Research Article

The Economic Benefit from Business Interaction between Different Business Activities through High-Speed Rail Operation: An Experimental Concept for the Business Interactive Accessibility and Its Application

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Abstract: This study evaluates the impact of the business interactive accessibility (BIA) by high-speed railway (HSR) of Japan. The BIA by HSR is a potential interaction for business purposes by HSR, based on the accessibility. Socio-economic conditions affect the BIA, but they have been only considered partially in the accessibility of previous studies. This study develops new variables, Densely-Buoyant District (DBD) at the micro-level and Densely-Buoyant Prefecture (DBP) at the macro-level. The indices denote the BIA considering socio-economic conditions: firms, workers, business scale, and distance between firms within a region. To examine the impact of DBP by HSR, we utilize the production function including DBP, prefecture-fixed effects, and time-fixed effects. The result suggests that DBP enhanced by HSR increases productivity. DBP of the secondary industry and tertiary industry enhances productivity, but not the primary industry. Therefore, the BIA by HSR in the secondary and tertiary industries contributes to regional growth.

Keywords: High-Speed Rail, Shinkansen, Accessibility, Business Interaction

1. INTRODUCTION

High-speed rail (HSR) is for passenger transportation, so the impact of HSR on a region has to do with the travel purpose of HSR passengers. One of the major travel purposes of HSR passengers is business travel. The business travel is for a new contract, meeting, and knowledge exchange, which contribute to regional productivity. In this study, the business travel of HSR passengers is named as a business interaction between regions by HSR.

Accessibility is a potentiality of interactions between regions (Hansen, 1959). Based on the notion of accessibility, the potentiality of business interaction can be defined as a business interactive accessibility. HSR reduces travel time enhancing the business interactive accessibility, and the enhanced accessibility by HSR promotes regional growth. Therefore, HSR can be regarded as a catalyst to maximize the impact of business interactive accessibility.

Not only HSR but also diverse socio-economic conditions affect the business interactive accessibility. For example, a region having a large firm employing numerous workers may be more interacted with other regions, compared to a region consisting of numerous small firms employing a few workers. This explains that the regional business scale may be related to the business interactive accessibility by HSR. If numerous small firms are concentrated in a region,
they may create a regional specialization, which leads to more business interaction with other regions than the region with one large company. The agglomeration effects can be also maximized when firms are close to each other within a region. This explains that a distance between firms within the region also influences the business interactive accessibility. However, these socio-economic conditions have been less considered in estimating the accessibility in previous studies until now, in spite of its importance. Therefore, if considering the socio-economic condition in the accessibility, we can shed light on the impact of the business interactive accessibility by HSR on productivity in more detail.

This study aims to estimate the impact of the business interactive accessibility by HSR on productivity, with consideration for the socio-economic condition. We develop a new index named Densely-Buoyant District (DBD) showing the business interactive accessibility by HSR at the micro-level. At the macro-level, we utilize Densely-Buoyant Prefecture (DBP), which is the DBD estimation at the prefecture-level. DBD and DBP consider the business scale, the distance between firms within a region, firms and workers, and HSR travel time. We first estimate DBD at the micro-level and second analyze the impact of DBP on productivity by using a production function based on the panel data analysis. Section 2 discusses literature reviews, and section 3 introduces DBD. Section 4 analyzes the impact of DBP on productivity. The final section derives conclusions and suggests recommendations for future studies.

2. LITERATURE REVIEW

HSR mainly affects tourism-related industries (Lin, 2017; Sun and Mansury, 2016). However, the impact of HSR may be more effective in industries requiring creativity and human interactions, such as FIRE (Finance, Insurance, and Real Estate), IT, and business service (Lin, 2017) than tourism-related industries. For example, HSR can promote face-to-face contact by reducing travel time. In Japan, Nagano Shinkansen contributes to knowledge diffusion through increasing collaborations between regions (Inoue et al., 2017). In China, manufacturing industries may be both positively and negatively affected by HSR (Sun and Mansury, 2016). The increasing density of manufacturing firms in a region may raise total output, by the agglomeration of firms. However, there may be job losses caused by a transition from a labor-intensive structure to a capital-intensive structure (Sun and Mansury, 2016). This transition relocates and replaces traditional manufacturing industries. Therefore, we can assure that the impact of HSR may depend on industrial classification.

Transportation enhances the time-and cost-efficiency of producers, consumers, and employees. One of the benefits from the enhanced time-and cost-efficiency is the agglomeration effects reducing transaction costs, sharing skilled-labor pool, and knowledge-spillovers (Marshall, 1920). We can also imagine the agglomeration effects through physical proximity between firms within a region. The proximity between firms increases the business interaction between firms within a region. However, a relationship between the agglomeration effects and transportation investments can be distinctive corresponding to the industrial sectors (Wetwitoo and Kato, 2017).

The impact of HSR depends on the regional characteristic since the accessibility by HSR is related to the population density, urban scale, and economic development (Jiang and Chu, 2017). Cho et al. (2016) explain that productivity is higher in HSR passing cities than non-passing cities, by analyzing the case of Japanese Shinkansen at the prefecture-level. They propose that the vicinities of major cities are less affected by HSR. Further, the authors point out that there is an outflow from small and intermediate cities to large cities. However, small- and intermediate cities can be also benefited from the HSR operation. Gutiérrez (2001) argues
that the accessibility of small-intermediate cities can be more enhanced by HSR than large cities. Even if large cities may be benefited more from the HSR operation through sufficient productivity, human-resources, and capitals, than small cities, the elasticity of the small cities could be higher than the large cities. This is because HSR can complement the inter-regional transportation in small cities with less developed inter-regional infrastructure if small cities are accessible to HSR. A difference between large cities and small cities means the different socio-economic conditions between regions, and the difference may affect the accessibility.

The previous studies emphasize that the impact of HSR can be different across the industrial sectors. The business interactive accessibility can be also affected by regional socio-economic conditions. Regarding the interaction of the socio-economic condition on the business interactive accessibility, we can assume that the degree of HSR impact is related to the business scale of a region and physical proximity between firms within a region. We organize the accessibility functions of previous studies in Table 1, then examine what factors have been considered in the accessibility function by considering the above discussions.

<table>
<thead>
<tr>
<th>Category</th>
<th>Authors</th>
<th>Function</th>
<th>Transport</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classical accessibility</td>
<td>Wetwitoo and Kato (2017)</td>
<td>(1) ( ED_{nit} = \sum_j \frac{E_{jt}}{T_{jit}} )</td>
<td>Interregional</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) ( ED_{nit} = \sum_j \frac{E_{njt}}{T_{jit}} )</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3) ( ED_{nit} = \sum_j \sum_m \gamma_{nmj} \frac{E_{mj}}{T_{jit}} )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Yi and Kim (2018)</td>
<td>(4) ( ACC_{i}^{\text{Road}} = \frac{\text{Pop}_i}{\exp\beta_i^{\text{Road}}} + \sum_j \frac{\text{Pop}_j}{\exp\beta_j^{\text{Road}}} )</td>
<td>Road</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5) ( ACC_{i}^{\text{Rail}} = \frac{\text{Pop}_i}{\exp\beta_i^{\text{Rail}}} + \sum_j \frac{\text{MIN}(\text{Pop}_j;\text{Cap}_i)}{\exp\beta_j^{\text{Rail}}} )</td>
<td>Railroad</td>
</tr>
<tr>
<td>Weighted average</td>
<td>Gutiérrez (2001)</td>
<td>(6) ( \text{Econoimc potential}_i = \sum_j \frac{\text{M}<em>j}{T</em>{ij}} )</td>
<td></td>
</tr>
<tr>
<td>travel time</td>
<td>Sun and Mansury (2016)</td>
<td>(7) ( WATT_{it} = \frac{\sum_j (T_{jit} \cdot M_j)}{\sum_j M_j} )</td>
<td>HSR</td>
</tr>
<tr>
<td></td>
<td>Diao (2018)</td>
<td>(8) ( WATT_{it} = \frac{\sum_j (T_{jit} \cdot \text{GDP}_j)}{\sum_j \text{GDP}_j} )</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(9) ( WATT_{it} = \frac{\sum_j (T_{jit} \cdot \text{GDP}_j)}{\sum_j \text{GDP}_j} )</td>
<td></td>
</tr>
</tbody>
</table>

*ED*: effective density, *E*: employment, \( \gamma \): industrial interaction, *ACC*\(^{\text{Road}}\): Road accessibility, *ACC*\(^{\text{Rail}}\): Rail accessibility, *Pop*: population, *Cap*: railway capacity, *M*: a mass of attractiveness, *n, m*: industry *n, m*, *T_{jit}*: travel time between area *i* and *j* at time *t*, \( \beta \): travel decay

There are two representative approaches in estimating the accessibility: Weighted average travel time (WATT) and classical accessibility. WATT shows the importance of minimal travel time without travel decay, unlike classical accessibility based on the gravity model (Gutiérrez and Urbano, 1996). In WATT, travel time is regarded as a weight for a regional attractiveness. Classical accessibility is mainly calculated by the attractiveness of a region and travel time between regions. The classical accessibility is based on the gravity model and considers travel decay in the function (Yi and Kim, 2018; Gutiérrez, 2001). Wetwitoo and Kato (2017) did not consider the travel decay, instead, they emphasize agglomeration effects of one industry and of between industries. For example, in Equation (3), the authors include the weight of the inter-industrial interaction \( \gamma_{nmj} \). The different subscripts *m, n* explain the accessibility of industry *m* interacted with different industry *n*. Function (1) ~ (3) and (6) of Table 1 concentrate on the
inter-regional interaction. However, (4) and (5) of Yi and Kim (2018) consider not only inter-regional interaction but also an intra-regional interaction.

To sum up, first, the attractiveness of the accessibility function decides the meaning of the interaction. For example, using employment as the attractiveness is more appropriate to explain the business interactive accessibility than population. Second, the accessibility functions usually utilize only one attractiveness, even though there is the weight as like function (3) and (5). Last, the socio-economic condition is less considered in previous approaches. For instance, the business scale and the proximity between firms within a region can be considered as the socio-economic conditions. Therefore, in this study, the business interactive accessibility by HSR considers two attractiveness and two socio-economic conditions.

3. CONCEPT OF DENSELY-BUOYANT DISTRICT AND ITS APPLICATION

3.1 Concept of Densely-Buoyant District

Based on the accessibility, we develop a new index Densely-Buoyant District (DBD), explaining the business interactive accessibility with consideration for the socio-economic conditions. DBD describes the potentiality of business interaction and assumes all kinds of business interactions between different firms and headquarter and branches. DBD can be used not only at the macro level but also at the micro-level.

Compared to previous studies’ accessibility function, DBD employs two major attractiveness: firms and workers. The potentiality of the business interaction is described as workers visiting firms, for knowledge-exchanges, meetings, and new contracts, based on face-to-face contact. Firms gain benefits from business interaction between firms. The concept of DBD is described in Figure 1.

Case A: Intra interaction A  
Case B: Intra interaction B  
Case C: Inter interaction

Figure 1. Concept of the business interaction in DBD

Case A and B of Figure 1 describe that workers of firm 1 visit to firm 2 within district $i$. Firms close to each other within a district more interact with each other. Case A shows the business interaction between firms far away from each other within a district. Case B explains the business interaction when firms are close to each other within a district. Case B has more business interactive possibilities than case A. Case C describes the business interaction between firms located in different districts. Case C shows district $i$’s workers visiting district $j$’s firms and district $j$’s workers visiting $i$’s firms. The travel of workers between different districts $i, j$ can be achieved by HSR. Therefore, Figure 1 explains that a worker becomes an agent visiting a firm by HSR. This concept of visiting by worker considers both firm and worker as the attractiveness of each district, while previous studies only employ one attractiveness as like population, employees, and gross domestic productivity (GDP).
3.2 The Function of Densely-Buoyant District

Workers visiting firms explain two attractiveness of a district: firms and workers. In addition to the attractiveness, DBD takes into accounts two regional socio-economic conditions in order to explain the business interactive accessibility. First, the business scale of a district affects the business interaction degree. Cho et al. (2016) point out that large cities may be more benefited from HSR, than small and intermediate cities. Similarly, a large scale firm can be more interactive with other firms. For example, on the one hand, a district having one large firm employing many workers has a different potentiality of the business interaction, compared to a district having numerous firms employing a few workers. On the other hand, if a district consists of numerous small companies employing a few workers, the district may result in the regional specialization enhancing the business interaction. Second, a distance between firms within a district affects a potentiality of the business interaction. If firms within a district are close to each other, the potential intra-business interaction can be enhanced. Then the enhanced intra-business interaction leads to an increase in inter-districts business interaction. Therefore, DBD can be increased when firms are close to each other in a district through the agglomeration effects resulted from physical proximity.

Let us show an example by using prefecture-level data. Figure 2 presents a relationship between nominal GDP, firms ($F$) multiplied by workers ($W$), and business scale (workers divided by firms, $W/F$), in 8 years of Japanese prefectures. X-axis and Y-axis denote $F \times W$ and GDP respectively. Point size is the business scale of each prefecture each year. Figure 2 shows that the larger $F \times W$ and business scale increase, the higher GDP rises. This explains that it is required to consider the regional business scale in estimating DBD.

![Figure 2. Relationship between F*W, GDP, and business scale](image)

Figure 3 shows a relationship between GDP and business scale. GDP may exponentially increase by the business scale. This means that the exponential form of the business scale may be more effective in estimating DBD. We consider four different forms of the business scale: business scale ($s_{It}$), $e^{s_{It}}$, min-max rescaled business scale ($S_{It}$), and $e^{S_{It}}$. $I$ and $t$ denote...
prefecture and year each. Min-max rescaling is used for the normalization. We linearize each business scale form to GDP ($\text{GDP}_{it}$), then compare the $R^2$ of each form. The $R^2$ is the highest in the $e^{S_{it}}$ form. Therefore, in estimating DBD, we utilize the $e^{S_{it}}$ form for the business scale.

Figure 3. Relationship between GDP and business scale

$$DBD_{it} = f(S_{it}, W_{it}, F_{it}, P_{it}, S_{jt}, W_{jt}, F_{jt}, P_{jt}, d_{ij}^\gamma) = DBD_{it}^{\text{intra}} + DBD_{it}^{\text{inter}}$$  \hfill (1)

$$DBD_{it}^{\text{intra}} = e^{S_{it}} * W_{it} * (F_{it} - 1) * P_{it}$$  \hfill (2)

$$DBD_{it}^{\text{inter}} = DBD_{it}^{\text{visiting}} + DBD_{it}^{\text{visitor}} = \sum_j \frac{e^{S_{jt} + W_{jt} + F_{jt} + P_{zjt}}}{d_{ij}^\gamma} + \sum_j \frac{e^{S_{jt} + W_{jt} + F_{jt} + P_{zjt}}}{d_{ij}^\gamma}$$  \hfill (3)

$$S_{it} = \frac{s_{it} - \min (s_{it})}{\max (s_{it}) - \min (s_{it})}$$  \hfill (4)

$$s_{it} = \frac{W_{it}}{F_{it}}$$  \hfill (5)

where,

- $\forall i \in I, \forall j \in J$, and $(i \neq j)$
- $i, j$ : district $i, j$
- $F_{it}, W_{it}$ : the number of firms and workers of district $i$ at time $t$ respectively
- $d_{ij}^\gamma$ : travel distance or travel time between district $i, j$ with travel decay $\gamma$
- $z$ : a set of districts including bordering districts of district $i$ and district $i$
- $P_{zit}$ : weight of distance between firms within district $i$
- $S_{it}$ : normalized business scale of district $i$
- $s_{it}$ : business scale of district $i$

Equation (1) ~ (5) explains DBD function. The DBD function consists of five major factors: the regional business scale, the distance between firms within a district, firms, workers, and the travel time. $DBD_{it}$ is DBD of district $i$ at time $t$ and the sum of $DBD_{it}^{\text{intra}}$ and $DBD_{it}^{\text{inter}}$. $DBD_{it}^{\text{intra}}$ of Equation (2) is the function for case A and B of Figure 1. This explains worker visiting firms ($W_{it} * (F_{it} - 1)$) within the same district $i$. In Equation (2), we subtract
1 from the total number of firms. The business interaction is achieved between different firms. Therefore, the firm which workers belong should be excluded in $DBD_{it}^{\text{intra}}$, to explain workers visiting firms that the workers do not belong to. If there is only one firm in a district, it means that there is no interaction between firms within the district since there are no other firms. $DBD_{it}^{\text{inter}}$ is the business interaction between district $i$ and $j$, as like case C of Figure 1.

$p_{zit}$ is an index showing the proximity between firms within a district and explains agglomeration effects attributed to a geographical concentration of firms. Small letter $s_{it}$ explains the business scale of district $i$. Capital letter $S_{it}$ is a normalized index of $s_{it}$ by min-max scaling. $DBD_{it}^{\text{visiting}}$ shows district $i$’s workers visiting firms located in different district $j$. $DBD_{it}^{\text{visitor}}$ signifies district $j$’s workers visiting firms of district $i$. $DBD_{it}^{\text{visiting}}$ and $DBD_{it}^{\text{visitor}}$ have a different subscript order in Equation (3). In Equation (3), $d_{ijt}^{\gamma}$ explains travel cost between $i$ and $j$ with travel decay $\gamma$. Table 2 compares classical accessibility, WATT, and DBD. DBD contains two socio-economic conditions and two attractiveness.

<table>
<thead>
<tr>
<th>Classical accessibility</th>
<th>WATT</th>
<th>DBD</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sum_j \frac{M_{jt}}{T_{ijt}} \over \sum_j M_{jt}$</td>
<td>$\sum_j T_{ijt} * M_{jt}$</td>
<td>$e^{s_{it} * W_{it} * (F_{it} - 1) * p_{it} + \sum_j e^{s_{jt} * W_{jt} * F_{ji} * p_{jit}}}$</td>
</tr>
</tbody>
</table>

$M_{jt}$: a mass of attractiveness (i.e. population and worker), $T_{ijt}$, $d_{ijt}^{\gamma}$: travel cost

### 3.3 Applying DBD Function to the Mesh Level

We estimate the DBD value of 500m*500m mesh (hereafter district) of Japan in 2014. We utilize a straight-line distance between physical centroids of district $i$ and $j$ ($d_{ijt}^\gamma$), for the simplicity in its calculation for all districts. The $\gamma$ value is assumed as 1 for simplicity as well.

We utilize a proxy variable, explaining the distance between firms within a district ($P_{zit}$). A firm within a district can be located close to one of bordering districts for the business interaction with firms in the bordering district if the bordering district has a large number of workers. A firm can be also located at the center of a district if the district has a lot of workers. Locations of firms may depend on non-neighbor districts through transportation networks. However, these non-bordering districts’ impact is not included for the simplicity, since all districts of Japan are targeted. Therefore, we assume that the potential location of firms within a district is affected by the number of workers of district $z$. $z$ is a set of district $i$ and $i$’s bordering districts ($j$ s). A location of $k$ th firm within district $i$ follows the Bernoulli distribution as shown in Equation (6). $l_{kzt}$ implies a probability of the firm’s location.

$$l_{kzt} \sim \text{Bernoulli} \left( \frac{W_z}{\sum_z W_z} \right)$$  \hspace{1cm} (6)

$$p_{zit} = 1 - p_{zit} = 1 - \sum_n \frac{\text{var}(l_{kzt})}{n}$$  \hspace{1cm} (7)

where,

- $l_{kzt}$ : 1 if $k$th firm is located near to the one of bordering districts, 0 if not
- $z$ : $i, j$, and $z$ is only valid when $W_z > 0$
- $\text{Var}(l_{kzt})$ : variance of $l_{kzt}$ (= $l_{kzt}[1 - l_{kzt}]$)
- $n$ : the number of the valid district $z$
- $p_{zit}$ : index showing a distance between firms within district $i$ at time $t$
A distance between companies \( p_{zit} \) within district \( i \) is calculated by the mean of the variance of \( l_{kzt} \), as shown in Equation (7). We assume that a short distance between firms augments benefit by increasing the business interaction. Therefore, \( p_{zit} \) is inversely proportional to the business interaction. \( P_{zit} \) explains the inverse relation. The maximum \( P_{zit} \) value is 1, showing no reduction in the potentiality of the business interaction by the distance between firms within district \( i \), as shown in Figure 4 (D). For example, most of the firms of district \( i \) can be located at the center of \( i \), since firms are not affected by workers of bordering districts. The low \( P_{zit} \) value of Figure 4 (A) indicates the weak potential business interaction within a district. \( P_{zit} \) also explains that firms in district \( i \) may be more related to district \( j \)’s firms close to the border of district \( i \). Since the mesh data is originally divided with no criterion, it cannot be assured whether a firm of \( i \) is closely related to firms within \( i \) or not.

![Table](image)

**Figure 4.** Estimating distance between firms within a district

![Kanto area](image) ![Kansai area](image)

**Sendai** ![image](image) **Fukuoka**

**Figure 5.** Result of DBD at the mesh-level
The example of the estimated DBD is shown in Figure 5. Most of the districts belonging to the major cities, such as Tokyo and Osaka, have high DBD. DBD value is the highest in districts close to Shinkansen station in the major cities. Red-point is the HSR station, and the red-colored district has a higher DBD value than others. The result explains that business interaction is intensified when business activities are agglomerated. This tendency may occur especially near the HSR station.

4. VERIFYING UTILITY OF DBD AT THE PREFECTURE-LEVEL

4.1 Introduction of Analysis

Although we estimated DBD in the mesh level, a relationship between HSR, DBD, and productivity should be verified. However, there is no available productivity data at the mesh-level, so the impact of DBD on productivity cannot be directly verified. Instead, we make use of DBP (Densely-Buoyant Prefecture), which is the DBD value at the prefecture-level, to verify the relationship between HSR, DBP, and productivity.

Improving accessibility increases the interaction between regions, and the increased interaction leads to firms to become more productive (Chen and Silva, 2013). HSR reduces travel time, so DBP can be increased by HSR. The high DBP means that the region may have more opportunities for business interaction then may increase regional productivity.

This chapter verifies the statistical significance of DBP and the relation between HSR, DBP, and productivity. We first utilize Difference-In-Difference (DID) method, to examine a relationship between HSR and DBP. Then, we use the production function including the DBP variable, to show the relationship between DBP and productivity and to verify the statistical significance of DBP. The production function using labor and capital has been often used to examine the impact of inter-region accessibility of transportation in previous studies (Yi and Kim, 2018; Wetwitoo and Kato 2017). This study hypothesizes that DBP increased by HSR augments productivity at the prefecture-level.

We analyze 46 prefectures of Japan except for Okinawa Prefecture, far from the mainland of Japan. We utilize workers, firms, working-age population, private-capital stock, and nominal GDP, provided by the economic and fiscal policy data by the Cabinet Office of the Japanese Government. We select eight years from 1981 to 2014, based on the obtainable data of worker and firm at the prefecture-level. A panel data structure at the prefecture-level is used in the production function. The data structure is organized in Table 3.

<table>
<thead>
<tr>
<th>Category</th>
<th>Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target (Areal unit)</td>
<td>46 (prefectures)</td>
</tr>
<tr>
<td>Data name</td>
<td>Worker, firm, private-capital stock, nominal GDP, and working-age population (15~64 years old)</td>
</tr>
<tr>
<td>Panel structure</td>
<td>Case=368, N=46, T=8</td>
</tr>
</tbody>
</table>

4.2 DBP Functional Form and Data Detail

Equation (8) ~ (10) is similar to Equation (1) ~ (5). Subscript $i$ and $j$ implies a prefecture.
\[ DBP_{it} = f(S_{it}, W_{it}, F_{it}, P_{it}, S_{jt}, W_{jt}, F_{jt}, P_{jt}, d^Y_{ijt}) = DBP_{it}^{\text{intra}} + DBP_{it}^{\text{inter}} \]  
\[ DBP_{it}^{\text{intra}} = e^{s_{ijt} W_{it} (F_{it} - 1) P_{it}/t_{it}} \]  
\[ DBP_{it}^{\text{inter}} = DBP_{it}^{\text{visiting}} + DBP_{it}^{\text{visitor}} = \sum_j e^{s_{ijt} W_{it} F_{jt} P_{jt} / \tau_{ijt}} + \sum_j e^{s_{ijt} W_{jt} F_{it} P_{it} / \tau_{ijt}} \]  
\[ t_{iit} = \frac{1}{2} * \sqrt{\frac{\text{area}_{ii} \gamma s_{iit}}{\pi}} \]  
\[ P_{it} = \frac{1}{2} * \sqrt{\frac{F_{it} / \text{area}_{it}}{\pi}} \]

where,

\( \forall j \in J \) and \( i \neq j \)

- \( t_{iit} \) : intra-travel time of prefecture \( i \) at year \( t \)
- \( T_{ijt}^\gamma \) : the fastest travel time between centroids of prefecture \( i \) and \( j \) by HSR
- \( \text{area}_{it} \) : land area of \( i \) at year \( t \)
- \( i\gamma s_{iit} \) : intra-speed by a vehicle within \( i \), assuming 60km/h at year \( t \)
- \( \pi \) : circular constant

\( DBP_{it} \) is the potentiality of the business interaction of prefecture \( i \) by HSR. \( DBP_{it}^{\text{intra}} \) is a potentiality of intra-interaction within prefecture \( i \), and \( DBP_{it}^{\text{inter}} \) is a potentiality of inter-interaction between \( i \) and different prefectures. \( DBP_{it}^{\text{visiting}} \) describes prefecture \( i \)'s workers visiting firms located in different prefectures. \( DBP_{it}^{\text{visitor}} \) denote prefecture \( j \)'s workers visiting firms at prefecture \( i \). We consider intra-travel time \((t_{iit})\) in \( DBP_{it}^{\text{inter}} \) of Equation (9). DBD does not consider intra-travel time since the land area of a district is small and all districts have the same land area. On the contrary, in DBP, each prefecture has a different land area, and the land area is also very large, so it is indispensable to consider intra-travel time. We assume that each prefecture has a circular shape, so estimating intra-travel time is shown in Equation (11) (Yi and Kim, 2018; Gutiérrez et al., 2011). \( P_{it,j} \) is expressed in Equation (12). Eq. (12) is almost similar to Eq. (11), but a density of firms \((F_{it}/\text{area}_{it})\) replaces \( \text{area}_{it} \) of Eq. (11), to consider the geographical concentration of firms.

\[ T_{ijt} = \min(t_{iit}^{\text{intra}} + t_{iit}^{\text{HSR, st}} + t_{jyt}^{\text{HSR, st}} + t_{jyt}^{\text{intra}}) \]  
\[ t_{iit}^{\text{intra}} = \frac{1}{2} * \sqrt{\frac{\text{area}(1 + n_{iit}^{\text{HSR, st}})}{\pi}} / i\gamma s_{iit} \]  
\[ t_{iit}^{\text{HSR, st}} = d_{iit} / i\gamma s_{iit} \]  
\[ t_{jyt}^{\text{HSR, st}} = d_{jyt} / HSRs_{xyt} \]

where,

- \( x, y \) : departure and arrival HSR station
- \( t_{iit}^{\text{intra}} \) : intra-travel time with HSR stations of \( i \) as a center at year \( t \)
- \( t_{iit}^{\text{HSR, st}} \) : travel time from the geographic centroid of \( i \) to HSR station \( x \) at year \( t \)
- \( t_{xyt}^{\text{HSR, st}} \) : HSR travel time between \( x \) and \( y \) at year \( t \)
- \( n_{iit}^{\text{HSR, st}} \) : the number of HSR stations within \( i,j \) at year \( t \)
- \( d_{iit} \) : straight-line distance from the physical centroid of \( i,j \) to HSR station \( x,y \)
- \( d_{xyt} \) : distance between two HSR stations of \( x,y \) along HSR line at year \( t \)

\( HSRs_{xyt} \) : maximum HSR speed along the HSR line between \( x,y \) at year \( t \)
Total travel time $T_{ijt}$ follows in Equation (13) ~ (16). $T_{ijt}$ is the sum of intra-travel time within prefecture $i$, straight-line travel time from a geographical centroid of $i$ to a departure HSR station, travel time between HSR stations of departure and arrival, straight-line travel time from an arrival HSR station to a geographical centroid of $j$, and intra-travel time within $j$. For $s_{ii}$ and $d_{ix}$, we assume a vehicle driving at the speed of 60km/h. $t_{HSTR}$ is calculated by the maximum HSR speed on each HSR line at each year. $T_{ij}$ is the fastest travel time, and the measurement of $T_{ijt}$ is in minutes.

Travel decay $\gamma$ represents resistance to a distance. We estimate $\gamma$ by using railway passenger flow data between prefectures, provided by Ministry of Land, Infrastructure, Transport, and Tourism (MLIT) of the Japanese government. This railway passenger data may be useful for solving a problem caused by no consideration for HSR passengers in the DBP estimation. There are two approaches to estimate $\gamma$: exponential decay function, and power decay function. Rosik et al. (2015) propose that the exponential function is effective in the international and national level, while the power function is appropriate for a short distance.

\begin{align*}
A: & \text{Estimated distance-decay} \\
\gamma \neq j & \quad OD_{ij} = \alpha \cdot \text{pop}_{i}^{\beta_i} \cdot \text{pop}_{j}^{\beta_j} \cdot e^{-\gamma T_{ijt}} \\
R^2 & = 0.689^* \\
\gamma & = 0.018816^*
\end{align*}

$\text{pop}_{i,j}$: population of prefecture $i,j$

Hereafter, * means statistically significance at the 95% level

\begin{align*}
B: & \text{Gini coefficient of variables} \\
\gamma \neq j & \quad OD_{ij} = \alpha \cdot \text{pop}_{i}^{\beta_i} \cdot \text{pop}_{j}^{\beta_j} \cdot e^{-\gamma T_{ijt}} \\
R^2 & = 0.689^* \\
\gamma & = 0.018816^*
\end{align*}

\begin{align*}
C: & \text{Box-plot of logarithm when } \gamma = 0.018816 \\
D: & \text{Box-plot of logarithm when } \gamma = 1
\end{align*}

Figure 6. Travel decay result and descriptive graphs

Yi and Kim (2018) estimate the decay parameter by using the population of origin and destination and origin-destination (OD) travels, based on the exponential form, as shown in Figure 6 (A). Although this study utilizes the DBP function, we employ the same function used by Yi and Kim (2018), for its simplicity in the estimation. Railway passenger flow data of MLIT do not classify trip purposes and only provide the sum of railway passengers of the conventional railway and HSR. This means that the OD data cannot sort the travel purpose of railway passengers. Considering this limitation, it may be general to assume that the number of railway passengers is affected by the number of population of origin and destination. Therefore, we utilize a function in Figure 6 (A), which is employed by Yi and Kim (2018), to estimate $\gamma$. Estimating travel decay $\gamma$ is based on 2014 the recent year of in this study since there is no OD data for the 1980s. Figure 6 (A) is easily estimated by log-transformation. The $\gamma$ value of $T_{ijt}$
of Figure 6 (A) is used for the travel decay in estimating the DBP. We also consider a general γ value 1 for the travel decay. Therefore, DBP takes two different γ values, 0.018816 and 1.

Figure 6 (B, C, and D) explains the summaries of data and DBP. First, Figure 6 (B) shows Gini coefficients of firms, workers, GDP, HSR travel time, and two DBPs having different travel decay γ. These variables may be unevenly distributed between prefectures since large cities occupy more capital and economic activities than small cities. The Gini coefficient can explain this inequality. Figure (B) suggests that DBP is unevenly distributed compared to other variables. Second, Figure 6 (C) and (D) compare a difference between HSR passing prefectures and non-passing prefectures. The standard deviation and the mean of DBP and GDP are higher in HSR passing prefectures than non-HSR passing prefectures. Tokyo, Osaka, and Kanagawa are identified as an outlier, but we include them in the analysis. These are the metropolitan areas, so it is unrealistic to exclude them in the analysis. From Figure 6, we can guess that there is a gap in DBP and GDP between prefectures having HSR station and prefectures having no HSR station.

4.3 Difference-In-Difference Design of DBP and GDP

As shown in Figure 4 (D), to clarify the impact of HSR, we utilize DID estimation. DID is widely employed in previous studies (Diao, 2018; Albalate et al., 2017; Sun and Mansury, 2016) to shed light on the difference between before and after policy. If a policy is applied to a target, the target is named as a treatment group and has a dummy value 1. DID classifies before-and after-effects based on the specific time when a policy is applied. Each HSR station was differently opened in each corridor and each station. Therefore, we utilize a multi-year dummy variable having dummy value 1 for prefectures served by HSR after the HSR service, and 0 for non-passing prefectures before HSR opening. Albalate et al. (2017) take the semi-log equational form in DID estimation to estimate semi-elasticities. This study takes the semi-log form as well. A hypothesis is that DBP and GDP are increased after HSR opening in prefectures having the HSR station.

\[
\ln \text{dependent} = \beta_0 + \beta_{\text{treat}} \text{treat}_i + \sum_{t=2}^{\gamma} \beta_{\text{year}} \text{year}_t + \beta_{\text{HSR}} \text{after}_it \ast \text{treat}_i\tag{17}
\]

In Equation (17), \text{treat}_i is the treatment dummy variable having value 1 or 0. \text{year}_t is the year-fixed effect, and \text{after}_it explains a dummy variable 1 for the prefecture after HSR opening in the prefecture. \text{after}_it \ast \text{treat}_i can show the impact of HSR after HSR opening in the HSR passing prefecture. Table 4 shows a result of the DID estimation. The result suggests that DBP of γ 0.018816 (γ=1) and GDP increase about 100.89% (169.31%) and 92.44% respectively after the HSR operation in prefectures having HSR station. This shows that prefectures served by HSR have experienced increasing DBP and GDP after HSR opening.

<table>
<thead>
<tr>
<th>γ of DBP</th>
<th>\ln dependent</th>
<th>\text{R}^2</th>
<th>\text{Constant}</th>
<th>\beta_{\text{HSR}}</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.018816</td>
<td>\ln DBP_{\text{city}}</td>
<td>0.3405*</td>
<td>23.78461*</td>
<td>1.00893*</td>
</tr>
<tr>
<td>1</td>
<td>\ln GDP_{it}</td>
<td>0.4066*</td>
<td>18.28602*</td>
<td>1.69314*</td>
</tr>
</tbody>
</table>

4.4 Analysis of DBP

The DID result shows that DBP and GDP are affected by HSR. However, it is still required to
verify the statistical significance of DBP and the impact of DBP on productivity. This study makes use of a production function using labor \((L_{it})\) and capital stock \((K_{it})\) based on panel data.

\[
\begin{align*}
GDP_{it} &= g(DBP_{ity})f(L_{it}, K_{it}) = DBP_{ity}^\beta L_{it}^\beta K_{it}^\beta \\
\ln GDP_{it} &= \beta_{DBP} \ln DBP_{ity} + \beta_L \ln L_{it} + \beta_K \ln K_{it} \\
\ln GDP_{it} &= \beta_{DBP} \ln DBP_{ity} + \beta_L L_{it} + \beta_K K_{it} \\
\end{align*}
\]

In Equation (18) ~ (19), \(DBP_{ity}\) is DBP of prefecture \(i\) at year \(t\), when DBP takes specific travel decay value \(\gamma\). For \(L_{it}\), it is general to employ the number of workers. However, DBP takes the number of workers as a variable, so employing the same data for \(L_{it}\) may result in serious multicollinearity between DBP and \(L_{it}\). Therefore, the working-age population from 15 to 65 years old is used for \(L_{it}\). Private capital stock and nominal GDP are employed for \(K_{it}\) and \(GDP_{it}\) respectively.

This study has the panel data structure of large target cases (46 prefectures) and small-time series (eight years), so we do not worry about the non-stationarity. We conduct the Hausman test, having a null hypothesis that the Random Effects Model (REM) is more appropriate than the Fixed Effects Model (FEM). The results of the Hausman test for two different DBPs are shown in Table 5. The result shows that FEM is more effective than REM in two DBPs having different travel decay. FEM can remove unobserved effects and time-invariant heterogeneity by covering the effects of parameters of interest within an individual over time between observations (Gelman and Hill, 2006; Halaby, 2004).

<table>
<thead>
<tr>
<th>(\gamma)</th>
<th>0.018816</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chisq.</td>
<td>97.989*</td>
<td>55.673*</td>
</tr>
<tr>
<td>df</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

There are three kinds of fixed effects: the individual-fixed, time-fixed, and individual-and time-fixed effects. Wetwitoo and Kato (2017) used all of the three fixed effects for estimating the impact of interregional transportations. Shen et al. (2015) and Demizu et al. (2017) utilized the individual fixed effects in order to control the unobserved characteristic in estimating HSR’s impact. We employ the individual-fixed, time-fixed, and individual-and time-fixed effects in the production function. Individual-fixed, time-fixed, and individual-and time-fixed consider the unobserved effects of the prefecture, year, and both prefecture and year respectively. Functions considering these fixed effects are expressed in Equation (20) ~ (22) respectively.

\[
\begin{align*}
\ln GDP_{it} &= \beta_{DBP} \ln DBP_{ity} + \beta_L L_{it} + \beta_K K_{it} + \delta_i + \theta_t + e_{it} \\
\ln GDP_{it} &= \beta_{DBP} \ln DBP_{ity} + \beta_L L_{it} + \beta_K K_{it} + \theta_t + e_{it} \\
\ln GDP_{it} &= \beta_{DBP} \ln DBP_{ity} + \beta_L L_{it} + \beta_K K_{it} + \delta_i + \theta_t + e_{it}
\end{align*}
\]

\(\delta_i, \theta_t,\) and \(e_{it}\) signify the prefecture-fixed variable, year-fixed variable, and error term respectively. Previous studies show that HSR’s impact is different by each industry, so this study estimates each \(DBP_{ity}\) of the primary industry, secondary industry, and tertiary industry. We also estimate the \(DBP_{ity}\) value of the entire industry, which is the sum of primary, secondary and tertiary industries. The primary industry consisting of agriculture, fishery, and forestry may have little business interaction by HSR, while the business interaction in secondary and tertiary industries may be maximized by HSR. Consequently, we acquire 24 FEM results composed of two different DBPs, four different industrial classifications, and three kinds of fixed effects.
A problem of the panel data analysis is heteroscedasticity in the error term. If there is heteroscedasticity in the model, it brings about small p-value of input variables even if heteroscedasticity does not affect coefficients of the variables. Therefore, even a variable, which is originally unrelated to a dependent variable, can be regarded as an important factor. We conduct the Breusch-Pagan test (Breusch and Pagan, 1979) to identify heteroscedasticity. The result of the Breusch-Pagan test suggests that there is heteroscedasticity in FEM. When heteroscedasticity is observed, robust covariance matrix estimation can solve the problem. This robust covariance matrix estimation can obtain unbiased standard errors. We follow the robust covariance matrix estimation proposed by Arellano (1987) to obtain an adjusted result.

4.5 Result

Table 6 shows the result of each model having a different fixed effect when DBP of each industry has a different travel decay. A positive coefficient of DBP indicates that the business interactive accessibility enhanced by HSR enhances productivity. There is a negative coefficient of labor input in some results. This may be attributed to the correlation between DBP and the labor input, even though we tried to avoid the risk.

First, in the individual-fixed effects models, 1% increases of DBP in the entire industry augment GDP by about 0.82% and 0.25% respectively, when \( \gamma \) of DBP is 0.018816 and 1 each. The secondary and tertiary industries increase GDP by about 0.34% and 0.45% respectively, when \( \gamma \) is 0.018816. When \( \gamma \) is one, 1% increases in the secondary industry and tertiary industry each enhance GDP by 0.23% and 0.13% each. However, the primary industry is inversely proportional to GDP.

Second, the coefficient direction of DBP in the time-fixed effects model is the same as the individual-fixed effects model. The primary industry is inversely proportional to GDP, while the entire, secondary, and tertiary industries enhance GDP. The time-fixed effects models have a higher within \( R^2 \) than the individual-fixed effects model in each industry.

Third, in the individual-and time-fixed effects model, DBP of the primary industry is statistically insignificant at the 90% level, when \( \gamma \) of DBP is 0.018816. When \( \gamma \) of DBP is 1, the coefficient of DBP is statistically significant only in the secondary industry at the 95% level. In the individual-and time-fixed effects model, the number of statistically significant coefficients of input variables is fewer than other fixed-effects models. The similar results are observed in Wetwittoo and Kato (2017), they suppose that the poor significance of input in the individual-time fixed effects is caused by a correlation of individual-fixed and time-fixed. In this study, we also suppose that there is a correlation between input variables.

To sum up the results of FEM, we can derive three major points. First, the DBP value of the primary industry is inversely proportional to productivity. This negative coefficient of the primary industry may come from the fact that the prefecture mainly consisting of the primary industry has low productivity. The business interaction of the primary industry is, in fact, less affected by HSR even in the real world. Second, the potentiality of the business interaction in the secondary industry generally increases productivity. Although previous studies mainly emphasize the impact of HSR on the service and tourism-related sectors, our result suggests that the business interaction of the secondary industry can spur economic growth as well. Examples of the business interaction of the secondary industry are mainly meetings, new contracts, and knowledge exchanges. These activities of the secondary industry have much larger productivity than individual tourism and service industries. Lastly, the tertiary industry also increases GDP in the individual-fixed and time-fixed effects models. The positive impact of HSR on industries belonging to the tertiary industry is already verified in the previous studies (Lin, 2017; Sun and Mansury, 2016).
Table 6. Results of fixed-effects model

<table>
<thead>
<tr>
<th>Model (γ=0.018816)</th>
<th>DBP of industry</th>
<th>Within $R^2$</th>
<th>Overall $R^2$</th>
<th>$DBP_{it}$</th>
<th>$L_{it}$</th>
<th>$K_{it}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-fixed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entire</td>
<td>0.92099*</td>
<td>0.99373*</td>
<td>0.81764*</td>
<td>-0.22987↓</td>
<td>0.63065*</td>
<td></td>
</tr>
<tr>
<td>Primary</td>
<td>0.9286*</td>
<td>0.99434*</td>
<td>-0.12306*</td>
<td>0.43474*</td>
<td>0.65334*</td>
<td></td>
</tr>
<tr>
<td>Secondary</td>
<td>0.935*</td>
<td>0.99485*</td>
<td>0.33788*</td>
<td>-0.01981</td>
<td>0.77022*</td>
<td></td>
</tr>
<tr>
<td>Tertiary</td>
<td>0.88053*</td>
<td>0.99053*</td>
<td>0.44595*</td>
<td>0.50566*</td>
<td>0.49227*</td>
<td></td>
</tr>
<tr>
<td>Time-fixed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entire</td>
<td>0.99315*</td>
<td>0.99368*</td>
<td>0.41182*</td>
<td>0.22583*</td>
<td>0.35763*</td>
<td></td>
</tr>
<tr>
<td>Primary</td>
<td>0.98665*</td>
<td>0.98767*</td>
<td>-0.03626*</td>
<td>0.53208*</td>
<td>0.55249*</td>
<td></td>
</tr>
<tr>
<td>Secondary</td>
<td>0.98895*</td>
<td>0.98979*</td>
<td>0.20277*</td>
<td>0.47204*</td>
<td>0.36866*</td>
<td></td>
</tr>
<tr>
<td>Tertiary</td>
<td>0.99166*</td>
<td>0.99229*</td>
<td>0.32601*</td>
<td>0.22568*</td>
<td>0.45905*</td>
<td></td>
</tr>
<tr>
<td>Individual-and Time-fixed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entire</td>
<td>0.26967*</td>
<td>0.9978*</td>
<td>0.49132*</td>
<td>-0.08008</td>
<td>0.14247↓</td>
<td></td>
</tr>
<tr>
<td>Primary</td>
<td>0.21138*</td>
<td>0.99762*</td>
<td>-0.01686</td>
<td>0.2865*</td>
<td>0.23118*</td>
<td></td>
</tr>
<tr>
<td>Secondary</td>
<td>0.2708*</td>
<td>0.9978*</td>
<td>0.23651*</td>
<td>0.19813*</td>
<td>0.12638↓</td>
<td></td>
</tr>
<tr>
<td>Tertiary</td>
<td>0.23285*</td>
<td>0.99769*</td>
<td>0.3202↓</td>
<td>-0.03601</td>
<td>0.18742*</td>
<td></td>
</tr>
<tr>
<td>Model (γ = 1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual-fixed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entire</td>
<td>0.89303*</td>
<td>0.99152*</td>
<td>0.24636*</td>
<td>0.63014*</td>
<td>0.55148*</td>
<td></td>
</tr>
<tr>
<td>Primary</td>
<td>0.92774*</td>
<td>0.99427*</td>
<td>-0.11874*</td>
<td>0.42761*</td>
<td>0.6869*</td>
<td></td>
</tr>
<tr>
<td>Secondary</td>
<td>0.92021*</td>
<td>0.99367*</td>
<td>0.22807*</td>
<td>0.33181*</td>
<td>0.6615*</td>
<td></td>
</tr>
<tr>
<td>Tertiary</td>
<td>0.87865*</td>
<td>0.99038*</td>
<td>0.12718*</td>
<td>0.84398*</td>
<td>0.54075*</td>
<td></td>
</tr>
<tr>
<td>Time-fixed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary</td>
<td>0.98659*</td>
<td>0.98761*</td>
<td>-0.03698*</td>
<td>0.52727*</td>
<td>0.56343*</td>
<td></td>
</tr>
<tr>
<td>Secondary</td>
<td>0.98793*</td>
<td>0.98885*</td>
<td>0.07098*</td>
<td>0.5276*</td>
<td>0.44221*</td>
<td></td>
</tr>
<tr>
<td>Tertiary</td>
<td>0.98997*</td>
<td>0.99074*</td>
<td>0.11823*</td>
<td>0.44755*</td>
<td>0.4437*</td>
<td></td>
</tr>
<tr>
<td>Individual-and Time-fixed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entire</td>
<td>0.21073*</td>
<td>0.99762*</td>
<td>0.03108*</td>
<td>0.27489*</td>
<td>0.20113*</td>
<td></td>
</tr>
<tr>
<td>Primary</td>
<td>0.21241*</td>
<td>0.99763*</td>
<td>-0.0158</td>
<td>0.27995*</td>
<td>0.23879*</td>
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</tr>
<tr>
<td>Secondary</td>
<td>0.22255*</td>
<td>0.99766*</td>
<td>0.05227*</td>
<td>0.29725*</td>
<td>0.17288*</td>
<td></td>
</tr>
<tr>
<td>Tertiary</td>
<td>0.20807*</td>
<td>0.99761*</td>
<td>0.01953</td>
<td>0.27017*</td>
<td>0.21125*</td>
<td></td>
</tr>
</tbody>
</table>

Note: * is statistically significant at the 95% level, and ↓ is statistically significant at the 90% level.

5. CONCLUSION

This study aims at estimating the impact of the business interactive accessibility by HSR on productivity. A hypothesize is that HSR enhances the business interactive accessibility, then the accessibility increased by HSR raises productivity. We develop new indices, DBD for the mesh level and DBP for the prefecture-level, which explain the business interactive accessibility by HSR with consideration for the socio-economic conditions. We estimate DBD and DBP, then evaluate the impact of DBP on productivity. First, DBD is mainly higher in meshes located in the major cities and close to the HSR station of the major cities. Second, the result of DID shows that GDP and DBP of prefectures with HSR increase after HSR opening. Lastly, the
production function suggests that the DBP values of the entire industry, secondary industry, and tertiary industry enhance GDP in the individual-fixed effects and time-fixed effects models.

We derive the two major points of this study. First, this study emphasizes the importance of the socio-economic condition in estimating the business interactive accessibility. The business scale and the distance between firms within a region should be considered in estimating the business interactive accessibility by HSR. The impact of HSR may be over-and under-estimated if there is no consideration for these socio-economic conditions. Considering that HSR has been rapidly developing in Asia countries, such as China, Korea, Taiwan, and even in Vietnam and India, the business interactive accessibility can be employed to evaluate the impact of HSR on the potential business interaction in these countries. For example, in China, there is the impact of HSR on the manufacturing sector, but no significant indirect impact of the manufacturing from HSR on productivity (Sun and Mansury, 2016). However, if employing the business interactive accessibility, the impact of the secondary industry from HSR may be re-evaluated. Second, not only the tertiary industry but also the secondary industry can be benefited from HSR. The positive impact of the tertiary industry or tourism from HSR is already proved in Japan (Sato and Yoshitomi, 2017) and China (Lin, 2017; Sun and Mansury, 2016). Our result further emphasizes that HSR enhancing the business interactive accessibility of the secondary industry can augment productivity in Japan.

This study has a few limitations. First, it is required to consider the business interaction between different industries. For example, the manufacturing sector can be benefited from the service-related sectors, and vice versa. Second, in the production function, the labor and capital stock have different units. The working-age population is a demographic factor in the personal level, whereas the capital stock is the monetary factor in the aggregated level. If keeping consistency between the inputs, for example, considering the average wage of the prefecture with the number of employees, the analysis of the future study will become more valid.

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