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An empirical model of land use and railway co-development in Sydney

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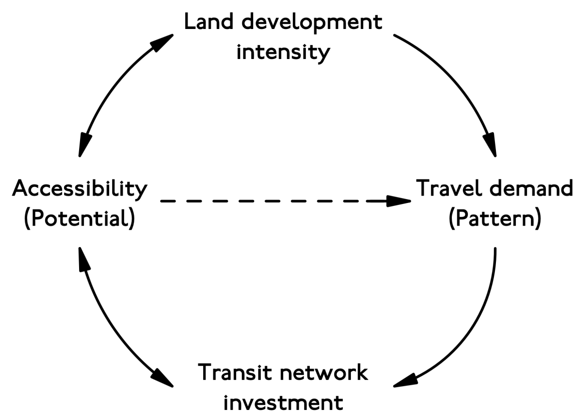
1. Introduction

Land use and transport have a long and complex history of mutual influence. The invention of steam engine locomotives led to the opening of the first railway in 1825 (Vuchic, 2005). After the onset of the Industrial Era, due to the location of job opportunities like factories in urban areas, rural populations began to migrate to cities, causing large scale urbanization and urban expansion (Lierop et al., 2017). As walking distances increased, new modes of transport were deployed to move the labor force across growing urban areas.

The transit systems enable mass movement, and as such, they enable higher densities for certain activities in some places. By increasing the ability of firms (and jobs) to cluster in the urban core, transport networks are simultaneously creating a push factor decreasing housing densities in those places by making housing in the core more expensive and a pull factor giving housing outside the core greater accessibility. Transport-land use interaction is theorized to be a joint development process of infrastructure and land development location as a positive feedback cycle: transport infrastructure produces accessibility that induces land development which induces transport demand and increases accessibility increasing the production of transport networks (i.e. inducing supply) and further intensifying land development (D. Levinson, 2007; D. Levinson and Xie, 2011; King, 2011; D. M. Levinson, 1998; Anderson, D. Levinson, and Parthasarathi, 2013; Kasraian, Maat, and Wee, 2016).

In most analyses, the relationship between infrastructure and travel demand has been considered as a one-way process with infrastructure network (supply) as the explanatory variable and traffic (demand) as the dependent variable (D. Levinson, 2007). While these studies provide some understanding of the characteristics of transit networks, there is a lack of knowledge on how transit networks and land use evolve into their current unique state, form, and structure patterns as they are born, grow, mature, and decline over time. It is widely believed that high population density is an important factor in the success of transit systems (density represents potential ridership, high ridership allows higher frequency of service lowering wait times, and density allows tighter spacing between services, thus reducing the time to access the transit service, both reinforcing demand in what is referred to as the Mohring effect (Mohring, 1972; Bar-Yosef, Martens, and Benenson, 2013)). However, just because transport depends on high population density for success does not necessarily mean that either high density areas generate public transport investment or transit creates high-density areas around stations (D. Levinson, 2007). Although a variety of actors are involved in developing an urban transit networks that pursue their interest (Cats, 2017), there is a research gap to understand the co-evolution of land use and large-scale transit systems.

Figure 1: Land use and transit network interaction



This paper aims to investigate the theory of interaction between land use and rail network (Badoe and Miller, 2000; Wegener, 2021) and disentangle the questions of induced development and induced supply. It examines whether the growth of a suburb encourages the construction of a new rail stop, or whether the rail system acts as a centralized (or decentralized) influence in determining population density. We investigate the direct and indirect links between land development and transit investments using the concept of accessibility. We develop an empirical model to capture the Greater Sydney area's historical evolution of land use and rail networks.

2. Theory and hypothesis

We test whether the interaction between land use and transport network is a positive feedback loop: improvements on one side lead to more on the other side, though with different speeds and time lags. This interaction has been conceived as a complex system with many components which is well discussed in the literature (Wegener, 2021). However, this study posits that the interaction between land development and transport investment can be conceived as a simplified feedback loop through the concept of accessibility as a potential force that dictates travel behaviors. To investigate the causal relationship between land use and transit development, accessibility can be used as a medium to justify the spatio-temporal co-development process in an urban environment. Throughout this article, the term 'land use' refers to population density.

The co-development or co-deployment theory being tested in this study is whether land use development leads to the future development of transit networks or in converse, the expansion of the transit network drives land use. When and how much the development of one leads to more development of the other is still a question. This has been brought to light in the literature. In the core of London, existing development lead to the improvement of railway system which in turn enhance the commercial development which leads to more rail investment. However, in the periphery of London, the transit network increase the population density which attracts more investments on the network and essentially leads to more land development (D. Levinson, 2007).

Other cases are also possible. One expects that rail promotes suburbanization, shifting the population from the Sydney CBD to the periphery where land is significantly less expensive than the CBD, since the value of land in the Sydney CBD appreciated for commercial activities benefiting from agglomeration economies, while decreasing for residential activities as the periphery supplies more

land for development within an accessibility travel time threshold. This will drop the residential density significantly for the Sydney CBD while increasing it in the periphery.
In this study, we model the co-development of land use and transit networks with two different approaches. We describe a direct relationship between land use and transit elements in the first approach, in which both are the main driving forces of each other. The second approach tests an indirect interaction where both transit and land use create potential forces to attract each other in a positive cycle. We consider this possibility as a link between land development intensity and transit network development since it is, by definition, analogous to the concept of accessibility. We also test the hypothesis that both direct and indirect elements exist in a model.

2.1. Accessibility

Accessibility is the ease of reaching desired activities for the residents of a city. Calculating accessibility is a way to measure the number of opportunities reachable in a specific time threshold.
Due to the lack of historical employment data, this study focuses on population data as a surrogate, as locations with higher job access tend to have higher population access as well (Wu and D. Levinson, 2019). Therefore, the accessibility to population (Equation 1) will be measured to investigate the primacy of each suburb and how favorable they are to attract people and transit services.

$$A_i = \sum_{j=1}^{J} P_j f(C_{ij})) \tag{1}$$

Where: A_i gives the cumulative opportunities of block i, P_j is the population of block j, C_{ij} is the generalized travel cost (in terms of time) from region i to region j, and $f(C_{ij})$ is the impedance function:

$$f(C_{ij}) = \begin{cases} 1 & \text{if } C_{ij} \leq T \\ 0 & \text{otherwise} \end{cases}$$

The access (accessibility) is measured at the mesh block level for four time thresholds (15-, 30-, 45-, and 60-minute) by transit including trams (and then light rails), trains, and buses. In order to aggregate the access measures to the suburb level, a person-weighted average of the mesh blocks in each suburb is calculated as Equation 2.

$$A_I = \frac{\sum(P_i \times A_i)}{\sum^I P_i} \quad \forall i : i \in I \tag{2}$$

where A_I is the access of suburb I, and P_i is the population of the blocks inside suburb I.

2.2. Spatial correlation and spatial weights

The spatial proximity among neighbors creates spatial dependence and numeric similarity among their observed attributes. This spatial interaction is referred to as *spatial lag* and is considered in the panel data regression. The spatial dependence means some characteristics of an area are correlated with its adjacent neighbors and to capture that effect in the regression analysis, a neighbors-weighted measure of the independent variable can be considered as another regressor. The weights are based on the adjacency matrix and how it has been defined. Different definitions and types of

Table 1: Hypotheses

	Population density is positively associated with:	Tram stop density is positively associated with:	Train station density is positively associated with:
	lagged:		
Common assumption	population density neighbors population density	tram density neighbors tram density	train density neighbors train density
	change in:		
H1: direct interaction	density of tram stops density of train stations	population density density of train stations	population density density of tram stops
H2: indirect interaction	30-min access	30-min access	30-min access
H3: mixed indirect interaction	30-min access density of tram stops density of train stations	30-min access population density density of train stations	30-min access population density density of tram stops

neighborhood exist in the literature including the ones that are based on the shared edges and vertices (such as Rook, Bishop, Queen neighbors) and some distance-based measures (such as KNN and binary distance functions). In this study, the weights are based on adaptive distance measure using a triangular decay function. Equation 3 formulates the weights of each neighbor in the weight matrix.

$$w_{i,j} = 1 - \frac{d_{i,j}}{max^K(d_{i,j})} : \quad i \neq j \tag{3}$$

where $d_{i,j}$ is the euclidean distance between the suburb centroids and $max^K(d_{i,j})$ is the maximum distance to the k nearest neighbors. For the sake of simplicity, only 4 nearest neighbors have been considered for each spatial entity. To have average-weighted values, we transform the weights into row-standardized format as Equation 4.

$$w'_{i,j} = \frac{w_{i,j}}{\sum_{j=1}^{J} w_{i,j}} \tag{4}$$

2.3. Panel regression model

A series of hypotheses (Table 1) are evaluated based on historical data to study the effect of railways on land use and how population density changes transit networks. The hypotheses are divided into direct, indirect, and mixed interactions. Direct interaction reflects the direct influence of transit on land use and vice versa. The indirect interaction takes the accessibility as an interface between transit and land use. In a mixed interaction, both direct and indirect relationships are used simultaneously.

These hypotheses have both temporal and spatial (space-time) lagged exogenous components. The temporal lag reflects the effect of previous state of a variable in time (temporally dependent on past values), whereas the spatial lag (or spatial dependency) considers what is the current condition of the adjacent spatial units (e.g. suburbs). Using the spatial lag of the dependent variables can capture some of latent unobservable factors (LeSage and Pace, 2009). The general form of a balanced data panel consists two dimensions and the space-time interaction is achieved through separability. There is no spatial spillover between time periods since the spatial weights remain constant over time. The general format of space-time interaction is shown by Equation 5.

$$y_t = \alpha + \phi y_{t-1} + \gamma W_N y_{t-1} + X_{t-1}\beta + \epsilon_t \qquad t = 1, ..., T \tag{5}$$

In order to consider both temporal heterogeneity and spatial correlation, several panel models are defined to predict residential density, tram stops density, and train stations density. As the density changes slowly, a one period (10 years) lag structure is considered to conduct the causality test. The result will test the listed hypotheses of the hypothesized mutual relationship between railway and land use development. A cross-sectional database has been generated at the suburbs geographical level to estimate the stated models. Equation 6 shows the general form of H3 model for predicting the population density based on the lagged population and changes in the accessibility and network density. The variables in H1 and H2 models would be a subset of the general form of the equation. Equation 7 and Equation 8 predict the density of tram stops and train stations, respectively (both in H3 format).

$$P_{i,t} = \alpha_1 P_{i,t-1} + \alpha_2 \sum_{j=1}^{N} W_N P_{j,t-1} + \alpha_3 \Delta A_{i,t,t-1} + \alpha_4 \Delta T_{i,t,t-1} + \alpha_5 \Delta R_{i,t,t-1} + \beta \tag{6}$$

$$T_{i,t} = \alpha_1 T_{i,t-1} + \alpha_2 \sum_{j=1}^{N} W_N T_{j,t-1} + \alpha_3 \Delta A_{i,t,t-1} + \alpha_4 \Delta R_{i,t,t-1} + \alpha_5 \Delta P_{i,t,t-1} + \beta \tag{7}$$

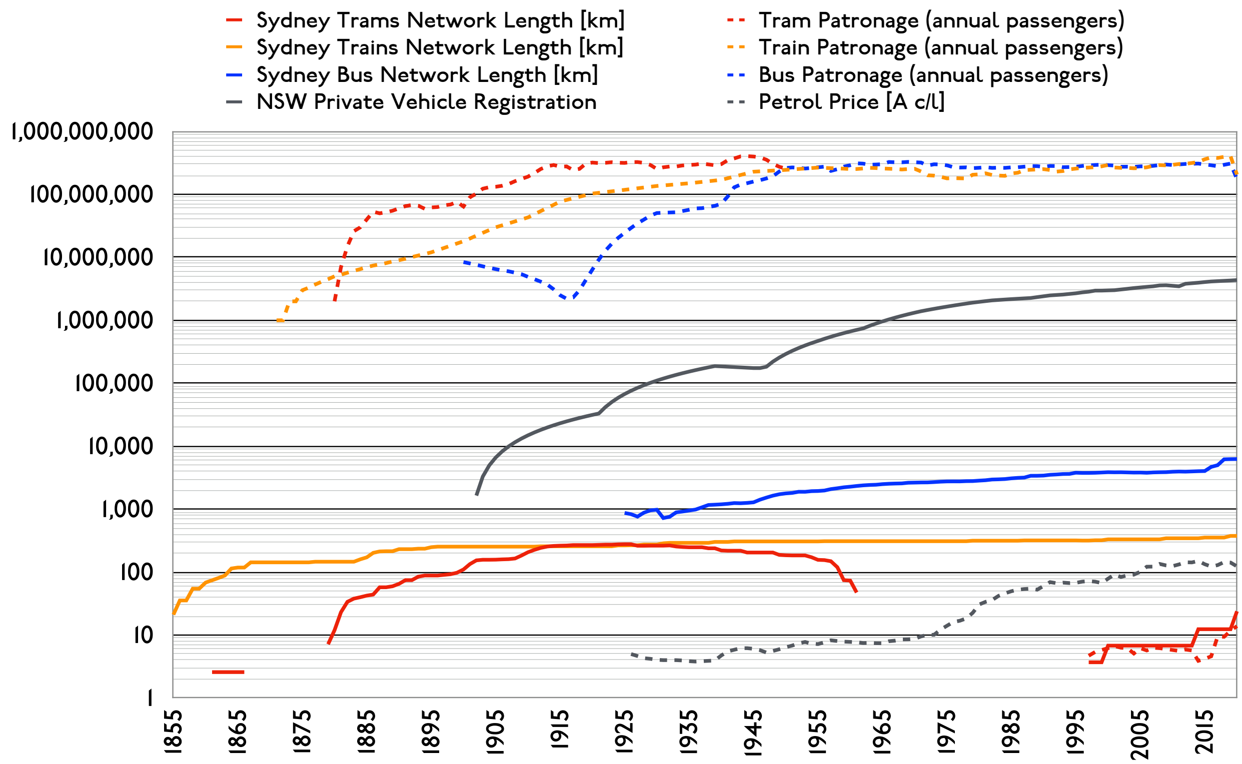
$$R_{i,t} = \alpha_1 R_{i,t-1} + \alpha_2 \sum_{j=1}^{N} W_N R_{j,t-1} + \alpha_3 \Delta A_{i,t,t-1} + \alpha_4 \Delta T_{i,t,t-1} + \alpha_5 \Delta P_{i,t,t-1} + \beta \tag{8}$$

where:
$P_{i,t}$ denotes the population density of district (i) at time t;
$P_{i,t-1}$ is the lagged population density in the previous time of district i;
$\Delta P_{i,t,t-1}$ is the change in the density of population on region i for one lag period (between t and $t-1$);
$R_{i,t}$ indicates the density of train stations in region (i) at time t;
$R_{i,t-1}$ is the lagged train density in the previous time of district i;
$\Delta R_{i,t,t-1}$ is the change in the density of train stations on region i for one lag period (between t and $t-1$).
$T_{i,t}$ represents the density of tram stops in region (i) at time t;
$T_{i,t-1}$ is the lagged tram density in the previous time of district i;
$\Delta T_{i,t,t-1}$ is the change in the density of tram stops on region i for one lag period (between t and $t-1$);
$\Delta A_{i,t,t-1}$ is the change in 30-minute access of region i for one lag period (between t and $t-1$);

2.4. Granger causality

Granger causality is a method for analyzing the causal relationships among variables across time series. The general equation (Equation 5) shows the observations of stationary variables of individuals in a time period t with one lag time step. The procedure to determine the existence of causality

Figure 2: The evolution of Sydney transit networks



is to check for meaningful and significant effects of lagged values of X on the present value of y (Lopez and Weber, 2017; Granger, 1969).

3. Data

3.1. Network data

The historical public transit systems in Sydney included tram, train, bus and ferry network. Due to the lack of historical schedule and route data, ferries are excluded from this study. Although, the technology of railways and buses had evolved over time, only the presence of the network and the provided services are considered. Therefore, all the stations, stops, and track lines were digitized and geo-coded with the opening and closure dates, and, all the schedules and operating routes have been transformed into a general transit feed specification (GTFS) format. Where applicable, the tram and train average speeds are considered to be 20 and 30 km/h, respectively. The geographical information is summarized on the currently defined state suburbs of New South Wales, Australia.

3.2. Population Data

Alongside the network data, the historical population data are required to estimate the co-development model. The historical census data were available at large-scale boundaries (usually at statistical or local government boundaries). Moreover, the jurisdiction boundaries were not consistent during time and changed many times. In order to test the discussed hypotheses using the proposed methods, boundaries must be rectified to be consistent across the study periods.

To address this challenge, first, all the historical census data were digitized within the original published boundaries for the census date. Second, to redistribute the population, the population is re-distributed across a finer mesh blocks (approx. equal to 100m by 100m cells in central business districts) proportional to the number of dwellings in each block as of 2016. Then the block population is re-aggregated into modern suburb boundaries. This transformation can be written as the Equation 9 respecting control totals.

$$P_{S_{i,t}} = \sum_{k=1}^{K} \frac{P_{C_t}}{\sum_{j=1}^{J} D_{M_{j,2016}}} \times D_{M_{k,2016}} : \quad \forall M_k \in S_i, \quad \forall M_j \in P_C \tag{9}$$

The reason for using 2016 dwelling information is twofold. Firstly, the number of dwellings is more correlated to the population distribution rather than the area of each boundary. Secondly, most dwellings remain in place since they were built, though older dwellings may be torn down and replaced with higher density development. This method probably overstates population away from the current suburb centers of activity in early years, but no historical population distribution at the block level is available, and we expect the errors in suburb level population are relatively small and do not unreasonably bias the analysis.

After the population distribution, the population density of each suburb is organized as panel data. It is worth mentioning that population is interpolated where necessary to account for missing data. In this study, 916 suburbs within the Greater Sydney boundary are considered.

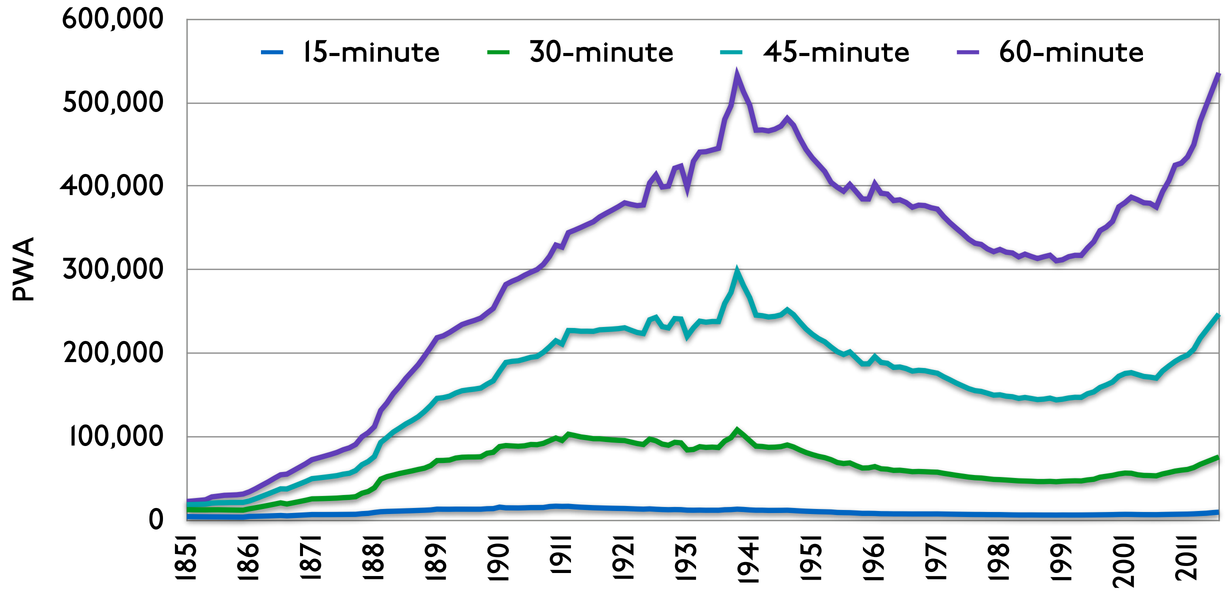
As mentioned earlier, the census boundaries were not constant historically, and many regions were undeveloped rural or bush areas prior to the dispersion of the population. There is no specific data about when exactly a region (or suburb) got developed and effectively became part of greater Sydney. However, the population for Sydney and surrounding local government areas are recorded (Coghlan, 1897).

4. Results

As discussed in the previous section, the historical land use and transit network have been digitized and the access to people has been calculated at the mesh block level for four different time thresholds (15-,30-,45-, and 60-minute). Results indicate that with the growing population and expanding transit networks, access has expanded from the central business district (CBD), where the City of Sydney was established, to the outskirts and evolved to today's state (illustrated in Figure 3). To compare the access in different years, the average person weighted access is recorded. Person weighted access by transit peaked in the 1940s, then fell and rose again to reach its current state. The reason for this could be that tram lines were removed, decreasing access, and it took some time to reclaim the lost access.

The dataset is separated into multiple time periods due to the distinct life-cycle trends of transit modes (as shown in Figure 2), including tram growth (1879-1930), the tram decline (1931-1961), the whole tram period (1879-1961), and the whole train period (1856-2016). The three hypotheses for modeling population density, tram stop density, and train station density at the suburb level of Greater Sydney were then investigated using Panel OLS regression for four time slices. The following subsections are organized by the explanatory variable these models test.

Figure 3: The historical average person weighted access (PWA) for 15-,30-,45-, and 60-minute time thresholds



4.1. Predicting population density

Table 2 shows the results for predicting population density for the City of Sydney and periphery within the tram period. Not surprisingly, overall population density of region i at time t is positively and significantly correlated with the lagged (10 years) population density of that region in all three hypotheses. In the first hypothesis (H1), the population density of periphery is positively associated with the lagged increase in the tram stops and train stations density. This finding corroborates our expectation that a new tram stop or train station drives an increase in the population density. However, in the City of Sydney, the tram and train were a decentralizing force to population. This could be due to the fact that non-residential land use outcompeted residential uses. Another significant predictor of population density in periphery is change in 30-minute access. Results for second hypothesis (H2) indicate that the indirect interaction outperforms the direct relationship between transit and land use. However taking both direct and indirect variables into account slightly increases the R^2. When considering access, the tram network acts as a decentralizing force for the population of a region. Also, there is no meaningful population spillover from/to adjacent neighbors in H1. In H2 and H3 the sign is negative, indicating a rise a neighbor population leads to a reduction in local population, in other words, neighboring suburbs act as substitutes.

4.2. Predicting tram stops density

Table 3 presents the results for the tram growth period. As expected, the dependent variable is highly correlated with the lagged tram stops density. In the periphery, the temporal and spatial lagged tram density (neighbors tram density in the previous ten years) has significant positive impact on tram density of region i at time t. Tram stops in neighbor suburbs are complements to stops in the suburb of interest. This is not true for City of Sydney suburbs. The lagged 10-year tram density of neighbors has negative impacts on tram density of others, although insignificant. In the first hypothesis, changes in lagged population density is positive in predicting the tram stops density of the periphery, whereas the lagged change in the train stations density is not significant. Furthermore, the lagged 30-minute access supports to be a significant explanatory variable (H2) in the development of the tram network. Similar to the population results, accounting for both direct and indirect variables slightly improves the R^2.

4.3. Predicting train stations density

Table 4 shows the results for train stations density models in the train growth period. The train stations density is highly correlated with the lagged train stations density. In the periphery suburbs, it is correlated with the lagged 10-year train stations density of the neighbors, so train stations are complements. The changes in population density and changes in access were the driving forces in the adding a train station in a region, corroborating H1 and H2. However, the lagged changes in the tram density is not able to explain the changes in the train network significantly. This finding negates the hypothesis that train network density is positively associated with changes in tram density. Taking both direct and indirect variables into account improves the R^2 marginally, similar to prior results.

5. Conclusion

Land development and network expansion have always been intertwined. Transport-land use interaction theory states that the co-development process of infrastructure and land use is a positive feedback cycle. The relationship can be conceived as direct connection between land use and transit elements, and indirect interaction through the concept of accessibility. This research tests three models to investigate the relationship between land use and the transit network historically. We examined the population growth and public transit networks expansion in Sydney between the years 1851 to 2016. Historical census and the transit network data were generated in GIS, and GTFS formats and the historical access to population were measured. The three panel regression models for explaining the population, tram, and train density in four different time horizons were estimated at the suburb level.

Results from the three models suggest that the expansion of the tram network and train railways led residential construction (increasing population density), and profoundly shaped the Sydney landscape. The results also support the hypothesis that the tram network expanded in response to the increased demand and where the train network acted as a complimentary mode. This result satisfy the the Granger causality analysis showing the causation effects between transport and land use. The Granger causality analysis aids in understanding the significance of causation effects in the context of statistical regression (Xie and D. Levinson, 2009). On the other hand, access to population was evaluated as an explanatory component in justifying the interdependencies of land use and transit network expansion. Results indicate that changes in 30-minute access have significant impact on the distribution of population density and the evolution of transit network.

This article found that the tram network both was a predecessor to population growth and that increases in the population density drove the tram network in turn. Dissimilarly, the Sydney train network partially had a smaller role in public transport since most of Sydney's population was well served by trams. This trend changed upon the opening of the Harbour Bridge (1932) and the City Circle extension to Sydney Trains. Today's conditions differ, and clearly population in greater Sydney is far more concentrated around train stations than elsewhere, and new growth is more likely to occur in train station catchment areas (Lahoorpoor and D. M. Levinson, 2020).

It is important to note that, unlike initial expectations, changes in tram density could not predict the train network (and vice versa). The reason might be threefold. First, they have experienced different life cycles. Second, the role of the train network differed since it was initially developed for the intercity travel and freight movements, and its deployment appears largely independent of tram change in the study period. Third, the design of the train network was much more a top-down decision-making process, and other factors were involved at the design stage, in particular serving freight and inter-city passenger markets rather than commuters.

There are some research suggestions that need to be discussed. First, in this study, the prediction models were developed based on accessibility to population. Accessibility to employment opportunities would increase the performance of the regression models, if historical employment by location data can be obtained. Second, future research should consider other factors involved in the co-development of land use and transit network. Considering other modes of transport such as private vehicles would also be beneficial, if localised vehicle ownership data can be found. Finally, in this study, the number of train stations and tram stops in a suburb were considered as the tram and train network in that suburb. More sophisticated indices, such as the number of stations/stops reachable in the 15-minute walk from the suburb's centroid (Lahoorpoor and D. M. Levinson, 2020) may increase the accuracy of the prediction.

References

Anderson, Paul, David Levinson, and Pavithra Parthasarathi. 2013. "Accessibility futures". In: *Transactions in GIS* 17.5, pp. 683–705.

Badoe, Daniel A and Eric J Miller. 2000. "Transportation–land-use interaction: empirical findings in North America, and their implications for modeling". In: *Transportation Research Part D: Transport and Environment* 5.4, pp. 235–263.

Bar-Yosef, Asaf, Karel Martens, and Itzhak Benenson. 2013. "A model of the vicious cycle of a bus line". In: *Transportation Research Part B: Methodological* 54, pp. 37–50.

Cats, Oded. 2017. "Topological evolution of a metropolitan rail transport network: The case of Stockholm". In: *Journal of Transport Geography* 62, pp. 172–183.

Coghlan, Timothy Augustine. 1897. *The wealth and progress of New South Wales*. 10. Government printer.

Granger, Clive WJ. 1969. "Investigating causal relations by econometric models and cross-spectral methods". In: *Econometrica: journal of the Econometric Society*, pp. 424–438.

Kasraian, Dena, Kees Maat, and Bert van Wee. 2016. "Development of rail infrastructure and its impact on urbanization in the Randstad, the Netherlands". In: *Journal of Transport and Land Use* 9.1, pp. 151–170.

King, David. 2011. "Developing densely: Estimating the effect of subway growth on New York City land uses". In: *Journal of Transport and Land Use* 4.2, pp. 19–32.

Lahoorpoor, Bahman and David M Levinson. 2020. "Catchment if you can: The effect of station entrance and exit locations on accessibility". In: *Journal of Transport Geography* 82, p. 102556.

LeSage, James and Robert Kelley Pace. 2009. *Introduction to spatial econometrics*. Chapman and Hall/CRC.

Levinson, David. 2007. "Density and dispersion: the co-development of land use and rail in London". In: *Journal of Economic Geography* 8.1, pp. 55–77.

Levinson, David and Feng Xie. 2011. "Does first last? the existence and extent of first mover advantages on spatial networks". In: *Journal of Transport and Land Use* 4.2, pp. 47–69.

Levinson, David M. 1998. “Accessibility and the journey to work”. In: *Journal of Transport Geography* 6.1, pp. 11–21.
Lierop, Dea van et al. 2017. “Evolution in Land Use and Transportation Research”. In: *Planning Knowledge and Research*. Routledge, pp. 130–151.
Lopez, Luciano and Sylvain Weber. 2017. “Testing for Granger causality in panel data”. In: *The Stata Journal* 17.4, pp. 972–984.
Mohring, Herbert. 1972. “Optimization and scale economies in urban bus transportation”. In: *The American Economic Review* 62.4, pp. 591–604.
Vuchic, Vukan R. 2005. *Urban transit: operations, planning, and economics*.
Wegener, Michael. 2021. “Land-use transport interaction models”. In: *Handbook of regional science*, pp. 229–246.
Wu, Hao and David Levinson. 2019. “Access across Australia”. In.
Xie, Feng and David Levinson. 2009. “How streetcars shaped suburbanization: a Granger causality analysis of land use and transit in the Twin Cities”. In: *Journal of Economic Geography* 10.3, pp. 453–470.

Table 2: Predicting population density. Tram period: 1879 to 1961

	Explanatory variables	Periphery					City of Sydney				
		Number of observations:		14192			Number of observations:		464		
		Coeff.	Std. Err.	T-stat	P-value	R^2	Coeff.	Std. Err.	T-stat	P-value	R^2
	Lagged population density (L10)	1.0454	0.0095	109.56	0		1.0064	0.0352	28.579	0	
	Lagged neighbors population density (L10)	0.0148	0.0054	2.7268	0.0064		-0.038	0.0216	-1.7626	0.0786	
H1	Change in tram stops density (L10)	78.333	3.9402	19.88	0	0.9365	-2.4971	37.224	-0.0671	0.9465	0.9771
	Change in train stations density (L10)	298.44	28.147	10.603	0		-147.3	614.88	-0.2396	0.8108	
	Constant	78.802	3.1318	25.162	0		1060.9	212.09	5.0019	0	
	Lagged population density (L10)	1.0331	0.0082	126.13	0		1.0055	0.0351	28.612	0	
H2	Lagged neighbors population density (L10)	-0.0065	0.0047	-1.4043	0.1603	0.9532	-0.0372	0.0215	-1.7266	0.0849	0.8541
	Change in 30-minute access (L10)	0.0244	0.0003	75.853	0		0.0032	0.0047	0.6775	0.4984	
	Constant	51.537	2.7129	18.997	0		981.96	230.72	4.256	0	
	Lagged population density (L10)	1.0339	0.0082	126.46	0		1.0058	0.0352	28.536	0	
	Lagged neighbors population density (L10)	-0.0074	0.0047	-1.5993	0.1098		-0.0375	0.0216	-1.7346	0.0835	
H3	Change in 30-minute access (L10)	0.0248	0.0003	71.678	0	0.9534	0.0038	0.005	0.7519	0.4525	0.8541
	Change in tram stops density (L10)	-16.332	3.6248	-4.5056	0		-12.743	39.657	-0.3213	0.7481	
	Change in train stations density (L10)	140.92	24.214	5.8199	0		-170	615.92	-0.276	0.7827	
	Constant	50.491	2.712	18.617	0		987.92	233.31	4.2343	0	

Table 3: Predicting tram stop density. Tram growth period: 1879 to 1930

	Explanatory variables	Periphery					City of Sydney				
		Number of observations:		8870			Number of observations:		290		
		Coeff.	Std. Err.	T-stat	P-value	R^2	Coeff.	Std. Err.	T-stat	P-value	R^2
	Lagged tram stops density (L10)	0.7309	0.0181	40.388	0		1.0042	0.0907	11.069	0	
	Lagged neighbors tram stops density (L10)	0.1666	0.0129	12.947	0		-0.0424	0.0626	-0.6775	0.4987	
H1	Change in population density (L10)	0.0006	2.90E-05	19.957	0	0.6805	-2.33E-05	7.69E-05	-0.3035	0.7617	0.6659
	Change in train stations density (L10)	-0.1093	0.0672	-1.6277	0.1036		-1.0789	0.9566	-1.1279	0.2604	
	Constant	0.0489	0.0087	5.6	0		2.1709	0.3098	7.0068	0	
	Lagged tram stops density (L10)	0.7744	0.0167	46.27	0		0.9428	0.0841	11.208	0	
H2	Lagged neighbors tram stops density (L10)	0.0965	0.0118	8.1768	0	0.7270	-0.0333	0.0577	-0.5778	0.5639	0.7145
	Change in 30-minute access (L10)	4.65E-05	1.05E-06	44.445	0		5.58E-05	8.00E-06	6.9768	0	
	Constant	0.0246	0.008	3.0787	0.0021		0.3659	0.3728	0.9815	0.3272	
	Lagged tram stops density (L10)	0.7754	0.0168	46.275	0		0.9452	0.0842	11.228	0	
	Lagged neighbors tram stops density (L10)	0.0989	0.012	8.2308	0		-0.0361	0.0578	-0.6242	0.533	
H3	Change in 30-minute access (L10)	4.80E-05	1.23E-06	39.026	0	0.7274	5.60E-05	8.01E-06	6.9884	0	0.7163
	Change in population density (L10)	-5.84E-05	3.13E-05	-1.8637	0.0624		-3.87E-05	7.10E-05	-0.5455	0.5859	
	Change in train stations density (L10)	-0.1819	0.0621	-2.9297	0.0034		-1.0811	0.8831	-1.2241	0.2219	
	Constant	0.0285	0.0081	3.5194	0.0004		0.4292	0.3794	1.1313	0.2589	

Table 4: Predicting train station density. Train period: 1856 to 2016

	Explanatory variables	Periphery					City of Sydney				
		Number of observations:		28384			Number of observations:		928		
		Coeff.	Std. Err.	T-stat	P-value	R^2	Coeff.	Std. Err.	T-stat	P-value	R^2
	Lagged train stations density (L10)	0.9855	0.0038	259	0		1.0078	0.0219	46.079	0	
	Lagged neighbors train stations density (L10)	0.0093	0.0028	3.3441	0.0008		-0.0079	0.0188	-0.4194	0.675	
H1	Change in population density (L10)	8.11E-06	1.22E-06	6.6665	0	0.9021	1.89E-06	2.82E-06	0.6698	0.5032	0.9116
	Change in tram stops density (L10)	-0.0001	0.0007	-0.1908	0.8487		0.0002	0.0023	0.0947	0.9246	
	Constant	0.0043	0.0005	8.3436	0		0.0234	0.0069	3.3825	0.0007	
	Lagged train stations density (L10)	0.9856	0.0038	259.22	0		1.0073	0.0218	46.116	0	
H2	Lagged neighbors train stations density (L10)	0.0078	0.0028	2.7917	0.0052	0.9023	-0.0077	0.0188	-0.4106	0.6814	0.9117
	Change in 30-minute access (L10)	5.53E-07	5.97E-08	9.257	0		2.39E-07	2.58E-07	0.9241	0.3557	
	Constant	0.0042	0.0005	8.235	0		0.0217	0.0073	2.9916	0.0029	
	Lagged train stations density (L10)	0.9856	0.0038	259.27	0		1.0076	0.0219	46.055	0	
	Lagged neighbors train stations density (L10)	0.0076	0.0028	2.7437	0.0061		-0.0081	0.0188	-0.4292	0.6679	
H3	Change in 30-minute access (L10)	5.05E-07	6.84E-08	7.392	0	0.9024	2.36E-07	2.72E-07	0.8664	0.3865	0.9117
	Change in population density (L10)	4.05E-06	1.34E-06	3.0342	0.0024		1.62E-06	2.83E-06	0.5715	0.5678	
	Change in tram stops density (L10)	-0.0016	0.0008	-2.1283	0.0333		-0.0004	0.0024	-0.1635	0.8702	
	Constant	0.0039	0.0005	7.4976	0		0.0214	0.0073	2.9179	0.0036	