matching from the central part of Tokyo and Kanagawa. The control group is selected with propensity score matching from candidate municipalities. The outcome variable is the number of the enterprises. The data source is the "*Census of Manufacture* (*Kogyo Toukei*)" for 1996–2015 (by Ministry of Economy, Trade and Industry).

3.7.3 Falsification test (placebo test)

We conduct a falsification test (placebo test) to verify the plausibility of the matching and robustness check for the causal effects which are detected in the previous section.

We only use the data set for central Kinki. We use matched municipalities from PSM, same as in the previous section. The period used here is set to 1997–2001, before the repeal of AIR, and the treatment year is set to 1999.

We report the results for the SE-DID and standard DID in Table 3.8 and 3.9. From the results, the entire treatment effect is not detected. Therefore, our matching is plausible, and our conclusion is acceptable.

Table 3.8 Results of the falsification test (placebo test) of the repeal of Act concerning the Industry Restriction in central Kinki using Spatial Error-DID with propensity score matching

	(1)	(2)	(3)	(4)
Treatment effect	-0.003	-0.003	0.000	-0.004
	(0.022)	(0.023)	(0.022)	(0.023)
GDP growth rate		-0.266		-0.067
		(0.519)		(0.517)
Share of transportation and machinery		0.038 **	0.036 **	
		(0.017)	(0.017)	
Intersept	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Rho	-0.121	-0.132	-0.134	-0.120

Note: Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Total number of periods is 5, number of periods before treatment is 2. The total number of observations for cross-sectional units is 44 (treated: 22, control: 22). The treatment group is selected with propensity score matching from the central part of Osaka and Kyoto. Control group is selected with propensity score matching from candidate municipalities. Outcome variable is the number of enterprises. Data source is "*Census of Manufacture* (*Kogyo Toukei*)" from 1996 to 2001 (by Ministry of Economy, Trade and Industry).

Table 3.9 Results of the falsification test (placebo test) of the repeal of Act concerning the Industry Restriction in central Kinki using standard DID with propensity score matching

	(1)	(2)	(3)	(4)
Treatment effect	-0.020	-0.021	-0.019	-0.020
	(0.024)	(0.025)	(0.024)	(0.025)
GDP growth rate		-0.266		-0.065
		(0.542)		(0.536)
Share of transportation and machinery		0.035 **	0.033 *	
		(0.018)	(0.017)	
Intersept	0.000	0.000	0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.004)

Note: Standard errors are in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Total number of periods is 5; number of periods before treatment is 2. The total number of observations for cross-sectional units is 44 (treated: 22, control: 22). The treatment group is selected with propensity score matching from the central part of Osaka and Kyoto. Control group is selected with propensity score matching from candidate municipalities. Outcome variable is the number of enterprises. Data source is "*Census of Manufacture* (*Kogyo Toukei*)" from 1996 to 2001 (by Ministry of Economy, Trade and Industry).

3.7.4 Another inspection

To support our results, we conduct another empirical investigation. Inspired by Fujiki and Hsiao (2015), we take a simple model to be estimated. The model is based on Hsiao et al. (2012). They conduct causal inference with regard to ATT ($\hat{\Delta}_t$) with the equation as

$$\hat{\Delta}_t = y_{1t}^1 - \hat{y}_{1t}^0 = y_{1t}^1 - \hat{a} - \hat{b} y_{it}^0, \quad t = T_1 + 1, \cdots, T, \qquad (3.24)$$

where $i = 1, 2, \cdots, N$ represents an index of cross-sectional units, $t = 1, 2, \cdots, T$ signifies the time index of observations, T_1 denotes the period when treatment is implemented, y_{it} expresses the outcome, y_{1t}^1 stands for the outcome of unit 1 which received treatment (1), y_{it}^0 denotes the outcome of the other units $i = 2, \cdots, N$ which did not receive treatment (0), and $\hat{y}_{1t}^0$ is counterfactual for unit 1.

To obtain estimated values of $\hat{a}$ and $\hat{b}$, regress $y_{1t}, t = 1, 2, \cdots, T$, on y_{it}, $t = 1, 2, \cdots, T$. In other words, regress the outcome of treatment unit before the treatment period on the outcome of non-treated units before the treatment period. As a consequence, one can predict counterfactual $\hat{y}_{1t}^0$.

Following Fujiki and Hsiao (2015), we select a non-treated prefecture with correlation coefficients of log of nominal GDP per capita during 1955–1964 of Osaka prefecture and other prefectures.[21] High correlation suggests that the prefectures are candidates for the regression. Data are extracted from the "*Annual Report on Prefectural Accounts (Kenmin Keizai Keisan)*" by the Cabinet Office and "*Population estimates (Jinkou Suikei)*" by the Statistics Bureau, MIC. We set only Osaka prefecture as a treated unit because municipal GDP data are not available. Therefore, our empirical examination is rather rough.

Results of correlation coefficients are presented in Table 3.10. Shizuoka shows the highest correlation coefficient. Nagano shows the second highest correlation coefficient. Shizuoka and Nagano are also prosperous areas of manufacturing. Therefore, ideal prefectures are selected for prediction here.

For low degrees of freedom, we select only Shizuoka prefecture for the regression. Results of the regression are presented in Table 3.11. Although the sample size is pretty small, it predicts well. As a consequence, we predict the counterfactual of Osaka prefecture after 1965 (after enactment of AIR). We predict from 1965 through 1994. The result is shown in Figure 3.3, which shows the apparent treatment effect after 1965. [22] If AIR is not implemented, then Osaka would have experienced higher economic growth.

The inspection here has a severe small-sample problem. Moreover, we investigate the causality of the whole industry, not the manufacturing sector. Additionally, the regional unit is prefecture, so a clear division of treated and control is impossible. Even considering these restrictions, the result here also states that the AIR hampers the economic growth of Osaka.

[21] We exclude Okinawa prefecture because the prefecture was returned to Japan in 1972.
[22] The strong Hanshin-Awaji earthquake occurred in 1995 so we stopped prediction before that time.

Table 3.10 Correlation coefficients of log of nominal GDP per capita of Osaka prefecture and other prefectures

	1955-1964
Osaka	1.000
Shizuoka	0.999
Nagano	0.999
Yamanashi	0.999
Kyoto	0.999
Yamagata	0.998
Shimane	0.997
Miyagi	0.997
Hokkaido	0.997
Gifu	0.997
Ishikawa	0.997
Kouchi	0.997
Shiga	0.997
Fukushima	0.997
Tokushima	0.997
Kanagawa	0.997
Aichi	0.997
Hyogo	0.997
Tochigi	0.997
Nara	0.996
Saitama	0.996
Iwate	0.996
Kagoshima	0.996
Fukui	0.996
Fukuoka	0.996
Aomori	0.995
Ibaragi	0.995
Tottori	0.995
Ehime	0.994
Tokyo	0.994
Gunma	0.994
Toyama	0.993
Oita	0.993
Kagawa	0.993
Okayama	0.993
Mie	0.993
Akita	0.993
Niigata	0.992
Yamaguchi	0.992
Chiba	0.992
Saga	0.992
Hiroshima	0.991
Kumamoto	0.991
Wakayama	0.989
Miyazaki	0.988
Nagasaki	0.985

Note: Coefficients are presented in descending order. The data source is the "*Annual Report on Prefectural Accounts (Kenmin Keizai Keisan)*" by the Cabinet Office and "*Population estimates (Jinkou Suikei)*" by the Statistics Bureau, MIC.

Table 3.11 Results for the regression of log of nominal GDP of Osaka on Shizuoka (1955–1964)

	Coefficients
Shizuoka	0.992 ***
	(0.018)
Constant	0.379 ***
	(0.093)

Note: Standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

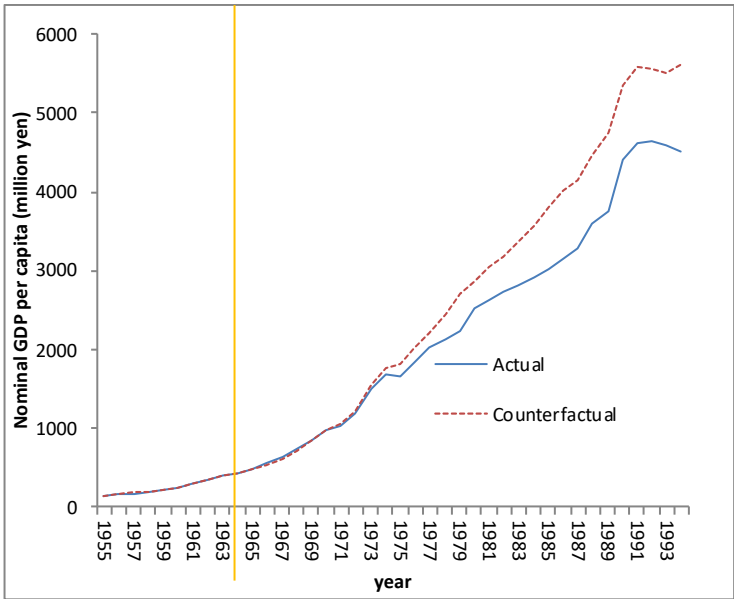

Figure 3.3 Actual and counterfactual of nominal GDP per capita of Osaka prefecture

Note: Prediction from the linear regression of log of nominal GDP per capita of Osaka on Shizuoka during 1955–1964. Predictions are shown for 1965–1994. The perpendicular line represents treatment period of AIR. Exponential is taken for the prediction, so the unit is million yen.

3.8 Conclusion

Great doubt persists about the obstruction of the growth of larger cities, especially for central Kinki, because of the Act concerning the Industry Restriction (AIR). Our results support this view: AIR hampered economic growth of central Kinki. Without Bai's model, empirical results indicate that central Metro is also hampered by the AIR. The results of the Monte Carlo simulation support the results from the

estimation using Bai's model and our proposed SE-DID model. Additional inspection also gives us another implication: if AIR had not been implemented, Osaka would have enjoyed higher economic growth.

The restrictive mode of law implementation leads to disturbance in the economic activity in some cases. Especially, at that time, the economy of Osaka or the central area of the Kinki region was more highly dependent on manufacturing compared with Tokyo or central area of the metropolitan area. After the 1980s to the 1990s, central Metro enjoyed centralization of service, finance, and information technology and communication sectors because of a changeover in the industrial structure of Japan: from manufacturing to tertiary industries. Concentration of these sectors was more intensive in central Metro rather than in central Kinki. Then, the economic situation in the Kinki region, which became rather severer than in the Metropolitan area, is partially attributable to the law.

Appendix for chapter 3

List of Government-ordinance-designated Cities, Core Cities, and Special Cities.

1) Names of Government-ordinance-designated Cities:

Sapporo, Sendai, Yokohama, Kawasaki, Saitama, Chiba, Sagamihara, Niigata, Nagoya, Hamamatsu, Shizuoka, Osaka, Kobe, Kyoto, Sakai, Hiroshima, Okayama, Fukuoka, Kitakyushu, and Kumamoto.

Names of Core Cities:

Asahikawa, Hakodate, Iwaki, Koriyama, Akita, Morioka, Kashiwa, Yokosuka, Takasaki, Kawagoe, Maebashi, Koshigaya, Kanazawa, Toyama, Toyota, Gifu, Okazaki, Nagano, Toyohashi, Himeji, Higashiosaka, Nishinomiya, Amagasaki, Hirakata, Toyonaka, Wakayama, Nara, Takatsuki, Otsu, Akashi, Yao, Kurashiki, Fukuyama, Shimonoseki, Kure, Matsue, Tottori, Matsuyama, Takamatsu, Kochi, Kagoshima, Oita, Nagasaki, Miyazaki, Kurume, Sasebo, and Naha.

We exclude Naha city because Naha is distant from the other municipalities and they follow a different economic trend.

2) Names of Special Cities:

Yamagata, Tokorozawa, Mito, Hiratsuka, Soka, Kasukabe, Chigasaki, Yamato, Atsugi, Tsukuba, Ohta, Isezaki, Kumagaya, Odawara, Kofu, Nagaoka, Fukui, Joetsu, Ichinomiya, Yokkaichi, Kasugai, Fuji, Matsumoto, Numazu, Suita, Ibaraki, Kakogawa,

Neyagawa, Takarazuka, Kishiwada, and Saga.

Chapter 4
Business Cycle Spatial Synchronization: Measuring a Common Indicator

4.1 Introduction

During the last couple of decades, increased international trade, increased capital flows, economic integration, and financial markets openness have all occurred. The decline in transport costs have decreased economic distances and have increasingly integrated economies. On the one hand, in recent years, economic turmoil caused by crises, such as Asian Financial Crisis 1997 or collapse of Lehman Brothers in the United States on September 2008, has constituted a grave concern for policymakers. Such an exogenous shock causes economic instability to a greater or lesser degree. If economic distance has decreased, then business cycle synchronization might increase and economic shocks in one country might affect the respective economies of other countries more severely. Furthermore, business cycle synchronization is presumed to be inflated by such shocks.

We specifically examine the Asia–Pacific business cycle because we recently have seen intensified trade or cross-border capital flows, business trips, and business transactions among Asia–Pacific countries. Therefore, the Asia–Pacific economy is apparently integrated to some degree. Actually, Asia–Pacific economic integration has proceeded. For instance, Free Trade Agreements (FTAs) and Economic Partnership Agreements (EPAs) are in force among several countries in the Asia–Pacific. The ASEAN Free Trade Area (AFTA) is now virtually established. Additionally, negotiation for Regional Comprehensive Economic Partnership (RCEP) is underway. The RCEP includes the 10 ASEAN countries, Japan, China, Korea Rep., Australia, New Zealand, and India. These integrations might intensify Asia–Pacific business cycle synchronization.

As described herein, we use a spatial econometric model for time series data and re-examine business cycle synchronization in the Asia–Pacific to verify the relations between synchronization and business cycle volatility. We also compare the results for the Euro Area (EA).

Many studies specifically examine business cycle synchronization. The majority of studies verify the hypothesis: does intensified trade cause business cycle synchronization?

Frankel and Rose (1998), in their seminal study, explore the relationships between business cycle synchronizations which are measured using simple correlation coefficients of pairwise countries and their factors. Other studies which follow them also use correlation coefficients or some extended version of it as a proxy for business cycle synchronizations of pairwise countries and verify the causality between synchronizations and structural factors (Clark and Wincoop, 2001; Imbs, 2004, 2006; Kose and Yi, 2006; Baxter and Koupiratsas, 2005; Calderón et al., 2007; Inklaara et al., 2008; Cerqueira and Martins, 2009; Aritis and Okubo, 2011; Fidrmuc et al., 2012; Duval et al., 2016, Belke et al., 2017; and Gong and Kim, 2018). Frankel and Rose (1998) find a strong positive relation between intensified trade and business cycle synchronization.

These papers mainly shed light on G7 or OECD countries.[23] Some studies, such as those by Crosby (2003), Shin and Wang (2004), Kumakura (2006), Moneta and Rüffer (2009), Rana et al. (2012), and He and Liao (2012) specifically examine Asia or the Asia–Pacific region. Most of these studies also merely use a Pearson correlation or some extended version of it to gauge business cycle synchronization.

Therefore, in many studies, the data are averaged over time; synchronization is defined as a pairwise cross-country correlation. Stock and Watson (2005) analyze synchronizations of G7 business cycles using band-pass-filter for each G7 country and G7 average. They state that G7 business cycle is less synchronized for 30 years after the 1970s' greatest synchronization. However, the measurement of business cycle synchronization is basically also based on pairwise structure.

Additionally, many studies incorporate the distance or geographic adjacency among countries, or gravity-like variables (Frankel and Rose, 1998; Clark and Wincoop, 2001; Imbs, 2004, 2006; Baxter and Koupiratsas, 2005; Calderón et al., 2007; Inklaara et al., 2008; and Fidrmuc et al., 2012). Similarly to this, Kose and Yi (2006) employ transportation costs. In this manner, although geographical distance or spatial

[23] Exceptions are Imbs (2004) who includes Peru, the Philippines, and South Africa among the 24 countries, Baxter and Koupiratsas (2004) include over 100 countries. Calderón et al. (2007) use 147 countries' data. Duval et al. (2016) assess 63 advanced and emerging economies. Gong and Kim (2018) cover East Asia, Latin America, and Central and Eastern Europe.

heterogeneity is substantial in business cycle synchronization, few studies use spatial econometric methods.

Badinger (2013) estimates the output volatility spillover effect parameter with a unique approach. He applies a spatial econometric method to the field of business cycle and interprets the "spatial parameter" as a volatility spillover effect. However, he merely applies cross-sectional spatial econometric method. Therefore, a lack of the information exists for the time dimension in estimating "spatial parameter". It is important to analyze business cycles in space and time simultaneously in a model. Additionally, because we examine business cycle synchronization in the Asia–Pacific and EA, a lack of sample size occurs in the cross-sectional dimension if we use cross-sectional spatial econometric method. In this study, sample size for cross-sectional dimension is 13 for the Asia–Pacific and 11 for EA: we face severely insufficient sample size for estimation. In gauging Asia–Pacific business cycle synchronization and EA business cycle synchronization, panel datasets bring better sample size in estimation.

Meanwhile, Ductor and Leiva-Leon (2016) investigate the global common time-varying synchronization. They conclude that the business cycle synchronization was moderate until the late 1990s, increased in the early 2000s, and it reached its maximum value at the end of 2008. This result is contrary to Stock and Watson (2005).

As we see in the empirical analysis, the findings of Ductor and Leiva-Leon (2016) are very similar to the results of this chapter. Additionally, these two studies (Badinger, 2013 and Ductor and Leiva-Leon, 2016) are the closest to our area of interest: measuring a common indicator.

The term *synchronization* is slightly different from that used in earlier papers. Synchronization as used in many papers stands for pairwise cross-country correlations. Ductor and Leiva-Leon (2016) use the Leiva-Leon's (2017) approach which measures the business cycle synchronization of pairwise countries over time. Therefore, to ensure accuracy, Ductor and Leiva-Leon (2016) also use the pairwise model, and they use pairwise synchronization for extracting a common business cycle synchronization indicator using simple averaging and principal component analysis. For this, they conduct a two-step calculation. [24] Furthermore, their first step in measuring pairwise synchronization is based on regime-switching model, i.e., measuring state: expansion or recession. Our focus is on synchronization of the level of business cycle, not on

[24] They construct another more comprehensive method using dynamic factor models to extract the global factor. However, the output is still dependent on pairwise structure, i.e., movements between each country and global.

synchronization of the state of business cycle.

In this chapter, building on Badinger (2013), we use a more elaborate model: time-varying spatial parameter method. Blasques et al. (2016) propose time-varying spatial parameter estimation. The estimation became possible using Generalized Autoregressive Score (GAS) models. This study would be the first application of time-varying spatial parameter in measuring business cycle synchronization. We define synchronization as a common indicator among selected countries and we calculate a common indicator using a more elaborate one-step approach, unlike Ductor and Leiva-Leon (2016). Additionally, we will take a different standpoint from that strand of studies. Instead of conducting structural analyses using data of trade intensity or structural similarity, we verify the relations between business cycle synchronization and volatility of the business cycle. Although most of earlier papers specifically present examination of long-term economic relations (because they averaged data for sub-sample span in calculating pairwise synchronizations), this paper specifically examines the short-run effects.

We will verify the following question. How would business cycle synchronization be affected by business cycle volatility or economic shocks? Business cycle volatility tends to be high during economic crises. Therefore, our prediction is that if some huge economic crisis occur, business cycles will move synchronously toward the same direction, i.e., acute downturn and rapid recovery. This is not precisely stated in earlier work conducted in this area. However, the work done by Ductor and Leiva-Leon (2016) is an exception, so we will re-examine the question using a more elaborate way. We also investigate whether business cycle synchronization increases with the degree of integration among countries or not. We compare the Asia–Pacific with EA, where countries are more closely integrated.

The remainder of the paper is presented as follows. Section 2 states related studies, whereas Section 3 provides data and methods used for estimation. Section 4 presents estimation results and discussion. Section 5 states conclusions.

4.2 Related literature

We list the related literature, which specifically examines business cycle synchronization of the Asia–Pacific region.

Crosby (2003) examines GDP correlations between two countries, with an attempt to explain business cycle synchronization using some explanatory variables in a

sample of 13 Asia–Pacific countries' annual data. The results show that trade is not an explanatory factor for correlations in the Asia–Pacific region but structural similarities among countries are determinant factors for business cycle correlations. Shin and Wang (2004) employ annual data for real GDP, which are collected for 12 Asian countries. Their finding is that increase in trade does not necessarily trigger close business cycle co-movements.

Kumakura (2006) verify the relationship between trade and business cycle correlations among 13 Asia–Pacific countries using annual GDP data. The findings show that, although trade accounts for international business cycle correlations, a more important determinant is the extent of specializations in the electronics industry. Moneta and Rüffer (2009) use a dynamic common factor model and extract common factors in real GDP growth using quarterly real GDP data for 10 Asian countries. They calculate correlation between GDP growth and common factors to elucidate the business cycle synchronization. They conclude that the synchronization appears to reflect strong export synchronization.

Rana et al. (2012) examine the relationship between trade intensities and business cycles synchronization in East Asia and Europe (EU-15). They use annual real GDP data for 10 East Asian countries and the EU-15. They conclude that intra-industry trade, rather than inter-industry trade, is the major explanatory factor for business cycle synchronization. He and Liao (2012) use quarterly data of real GDP of nine emerging Asian economies and G-7 countries. In measuring business cycle synchronization, they conduct variance decomposition and conclude that "although emerging Asian economies cannot decouple completely from the advanced economies, they have sustained a strong independent business cycle among themselves."

4.3 Data and methodology

4.3.1 Data description

In deciding the country range for the Asia–Pacific region, we follow RCEP. The selected 13 Asia–Pacific countries are Australia, China, Hong Kong, Indonesia, India, Japan, Korea Rep., Malaysia, New Zealand, Philippines, Singapore, Taiwan, and Thailand.[25] For EA, we select countries based on the Euro Area 11 that had adopted the Euro in 1999, Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy,

[25] Because of difficulties in data availability, the other countries defined in RCEP are excluded.

Luxembourg, the Netherlands, and Portugal.

We use quarterly GDP data which correspond to the business cycle. The data are from 1996:Q4 – 2017:Q4 and are extracted from the "Global Economic Monitor", World Bank.[26] GDP is at market prices, constant 2010 local currency unit, millions and seasonally adjusted.[27] Because the output is known to be a non-stationary series, and to remove the linear trend for extracting short or medium-term fluctuation, we use the quarterly GDP growth rate.

In the Asia–Pacific case, we use one-quarterly lag of growth rate of the US GDP and EA common business cycle movement, for exogenous variables. In the EA case, we use one-quarterly lag of growth rate of the US GDP and Asia–Pacific common business cycle movement as exogenous variables. Common business cycle movement is calculated applying dynamic factor model for which we describe steps at Section 3.

Figure 4.1 depicts the GDP quarterly growth rates of Asia–Pacific countries. A downward trend is found around 1997 (Asian Financial Crisis) and around 2008 through 2009 (Collapse of Lehman Brothers in the United States (US) on September 2008). A dispersed trend is apparent elsewhere. Figure 4.2 shows the quarterly GDP growth rates of EA countries. A downturn is also apparent at around 2008–2009, but not around 1997. A downward trend during 2008–2009 is clearer in EA than in the Asia–Pacific.

[26] Data for India is only from 1996 Q2.

[27] Data of Malaysia is from 2005 Q1only. Therefore, we also use GDP growth (year-on-year, %) data from ADB "Economic and Financial Indicators"; we obtain Malaysia's GDP data during 1993 Q2 – 2004 Q4 by calculating backward and seasonally adjusting with X-13ARIMA-SEATS.

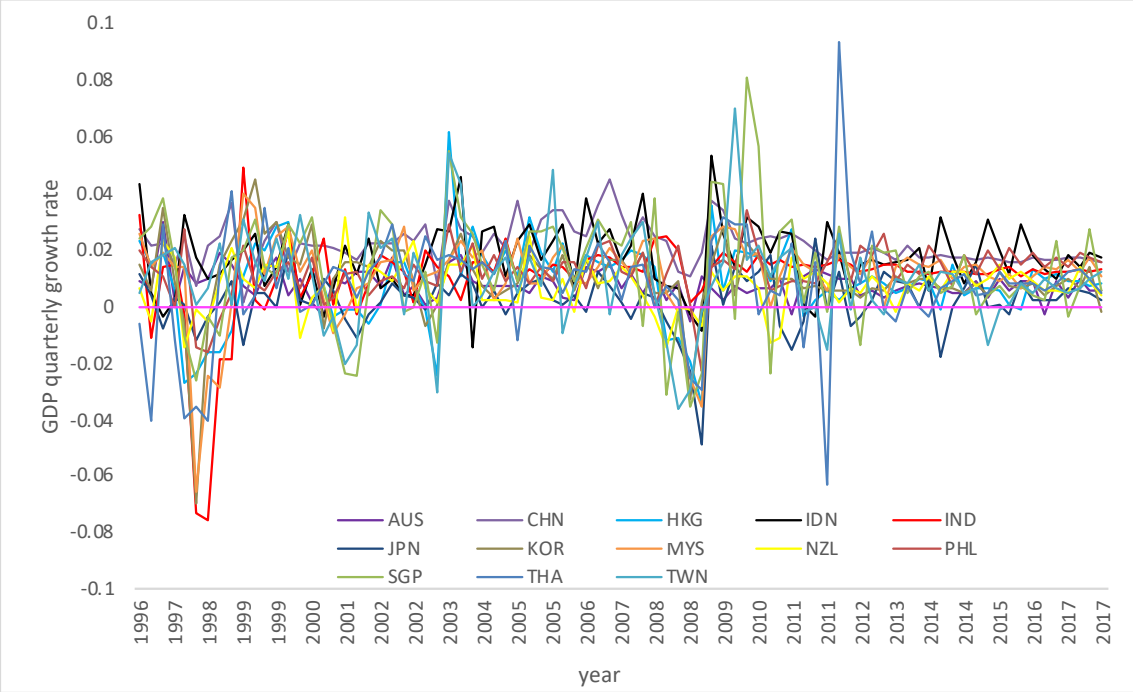

Figure 4.1 GDP quarterly growth rates of Asia–Pacific countries (1994:Q4 – 2017:Q4)

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUS, Australia; CHN, China; HKG, Hong Kong; IDN, Indonesia; IND, India; JPN, Japan; KOR, Korea Rep.; MYS, Malaysia; NZL, New Zealand; PHL, Philippines; SGP, Singapore; THA, Thailand; and TWN, Taiwan.

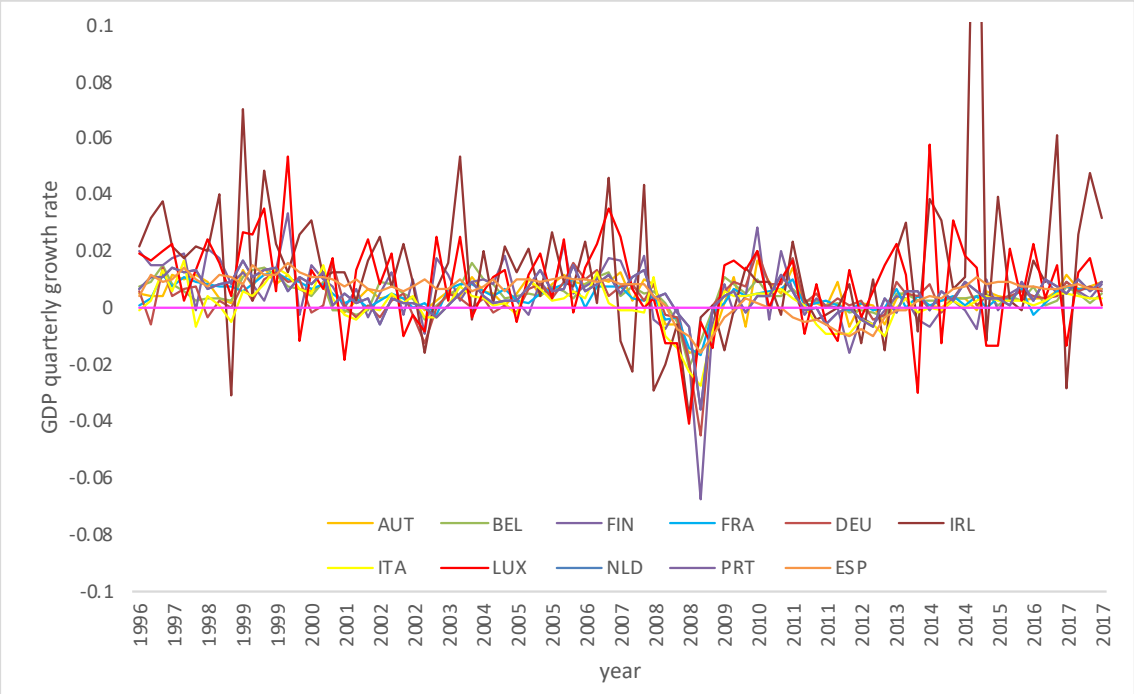

Figure 4.2 GDP quarterly growth rates of Euro Area 11 countries (1994:Q4 – 2017:Q4)

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUT, Austria; BEL, Belgium; DEU, Germany; ESP, Spain; FIN, Finland; FRA, France; IRL, Ireland; ITA, Italy; LUX, Luxembourg; NLD, The Netherlands; and PRT, Portugal.

Descriptive statistics are presented in Table 4.1 and 4.2. For the Asia–Pacific, high growth is found in China, India, and Singapore. Singapore, Thailand, and Taiwan show high standard deviations. For the EA, Ireland and Luxembourg show high growth rates. Standard deviations are high for Ireland, Luxembourg, and Finland.

Table 4.1 Descriptive statistics of GDP quarterly growth rates of Asia–Pacific countries (1996:Q4 – 2017:Q4)

	Mean	Standard deviation	Median	Max	Min
AUS	0.008	0.005	0.007	0.030	−0.005
CHN	0.022	0.007	0.021	0.045	0.001
HKG	0.008	0.014	0.009	0.061	−0.034
IDN	0.017	0.012	0.017	0.053	−0.014
IND	0.010	0.016	0.013	0.049	−0.076
JPN	0.002	0.010	0.003	0.024	−0.049
KOR	0.010	0.014	0.009	0.045	−0.070
MYS	0.011	0.015	0.014	0.040	−0.065
NZL	0.007	0.009	0.008	0.032	−0.015
PHL	0.012	0.009	0.013	0.034	−0.023
SGP	0.013	0.020	0.012	0.081	−0.036
THA	0.008	0.020	0.009	0.094	−0.063
TWN	0.010	0.017	0.009	0.070	−0.037

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUS, Australia; CHN, China; HKG, Hong Kong; IDN, Indonesia; IND, India; JPN, Japan; KOR, Korea Rep.; MYS, Malaysia; NZL, New Zealand; PHL, Philippines; SGP, Singapore; THA, Thailand; and TWN, Taiwan.

Table 4.2 Descriptive statistics of GDP quarterly growth rates of Euro Area 11 countries (1996:Q4 – 2017:Q4)

	Mean	Standard deviation	Median	Max	Min
AUT	0.005	0.006	0.005	0.017	−0.015
BEL	0.004	0.005	0.004	0.016	−0.021
DEU	0.004	0.008	0.004	0.020	−0.045
ESP	0.005	0.007	0.008	0.016	−0.016
FIN	0.005	0.012	0.005	0.034	−0.068
FRA	0.004	0.005	0.004	0.013	−0.016
IRL	0.015	0.030	0.011	0.217	−0.038
ITA	0.001	0.007	0.002	0.016	−0.028
LUX	0.009	0.016	0.012	0.057	−0.041
NLD	0.005	0.007	0.005	0.017	−0.036
PRT	0.003	0.008	0.004	0.022	−0.023

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUT, Austria; BEL, Belgium; DEU, Germany; ESP, Spain; FIN, Finland; FRA, France; IRL, Ireland; ITA, Italy; LUX, Luxembourg; NLD, The Netherlands; and PRT, Portugal.

We present simple correlation coefficients of GDP quarterly growth rates in Tables 4.3 and 4.4.

High correlation is found for Malaysia and Hong Kong, Malaysia and Indonesia, and Singapore and Malaysia. These countries are known as Indonesia–Malaysia–Singapore Growth Triangle. Singapore, Hong Kong, and Malaysia also show high correlation. A main driving force for their economies is known as China funds: a common feature for these countries. Other strong relations are apparent for Malaysia and Korea Rep. and Singapore and Korea Rep.

Turning to EA, an interesting feature is that the correlation is higher than Asia–Pacific, in general. Exceptions are Ireland and Luxembourg. Furthermore, Spain and Germany and Portugal and Germany exhibit low correlation.

Table 4.3 Correlation of GDP quarterly growth rates of Asia–Pacific countries (1996:Q4 – 2017:Q4)

	AUS	CHN	HKG	IDN	IND	JPN	KOR	MYS	NZL	PHL	SGP	THA	TWN
AUS													
CHN	0.247												
HKG	0.042	0.377											
IDN	0.015	0.257	0.293										
IND	−0.152	0.040	0.404	0.109									
JPN	0.034	0.260	0.428	0.258	0.148								
KOR	0.298	0.298	0.492	0.177	0.459	0.243							
MYS	−0.028	0.241	0.620	0.298	0.683	0.418	0.688						
NZL	0.137	0.047	0.420	0.087	0.174	0.203	0.350	0.260					
PHL	−0.034	0.140	0.446	0.334	0.513	0.396	0.334	0.606	0.182				
SGP	0.161	0.356	0.648	0.266	0.291	0.373	0.505	0.546	0.296	0.395			
THA	0.107	0.240	0.349	0.104	0.345	0.350	0.386	0.368	0.358	0.293	0.368		
TWN	0.283	0.308	0.443	0.217	0.051	0.213	0.295	0.333	0.124	0.120	0.441	0.272	

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from “Global Economic Monitor”, World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUS, Australia; CHN, China; HKG, Hong Kong; IDN, Indonesia; IND, India; JPN, Japan; KOR, Korea Rep.; MYS, Malaysia; NZL, New Zealand; PHL, Philippines; SGP, Singapore; THA, Thailand; and TWN, Taiwan. Densely shaded cell shows higher correlation.

Table 4.4 Correlation of GDP quarterly growth rates of Euro Area 11 countries (1996:Q4 – 2017:Q4)

	AUT	BEL	DEU	ESP	FIN	FRA	IRL	ITA	LUX	NLD	PRT
AUT											
BEL	0.711										
DEU	0.647	0.593									
ESP	0.554	0.541	0.390								
FIN	0.615	0.582	0.627	0.578							
FRA	0.736	0.710	0.696	0.637	0.661						
IRL	0.172	0.246	0.136	0.304	0.077	0.252					
ITA	0.699	0.757	0.693	0.684	0.633	0.780	0.259				
LUX	0.396	0.455	0.355	0.364	0.399	0.381	0.313	0.398			
NLD	0.628	0.590	0.658	0.666	0.666	0.720	0.227	0.678	0.229		
PRT	0.508	0.493	0.370	0.659	0.584	0.579	0.266	0.535	0.317	0.657	

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUT, Austria; BEL, Belgium; DEU, Germany; ESP, Spain; FIN, Finland; FRA, France; IRL, Ireland; ITA, Italy; LUX, Luxembourg; NLD, The Netherlands; and PRT, Portugal.

4.3.2 Spatial GAS model

To measure business cycle synchronization, we estimate the time-varying spatial parameter. Blasques et al. (2016) propose time-varying spatial parameter estimation. The estimation becomes possible using Generalized Autoregressive Score (GAS) models, which have been applied in many areas, including modeling time-varying dependence structures. The GAS models is proposed by Creal et al. (2008).[28] The GAS model is based on the score and likelihood evaluation is straightforward in the GAS model.

Blasques et al. (2016) extend the static Spatial Durbin model (SDM) by introducing a time-varying spatial dependence parameter. The SDM for panel data is

$$y_t = \rho W y_t + \beta_1 \iota_n + A_t \beta_2 + W A_t \beta_3 + e_t,$$
$$e_t \sim p_e(e_t; \Sigma, \lambda),\ t = 1, \cdots, T, \qquad (4.1)$$

where $y_t = (y_{1t}, \cdots, y_{nt})'$ is a vector of the dependent variable observed for n cross-section and t represents time dimension, ρ denotes spatial dependence parameter, W stands for an $n \times n$ spatial weight matrix, β_1 is constant, ι_n expresses vector of 1s, A_t is $n \times k$ exogenous variables, β_2 and β_3 are parameters, and e_t signifies an $n \times 1$ vector of error component with density $p_e(e_t; \Sigma, \lambda)$, mean zero, unknown

[28] A revised paper is published as Creal et al. (2012).

$k \times k$ covariance matrix Σ, and parameter vector λ.

We rewrite the SDM model as

$$y_t = \rho W y_t + X_t \beta + e_t, \qquad (4.2)$$

where $X_t \coloneqq (\iota_n : A_t : WA_t)$ and $\beta \coloneqq (\beta_1, \beta_2', \beta_3')'$. DGP of the SDM model is,

$$y_t = (I_n - \rho W)^{-1} X_t \beta + (I_n - \rho W)^{-1} e_t.$$

We reform the model (4.2) with introduction of time-varying spatial parameter ρ_t as

$$\begin{gathered} y_t = \rho_t W y_t + X_t \beta + e_t \\ e_t \sim p_e(e_t;\ \Sigma,\ \lambda),\ t = 1,\ \cdots,\ T, \end{gathered} \qquad (4.3)$$

where $\rho_t = h(f_t)$ is a monotonic transformation of time-varying parameter f_t. An appropriate link function $h(\cdot)$ is chosen such that $\rho_t \in (-1,\ 1)$.

The GAS framework is adoptable by estimating the time-varying parameter f_t. The updating equation of f_t is

$$f_{t+1} = \omega + A s_t + B f_t, \qquad (4.4)$$

where ω is a constant and A and B are unknown parameters, and where $s_t = S_t \cdot \nabla_t$ is a scaled score function.

The scaled score function is the first derivative of the log-likelihood function at time t with respect to f_t. The score function is given as $\nabla_t = \frac{\partial \ell_t}{\partial \rho_t} \cdot \frac{\partial h(f_t)}{\partial f_t}$, where $\rho_t = h(f_t)$ and

$$\ell_t = \ln p_e(y_t - \rho_t W y_t - X_t \beta,\ \Sigma;\ \lambda) + \ln|(I_n - \rho_t W)|. \qquad (4.5)$$

Blasques et al. (2016) use unit scaling such that $S_t \coloneqq 1$ and $s_t = \nabla_t$. The log determinant term accounts for the nonlinearity of the model in ρ_t.

Vectors of static parameters are defined as $\theta \coloneqq (\omega,\ A,\ B,\ \beta,\ \lambda)'$. Numerical maximization is used to estimate θ with the likelihood function shown below as

$$\mathcal{L}_T = \sum_{t=1}^{T} \ell_t. \qquad (4.6)$$

We consider the multivariate normal distribution for density p_e.[29] The log-likelihood function using the multivariate normal distribution is obtained as

$$\ell_t = \ln|(I_n - h(f_t)W)| - \frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln|\Sigma| \\ -\frac{1}{2}(y_t - h(f_t)Wy_t - X_t\beta)'\Sigma^{-1}(y_t - h(f_t)Wy_t - X_t\beta). \qquad (4.7)$$

The score function is

$$\nabla_t = \left(y_t'W'\Sigma^{-1}(y_t - h(f_t)Wy_t - X_t\beta) - tr(Z(f_t)W)\right)\cdot \dot{h}(f_t), \qquad (4.8)$$

where $tr(\cdot)$ is the trace operator, $Z(f_t) = (I_n - h(f_t)W)^{-1}$, and where $\dot{h}(f_t)$ is the first derivative of the transformation function h with respect to f_t.

If $h(f_t) = \gamma\tanh(f_t)$ with $\gamma \in (0, 1)$, then $\dot{h}(f_t) = \gamma(1 - \tanh^2(f_t))$, where $\tanh(\cdot)$ is a hyperbolic tangent function.

Finally, the feasible score function is shown below

$$s_t = \nabla_t = \left(y_t'W'\Sigma^{-1}\left(y_t - \gamma\frac{e^{f_t} - e^{-f_t}}{e^{f_t} + e^{-f_t}}Wy_t - X_t\beta\right) \right. \\ \left. - tr\left(\left(I_n - \gamma\frac{e^{f_t} - e^{-f_t}}{e^{f_t} + e^{-f_t}}W\right)^{-1}W\right)\right)\cdot\gamma\left(1 - \left(\frac{e^{f_t} - e^{-f_t}}{e^{f_t} + e^{-f_t}}\right)^2\right). \qquad (4.9)$$

We designate this model as the Spatial GAS model. For estimation, we set adequate starting values for each parameter and f_t and evaluate log-likelihood for each period (we call this step local evaluation) and estimate parameters with optimization

[29] Multivariate *t*-distribution is also considered by Blasques et al. (2016).

associated with equation (4.7) (we call this global evaluation).[30]

We incorporate spatial weight matrix W in the model. For our study, the spatial weight matrix is specified as the inverse distance and export value between countries i and j.

Business cycles of geographically nearer countries and those with higher trade intensity are more influential than those of distant and less trade-intensive countries. Therefore, if ρ_t shows a high value, then the geographically or economically closer countries' business cycles are synchronized. In other words, ρ_t corresponds to the spatial dependence of business cycles among countries. Consequently, ρ_t represents the degree of business cycle synchronization in our context.

If ρ_t is negative, then the closer countries' business cycles move in opposite directions. If the value of ρ_t is close to 0, the business cycles are dispersed so no spatial dependence is found. We are able to estimate a time-varying common business cycle synchronization indicator only through a spatial econometric model, with accompanying spatial parameters. The merit for the Spatial GAS model is in using information of the full sample.

4.3.3 Spatial panel model

To complement our main results, we use spatial panel econometric methods (Anselin, 2001; Baltagi et al., 2003; Elhorst, 2003, 2009; and Anselin et al., 2008).

We describe the spatial panel model as

$$y = \rho(I_t \otimes W_n)y + X\beta + u. \quad (4.10)$$

This is the spatial autoregressive (SAR) structure for which y is an $nt \times 1$ dependent variable and X is an explanatory variable of the $nt \times k$ matrix. Also, ρ corresponds to spatial dependence parameter of autoregressive process with $|\rho| < 1$, I_t is the identity matrix with dimension t, and W_n is the $n \times n$ spatial weight matrix. Altogether, in each time period, we have $n \times n$ spatial weight matrices.

$u\ of\ equation\ (4.10)$ is the disturbance vector written as

$$u = (\iota_t \otimes I_n)\mu + \varepsilon, \quad (4.11)$$

[30] We choose "simulated annealing" as an optimization method.

where ι_t represents a $t \times 1$ vector of ones, I_n denotes the $n \times n$ identity matrix, μ stands for a vector of time-invariant individual specific effects, and ε_{it} follows $\varepsilon_{it} \sim \mathrm{N}(0, \sigma^2)$. In each time period, we have identity matrix with dimension n, which is associated with μ the vector of individual specific effects. This model depicts a one-way error component. Estimation is conducted via maximum likelihood method.

Actually, W_n is fixed over time, if one uses rolling estimation, then this parameter ρ moves toward the time period.

4.3.4 Estimation strategy

We respectively estimate time-varying spatial parameter ρ_t for 13 countries in the Asia–Pacific region and 11 countries in EA.

For estimation of the Spatial GAS model, we set the equation as

$$y_{it} = \rho_t \sum_{j=1}^{N} w_{ij}\, y_{jt} + \beta_1 x_{1t-1} + \beta_2 x_{2t-1} + e_{\mathrm{it}},$$

$$e_t \sim N(0, \sigma^2), \qquad (4.12)$$

where y_{it} stands for the GDP quarterly growth rate in the Asia–Pacific region or EA, y_{jt} expresses growth rate of the other countries' quarterly GDP in the Asia–Pacific region or EA accompanied by spatial weight matrix W_n, ρ_t denotes the time-varying spatial parameter, i.e. synchronization indicator, w_{ij} stands for components of $n \times n$ inverse distance weight matrix W_n, x_{1t-1} signifies the one-quarter lag of growth rate of GDP of the US, x_{2t-1} represents the one-quarter lag of common business cycle movement of EA for the Asia–Pacific dataset, one-quarter lag of common business cycle movement of the Asia–Pacific for EA dataset, β_1, β_2 is a parameter, and e_{it} represents the idiosyncratic error. The sample period is 1996:Q4 – 2017:Q4. The sample size is 85 for the time dimension.

The spatial weight matrix is $W_n = W_n^d \circ W_n^e$, where W_n^d is the spatial weight matrix of distance and W_n^e is the spatial weight matrix of export value. Each element of spatial weight matrix W_n is $w_{ij} = w_{ij}^e w_{ij}^d$. Diagonal elements of W_n are set to 0 and as a convention, each row of W_n is normalized to 1.[31]

Off-diagonal elements of W_n^d, distance, denote the inverse distance of 1000 km

[31] To be precise, each W_n^d and W_n^e are row normalized to 1, and we produce them to make W_n; finally W_n is row normalized again to 1.

unit between countries i and j and are expressed as a gravity-like model,

$$w_{ij}^{d} = \frac{1}{dist_{ij}^{2}}, \qquad i \neq j, \qquad (4.13)$$

(Anselin, 2002), where $dist_{ij}$ is the distance separating countries i and j. Here, CEPII's GeoDist is used for bilateral distance data: the distance between countries' respective capitals.[32]

Off-diagonal elements of W_n^e are export values, which are calculated as

$$w_{ij}^{e} = \frac{export_{ij} + export_{ji}}{2}, \qquad (4.14)$$

where $export_{ij}$ represents the export value from country i to j; $export_{ji}$ is the export value from country j to i. The export value is extracted from the United Nations Conference on Trade and Development. Data are in thousands of United States dollars and are annual so that the data are averaged over the sample period.

Common business cycle movements in the Asia–Pacific and EA are estimated through a dynamic factor model. A simple dynamic factor model in state-space representation is presented in equations (4.15) and (4.16).

$$x_t = x_{t-1} + w_t, \quad w_t \sim MVN(0, \Omega), \qquad (4.15)$$
$$y_t = Zx_t + v_t, \quad v_t \sim MVN(0, R), \qquad (4.16)$$

where y_t represents the GDP growth rate, x_t stands for a hidden trend (i.e. common business cycle movement), and Z denotes factor loadings. The model is estimated via a Kalman filter.

A common movement is estimated using each country's GDP growth rate, so the common movements can be interpreted as an approximation of the Asia–Pacific or EA GDP growth rates.

For spatial panel method, we estimate the following spatial autoregressive (SAR) type equation as

[32] Mayer, T. and Zignago, S. (2011) "Notes on CEPII's distances measures: the GeoDist Database," *CEPII Working Paper*, 2011-25.

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij}\, y_{jt} + \beta_1 x_{1t-1} + \beta_2 x_{2t-1} + u_{\mathrm{it}},$$

$$u_{it} = \mu_i + \varepsilon_{it}, \;\; \varepsilon_{it} \sim N(0, \sigma^2), \qquad (4.17)$$

where the notations for y_{it}, w_{ij}, x_{1t-1}, and x_{2t-1} are the same as those of equation (4.12) above. In addition, ρ is a spatial parameter, μ_i represents time-invariant individual specific effects, and ε_{it} is the idiosyncratic error.

For retaining the sample size, spatial panel estimation is conducted with *T*=8, i.e., the time span will be two years. We shift the time window from 1996:Q4 – 1997:Q4, 1997:Q1 – 1998:Q1, …, 2016:Q4 – 2017:Q4. Therefore, the estimation will be conducted several times, i.e. rolling estimation will be conducted.

4.4 Estimation results and discussion

4.4.1 Basic results

Results obtained for the Asia–Pacific region are shown in Figure 4.3. Those for EA are shown in Figure 4.4. Estimated *rho* (ρ_t) by Spatial GAS model (*S-GAS rho* hereafter), *rhos* (ρ) by spatial panel model (*SAR-8 rho* hereafter), and common business cycle movements (*CO* hereafter) are depicted in Figures 4.3 and 4.4. Hereinafter, a point of times displayed in figures present $\left(\frac{1}{2}\mathrm{T}+1\right)^{\mathrm{th}}$ periods of each spatial panel estimation, i.e. for *T*=8, the fifth period.

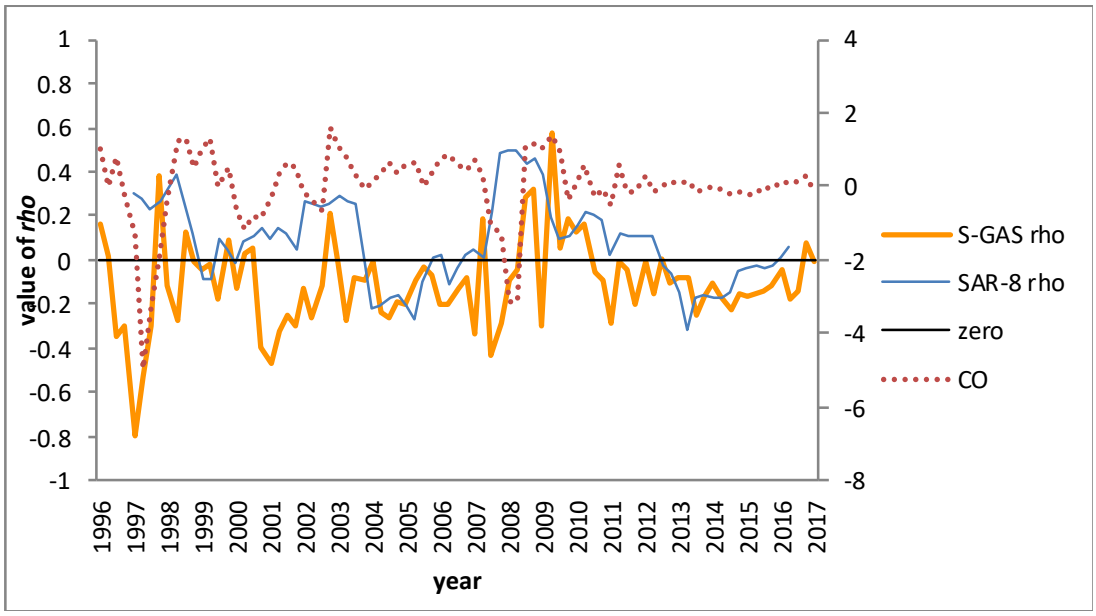

Figure 4.3 Estimated synchronization indicator for the Asia–Pacific using Spatial GAS model and spatial panel method and the common business cycle movements in the Asia–Pacific

Note: *S-GAS rho* is estimated *rho* under Spatial GAS model and *SAR-8 rho* is estimated *rhos* under spatial panel model with $\mathrm{T} = 8$. *CO* is the estimated common business cycle movements in the Asia–Pacific via a Kalman filter. The scale of *CO* is on the right side vertical axis. The horizontal axis means $\left(\frac{1}{2}\mathrm{T}+1\right)^{\mathrm{th}}$ of the estimated period for estimated *rhos* under spatial panel model: 2009:Q1 means 2008:Q1 – 2009:Q4 for *T*=8.

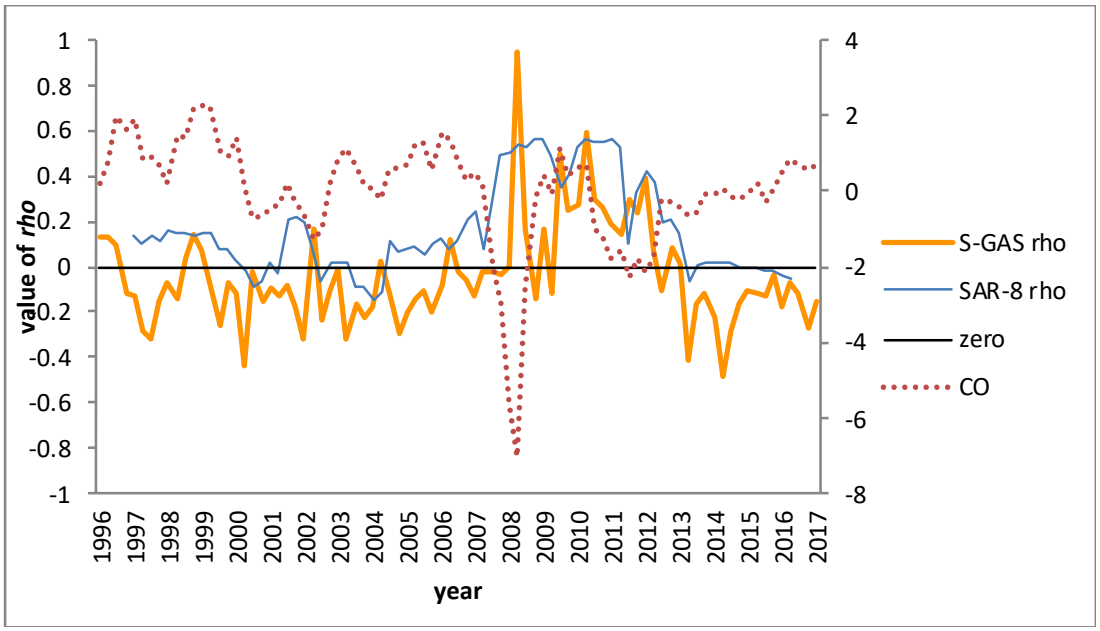

Figure 4.4 Estimated synchronization indicator for Euro Area using Spatial GAS model and spatial panel method and common business cycle movements in Euro Area

Note: *S-GAS rho* is estimated *rho* under Spatial GAS model and *SAR-8 rho* is estimated *rhos* under spatial panel model with $T = 8$. *CO* is the estimated common business cycle movements in Euro Area via a Kalman filter. Scale of *CO* is on the right-side vertical axis. The horizontal axis means $\left(\frac{1}{2}T + 1\right)^{th}$ of the estimated period for estimated *rhos* under spatial panel model, e.g., 2009:Q1 means 2008:Q1 – 2009:Q4 for *T*=8.

The results in Figure 4.3 show that for the Asia–Pacific case, *S-GAS rho* climbs steeply in late 1997 to early 1998 and reaches its peak in 1998:Q3. Another peak is found around 2008 through 2010. The first peak of *S-GAS rho* is in 2008:Q1. The second peak is in 2010:Q1. The first wave corresponds to the recession from Asian Financial Crisis on 1997. This result is in accordance with Moneta and Rüffer (2009), who pointed out that the "Asian crisis clearly caused an increase in overall synchronization." The second wave stems from the shock by collapse of Lehman Brothers in September 2008. The other peak is in 2003:Q3, caused by the collapse of the dot-com bubble (or internet bubble).

SAR-8 rho from spatial panel model shows a similar tendency, but the peaks of the wave differ slightly from those of earlier obtained results. Furthermore, from our estimation approach, the wave is loose because *SAR-8 rho* is averaged over two years. CO (dotted line) in the Asia–Pacific shows a great recession occurred in 1997 and a recession occurred around 2008.

For the EA case shown in Figure 4.4, one clear peak of *S-GAS rho* is in 2009:Q1,

which corresponds to the economic shock from the collapse of Lehman Brothers on September 2008. The peak is steeper than in the Asia–Pacific case. Another two peaks are found in 2010:Q2 and 2011:Q1. These peaks correspond to the European sovereign debt crisis. This crisis took place from the end of 2009; it lasted until 2012. Therefore, we have another but weaker peak in 2012:Q4. These peaks are not clear for the Asia–Pacific case.

SAR-8 rho in EA shows a similar tendency, again. *CO* in EA shows a great recession in 2008. From this, recession stemming from the collapse of Lehman Brothers on September 2008 was more severe in EA than in the Asia–Pacific. A steeper peak in EA around 2008 is plausible. As might be apparent from the high business cycle correlation among EA countries in Table 4.4, business cycle synchronization is related to the degree of economic integration to some extent.

In either the Asia-Pacific or EA case, the value of *S-GAS rho* remains around zero when the *CO* value is around or over zero, i.e. the economic situation is not in a bad phase. Therefore, the business cycle is not synchronized in such a phase but is in divergence. The Great Moderation from the mid-1980s to 2007 is a period of calm volatility in macroeconomics, except for the Asian Financial Crisis in 1997.[33]

Therefore, common large shocks lead to prominently synchronized business cycles of countries closer to each other within the Asia-Pacific and EA. However, *S-GAS rho* settles down after economic crises. These facts indicate a different tendency from that found by Moneta and Rüffer (2009) who point out lasting effects after the economic crisis. Our main results are in line with that of Ductor and Leiva-Leon (2016). Their results show that after the Great Moderation period, synchronization increased to its peak at the end of 2008. They also point out that the phase of business cycle differs between European countries and emerging markets from other countries because of European debt crisis. Additionally, our results show that the short-term fluctuation is not clear in *SAR-8 rho*; *S-GAS rho* is useful for inspecting short horizons and movements per month.

4.4.2 Comparison between synchronization and volatility

Next, we verify the relations between estimated *S-GAS rho* and business cycle volatilities of Asia–Pacific and EA. The instantaneous volatility of business cycles is estimated with the GARCH (1, 1) model. The GARCH (p, q) model is described below as

[33] There are other exceptions. The crises in Mexico, Russia, and Brazil in 1994-95, 1998, and 1999, respectively.

$$y_t = \mu + \epsilon_t, \qquad (4.18)$$

$$\epsilon_t = \sigma_t z_t, \ \sigma_t > 0, \ z_t \sim N(0, 1), \qquad (4.19)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, \qquad (4.20)$$

where y_t denotes the common GDP growth rate, as already estimated above, σ_t^2 represents instantaneous volatility of business cycle (*vol* hereafter). The estimation period is 1996:Q3 – 2017:Q4: the sample size is 86.

As a result, from Figures 4.5 and 4.6 in which *S-GAS rho* and *vol* are described, it is noteworthy that *S-GAS rho* and *vol* show considerably similar motions in the cases the Asia–Pacific or EA. Therefore, when economic shocks occurred and the business cycle volatility soars, business cycle synchronization will be similarly inflated.

Two cases are assumed for business cycle synchronization. For instance, presuming geographically or economically closer countries A, B, and C. The first case is that some exogenous economic shock will influence country A. Then, B and C are contemporaneously affected by country A and mutually interact. The second case is that all countries (A, B, and C) might be affected by a common exogenous shock contemporaneously. A second case is that an exogenous common economic shock will contemporaneously but independently influence countries A, B, and C, and that they move in the same direction, i.e., growth rates will decrease at similar magnitudes simultaneously, without economic propagation among countries A, B, and C.

Selover et al. (1999) conclude that a major force underlying the international business cycle synchronization might be the “mode-locking” phenomenon. It refers to the situation when slight vibrations are transmitted from one clock to another, and this leads to the clocks oscillating at roughly the same frequency. Accordingly, in this study, we treat business cycle synchronization as a first case: there exists a propagation mechanism.

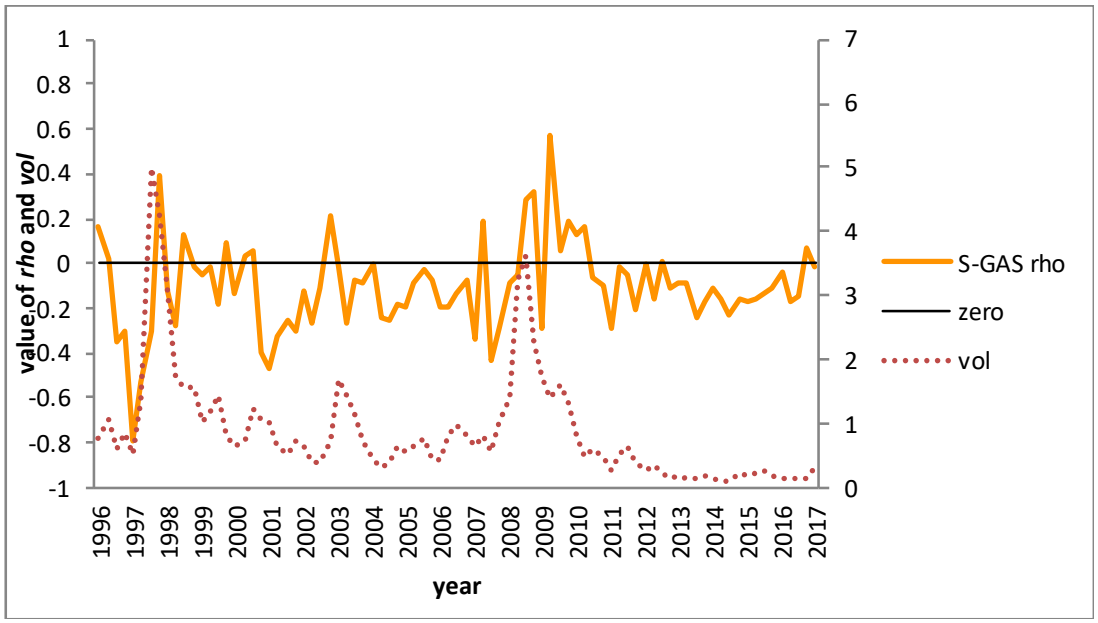

Figure 4.5 Estimated synchronization indicator with Spatial GAS model, and business cycle volatility of the Asia–Pacific

Note: *vol* is the estimated volatility of common business cycle movements in the Asia–Pacific using GARCH. Scale of *vol* is on the right side vertical axis.

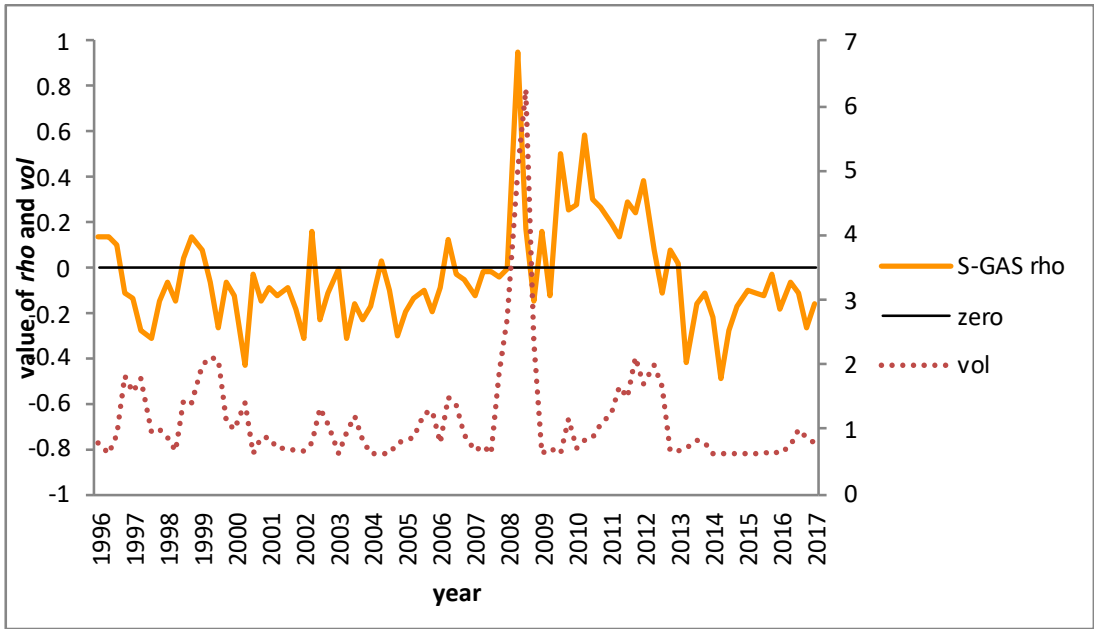

Figure 4.6 Estimated synchronization indicator with Spatial GAS model, and business cycle volatility of Euro Area

Note: *vol* is the estimated volatility of common business cycle movements in Euro Area using GARCH. The scale of *vol* is on the right-side vertical axis.

4.5 Conclusion

Instead of using structural analyses, in this study, we explore short time effects using one-step methodology. We apply space–time econometric methodology: spatial generalized autoregressive score model by Blasques et al. (2016) for measuring business cycle synchronization. We estimate a "spatial parameter" which denotes a "business cycle synchronization indicator." Business cycle synchronization is defined as a common indicator that is time-varying.

The estimated business cycle synchronization indicator show a high value during economic turmoil, such as the Asian crisis of 1997, the collapse of the dot-com bubble (or internet bubble), European sovereign debt crisis, and the collapse of Lehman Brothers in 2008.

Our finding is that when common business cycle movements show severe economic shocks, business cycle synchronization exhibits high values. In addition to this, when economic shocks occurred and business cycle volatility soared, business cycle synchronization is inflated similarly. However, when the economic situation is not in a bad phase, the business cycle is not synchronized. Finally, based on our results, business cycle synchronization is related to some extent to the degree of economic integration.

With the recent increase in economic integration, exogenous shocks increase geographically and economically closer countries' business cycle synchronization to each other, and such shocks cause economic instability.

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Chapter 1

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