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**The influence of improved rail accessibility on land
prices: evidence from Japan**

MSc Thesis

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Abstract

The train era was thought to be well and truly over. Indeed, many long-haul travellers now prefer air travel to rail travel. But due to various present-day challenges, train transport could be a window of opportunity again. Besides, investments in infrastructure are seen as a perfect tool to improve the regional economy. After all, accessibility can be crucial for firms choosing a location as it increases both business and consumer market access, which could lead to higher sales volumes and thus generates returns to scale. These economies of scale are location-specific, which means they can be capitalised in land prices. Consistent with this theory, we find that a 1% decrease in bilateral travel times via rail transport is associated with a 0.06% increase in land prices.

Short preface

From talks with a real estate consultancy firm in Amsterdam, it became known to me that the effect of improved accessibility on cities real estate markets is still a rather open area of research. This while climate change and growing cities are more and more pushing governments to upgrade public transport networks. From this notion my desire to study how accessibility affects regional economies began. I discussed the subject with professor Hans Koster, one of my professors, who quickly helped me set up a model. I would like to thank him very much for his support and encouragement throughout this project.

Chapter 1: Introduction

Investing in infrastructure is thought to be one of the key instruments that governments can use to give cities and regions an economic boost. After all, accessibility can be crucial for firms choosing a location as it increases both business and consumer market access, which could lead to higher sales volumes and thus generates returns to scale.

Allocation of investments in infrastructure is not random; they are not evenly distributed across regions as every project has different expected benefits, planning concerns, budget constraints, and so on. Moreover, benefits differ between projects because they result in different reductions in transport costs, which affects wages, population, trade, and industry composition (Redding and Turner, 2015). However, infrastructure allocation is not purely an issue of optimisation; politicians have in addition to economic motives, also political ones. Through the use of a model analysing the determinants of this allocation, Castells and Solé-Ollé (2005) were able to conclude that economic determinants seem to explain most of the allocation, but electoral productivity certainly also has a significant impact. In other words, the voters that can be won with the investment also has a significant effect on the allocation of infrastructure. Furthermore, they conclude that the central government appears to be more sensitive to this electoral productivity than regional governments (Castells and Solé-Ollé, 2005). Finally, Knight (2002) provides statistically and economically significant evidence that federal grants crowd out state government spending in the USA. Thus, the way governments distribute their infrastructure budget is far from straightforward.

And this is not a new phenomenon. Geographer Gregory (1988) argued that the invention of the steam train was the first way for governments to impact the distribution of economic activity, because it was not until then that infrastructure had the potential to provide easy and cheap access to raw materials. Fragmented 'canal-based' economies with mainly internal transport via the rivers, canals and seas changed to interconnected economies in which raw materials from the inland could be traded more profitably (Gregory, 1988).

Rail transport could now once again be a window of opportunity for governments, who look for an effective way to enhance the economy and prevent their networks from clogging up. In addition, concerns about global warming, our impact on the environment and our dependence on fossil fuels are an increasingly discussed topic. Chester and Horvath (2012) suggest that high-speed trains (HST) can be a sustainable mobility option as they can meet the increasing transport demands while being fuel efficient and have relatively few emissions. Furthermore, studies show that at short haul distances, HST transport is highly competitive with air transport (Park and Ha, 2006; De Rus and Inglada, 1997). In South-Korea, Park and Ha (2006) found that the demand for aviation between two Korean cities decreased with 72% after the Korea Train Express began operations in 2004, while De Rus and Inglada (1997) estimated that the high-speed train project 'Madrid-Sevilla corridor' would almost halve the air transport between the two Spanish regions, while increasing the overall transport of people and goods.

The benefits of these HSR are location-specific, which means they are reflected in land prices (Debrezion et al., 2011; Redding and Turner, 2015; Cordera et al., 2019). This is however only the case if high-speed lines are fully developed and old enough to be capitalised in land prices, which is why we study the economic benefits of the HSR 'Shinkansen' (which means 'new trunk line') in Japan. It made Japan's rail infrastructure network relatively extensive, which has led to many variations in accessibility over time. To clarify, the Japanese Shinkansen has been in existence for 45 years, only 17 years after the second HSR, the TGV, opened in France (Givoni, 2006). Furthermore, the Shinkansen transports about 160 million passengers a year, of which more than 100 million use

the Shinkansen for business travel (Bernard et al., 2019). It is therefore very likely that it has had an effect on the allocation of business activity, and thus has been capitalised in land prices.

The huge costs involved in these projects make the quantification of the economic benefits associated with accessibility improvement very relevant to society. Thus, the main question of this study is ‘What is the influence of improved rail accessibility on land prices?’.

This question will be answered on the basis of the following sub-questions:

- How do land prices within Japan differ across regions?
- To what extent does improved accessibility affect land prices?
- Does the magnitude of this effect change over time?

Chapter 2: Literature study

The previous section introduced the subject and the society's interest in this study. This section will delve into the approaches used in existing literature to study the effects of infrastructure and gives some helpful regional context about infrastructure in Japan.

2.1 Identification of causal effects

The impact of infrastructure and investments in it has concerned researchers extensively. This field of research is highly relevant to society since it is understood that the distribution of economic activity over regions and cities depends crucially on the transportation of people and goods. However, while this field of research is so relevant to society, the first major insights came only a few decades ago. Krugman (1992) suggested with his Core-Periphery Model that transport costs can explain agglomeration and dispersion forces, leading to a specific distribution of economic activity between two regions. Of course, this is a very simplified version of reality, used to get a better understanding of how firms choose location.

In the real world, identifying the causal effect can be quite a challenge. First of all, the economic impulse to a treated region does not only consist of growth, but also allocation of economic activity from one region to another (Redding and Turner, 2015). An illustration of this phenomena can be found in the appendix (Figure 3). Moreover, the complexity of research arises from the fact that transport costs or accessibility are very broad concepts for which investigators use different indicators and proxies. Kalmanje and Kockelman (2004) state that average travel time reduction is a good measure to identify benefits resulting from policies and investments, and conclude that the benefits are also capitalised in house prices. Metz (2008) states that the benefits of investments in infrastructure are often not only found in average travel time reductions, but can also increase welfare through more economic participation opportunities because people can travel further in the same time. Niedzielski and Boschmann (2014) also find that average travel time is a good indicator of accessibility, but that increased average travel distance also certainly is a considerable part of the welfare benefits resulting from investments in infrastructure. Interestingly, for our study we have been able to analyse data on average bilateral travel times from Japan. Therefore, we have the opportunity to observe quite correctly the shortening of bilateral travel times through investments in infrastructure. More on how we analysed the data can be found in the method section.

Another problem faced in this field of research is that investments in infrastructure are not distributed randomly. Or to put it in economic terminology: there might be correlation between the allocation of an infrastructure project and unobserved local economic features, which creates endogeneity problems as treatment is non-random. For instance, it's highly plausible that benefits or market access can have an impact on the allocation of infrastructure investments and vice versa.

Another example which indicates endogeneity issues could be the fact that the amenities of a region can have an effect on both benefits and the infrastructure. Therefore, any proxy variable one would use for infrastructure is not predetermined.

Countering these endogeneity issues, Ahlfeldt et al. (2015) studied the effects of agglomeration and dispersion forces on the land prices in Berlin. He argued that the division and reunification of Berlin can be seen as an external shock that can be used to separate the agglomeration forces from heterogeneity in vocational fundamentals. His model describes that every worker that moves to the city maximises his or her utility. They choose a block that has the optimal amount of amenities, supply of floorspace, productivity and access to the transport network in comparison to their income. The paper concludes that returns to scale resulting from the city's population decay fast when travel times increase. Moreover, a part of the paper gave a microeconomic foundation for a gravity equation, which yields commuting probabilities between pairs of blocks (Ahlfeldt et al., 2015). These probability estimates are a good indicator for accessibility, as accessibility can be defined as the opportunity for a person or firm to participate in activity in a certain place (Jones, 1981).

A second study that is argued to have resolved endogeneity issues in this field of research is a paper by Donaldson (2015). He used records of economic activity in India collected by the British government throughout its colonial presence. He argued that since the network was built from a military perspective, the economic characteristics of Indian regions would not have affected the allocation of this network. Therefore, a new railway link between two districts can be seen as predetermined. It is an external shock that would lower their bilateral trade costs, allowing consumers to buy goods from the district where prices for a particular commodity are lowest, and producers can sell more of what they produce best. The price difference between the selling price and the selling price in the cheaper area is seen as the trade costs. Using empirical analysis he concluded that the railroads increased trading volumes, decreased the inter-regional price gap of different commodities and thus reduced trading costs. As an indicator of the benefits of this trade, the effect on the incomes of local farmers was used, which rose by 16% within the average region as a result of the new infrastructure (Donaldson, 2015).

Furthermore, land prices vary systematically with respect to some spatial features of the location of the land, one such feature being the accessibility of the location. Therefore, studies use land prices to measure market accessibility, as market accessibility is capitalised in these price levels of land (Srour et al., 2002; Osland and Thorsen, 2008; Ahlfeldt et al., 2015).

Improved accessibility is obviously not the only driver affecting land prices in Japan. Because predetermined natural features of a region can affect infrastructure as well as land prices, one usually wants to control for this in regression analyses. Okada (1994) states that because Japan has a limited area that is suitable for development, urban areas are clustered close to the coast and in the lower parts of the country. Therefore, we control over the distance from the coastline, the mean elevation of a municipality and the amount of developable land in the municipality. More on the natural characteristics and how it affected Japan's infrastructure network and urban sprawl in the next subsection.

2.2 Historical background and regional context

Japan has many physical and socioeconomic aspects that have affected the development of its infrastructure network. Okada (1994) describes that Japan has 120 million inhabitants divided over 377.000 square kilometres of land area. However, these inhabitants live very clustered in urban areas along the coast. This is where the relatively limited area that is suitable for development is located, as the inland areas are dominated by steep slopes and mountains. Due to urbanisation on the coast, much

of the freight transport has traditionally taken place by sea, which is why freight transport is still shipping orientated. This does not account for active passenger rail transportation, as the three largest metropolitan areas (respectively Tokyo, Osaka and Nagoya) are located on a linear line with each other along the coastal plain, which made them perfectly suitable for rail development (Okada, 1994; also check figure 4 in the appendix).

Today, Japan developed its Shinkansen line to a highly efficient and reliable transport network, which holds a considerable share of active passenger railway transportation for the past years (Demizu, 2017). For instance, the rail share of the modal split between Hachinohe and Tokyo increased by 15% after its Shinkansen connection was constructed (Demizu, 2017). Especially the high frequency, short station distance, good integration with other transport services and the high operating speeds make long-haul travelling with the Shinkansen line very attractive (Okada, 1994). The modal split is visualised with a graph, which can be found in the appendix (Figure 5), it shows that the Shinkansen is especially popular for long-distance journeys.

To get a handle on the effect of this mode of transportation on land prices and how it changes over time, this study investigates the effects of improved accessibility of rail transport on a regional level. Japan is divided into 47 prefectures, each prefecture is subsequently divided into numerous municipalities. The regional scale and location of these regions can be found in the appendix (Figure 6). They are relevant due to the importance of the relative position of regions in understanding the spatial organisation of economic activity.

Chapter 3: Method

First of all, a literature study has been conducted on approaches used in existing literature and to give some helpful regional context about infrastructure in Japan, which can be found in the previous section. The rest of this study has an empirical approach consisting of two parts, first the data was obtained and visualised, after which an economic analysis was applied to estimate a causal relationship.

3.1 Data

Professor Hans Koster provided a dataset which contained a diverse range of variables with various sources. First of all, this included data on population and employment at municipality level from 1957 to 2014. Moreover, information about each municipality's location was provided by the *National Land Numerical Information of the Ministry of Land, Infrastructure, Transport and Tourism*. Since some boundaries of these municipalities changed in the time span of the data and this could cause a potential bias, the provided data has consistent geographical units based on the definition and boundaries of municipalities in 2015. Data on total employment for each municipality was obtained from the *Establishment Census* for 1957, 1972, 1978, 1981, 1986 and 1991, the *Establishment and Enterprise Census* for 1996, 2001 and 2006 and the *Economic Census for Business Frame* for 2009 and 2014. Moreover, the data contains data on the population of each municipality from the *Census of Population* for 1955, 1960, 1965, 1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, 2008 and 2013. The population data was matched to the employment data to the closest years for which we observed employment. Data on the expressway network and railway network come from the *National Land Numerical Information*. Therefore, the dataset contains whether and since when a municipality was connected to the Shinkansen network and what the distance to the nearest station was for each municipality. After this, the *JTB Timetable* and the *JR Timetable (Kotsu Shinbunsha)* have been consulted to provide information about average train speed. This together with information on the

road network from the *National Land Numerical Information* and *Road Traffic Census* provided the dataset with information on the bilateral travel time via rail and road networks. Furthermore, data from municipalities outside Hokkaido, Honshu, Shikoku and Kyushus were dropped as these municipalities are located on islands that do not have a relative position within the infrastructure network. Therefore, the dataset has a sample of 1658 municipalities, of which three municipalities are missing data about employment in 2014. All variables include both a time component and a spatial component, on prefecture and municipality level and structured as panel data.

Lastly, we reported descriptive statistics of all used variables (table 4), and visualised the spatial distribution of land prices on a map (Figure 1).

3.2 Econometric analysis

The baseline specifications of this study focussed on finding the right scope of control variables and location fixed effects. Further specifications have been set up to examine possible interaction. The specifications hereafter will examine if the results are robust. Some simple taxonomy is essential to support each of these specifications. Firstly, t indexes time periods, while i indexes municipalities. $landprice_{it}$ denotes the dependent variable land prices, whilst $ttrw_{it}$ denotes the bilateral travel time by rail and $ttrd_{it}$ denotes the bilateral travel time by road. Furthermore, X_{it} denotes a vector of time- and location-specific control variables. Lastly, δ_i indicates location-specific time-invariant unobservables, θ_t indicates a common time effect for all municipalities, and ε_{it} denotes the time-varying location-specific residual.

Thus, regression (i) denotes the ‘base’ regression. One might argue that the natural advantages of a region can affect the allocation of infrastructure as well as land prices. Therefore, regression (ii) adds control variables concerning natural advantages. One could also claim that unobserved location factors cause endogeneity issues, as productivity or amenities affect the allocation of infrastructure as well as land prices (Redding and Turner, 2015). Therefore, regression (iii) estimates the effect when controlling for location-specific unobservables at the prefecture level. Finally, regression (iv) estimates the effects of travel time on the dependent variable while controlling for both observed natural advantages and unobserved location factors. Note that all regressions control for a common time effect for all municipalities, to control for factors changing each year that are common to all municipalities for a given year. For that matter, recall that standard fixed effects modules might not be able to absorb multiple fixed effects. Therefore, the Stata module 'REGHDFE' was used to perform linear or instrumental-variable regressions while absorbing multiple fixed effects (Correia, 2019). Moreover, it was also checked whether long difference fixed effects estimated approximately the same effect. Regression (iv) is our preferred regression as the model is formulated as the intracity regression in the previously mentioned paper by Redding and Turner (2015). Every robustness check will begin with this preferred regression.

- (i) $\log landprice_{it} = \beta_0 + \log \beta_1 ttrw_{it} + \log \beta_2 ttrd_{it} + \theta_t + \varepsilon_{it}$
- (ii) $\log landprice_{it} = \beta_0 + \log \beta_1 ttrw_{it} + \log \beta_2 ttrd_{it} + \beta_3 X_{it} + \theta_t + \varepsilon_{it}$
- (iii) $\log landprice_{it} = \beta_0 + \log \beta_1 ttrw_{it} + \log \beta_2 ttrd_{it} + \theta_t + \delta_i + \varepsilon_{it}$
- (iv) $\log landprice_{it} = \beta_0 + \log \beta_1 ttrw_{it} + \log \beta_2 ttrd_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$

One could state that the magnitude of the effects of improved rail accessibility on land prices changes over time. An argument could be that the expansion and improvement of its HSL could increase the importance of rail accessibility and thus increase the capitalisation effect. Therefore, we conducted a regression controlling for interaction terms for travel time via railway and road interacting with a time variable. Furthermore, we clustered the residuals at municipality level as non-independence between

time periods within each unit (autocorrelation in residuals) seems plausible. Lastly, I checked if we find similar results if we only analyse data from a consecutive subset of the years in the dataset. The specifications are therefore as follows.

- (i) $\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$
- (ii) $\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3(\log \text{ttrw}_{it} * \text{year}) + \beta_4(\log \text{ttrd}_{it} * \text{year}) + \theta_t + \delta_i + \beta_5 X_{it} + \varepsilon_{it}$

Furthermore, one could argue that previous specifications have endogeneity issues, as unobserved location specifics can have an influence on the allocation of infrastructure and land prices. Therefore, we checked if the model estimates the same causal effect when we focus on six different sub-regions. It would be for instance more plausible that the effect of unobserved location specifics on the allocation of infrastructure would be the same in regions within 25 kilometres of the coastline, as these are historically more urbanised and developed (Okada, 1994). The opposite might be the case for inland regions that are located 25 kilometres or more from Japan's coastline (Okada, 1994). Moreover, one could argue that municipalities located at the same distance from the network are more comparable, as unobserved location specifics might affect all regions within the subset the same. Ghani and Goswami (2016) proposed including regions that are connected and thus are a node region. From there, we build up to subsets of less than 10 kilometres from the network, less than 25 kilometres from the network and less than 50 kilometres from the network.

(full dataset)	$\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$
(regions within 25 km of coastline)	$\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$
(inland regions)	$\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$
(connected/ node)	$\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$
(<10 km from Shinkansen station)	$\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$
(<25 km from Shinkansen station)	$\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$
(<50 km from Shinkansen station)	$\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$

It could be argued that previous ordinary least squares (OLS) regressions comparing treated and untreated municipalities are still unlikely to estimate the causal effect of transport improvement without bias, because the selection of municipalities in the treatment group is not random. In other words, unobserved location specifics still can cause a bias in estimating the effect of infrastructure as unobserved location specifics still have an effect on both infrastructure and land prices. Redding and Turner (2015) considered three different approaches that can mitigate endogeneity concerns: apply an inconsequential unit approach, use planned route instrumental variables and use historical route instrumental variables. The latter can be used for our analysis, as we have data on bilateral travel times in 1872 via train and road. In regression (ii) we consider only the train infrastructure variable as endogenous with bilateral travel times in 1872 as instruments, in regression (iii) we consider both rail and road infrastructure as endogenous with bilateral travel times in 1872 via train and road as instruments. The instruments used are proven to be relevant as they can explain a considerable part of the variance of the endogenous variables. Thereby, one could argue that it satisfies the exclusion restriction as it is a reasonable assumption that the bilateral travel time of 1872 can only be correlated with land prices through its effect on current bilateral travel times. Yet, unfortunately, this can only be argued, but not proved.

- (i) $\log \text{landprice}_{it} = \beta_0 + \log \beta_1 \text{ttrw}_{it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$
- (ii) $\log \text{landprice}_{it} = \beta_0 + \log \beta_1 Z_{1it} + \log \beta_2 \text{ttrd}_{it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$
- (iii) $\log \text{landprice}_{it} = \beta_0 + \log \beta_1 Z_{1it} + \log \beta_2 Z_{2it} + \beta_3 X_{it} + \theta_t + \delta_i + \varepsilon_{it}$

Chapter 4: Research findings and analysis

This section presents and discusses the results obtained by following the methodology outlined in the previous chapter. As previously argued, land prices are the result of various location-specific factors, including the location specific market access. That this correlation indeed does exist seemed apparent when we have a look at the map below (Figure 1), where the spatial distribution of land prices was visualised on a map. The three big three metropolitan regions are directly notable by their outstanding land prices. To identify a causal relationship, however, one must look deeper into the data. The descriptive statistics of the data used are reported in the Appendix (Table 4).

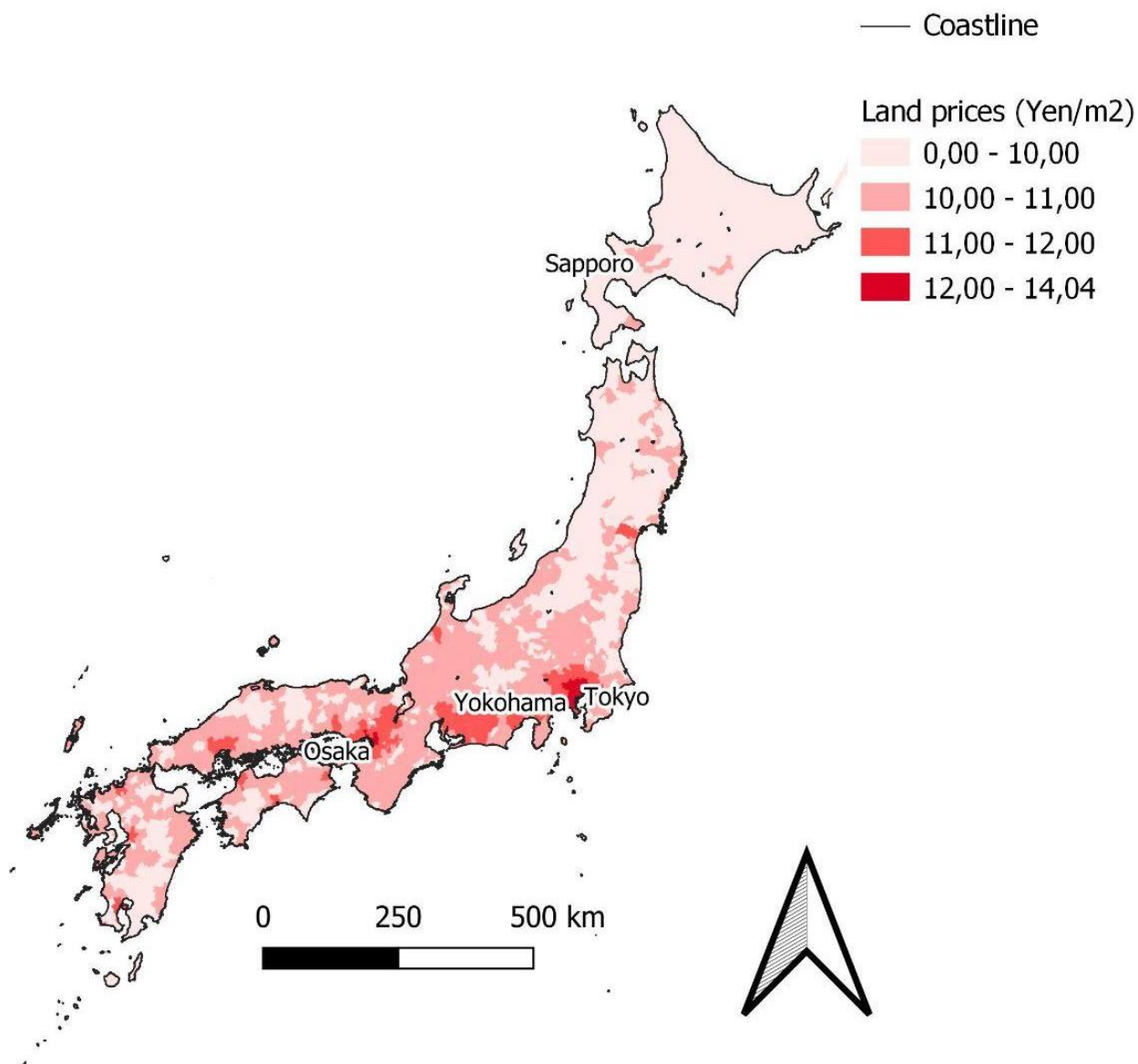


Figure 1. Spatial heterogeneity of land prices

4.1 Fixed effects estimation

We begin the analysis with fixed effects estimations, which are our baseline specifications and are reported in table 1. First of all, specification (i) is the most simplistic and thus somewhat naive specification where we only control for time fixed effects. As one might expect, the coefficients indicate that a reduction of bilateral travel times result in higher land values. Thus, the coefficient

indicates capitalisation; a 1% decrease in bilateral travel times via rail transport is associated with a 0.07% increase in land values and a 1% decrease in bilateral travel times via the road network is associated with a 0.05% increase in land values, both being statistically significant. Specification (ii) shows that when we include covariates that control for observed natural advantages, that is, for every municipality the distance to the coastline, mean elevation and amount of developable land leads to very similar coefficients. Furthermore, we have a model (iii) where we control for unobserved prefecture fixed effects as we assume that something within the region may bias the outcome variables. Interestingly, the coefficients of the infrastructure variables seem consistent which implies that while the unobserved characteristics of the prefectures explain a considerable extra part of the variance of Japan's land values, the magnitude of the effect is consistent. Finally, the preferred specification (iv) includes both observed natural advantages and unobserved prefecture fixed effects. They estimate that a 1% decrease in bilateral travel times via rail transport is associated with a 0.06% increase in land values and a 1% decrease in bilateral travel times via the road network is associated with a 0.07% increase in land values. Moreover, long difference fixed effects estimates showed similar results, respectively 0.06 and 0.08%.

Table 1. Baseline specifications (dependent variable: the log of land value)

	(i) loglandvalue	(ii) loglandvalue	(iii) loglandvalue	(iv) loglandvalue
Bilateral travel time via rail	-0.0661*** (-27.08)	-0.0390*** (-15.31)	-0.0662*** (-16.33)	-0.0584*** (-13.90)
Bilateral travel time via road	-0.0457*** (-16.39)	-0.0827*** (-27.98)	-0.0549*** (-11.00)	-0.0727*** (-14.52)
Distance to coastline		-0.000650*** (-25.08)		-0.000390*** (-12.22)
Mean elevation		-0.0000283*** (-14.66)		-0.0000302*** (-12.78)
Developable land		0.0000124*** (4.96)		0.0000421*** (16.88)
Year fixed effects	Yes	Yes	Yes	Yes
Prefecture fixed effects	No	No	Yes	Yes
<i>N</i>	13264	13264	13264	13264
<i>R</i> ²	0.505	0.546	0.711	0.724

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Interaction

Table 2 provides some evidence of the presence of interaction; specification (ii) implies that the influence of improved rail accessibility on land prices increases over time. This is in line with Demizu et al. (2017), as they argue that the Shinkansen is becoming increasingly important. Our results imply that the overall estimated effect of 1% of bilateral travel time reduction is now 0.02% plus the interaction effect, which is estimated to be -0.00202 multiplied by a specific year minus the starting year of the data (i.e. 1957 is year 0). To make this little easier to follow, the interaction effect is

visualised in Figure 2. Moreover, when only analysing the interaction from different consecutive subset of years we find similar results. Furthermore, it is interesting to note that while the capitalisation of bilateral travel time reduction via rail seems to increase, the capitalisation of bilateral travel time reduction via the road network seems to decrease. However, the cause of this is beyond the scope of this research.

Table 2. Interaction effects (dependent variable: the log of land value)

	(i) loglandvalue	(ii) loglandvalue
Bilateral travel time via rail	-0.0584*** (-13.90)	0.0234* (2.57)
Bilateral travel time via road	-0.0727*** (-14.52)	-0.154*** (-14.92)
Int: Bilateral travel time via rail #Year		-0.00202*** (-14.01)
Int: Bilateral travel time via road #Year		0.00198*** (11.84)
Topographical control variables	Yes	Yes
Year fixed effects	Yes	Yes
Prefecture fixed effects	Yes	Yes
<i>N</i>	13264	13264
<i>R</i> ²	0.724	0.727

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

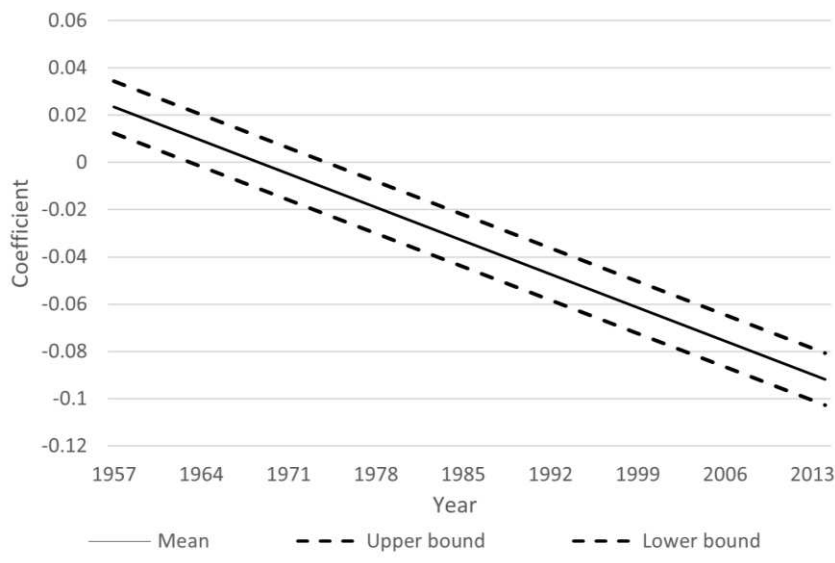


Figure 2. Interaction estimates show that capitalisation of bilateral travel time reduction by rail increases

4.3 Robustness

Table 3 provides evidence that the same causal effect can be found when we focus on six different sub-regions. However, the magnitude of the causal effect seems to vary somewhat between the different sub-regions. Regressions (ii) and (iii) show that the capitalisation of bilateral travel time reduction is greater and more significant in coastal regions than in inland regions. In coastal municipalities, a 1% decrease in bilateral travel times for both networks would correspond to a 0.08% increase in land value, while for inland regions via rail transport and road transport these are 0.02 and 0.04% respectively. This could be due to low demand levels and therefore low profitability associated with investments in infrastructure in Japan's inland regions, which was also concluded in the paper studying the effects of infrastructure in remote regions in Spain by González-González and Nogués (2019). Specifications (iv) and (v) regarding the regressions only including the municipalities that have a station or have one in close proximity have estimated a relatively small effect with relatively low significance. This could be due to the concept that a connection to a new infrastructure network is very dependent on the size of local markets as stated by Koster et al. (2021). This paper concluded that getting a connection to the Shinkansen line is not always advantageous for intermediate and remote regions as a connection can in fact make companies leave because of increasing competition (Koster et al., 2021). Sub-region regressions (vi) and (vii) show that for municipalities located further from a Shinkansen station, a 1% decrease in bilateral travel times via rail transport is associated with a 0.03 - 0.05% increase in land values and a 1% decrease in bilateral travel times via the road network is associated with a 0.08% increase in land values, which are somewhat consistent with our preferred specification.

Table 3. Robustness check: Comparable sub-regions (dependent variable: the log of land value)

	(i) (full dataset)	(ii) (coastal <25km of coastline)	(iii) (inland >25km of coastline)	(iv) (connected / node)	(v) (<10km from shinkansen station)	(vi) (<25km from shinkansen station)	(vii) (<50km from shinkansen station)
	loglandvalue	loglandvalue	loglandvalue	loglandvalue	loglandvalue	loglandvalue	loglandvalue
Bilateral travel time via rail	-0.0584*** (-13.90)	-0.0841*** (-17.59)	-0.0182** (-2.96)	-0.0577* (-2.39)	-0.0171 (-1.86)	-0.0330*** (-4.77)	-0.0537*** (-8.94)
Bilateral travel time via road	-0.0727*** (-14.52)	-0.0816*** (-14.45)	0.0426*** (-4.58)	-0.0890** (-2.92)	-0.0450** (-2.61)	-0.0845*** (-7.80)	-0.0810*** (-9.90)
Topograph ical control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	13264	8352	4912	558	1512	5512	8656
<i>R</i> ²	0.724	0.766	0.675	0.857	0.837	0.768	0.733

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the previous sections, I described that one could still question previous estimates due to endogeneity problems. We therefore further investigate the effects of bilateral travel time reduction on land prices by using a historical route instrumental variables approach suggested by Redding and Turner (2015). Specification (ii) regards only bilateral travel time by rail as endogenous and is instrumented by the bilateral travel time by rail in 1872. Specification (iii) uses the same approach but regards both bilateral travel time by rail and road as endogenous and instruments both through bilateral travel times by rail and road in 1872. Fortunately, the results show that our estimates are quite robust compared to our preferred specification (i); the coefficient indicates that a 1% decrease in bilateral travel times via rail transport is associated with a 0.05% increase in land prices and suggests that our preferred specification only overestimates the effect by more or less 0.005%. Note that the instruments used are proven to be relevant as they can explain a considerable part of the variance of the endogenous variables.

Table 4. Robustness check: IV (2SLS) (dependent variable: the log of land value)

	(i) OLS	(ii) 2SLS	(iii) 2SLS
Bilateral travel time via rail	-0.0584*** (-13.90)	-0.0490*** (-14.20)	-0.0537*** (-15.57)
Bilateral travel time via road	-0.0727*** (-14.52)	-0.0804*** (-16.59)	-0.0691*** (-14.04)
Topographical control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Prefecture fixed effects	Yes	Yes	Yes
<i>N</i>	13264	13264	13264

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 5: Conclusion

Investments in infrastructure are generally seen as a perfect tool to improve the regional economy. After all, accessibility can be crucial for firms choosing a location as it increases both business and consumer market access, which could lead to higher sales volumes and thus generates returns to scale. However, these infrastructure projects are often immensely expensive. Therefore, this study makes an effort to quantify the effect of accessibility on land prices. Interestingly, for our study we have been able to analyse panel data on average bilateral travel times from Japan. This allowed us to apply intracity regressions as described by Redding and Turner (2015). Consistent with the general belief that location-specific accessibility is capitalised in land prices, we found that a 1% decrease in bilateral travel times via rail transport is associated with a 0.06% increase in land prices. Moreover, we found evidence that the capitalisation of the effects of Japanese railway and HSR increases over time and thus becomes more important, which is in line with the paper of Demizu et al. (2017). In conclusion, we argue that investing in infrastructure is still a useful instrument that governments can use to allocate and stimulate economic activity.

We already briefly mentioned that trains can potentially help in tackling environmental problems. Future studies therefore may also cover the effects of accessibility improvement on the modal split. Moreover, it is interesting whether this effect can also be found outside Japan, since many other countries have a much less efficient train network. Finally, if sufficient data would become available, future studies could investigate whether the effects of accessibility on land prices differ per land-use purpose.

Literature

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., & Wolf, N. (2015). The economics of density: Evidence from the Berlin Wall. *Econometrica*, 83(6), 2127-2189.

Bernard, A. B., Moxnes, A., & Saito, Y. U. (2019). Production networks, geography, and firm performance. *Journal of Political Economy*, 127(2), 639-688.

Castells, A., & Solé-Ollé, A. (2005). The regional allocation of infrastructure investment: The role of equity, efficiency and political factors. *European Economic Review*, 49(5), 1165-1205.

Chester, M., & Horvath, A. (2012). High-speed rail with emerging automobiles and aircraft can reduce environmental impacts in California's future. *Environmental research letters*, 7(3), 034012.

Correia, S. (2019). REGHDFE: Stata module to perform linear or instrumental-variable regression absorbing any number of high-dimensional fixed effects.

- De Rus, G., & Inglada, V. (1997). Cost-benefit analysis of the high-speed train in Spain. *The annals of regional science*, 31(2), 175-188.
- Donaldson, D. (2015). Railroads of the Raj: Estimating the impact of transportation infrastructure. *American Economic Review*, 108(4-5), 899-934.
- Demizu, F., Li, Y. T., Schmöcker, J. D., Nakamura, T., & Uno, N. (2017). Long-term impact of the Shinkansen on rail and air demand: analysis with data from Northeast Japan. *Transportation Planning and Technology*, 40(7), 741-756.
- Ghani, E., Goswami, A. G., & Kerr, W. R. (2016). Highway to success: The impact of the Golden Quadrilateral project for the location and performance of Indian manufacturing. *The Economic Journal*, 126(591), 317-357.
- González-González, E., & Nogués, S. (2019). Long-term differential effects of transport infrastructure investment in rural areas. *Transportation research part A: policy and practice*, 125, 234-247.
- Gregory, D. (1988). The production of regions in England's industrial revolution. *Journal of historical geography*, 14(1), 50-58.
- Givoni, M. (2006). Development and impact of the modern high-speed train: A review. *Transport reviews*, 26(5), 593-611.
- Jones, S. R. (1981). Accessibility measures: a literature review. Publication of: Transport and Road Research Laboratory, (TRRL LR 967 Monograph).
- Knight, B. (2002). Endogenous federal grants and crowd-out of state government spending: Theory and evidence from the federal highway aid program. *American Economic Review*, 92(1), 71-92.
- Koster, H., Tabuchi, T., & Thisse, J. F. (2021). To be connected or not to be connected? The role of long-haul economies.
- Krugman, P. (1992). *Geography and trade*. MIT press.
- Metz, D. (2008). The myth of travel time saving. *Transport reviews*, 28(3), 321-336.
- Okada, H. (1994). Features and economic and social effects of the Shinkansen. *Japan Railway and Transport Review*, 3, 9-16.
- Osland, L., & Thorsen, I. (2008). Effects on housing prices of urban attraction and labor-market accessibility. *Environment and Planning A*, 40(10), 2490-2509.
- Park, Y., & Ha, H. K. (2006). Analysis of the impact of high-speed railroad service on air transport demand. *Transportation Research Part E: Logistics and Transportation Review*, 42(2), 95-104.
- Redding, S. J., & Turner, M. A. (2015). Transportation costs and the spatial organization of economic activity. *Handbook of regional and urban economics*, 5, 1339-1398.

Saizen, I., Mizuno, K., & Kobayashi, S. (2006). Effects of land-use master plans in the metropolitan fringe of Japan. *Landscape and Urban Planning*, 78(4), 411-421.

Srour, I. M., Kockelman, K. M., & Dunn, T. P. (2002). Accessibility indices: Connection to residential land prices and location choices. *Transportation Research Record*, 1805(1), 25-34.

Appendix

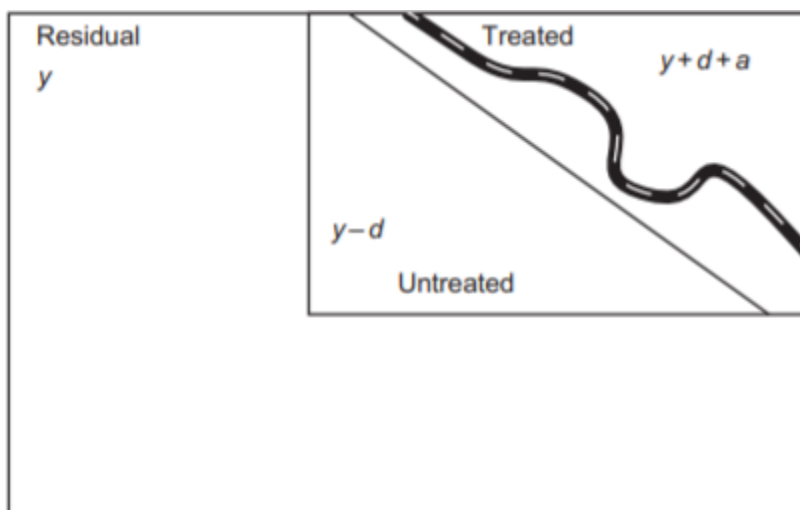


Figure 3. Sketch that illustrates that an economic impulse in the treated region consists of both growth and allocation. Note: y denotes the original economic activity in a region, d denotes the allocation of economic activity and a denotes new economic activity. Reprinted from Redding, S. J., &

Turner, M. A. (2015). Transportation costs and the spatial organization of economic activity. *Handbook of regional and urban economics*, 5, 1339-1398.

Shinkansen Lines (Current as of March 2016)



Figure 4. Shinkansen lines connecting mostly coastal cities, including planned extensions. Reprinted from nippon.com. (2016, March 1). Shinkansen Route Map. Retrieved April 26, 2022, from <https://www.nippon.com/en/features/h00077/>

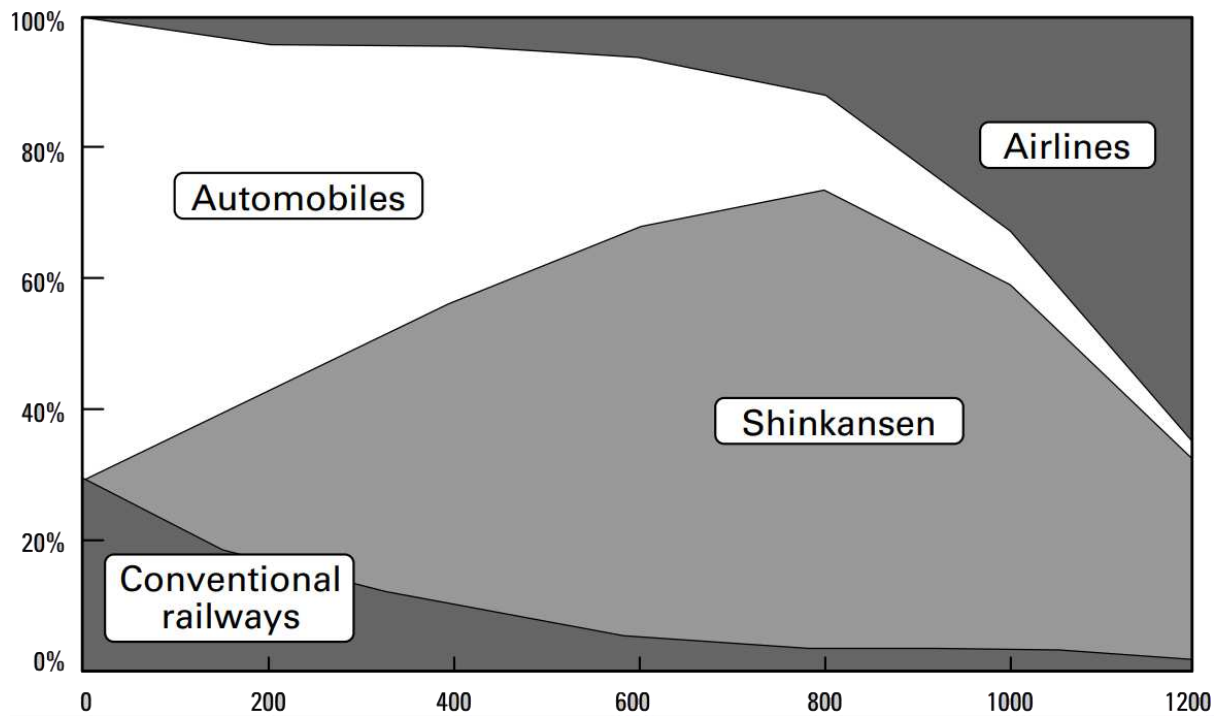


Figure 5. Modal split compared to distance of trip. Reprinted from Okada, H. (1994). Features and economic and social effects of the Shinkansen. *Japan Railway and Transport Review*, 3, 9-16.



Figure 6. The 47 prefectures of Japan with coloured regions. Reprinted from wikipedia.org. (2022, May 5). Prefectures of Japan with coloured regions. Retrieved May 11, 2022, from wikipedia.org/wiki/Prefectures_of_Japan

Table 4. Descriptive statistics

<i>Variable</i>	<i>Unit</i>	<i>Obs</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>Min</i>	<i>Max</i>
<i>Municipality</i>	<i>identifier</i>	<i>18,734</i>	<i>20698.94</i>	<i>14331.54</i>	<i>1100</i>	<i>90047</i>
<i>Prefecture</i>	<i>identifier</i>	<i>18,286</i>	<i>20.09308</i>	<i>14.15801</i>	<i>1</i>	<i>90</i>
<i>Land prices</i>	<i>yen per m²</i>	<i>13,480</i>	<i>10.6392</i>	<i>.8495075</i>	<i>7.9275</i>	<i>15.14149</i>
<i>Year</i>	<i>year</i>	<i>18,678</i>	<i>1990.091</i>	<i>16.52841</i>	<i>1957</i>	<i>2014</i>
<i>Bilateral travel time by train</i>	<i>minutes</i>	<i>18,678</i>	<i>641.7021</i>	<i>468.6621</i>	<i>209.7487</i>	<i>7168.469</i>
<i>Bilateral travel time by train in 1872</i>	<i>minutes</i>	<i>18,238</i>	<i>672.4136</i>	<i>485.8904</i>	<i>246.3111</i>	<i>7517.304</i>
<i>Bilateral travel time by road</i>	<i>minutes</i>	<i>18,678</i>	<i>875.6658</i>	<i>525.09</i>	<i>348.6505</i>	<i>3540.669</i>
<i>Bilateral travel time by road in 1872</i>	<i>minutes</i>	<i>18,238</i>	<i>908.116</i>	<i>541.0104</i>	<i>373.2372</i>	<i>3720.913</i>

<i>Distance to coastline</i>	<i>km</i>	<i>18,286</i>	<i>22.42619</i>	<i>18.49892</i>	<i>.0182651</i>	<i>85.44548</i>
<i>Mean elevation</i>	<i>m</i>	<i>18,286</i>	<i>284.8815</i>	<i>259.2683</i>	<i>0</i>	<i>1138.642</i>
<i>Developable land</i>	<i>km²</i>	<i>18,286</i>	<i>174.716</i>	<i>197.6528</i>	<i>0</i>	<i>1324.643</i>
<i>Presence of Shinkansen station</i>	<i>Dummy (0=no, 1=yes)</i>	<i>18,734</i>	<i>.0327213</i>	<i>.1779108</i>	<i>0</i>	<i>1</i>
<i>Distance to Shinkansen station</i>	<i>km</i>	<i>18,286</i>	<i>65.57427</i>	<i>94.48548</i>	<i>.3839913</i>	<i>508.8829</i>