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Chicken or egg? Transport and urban development in Berlin

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Abstract: Infrastructure and especially mass transit play a major role in urban economics and are the centre of many research questions. Probably due to simultaneous determination of infrastructure supply and demand most research is only carried out on the supply side driven relationship explaining how transport leads to urban development. The intention of the paper is to provide a new and purely empirical perspective on the chicken-and-egg-problem. We propose a panel VAR approach employing a unique data set for historic Berlin between 1870 and 1936. We argue that it is of a planner's interest to not only incorporate the supply side driven relationship but also the demand sided one. We turn the simultaneity problem into a purely empirical question since in practice it becomes difficult to derive theoretical implications from a comprehensive model that fully reflects all mutual interactions. Our analysis follows a twofold approach: Firstly, we estimate the interaction between population and transport. We then secondly extend the analysis by looking into the relation between land values and transport. Our estimates suggest a supply side driven relationship between transport and population and a positive reciprocal one between transport and land values. We conclude that new lines are not built entirely into undeveloped land but need to be connected to areas characterised by high land values to serve as a commuting mode.

Keywords: transport, land use, Berlin, history, panel vector autoregression
JEL classification: R12, R14, R41, N73, N74

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1. Introduction

Infrastructure and especially mass transit play a major role in economics and especially in urban economics. Transport improvements affect the location of people and firms generating welfare effects via reduced commuting and reduced shipping cost. Transport impacts on the allocation of land and has important implications for agglomeration economies and urban productivity.

Transport is therefore considered to be an important instrument to foster regional economic development. The European Union supports infrastructural investments in less developed regions with about 82 billion Euros which amounts up to 23.7% of the Structural and Cohesion Funds of 2007-2013 (European Commission 2007). The city of Berlin spent about 645 million Euros on public rail transport (Amt für Statistik Berlin-Brandenburg 2011). For the Olympic Games 2012 London invested even more than 6.5 billion British Pounds in the modernisation of its network (Transport for London 2012). Efficient urban planning therefore requires are profound understanding of how transport and urban development impact on each other.

This importance has been widely acknowledged and there is large literature body on the provision of new transport infrastructure. A popular question studied is how traffic reacts to the provision of new roads. Most analyses find a positive elasticity of vehicle kilometres travelled (VKT) to the supply of roads. Cervero (2002) provides an extensive review of these studies. The recent research focus has been on more carefully solving the identification problem stating that infrastructure supply and demand is determined simultaneously: Planners have certain expectations and infrastructure is not only built based on past but also on future/expected urban development.

One strand of literature opened up by Baum-Snow (2007) follows an instrumental variable (IV) approach using historic infrastructure plans to generate exogenous variation. By instrumenting recent highway development using a 1947 national interstate highway plan he establishes a causal relation between the provision of new highways in the US and suburbanization. Baum-Snow (2007) concludes that the construction of a new highway which passes through a central city depopulates the centre by 18%. Duranton and Turner (2011) extend the instrumenting literature introducing plans of historical major rail roads (1898) and expedition routes between 1835 and 1850. They predict an increase in VKT following the provision of new roads. Duranton and Turner (2012) further find empirical evidence for a positive population as well as a positive employment response caused by an increase in urban road stock following a similar IV approach. These results are replicated for Spanish highways and cities by Holl and Viladecans-Marsal (2011) and for Japan by Hsu and Zhang (2011). Baum-Snow, Brandt et al. (2012) have been carrying out similar analyses by investigating decentralisation trends in China. They point out the importance of infrastructure in countries which are still developing and highly invest into their infrastructure. They find comparable population elasticities for radial highway construction as have been reported for the western hemisphere.

A few of the aforementioned studies also investigate the effect of improvements in the public transport network. Baum-Snow, Brandt et al. (2012) show that railroads have a significant effect on industry location in China. Public transportation, however, has now effect on VTK in the US (Duranton and Turner 2011) whereas urban population grows with a city's stock of large buses (Duranton and Turner 2012).

Another attempt to deal with the simultaneity problem while predicting transport effects is to directly assume exogeneity in a quasi-experimental setting. A prominent example is Gibbons and Machin (2005) using the extension of London Jubilee Line during the 1990s. Their difference-in-difference approach yields a positive response of house prices to improved access. Quasi-experiments have also been used by Michaels (2008), observing a trade increase in rural US counties caused by the construction of the Interstate Highway System, or by Ahlfeldt and Feddersen (2011) who find a positive economic effect in two rural cities which received a connection to the high speed railway network. The exogenous variation of the two latter studies is based on the assumption that the rural locations did not get connected on purpose but by accident as the planners intended to connect major cities.

The quasi-experimental as well as the IV approach of circumventing the simultaneity problem share a common idea: They both generate exogenous variation in transport provision to separate supply and demand. What follows is an investigation of the isolated supply side effect of transport on the allocation of land use; a new line or road is built and the urban structure adjusts to the new situation. So far, demand side driven reactions of transport infrastructure have been largely ignored by economists. However, as initially argued, it is very likely that planners take future urban development into account when planning new roads and track, for instance to respond to residential commuting needs. Firms could also request a better access to workers and customers. There is very little literature on the demand side driven relation between transport and development. Levinson and Karamalaputi (2003) build an exception. Their analysis yields a positive effect of population on highway lane expansion in Minnesota.

However, the process must neither be exclusively supply nor exclusively demand side driven but could also work simultaneously. Levinson (2008) calls this joint process of infrastructure and land development co-development. In this situation, residents and firms incorporate the changes of the transport network in their location decision. At the same time rail extensions depend on the location of economic agents. Levinson (2008) empirically tests for a co-development process using a sample of 33 London boroughs for a time period between 1871 and 2001. He first tests whether a change in the transport network Granger causes population to raise (fall) in the periphery (CBD). In a rather ad-hoc approach, he then reverses the estimation equation to see whether population affects station density, too. The analysis confirms the hypothesised co-development process for London. In a follow-up study on the twin cities Minneapolis and St. Paul, Xie and Levinson (2010) could, however, find only evidence for a supply side driven relationship.

Unfortunately, Levinson's approach does not allow for a simultaneous adjustment of transport and land development. If the two variables influence each other one should account for simultaneous effects in order to obtain unbiased results. Cervero and Hansen (2002) apply a three-stage least square (3SLS) approach to simultaneously estimate induced demand and induced supply effects. They conclude that road supply has been a cause and a reaction to vehicle miles travelled for a sample of 34 California urban counties.

We consider our paper to be most closely related to Levinson (2008). We contribute to this line of literature in several ways: Firstly, we propose a panel vector autoregression (PVAR) model to estimate the causality direction between transport and urban development. While an isolated investigation of the supply sided provision of infrastructure can theoretically be conceptualised by

models which describe the allocation of economic activity (Alonso 1964, Mills 1969, Muth 1969) there already exist less theoretic work on the demand sided provision of transport. Firm location models (McFadden 1974, Carlton 1983) would generally expect private transport companies to invest only into the construction of lines where they yield the highest expected returns conditional on construction and operating costs. The location of a (rail) road or a station therefore depends on numerous cost factors like for instance the topography, potential economies of scales giving incentives to connect already existing stations which would lead to a clustering of the network, but also the willingness of residents/workers to pay for transport. We argue that in practice it becomes difficult to construct a comprehensive model that fully reflects all mutual interactions. Moreover, we argue that the theoretical implications of the circular relation between cause and effect are ambiguous. Consider for example how transport might react to population shocks. Reversing the logic of the monocentric city model one could argue that transport follows residents in the periphery as transport lowers commuting cost and residents have a preference for space (or amenity) consumption. Counterfactually arguing transport only follows firms in central areas as firms have additional incentives to cluster (Lucas and Rossi-Hansberg 2002). Firm location models, however, would suggest that transport is only built where return is highest. This could for instance result into a constrained provision of transport into only wealthy residential areas. As no clear theoretical implications exist we consider the relation between transport and urban development as a purely empirical issue.

In addition to the atheoretical motivation, the PVAR model also provides interesting methodological characteristics we want to exploit. PVARs have the great advantage of treating all variables endogenously. Causality is allowed to run in any direction. Moreover, this approach allows us to estimate the effects simultaneously. Impulse response functions further enable us to see how people/firms or transport respond to shocks over time and space. To the authors' knowledge this is the first paper applying PVAR in an intra-urban context.

Secondly, we extend Levinson (2008) by not only investigating the interaction between transport and population but also between transport and land values. Land values are of special interest in urban economics as they reflect the value of using land in the most profitable way. We also estimate a price anticipation model using announced rail stations instead of actually constructed ones. We separately estimate the two population and land value models for a core and a peripheral sample in order to allow for potential outbidding. Observing increased land values combined with depopulation in the centre would suggest an outbidding of people by firms. We further extend recent literature by allowing for a rather flexible distinction between central and peripheral areas to avoid the strong assumption of having fixed defined boundaries.

Thirdly, we employ a unique historic dataset for Berlin between 1870 and 1936 for our analysis. This period is characterised by great infrastructure projects as well as a strong growth in population which enables us to empirically address our research question. In line with Baum-Snow, Brandt et al. (2012) we argue that the analysis of public infrastructure during that time is of special interest as the city was industrialising, economically developing and characterised by huge transport investments somehow comparable to the process developing countries experience today. Moreover automobiles can be ignored as transport mode.

The intention of this paper is not to reject existing identifying strategies in dealing with the simultaneity problem in transport economics but to introduce a new method borrowed from macroeconomics to show how the open causality issue can be evaluated. The PVAR methodology thus provides an alternative approach to the "chicken-and-egg-problem". Our estimates suggest a clearly supply side driven relationship between transport and population and a positive reciprocal one between transport and land values. Price anticipation models do not yield additional explanation power suggesting that rail developers do not act in a risk-loving way. Moreover we conclude that the transport network was mainly built for commuting.

The remainder of the paper is structured as follows. In the next section we give a brief overview of the Berlin transport sector during our observation period and our historical dataset. This is followed by the introduction and application of a PVAR estimator for historic Berlin. We conclude the analysis in section four.

2. Historical Background and data

The public rail network in Berlin is made up of two different modes, namely a light rail system and the underground. We will give a short historic overview of its development in this chapter. We will then give a brief description our data.

2.1 Berlin rail sector

S-Bahn network

The light rail ("S-Bahn") as it is known today is a result of combining various suburban lines, ("Vorortsbahn"), the original city line ("Stadtbahn") and the circular line ("Ringbahn") in 1930. Therefore, there a various reasons and purposes why, where and how the S-Bahn was developed over the years which originate from the three different strands (Klünner 1985, Gottwaldt 1994, Kiebert 2004, Kiebert 2008):

The suburban lines connected Berlin with surrounding cities and its suburbs. Especially the early lines originate from long-distance connections to other important cities like Potsdam ("Stammbahn" 1838), Hamburg ("Hamburger Bahn" 1846) or Dresden ("Dresdner Bahn" 1887). Initially, the long-distance lines had to share their tracks with the new upcoming suburban lines. In 1891 a new tariff system for local mass transit was introduced pushing up the passenger numbers by about 30% and the suburban lines increasingly started to run on their own tracks. The majority of these lines were developed by public companies and planned by the government. For instance, the "Ostbahn" which was supposed to go through the Prussian regions of Pommern and East Prussia was built in order to develop the periphery along the tracks. The "Görlizer Bahn" (1866/67) or the "Wetzlarer Bahn" (also "Canon Train") linking Berlin with Metz at the French border were planned by the military in order to move troops more rapidly. Later on new lines were directly built for local mass transit in order to improve the access of the periphery like the North-South connection (1934-39). However, private developers like J.A.W. Carsten who financed the station "Lichterfelde" (1868) in order to sell his newly established country estates in that area intervened in the expansion of the S-Bahn network as well. The electronic company Siemens further financially supported the exploitation of the section between Fürstenbrunn and Siemensstadt (1905) in order to improve the commuting situation for its

workers. Moreover, Brothers Spindler, who ran a laundry and dying factory in Köpenick at the Eastern border of the city, were strongly in favour of building a transport line between Schöneweide and Spindlersfelde (1891). Hence, the suburban lines were driven by both the public and the private sector.

The city line went from Stralau-Rummelsburg to Westkreuz, Halensee and was built in 1882. This East-West connection running through the historical city centre was planned to decongest the traffic between Berlin's terminal stations. The tracks were mainly built on land owned by the government and the project was carried out publicly.

The first sections of the circular line Moabit-Gesundbrunnen-Potsdamer-Ringbahnhof and Moabit-Charlottenburg-(Westend)-Grunewald-Tempelhof were opened in 1881, and 1882 respectively. The circular line was financed by the state of Prussia but run by the Niederschlesisch-Märkische Eisenbahn, a public company owned by Prussia. The idea of the circular line was to connect radian lines going out of the centre with each other and the important terminal stations. Various parts of the new line were built into undeveloped land and thus outside the city border. Or as Elkins and Hofmeister (1988) state "The actual position of the ring line was a compromise between the desire to maximise utilization by being as close as possible to the core of the city and the desire to minimize land-acquisition costs by avoiding areas of existing urban development" (p. 114).

Like the circular line many other lines of the light rail system were built into undeveloped areas, connecting Berlin with other villages. Only the East-West and North-South connections went through the city centre. New villages were founded close to the new lines like for instance "Glienicke an der Nordbahn". Companies like AEG or Borsigwerke in Tegel even built new factories close by the new stations ("Kremmener Bahn"). Even though a few S-Bahn lines were developed upon request of the private sector, most of the lines were developed by the public sector. In the 1880s the majority of the long-distance lines, which were closely related to the rise of the suburban lines, were nationalised. However, most of the nationalised lines were still run independently. They had their own management as well as on own trains/coaches. From 1920 on, all lines were eventually nationalised under the "Reichseisenbahn".

U-Bahn network

The underground („U-Bahn") was developed about a third century later than Berlin's light rail system. The first line was opened in 1902 and went from Stralauer Tor (later Warschauer Brücke) to Potsdamer Platz and then to Zoo. The first underground was actually built on elevated tracks since Berlin government was afraid of damaging its newly installed drainage system. The project was pushed forward by the company "Siemens & Halske" which already back in 1891 proposed a densely linked network, connecting the historic city centre with its surrounding municipalities. The new line was eventually developed by the "Hochbahngesellschaft" a company jointly founded by Siemens & Halske and Deutsche Bank as the main funder. While the line's Eastern section until Nollendorf Platz was built on viaducts, the city of Charlottenburg successfully negotiated the tracks to run under the ground when passing though their territory. Not hiding the view at the prominent church "Kaiser-Wilhelm-Gedächtniskirche" was one of Charlottenburg's reasons for the changed routeing. In the West (Westend), the line was built into undeveloped land where Deutsche Bank owned land. The bank being involved in the development of the underground line was expecting rising land rents due to the improved access. Followed by the newly established connection Western Charlottenburg

turned into an attractive business area. The extension of the first line leading into central Berlin was hampered by the tram operator "Große-Berliner-Straßenbahn" being afraid of losing its monopolistic role in that area. Eventually, the line went via Mohrenstraße and Spittelmarkt through the city centre (Gottwaldt 1994).

It was especially the municipalities in the South West which planned to develop their unused land. They competed for wealthy citizens by turning it into attractive residential areas. The underground experienced a crucial role in developing these areas. The city of Schöneberg ("Schöneberger Linie" 1910) even planned and financed its own line between Nollendorfplatz and Hauptstraße (today Innbrucker Platz) in order to develop its Western territory. As the "Hochbahngesellschaft" did not expect any profits generated by the new line it was completely planned publicly. The land where the lines went through was changed significantly. Individually designed stations were built at prominent squares. A similar approach was followed by the villages of Wilmersdorf and Dahlem. Newly planned country estates and academic institutes were supposed to benefit from an improved access by constructing the "Wilmersdorf-Dahlemer U-Bahn" (1913). The line was divided into three sections regarding their ownerships: While the section between Wittenbergplatz and Nürnberger Platz belonged to the Hochbahngesellschaft, Nürnberger Platz-Breitenbachplatz was owned by the city of Wilmersdorf and Breitenbachpatz-Thielplatz by Domäne Dahlem. The line was extended until the lake "Krumme Lanke" in 1929. This extension was mainly financed by the land speculator and private developer Adolf Sommerfeld in order to connect his newly established residential quarters in Dahlem. Moreover, he wanted to improve the access to the surrounding woods, establishing them as recreational areas (Kurpjuweit and Meyer-Kronthaler 2009).

In contrast to the S-Bahn network, the initial idea of Berlin's underground was to serve the local mass transit. The lines were built into more central area. Moreover the network was developed later than the light rail system; the technology was superior allowing for underground tracks and planners as well as investors had already gained first experiences by evaluating the effects of the S-Bahn. Anecdotic evidence suggests that the rise of the U-Bahn was mainly driven by the idea of developing new land closely located the historical core (especially in the South West). Public as well as private planners competed for wealthy citizens and increasing land rents.

Even though the link between transport and land development is not completely clear when analysing the history of Berlin's transport system, the majority of the projects and newly constructed lines seemed to lead the development in an area and not the other way around.

2.2 Data

This part provides a brief overview over the historical data we will apply in the analysis. We basically need two variables: (i) a measure which describes the transport development (rail station density), (ii) variables which capture the urban development/the behaviour of the economic agents in the city (population and land values).

For computing rail densities, we have reconstructed the historic transport network of Berlin (Schomacker 2009, Mauruszat 2010, Straschewski 2011) for the entire observation period (1870-1936) in a geographic information system (GIS) environment. As in Levinson (2008) station densities for the combined network were computed using a kernel with a radius of 2 km (Silverman 1986). By choosing this radius we follow Gibbons and Machin (2005) who estimate a distance of 2 km as a

maximum distance people are willing to walk to the nearest station. By definition, the density measure reflects the degree of network concentration. It is high in areas which are characterised by a high number of stations in close distance, and low vice versa. The measure does however not incorporate the number of lines which run through a station, the travel time/speed and the frequency for which we do not have data for either. Figure 2.1 provides an overview of the development of the total transport network during our observation period. In 1870, they were only seven lines connecting surrounding cities with Berlin whereas each line had its own terminus station. The lines did not go into the very centre of the city and only a few stations were built along the tracks. Turning to 1936, we observe a massive development of the transport network. By that time, the circular line as well as the East-West and North-South connections were merged with the suburban lines. From 1902 on underground tracks were added to the rail network. The total number of stations increased from 18 in 1870 to 221 in 1936 (see also Table 2.1)

Table 2.1: Number of stations

Year	Number of stations		
	Light rail	Underground	Total
1870	18	0	18
1875	31	0	31
1880	55	0	55
1885	64	0	64
1890	65	0	65
1895	88	0	88
1900	96	0	96
1905	103	15	118
1910	109	28	137
1915	109	46	155
1920	112	46	158
1925	113	60	173
1930	120	94	214
1936	127	94	221

The population data for Berlin refer to the 93 municipalities (“Ortsteile”) as they were structured in 1936. The data were collected from the Statistical Yearbook of Berlin (Statistisches Amt der Stadt Berlin 1920) and aggregated to the municipality level. (Statistisches Amt der Stadt Berlin 1920)(Statistisches Amt der Stadt Berlin 1920)The observation area covers entire Greater Berlin. Between 1870 and 1936 population strongly grew from more than 900,000 up to about 4,200,000 inhabitants. Figure 2.2 illustrates the change in population over the observation period. Apart from a general increase for the whole of Berlin, a strong decentralisation pattern becomes visible.

The technician Gustav Müller (1881-1914) produced maps of land values at the plot level for Berlin between 1881 and 1914. The historical maps were georeferenced in a GIS environment and land values were extracted for six time periods at a plot level[4]. We then aggregated the values on the 1910 block level for inner Berlin. Figure 2.3 illustrates the development of the land values in Reichsmark between 1890 and 1914. The Müller maps have been used previously by Ahlfeldt and

[4] The land value data were extracted for 1881, 1890, 1896, 1900, 1904, 1910 and 1914.

Wendland (2011) in establishing the impact of the development of the urban rail system on the land value gradient in Berlin over the period 1890-1936. Whereas, Ahlfeldt and Wendland use only commercial land values, the data extracted for this study uses land values relating to all land uses.

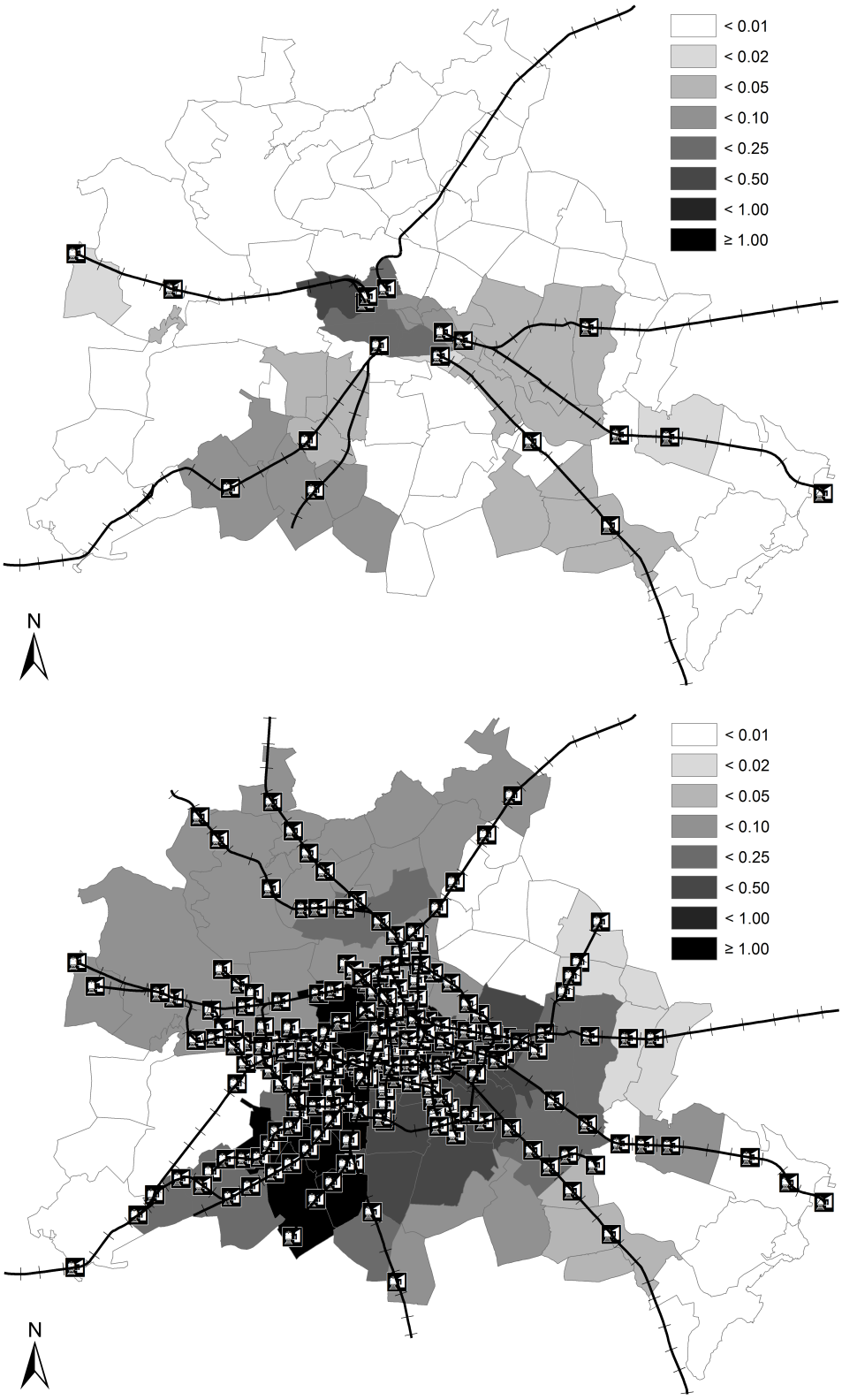
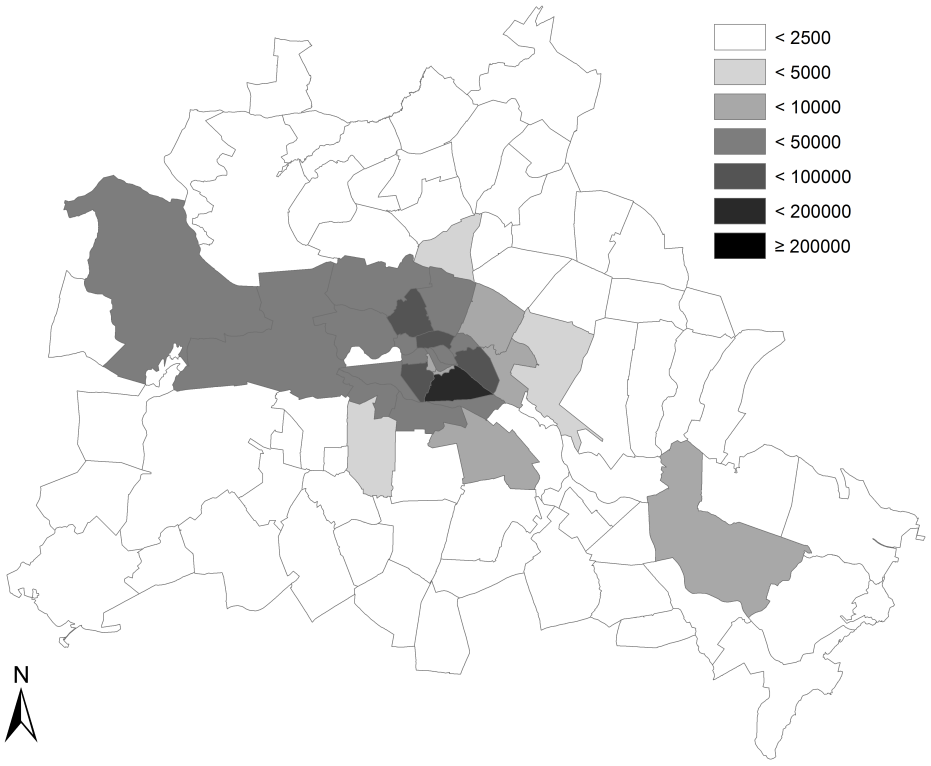
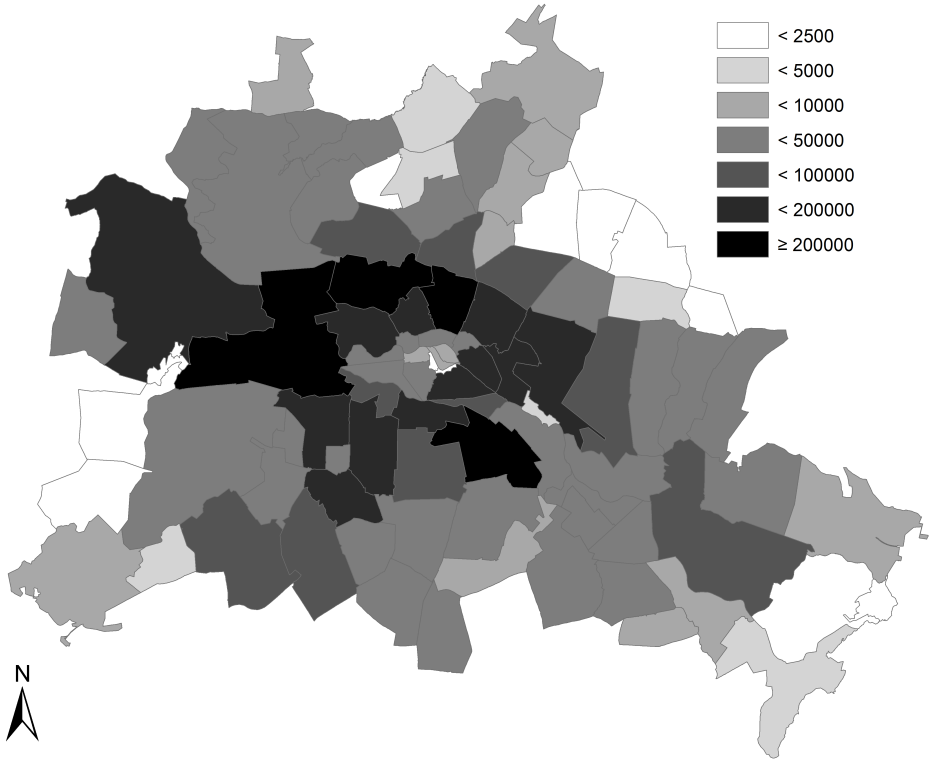


Figure 2.1: Rail station densities in 1870 and 1936.

The available historic data we need for creating our variables differ in time as well as in spatial coverage and level of detail. Since spatial aggregation/disaggregation results in a loss of information or biased estimates we work with distinct panels. We end up with two samples: (i) we estimate the interaction between transport and population on a municipality ("Ortsteile") level of 93 municipalities using data for roughly every five years from 1870 to 1936 (14 time periods), and (ii) the relation between transport and land values is estimated on a block level covering 2,481 blocks of the extracted Müller maps between 1881 and 1914 (7 time periods).



1870



1936

Figure 2.2: Population in 1870 and 1936.

1890

1914

Figure 2.3: Land values (in Reichsmark) in 1890 and 1914.

We distinguish between a core and peripheral region within the analysis to capture the presumably distinct behaviour of economic agents in the city. We follow the definition introduced by Leyden (1933) of "Berlin City" to determine the boundaries of the core. As suggested (and tested) by Ahlfeldt and Wendland (2011), we chose the underground station "Stadtmitte" (downtown) as centroid of the Central Business District (CBD)[5]. The station lies on the prestigious Friedrichstraße surrounded by the boulevards Unter den Linden and Leipziger Straße.

Table 2.2 and 2.3 provide a selection of the summary statistics for the municipality and the city block samples.

In the next section we will give a short literature review which sheds some light on the interaction between transport and the development of a city. This will set the background for our empirical analysis.

Table 2.2: Municipality sample summary statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
$railDens$	overall	0.211	0.3539	0	1.995	N = 1,302
	between		0.268	0.001	0.834	n = 93
	within		0.233	-0.503	1.372	T = 14
$population$	overall	29,743.77	56,296.1	0	354,684	N = 1,302
	between		47,686.39	0	216,328.3	n = 93
	within		30,298.21	-146,107.2	221,449.6	T = 14
$distance\ CBD$	overall	7.715	5.283	0	23.927	N = 1,302
	between		5.309	0	23.927	n = 93
	within		0	7.715	7.715	T = 14

[5] Throughout this paper, core and CBD will be used synonymously, even though both areas are not exactly the same.

Table 2.3: City block sample summary statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
$railDens$	overall	0.389	0.247	0	1.248	N = 15,034
	between		0.145	0	0.735	n = 2,486
	within		.207	-0.209	1.096	T = 6.047
$land\ values$	overall	159.523	239.052	0	2348	N = 15,034
	between		199.025	0	1502.143	n = 2,486
	within		117.688	-1043.33	1522. 384	T = 6.047
$distance\ CBD$	overall	4.038	1.935	.005	9.224	N = 17,526
	between		2.004	.005	9.224	n = 2,492
	within		0	4.0381	4.038	T = 7.032

3. Empirical analysis

3.1 Methodology

Panel vector autoregression originates from the vector autoregression (VAR) methodology (Sims 1980) but is applied on panel data instead of pure time series. A VAR model consists of a system of equations which are estimated simultaneously. Each variable in this system is explained by its own lags and lagged values of the other variables (Gravier-Rymaszewska 2012).

VARs have become very popular in applied empirical research mainly because they treat all variables as being endogenous and independent. No a priori theory of causal relations between the variables is required. Therefore PVARs are perfectly suited for our purposes: We do not need to derive comprehensive theoretical models which explain how transport leads the development of land, how developed land attracts transport or how both follow a co-development path. Neither do we need to formulate our empirical models in a rather ad hoc manner. PVAR enables us to estimate the effect simultaneously. Causality is allowed to run in any direction, from transport to urban development and from urban development to transport infrastructure (Konstantinos and Konstantinou 2011). Since we do not have a natural experiment but a period which is characterised by a battery of shocks – which reminds us of a rather macroeconomic set-up – the PVAR approach allows us to set up a model with only a small set of assumptions in order to interpret the impact of transport/development shocks.

Exploiting rich panel data sets, PVARs allow for unobserved individual heterogeneity. Even short panels improve asymptotic results as the sampling properties do not depend on the number of time-series observations but of cross-sectional observations (Gilchrist and Himmelberg 1999).

PVARs are still more popular in macro- than in microeconomic research. They have for instance been applied in analyses on monetary policy and investment behaviour (Love and Zicchino 2006, Assenmacher-Wesche and Gerlach 2008), the supply of development aid (M'Amanja and Morrissey , Osei, Morrissey et al. 2005, Gillanders 2011, Gravier-Rymaszewska 2012) or security economics (Konstantinos and Konstantinou 2011). In urban economics PVARs are not that commonly used yet. Exceptions are Miller and Peng (2006) who look for example into US housing price volatility as well

as Lee (2007) investigating the question whether the provision of public rental housing crowds out private investment. However, to the authors' knowledge this is the first paper applying PVAR in an intra-urban context.

Building on Holtz-Eakin, Newey et al. (1988) and Canova and Cicacarelli (2004) we specify a VAR as follows:

$$y_{i,t} = A_0 a_{i,t} + M_1 y_{i,t-1} + \cdots + M_p y_{i,t-p} + u_t \,, \qquad (4\text{-}1)$$

$$(i = 1, \dots, N; t = 1, \dots . T)$$

$$u_t = \mu_i + \nu_t + \varepsilon_{i,t} \qquad (4\text{-}2)$$

where $y_{i,t}$ is a κ x 1 vector of κ panel data variables, the $M's$ are κ x κ coefficient matrices of the lagged variables $y_{i,t}$, p denotes the number of lags and $a_{i,t}$ is a vector of deterministic terms (linear trend, dummy or a constant) with the associated parameter matrix A_0. The unobserved individual effect μ_i, the time effect ν_t and the disturbance term $\varepsilon_{i,t}$ jointly compose the error process u_t. We assume that u_t has zero mean, i.e. $E(u_t) = 0$, independent u_t's and a time invariant covariance matrix.

After having estimated the unknown parameters, the reduced form VAR allows us to run dynamic simulations. Impulse response functions (IRF) trace out how one variable reacts to shocks on another variable in the system, holding all other shocks equal to zero. In particular, we are interested in the reaction of urban development to transport shocks and vice versa. We then determine the importance of that particular shock by decomposing the variance.

Solving a system of multiple equations requires a careful VAR identification. To isolate the shocks in the IRF we need to orthogonalize the residuals. A common approach is to adopt a causal ordering of the variables in the VAR system based on economic reasoning (Choleski decomposition): The earlier a variable appears the presumably more exogenous it is. That means that *early* variables affect the following ones contemporaneously and with lags, whereas the *later* variables affect the previous variables only with lags.

Estimating a panel VAR imposes the restriction that the underlying structure is the same for each cross-sectional unit, meaning that all Berlin municipalities/city blocks have the same coefficient in the matrices M. However, in practice we would expect individual heterogeneity which would violate the aforementioned restrictions. In order to overcome this problem we introduce fixed effects μ_i in our model. But estimating (4-1) with fixed affects and applying the standard mean-differencing procedure generates biased estimates. This is because the fixed effects are correlated with the regressors due to the auto-correlated dependent variables (Arellano and Bond 1991, Arellano and Bover 1995, Blundell and Bond 1998). We therefore use forward-mean-differencing (also called Helmert transformation) to eliminate the fixed effects. This way we remove the mean of all future observations available for each municipality/block-time pair.[6] The Helmert transformation preserves the orthogonality between the variables and their lags which allows us to use the lags as instruments and estimate the coefficients by system GMM (Arellano and Bover 1995).

[6] See also Gilchrist and Himmelberg (1999), p. 257 f. for details.

We also time-demean the series by subtracting the mean of each variable computed for each spatial unit-year pair. This final transformation controls for time fixed effects ν_t.

For the analysis of the impulse response functions we need an estimate of their confidence bands. Standard errors for the IRFs are obtained by Monte Carlo simulations: We generate random draws of the VAR coefficients and recalculate the impulse responses using the estimated covariance matrix of the errors and the estimated coefficients. Repeating this procedure several times enables us to generate 5^{th} and 95^{th} percentiles of the distribution. These percentiles are then used as confidence intervals for the IRFs (Love and Zicchino 2006).

3.2 Empirical strategy

The empirical analysis follows a two-fold approach: Firstly, we look into the interaction between population and transport, secondly between land values and transport. Observing increased land values combined with depopulation in the centre would suggest an outbidding of people by firms and thus allows us to understand how urban land is used. Table 4.1 gives an overview of the two different approaches and samples used in the estimation.

Table 4.1: Twofold approach

				Sample	
Part	Method	Urban development indicator	Unit of analysis	Coverage	Time
1	Panel VAR	Population	Municipality	Gross Berlin	1870 - 1935
2	Panel VAR	Land values	Historical city block	Inner sample	1881 - 1914

The idea for the first part of our analysis originates from Levinson (2008). Levinson tests for Granger causality between population and transport development. Modelling rail density as station density, he tries to estimate the causal effect of rail density on population density (supply side driven) and the other way around (demand side driven), using 33 boroughs of London for a time period between 1871 and 2001. In contrast to Levinson (2008), we will not distinguish between different transport modes but treat the S-Bahn and U-Bahn networks as a combined network. As pointed out in section two, the two rails systems cannot be regarded as substitutes of each other. The light rail system was developed earlier and originates from inter-city connections. Conversely, the underground was built as public transport mode from the very beginning and runs through rather central areas. We will, however, distinguish between a core region and the periphery. We start with an exogenous distinction between the CBD and the periphery as defined by Leyden (1933). However, since a core region is a dynamic area which changes continuously over time, we depart from the assumption made by Levinson by allowing for a rather flexible distinction. Applying the total sample we interact our variables of interest with distance to CBD.

The PVAR model for the municipality sample then allows us to test the mutual relation between population and transport. However, this approach does only explain how people react to changes in the transport network. These results would hardly allow us to derive any adjustments in the actual land use pattern, i.e. we cannot really say how firms react and whether for instance an outbidding of residents occurs. Therefore, we extend Levinson (2008) by also looking into the interaction between land values and transport. Assuming that businesses strongly depend on agglomeration economies

in order to use land productively, they will pay a higher price for land as residents would do. They are therefore expected to outbid residents in the core who face a trade-off between commuting and space consumption. Overall, residents value density not as much as firms do, use land less productively and are thus only able and willing to pay a lower price. Therefore the relationship between land rents and transport development indicates how intense land is actually used. The interaction between population and transport as well as between land values and transport must neither be supply nor demand side driven but could also follow a co-development process where both sides affect each other.

In a first step we estimate PVAR model (4-1) with (i) $\{pop, railDens\}$ as a two-variable vector for $y_{i,t}$ and with (ii) $\{LV, railDens\}$ in the second one. Each variable in this system is explained by its own lags as well as by the lags of the other variables. We assume that there are no contemporaneous effects between rail infrastructure and population/land values due to sticky information/information delays (Inoue, Kilian et al. 2009) and physical contraints/"time-to-build effect" (Love and Zicchino 2006, Kilian 2011). The two PVAR models are estimated by system GMM[7] testing the hypotheses that one variable (Granger) causes the other variable (Holtz-Eakin, Newey et al. 1988). We derive the impulse response functions and variance decomposition for the different samples (total, core, periphery) to see how the variables react depending on their location.

Panel VAR estimation requires stationary variables since non-stationary data lead to inconsistent GMM estimates. There is a number of unit root tests like Levin, Lin et al. (2002), Im, Pesaran et al. (2003), Breitung (2000) etc. which test for stationarity. However, most of these tests are designed for long macroeconomic panels whereas our dataset is a rather short microeconomic one (N large, T small). We therefore apply a modified Fisher type test which combines the test results of testing each panel individually for a unit-root, either based on a Philipps-Perron or an Augmented Dickey Fuller test. As suggested by Choi (2001) for a large number of cross-sectional observations, we use the modified version of the inverse χ^2 transformation in order to test the null hypothesis of all panels having a unit root.

All aforementioned tests are first generation tests which assume cross-sectional independence, i.e. being independently and identically distributed across individuals. But particularly when working with spatial data this assumption is likely to be violated. Ignoring the problem of cross-sectional dependence could result into biased test statistics. We therefore additionally apply the second generation Pesaran (2007) test which allows for some form of cross-sectional dependence.

Unit root test as well as regression results are reported and discussed in the next part.

3.3 Results

We begin with the unit root tests. The test results are illustrated in Table 4.2. We run the individual unit root tests of the modified Fisher type test as Augmented Dickey Fuller (ADF) and as Philipps-Perron (PP) test. The inverse χ^2 transformed test statistic (Choi 2001) rejects the null hypothesis of all panels being non-stationary at a significance level of 1%. Only population at a municipality level is rejected at a 5% level. Hence, assuming cross-section independence the tests yield stationary series.

[7] We use the STATA routines `pvar` and `helm` by Inessa Love who developed the programs for their paper (Love and Zicchino 2006). The original programs are available at http://go.worldbank.org/E96NEWM7L0.

Table 4.2: Panel unit root tests.

			Choi (2001)		Pesaran (2003)
Panel	Variable		ADF	PP	
1	pop	test statistic	1.558**	3.0986***	-4.552***
		p-value	0.060	0.001	0.000
	$railDens$	test statistic	41.5964***	87.9883***	-4.646***
		p-value	0.000	0.000	0.000
2	lv	test statistic	120.8495***	190.833***	-
		p-value	0.000	0.000	-
	$railDens$	test statistic	17.9325***	125.3298***	-
		p-value	0.000	0.000	-

Notes: (1) Variables shown are logarithmised, time-demeaned and Helmert transformed, (2) lag length is chosen to be one based on significance, (3) ADF (PP) denotes a Fisher type test using Augmented Dickey-Fuller (Phillips-Perron), (4) results for the untransformed variables are not shown here; the tests for untransformed variables reject the unit root for all variables except population for ADF-Fisher and Pesaran test, (5) standard error in parentheses *** p<0.01, ** p<0.05, * p<0.1.

We then apply the Pesaran (2007) unit root test to control for potential cross-section dependence. The test rejects the null hypothesis of the series being non-stationary, $\mathrm{I}(1)$, for population and rail station density of the municipality-level dataset at a 1% level. Unfortunately, the city block sample is too short for performing a Pesaran unit root test. However, according to Sarafidis and Robertson (2009) the bias caused by potential cross-section dependence can be reduced when the series are time-demeaned prior the estimation. We find evidence for their proposition when comparing the Pesaran test results for the transformed with the results of the untransformed series of the longer municipality panel data.[8] We therefore expect the variables of the city block dataset to sufficiently fulfil the stationarity requirements, too, as we estimate the PVAR with time-demeaned and forward-mean-differed series.

Having confirmed the stationarity of our (transformed) series, we can now move on to the actual estimation of the PVAR. We begin our analysis by looking at the response of population to transport shocks. The main results of the 2-variable VAR are reported in Table 4.3 and Table 4.4. We first estimate the model for the total sample (column 1), followed by individual estimations of the subsamples for the core (2) and the periphery (3). Eventually we interact the endogenous variables with distance to CBD for the whole sample (4).

In all samples the population response to own shocks is positive, strong and stays relatively constant when moving from one sample to another. Focussing on the total sample in column (1), a positive shock to transport increases population at significance level of 5%. Figure 4.1 illustrates the respective impulse response functions for the total sample and the 5% error bands generated by Monte Carlo simulations. The transport shock raises population for roughly three time periods from whereon population stays at a constant level (see top right graph). We now estimate the impulse responses for the two subsamples separately. In the core population reacts negatively to a shock to

[8] The unit root test for the untransformed series are similar to the transformed ones. Only difference is that the null of being non-stationary cannot be rejected for population in the ADF-version of the modified Fisher type test and in the Pesaran one. Results are not reported due to space constraints but are available from the authors.

transport. The depopulation becomes stronger over time and a new level is reached after about five periods (top right graph in Figure 4.2). The outcome is in line with classic urban economic theory and firms are expected to outbid residents (population) in the CBD due to the improved accessibility. This explanation gets additional evidence when we restrict our estimation to the peripheral sample (column 3). The population response we observe is reversed; population reacts positively to a shock to transport. The evolution of the effect over time is comparable to the one in the total sample but stronger (top right graph in Figure 4.3). Residents bid out in the CBD relocate to the periphery. New transport infrastructure allows them to travel to the CBD and reduces commuting cost. We now depart from the exogenous determination of the core area by introducing binomial interaction terms between our endogenous variables and distance to CBD (in km; column 4). This specification reveals that the negative population response diminishes with distance to CBD. While total rail density drives out people in the CBD it attracts them again at a distance of about 2.35 km to the CBD (solid line in Figure 4.7). The subsample estimates as well as the flexible interacted version both yield similar and consistent results. Interestingly, the average distance from the CBD to the border of the core area indicated by Leyden is 2.32 km and thus very close to the estimates in column (4). The interacted model can therefore be also regarded as a robustness check.

We now approach the relation between transport development and population from the opposite direction (Table 4.4) and concentrate on the demand side driven relationship. If we derive theoretical implications from a reversed monocentric city model we would expect that residents living in the periphery demand public transport in order to lower their commuting costs while it is businesses in the CBD that demand an improved access to workers and customers. Hence, a positive response of station density to shocks is expected on the peripheral population and a negative one for the CBD. The results presented in Table 4.4 do actually tell a different story: Population does not have any statistically significant effect on station density, neither for the total nor for the subsamples. Adding the distance to CBD interaction terms does not lead to significant estimates either. These results are also confirmed by the impulse response functions (bottom left graphs of Figures 4.1, 4.2 and 4.3). The autocorrelation of the station density is a good indicator for persistency of the transport network due to the fact that the construction of railway tracks and stations is generally very time and cost intensive.

Table 4.3: Results for population PVAR model (dependent variable: population)

	(1) (total) pop	(2) (core) pop	(3) (periphery) pop	(4) (total) pop
pop_{t-1}	0.8004***	0.8184***	0.7920***	0.9471***
	(0.0302)	(0.0487)	(0.0314)	(0.0535)
$railDens_{t-1}$	0.0286**	-0.0859***	0.0359**	-0.0305**
	(0.0146)	(0.0197)	(0.0156)	(0.0176)
$pop_{t-1}\times distCBD^2$				0.0030***
				(0.0011)
$railDens_{t-1}\times distCBD^2$				-0.0006
				(0.0003)
$pop_{t-1}\times distCBD$				-0.0478*
				(0.0189)
$railDens_{t-1}\times distCBD$				0.01296*
				(0.0049)

Observations	1015	132	883	1015

Notes: (1) 1-lag VAR is estimated by GMM, (2) variables are estimated in logs, (3) variables are time-demeaned and Helmert transformed prior to estimation, (4) interacted model in last column estimated with six endogenous variables, (5) standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 4.4: Results for population PVAR model (dependent variable: station density)

	(1) (total) $railDens$	(2) (core) $railDens$	(3) (periphery) $railDens$	(4) (total) $railDens$
pop_{t-1}	-0.0293	-0.1393	-0.0217	-0.1638
	(0.0308)	(0.1182)	(0.0354)	(0.0869)
$railDens_{t-1}$	0.7448***	0.8028***	0.7392***	0.5226***
	(0.0787)	(0.0723)	(0.0838)	(0.0901)
$pop_{t-1}\times distCBD^2$				-0.0024
				(1.3794)
$railDens_{t-1}\times distCBD^2$				0.0007
				(0.0018)
$pop_{t-1}\times distCBD$				0.0423
				(0.0287)
$railDens_{t-1}\times distCBD$				0.0139**
				(0.0306)
Observations	1015	132	883	1015

Notes: (1) 1-lag VAR is estimated by GMM, (2) variables are estimated in logs, (3) variables are time-demeaned and Helmert transformed prior to estimation, (4) interacted model in last column estimated with six endogenous variables, (5) standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

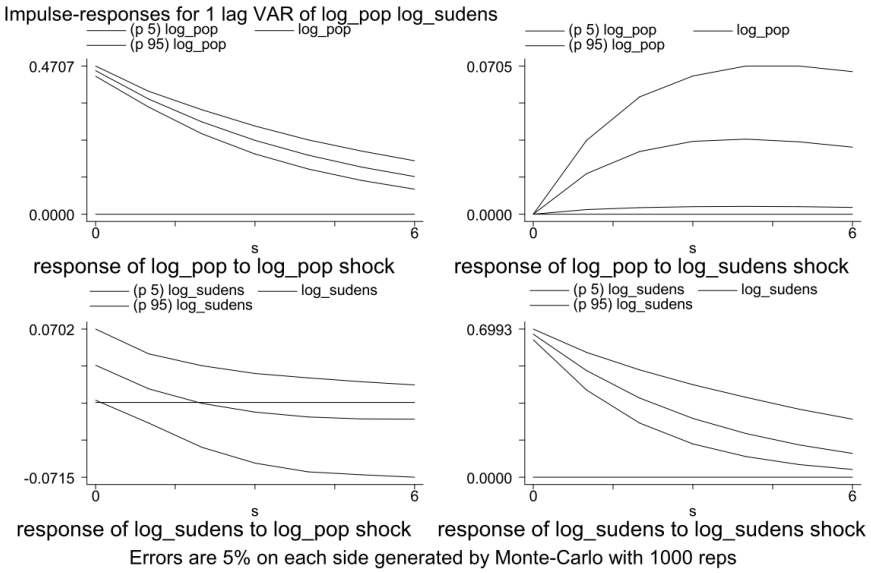


Figure 4.1 Impulse responses for total sample (population model).

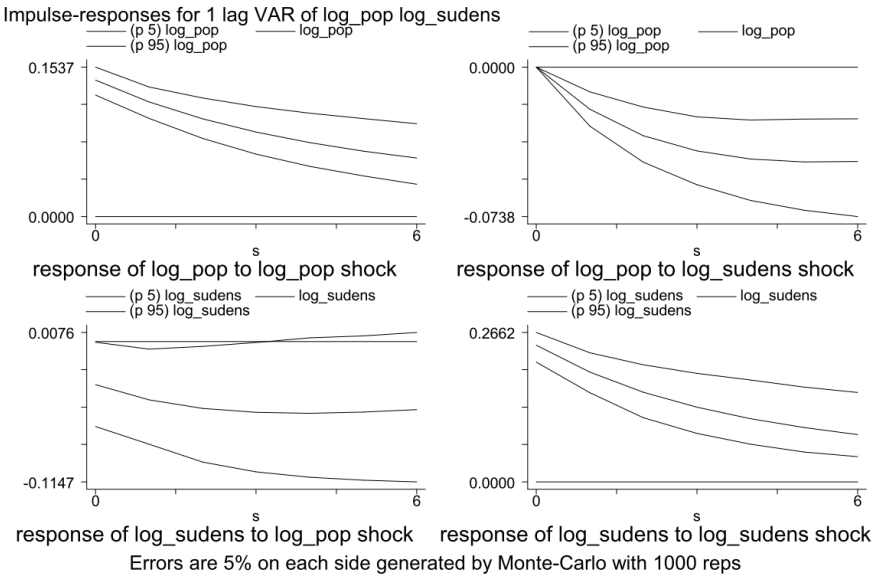


Figure 4.2 Impulse responses for core sample (population model).

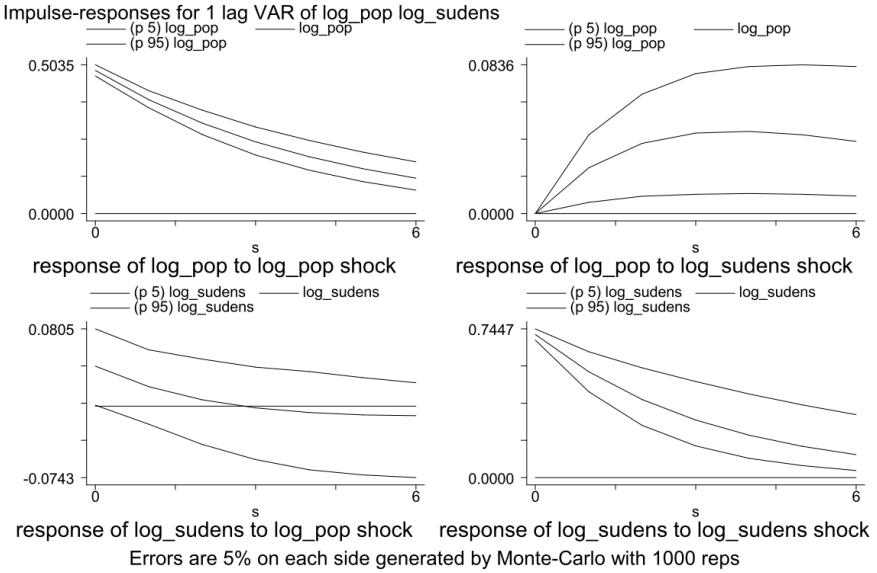


Figure 4.3 Impulse responses for periphery sample (population model).

The estimates reject the hypothesis of demand side driven transport development for the population approach. This suggests that the relation between transport and land development is purely driven by supply and resident's bargaining power is too weak to attract transport. Another explanation could be that the core is completely abandoned by people and firms for unobserved reasons. Hence, expecting a negative causal relationship in the core in order to predict firm's demand for transport might not be sufficient to draw any conclusions regarding the reaction of economic agents to transport shocks. We therefore extend Levinson (2008) by using standard land values to describe land development in the second part of our analysis.

Table 4.5: Results for land value PVAR model (dependent variable: land values)

	(1) (total) $lnLV$	(2) (core) $lnLV$	(3) (periphery) $lnLV$	(4) (total) $lnLV$

$lnLV_{t-1}$	0.5292***	0.5241***	0.5145***	0.2686***
	(0.0124)	(0.0254)	(0.0135)	(0.0537)
$railDens_{t-1}$	0.1571***	0.0758***	0.1996***	0.3181***
	(0.0134)	(0.0147)	(0.0185)	(0.0379)
$LV_{t-1}\times distCBD^2$				-0.0174***
				(0.0025)
$railDens_{t-1}\times distCBD^2$				0.0236***
				(0.0028)
$LV_{t-1}\times distCBD$				0.1434***
				(0.02389)
$railDens_{t-1}\times distCBD$				-0.1599***
				(0.0244)
Observations	7759	1992	5767	7759

Notes: (1) 1-lag VAR is estimated by GMM, (2) variables are estimated in logs, (3) variables are time-demeaned and Helmert transformed prior to estimation, (4) interacted model in last column estimated with six endogenous variables, (5) standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

We begin the second part of our analysis by estimating the VAR with land values and station density as endogenous variables and in particular we begin with the response of land values to shocks on the rail transport sector. The results are reported in Table 4.5. In all samples the dependent variable is auto correlated, i.e. past land values partially explain present values. Turning to the variable of interest, land values respond positively to shocks to station density. The shock induced land value growth reaches its maximum after two periods (top right graph in Figure 4.4). Then the effect declines again. However, the decay of the impulse response function becomes smaller after the maximum is reached indicating a slow ebbing away of the transport shocks. The effect is slightly stronger in the periphery (column 3) than in the core (column 2). The IRFs for the subsamples follow a similar pattern (top right graph in Figures 4.5 and 4.6). Finally, we interact the endogenous variables with distance to CBD again using polynomials up to order two (column 4). Land values still respond positively to transport over the entire geographical coverage. The effect becomes smallest at a distance of 3.4 km to the CBD (dashed line in Figure 4.7). Very central and very peripheral areas hence experience the highest rise in land values. This can be explained by the fact that transport improvements have the biggest impact in the very CBD probably due to agglomeration economies and in the periphery due to commuting reduction. As already indicated by the subsample estimations the effect seems to be slightly stronger in the periphery than in the CBD.

Table 4.6: Results for land value PVAR model (dependent variable: station density)

	(1) (total) $railDens$	(2) (core) $railDens$	(3) (periphery) $railDens$	(4) (total) $railDens$
$lnLV_{t-1}$	0.0788***	0.5705***	0.0733***	1.0039***
	(0.0061)	(0.0278)	(0.0082)	(0.0526)
$railDens_{t-1}$	0.7377***	0.6413***	0.6767***	0.5734***
	(0.0235)	(0.0221)	(0.0304)	(0.0371)
$LV_{t-1}\times distCBD^2$				0.0279***
				(0.0021)

$railDens_{t-1} \times distCBD^2$				-0.0069***
				(0.0025)
$LV_{t-1} \times distCBD$				-0.3301***
				(0.0207)
$railDens_{t-1} \times distCBD$				-0.0505***
				(0.0213)
Observations	7759	1955	5767	7759

Notes: (1) 1-lag VAR is estimated by GMM, (2) variables are estimated in logs, (3) variables are time-demeaned and Helmert transformed prior to estimation, (4) interacted model in last column estimated with six endogenous variables, (5) standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

The responses of the reverse shocks are illustrated in Table 4.6. Transport's autocorrelation is high in the land value model, too. If bargaining or purchase power is associated with high valued areas, higher land values are expected to attract rail developers. New lines demanded by residents and firms would be constructed. In fact, the VAR estimates yield a positive response of station density to shocks to land values for all the samples. What is worth noting is that particularly in the CBD rail developers respond to high land values. These findings can also be found when looking at the impulse response functions (bottom left graphs in Figures 4.4 to 4.6). Moreover, transport infrastructure responds immediately (strong positive decay for the first two periods and a positive intercept) to land value shocks. After the second period the transport reaction slowly diminishes over time. Finally, we add interaction terms to the model again. The transport response stays positive independent from the distance to CBD (dotted line in Figure 4.7). The reaction is minimised at a distance of 5.9 km to the CBD though. As already noted for the subsample estimates the response of station density to land value shocks is generally higher in the core region.

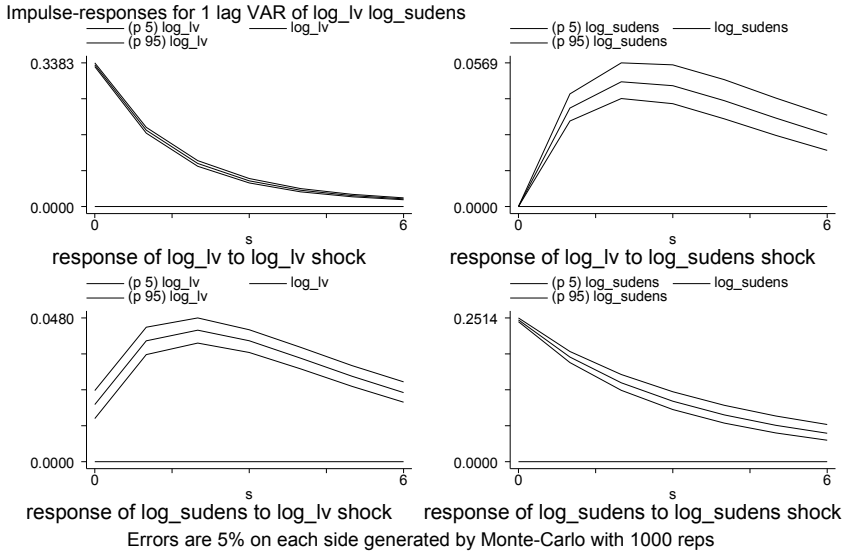


Figure 4.4 Impulse responses for total sample (land value model).

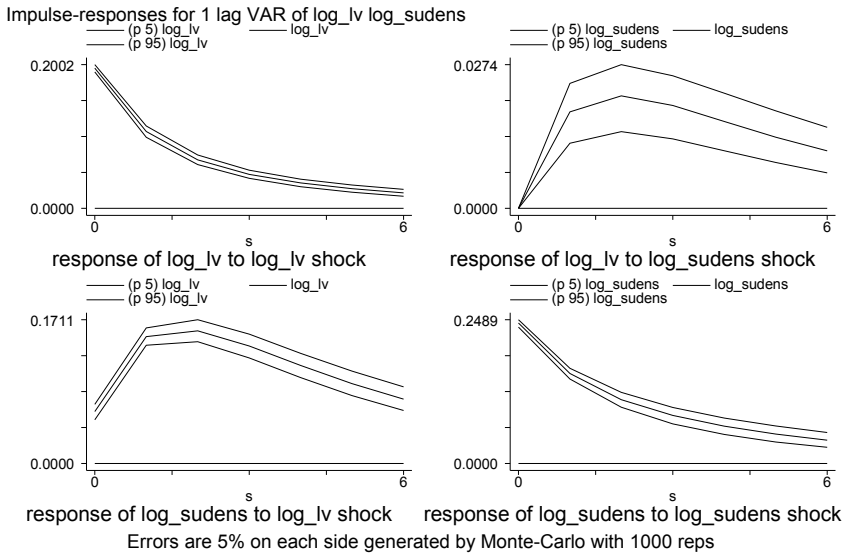


Figure 4.5 Impulse responses for core sample (land value model).

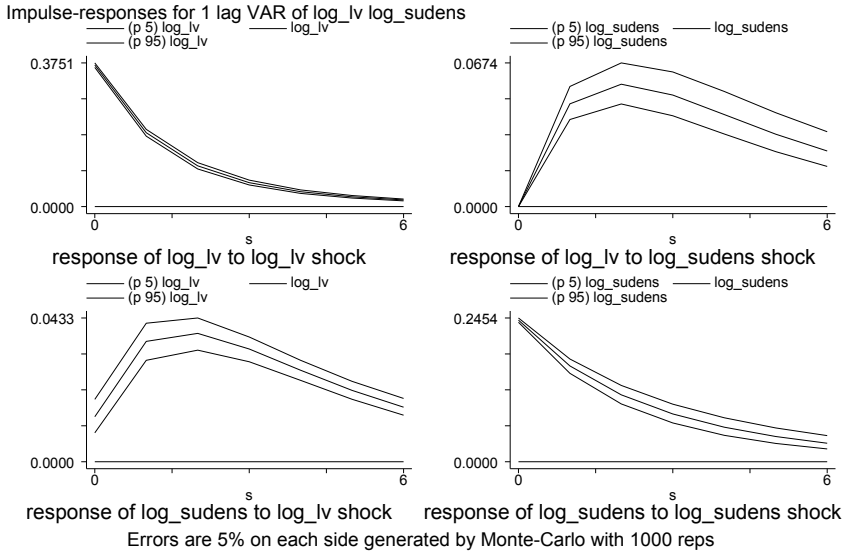


Figure 4.6 Impulse responses for periphery sample (land value model).

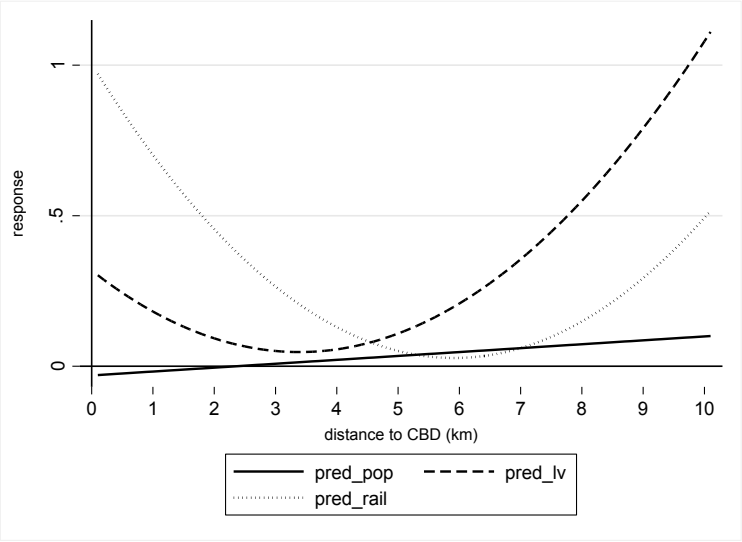


Figure 4.7: Average responses (distance to CBD in km).

We are now turning to the variance decompositions (Table 4.7) for the two different models to see which shocks are most important in explaining a variable through time. Population hardly explains variation in rail station density 10 periods ahead in the total sample (0.3%), whereas transport explains about 1.4% of the population variation. Looking at the subsamples, explanation power is much higher in the core for both models. Here station density explains about 17.5% of the population variation but only 2% in the periphery. Thus, the relationship between transport development and population is much stronger in the CBD than in the periphery.

The variance decomposition of the city block sample gives a similar picture. Explanation power of the transport variation is significantly higher in the core again. In general, land values explain the variation in rail density better than the other way around. In the core almost 49% of transport variation is explained, in the total sample still about 6%. Nevertheless, one should not ignore the impact of transport on the land values either. With twice the explanation power compared to the core transport still explains more than 6% of land value variation in peripheral areas.

Table 4.7: Variance-decompositions

		pop	$railDens$		lv	$railDens$
Total	pop	0.986	0.014	lv	0.935	0.065
	$railDens$	0.003	0.997	$railDens$	0.059	0.941
Core	pop	0.825	0.175	lv	0.969	0.031
	$railDens$	0.129	0.871	$railDens$	0.487	0.513
Periphery	pop	0.980	0.020	lv	0.937	0.063
	$railDens$	0.002	0.998	$railDens$	0.050	0.950

Notes: Percent of variation in the row variable explained by column variable (10 periods ahead).

Price anticipation

Based on the population sample estimates we would generally expect a relatively strong supply side driven relation between land values and transport. However, the land value sample estimations and especially the variance decomposition suggest a stronger causality running from land values to rail station density than the other way around. This could be due to the fact that information enter the market in advance and prices adjust directly after the construction of a new line has been announced. Investors anticipate a future rise in land values and the values increase already before the station has officially been inaugurated. Since we look at the reaction of current land values (t) to a lagged shock to station density ($t-1$) we miss any price adjustment which occurs already prior to t. To control for anticipation effects we re-estimate the land value PVAR model using announced station density instead of actual station density.[9] This approach enables us to overcome the identifying restriction of having no contemporaneous effects. We rely on the assumption that it takes (at least) one period to move from an announced to a constructed station (see Figure 4.8). However, using announced station density only serves as an appropriate estimation strategy for the supply-side driven relation. In the demand-side driven model, the adjustment period would not be shortened but extended by one additional period. Therefore we only focus our analysis on the supply side driven relation and move the remaining results to the appendix.

[9] Despite our view that population generally responds in a rather lethargic way and does not adjust as quickly as prices do, we also estimate a population anticipation model. The results are reported in the appendix.

Supply side Demand side

Figure 4.8: Price anticipation model.

The anticipation approach requires a careful collection of all announcement dates for each station constructed during our observation period. We use the first construction year for stations we do not find any information on the announcement date for.[10]

We need to re-run the unit root tests for the updated land value sample. Like the other variables announced station density, $An\_railDens$, is stationary when being time-demeaned and Helmert transformed (see Table 4.8).

Table 4.8: Panel unit root test (announced station density)

			Choi (2001)	
Panel	Variable		ADF	PP
2	$An\_railDens$	test statistic	40.7091***	222.4868***
		p-value	0.000	0.000

Notes: (1) Variables shown are logarithmised, time-demeaned and Helmert transformed, (2) lag length is chosen to be one based on significance, (3) ADF (PP) denotes a Fisher type test using Augmented Dickey-Fuller (Phillips-Perron), (4) results for the untransformed variables are not shown here, (5) standard error in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Interpreting Table 4.9 land values are still highly auto-correlated for the three geographical samples (total, core and periphery). The coefficients are slightly larger than in the base line regressions. Conversely, land values respond significantly weaker to announced station density whereas the coefficient is somewhat larger in the periphery. Looking at the impulse response functions (top right graphs in Figure 4.8, 4.9, 4.10), the shock induced land value growth already reaches its maximum after the first period. The response completely ebbs away over the displayed six periods. All three geographical samples share a similar IRF pattern. In the base line regression with actual station density the land value response is more persistent. As before we interact our endogenous variables with distance to CBD (column 4). The predicted response shapes a parabola which looks like a downward shifted version of the baseline land value predictions (Figure 4.11). The positive land value effect declines with distance to CBD, is negative between 2 and 4.5 km and rises with greater distance again. Apart from the negative part the pattern is comparable to the baseline model.

Table 4.9: Results for price anticipation PVAR model (dep. variable: land values)

	(1) (total) $lnLV$	(2) (core) $lnLV$	(3) (periphery) $lnLV$	(4) (total) $lnLV$

[10] We make use of the following sources for the research on the announcement dates of new stations: Dudczak and Dudczak (2012), Kurpjuweit and Meyer-Kronthaler (2009), Mauruszat (2011), Loop (Untergrundbahn), Luisenstädtischer Bildungsverein e.V. (2012), Senatsverwaltung für Stadtentwicklung und Umwelt (2012) and Straschewski (2011).

$lnLV_{t-1}$	0.5473***	0.4724***	0.5460***	0.1317***
	(0.0120)	(0.0301)	(0.0126)	(0.0617)
$An\_railDens_{t-1}$	0.0369***	0.0257***	0.0431***	0.2049***
	(0.0064)	(0.0071)	(0.0083)	(0.0204)
$LV_{t-1}\times distCBD^2$				-0.0266***
				(0.0026)
$An\_railDens_{t-1}\times distCBD^2$				0.0242***
				(0.0017)
$LV_{t-1}\times distCBD$				0.2202***
				(0.0259)
$An\_railDens_{t-1}\times distCBD$				-0.1537***
				(0.0128)
Observations	7590	1955	5635	7590

Notes: (1) 1-lag VAR is estimated by GMM, (2) variables are estimated in logs, (3) variables are time-demeaned and Helmert transformed prior to estimation, (4) interacted model in last column estimated with six endogenous variables, (5) standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

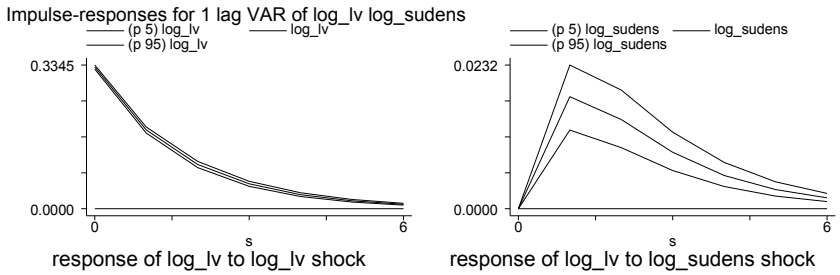


Figure 4.8 Impulse responses for total sample (price anticipation model).

Comparing the variance decompositions of the baseline model with the anticipation one (Table 4.11), announced station density hardly explains variation in land values ten periods ahead. With 0.4% of total variation in the total sample (0.6% in the core) the magnitude of the influence is negligibly small.

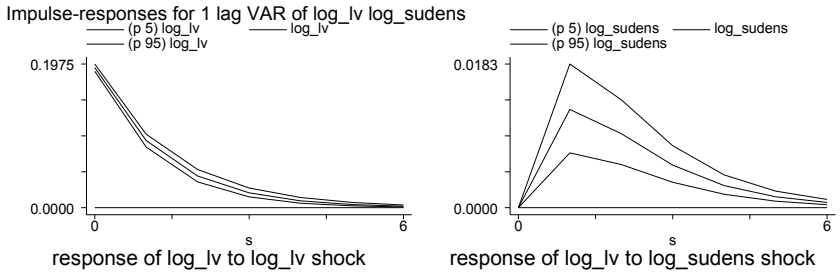


Figure 4.9 Impulse responses for core sample (price anticipation model).

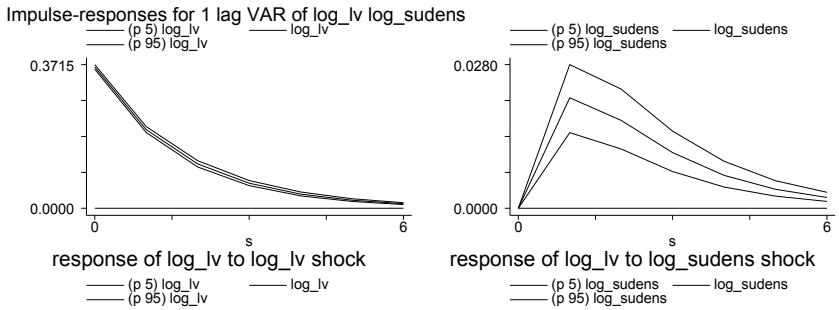


Figure 4.10 Impulse responses for periphery sample (price anticipation model).

Table 4.11: Variance-decompositions of the two land value models

		lv	$railDens$		lv	$An\_railDens$
Total	lv	0.973	0.027	lv	0.996	0.004
Core	lv	0.949	0.051	lv	0.994	0.006
Periphery	lv	0.974	0.026	lv	0.995	0.005

Notes: Percent of variation in the row variable explained by column variable (10 periods ahead).

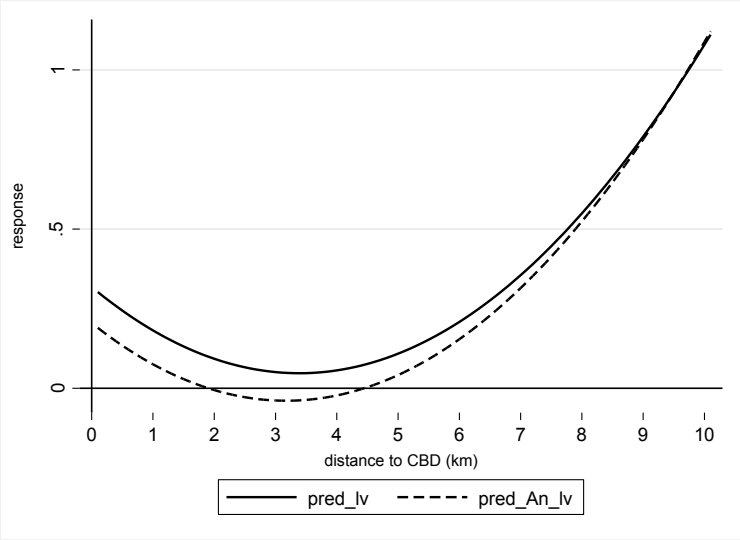


Figure 4.11: Average land value responses in price anticipation model (distance to CBD in km).

The estimates of the price anticipation model might suffer from a sample selection bias as we could not get information on the announcement data for all stations which we the proxied by the start date of a station's construction. Moreover, the assumption that it takes one period to move from an announced to a constructed station might also be violated. We therefore apply two artificial price anticipation models where we simply shift the land value data by one period from t to $t-1$ and in another model from t to $t-2$. A more detailed explanation of the models applied and its estimates is given in the appendix. The two artificially constructed models basically confirm our main results. There are some anticipation effects indicating that land values immediately react to transport shocks. Nevertheless, the magnitude of the adjustment is small when being compared to the baseline model.

By estimating the price anticipation model we have hypothesised that land values adjust immediately to changes in the transport network. We have regarded this as a potential explanation for the unexpectedly weak supply side driven response of land values in the original land value regression. The estimates, however, suggest the opposite: The anticipated land value effect is considerably low; economic agents wait for a new line to be developed first. Price anticipation and baseline model jointly indicate a co-development process, but with transport rather following land values than the other way around.

We finally control for different land use types to see whether the co-development between land value and transport is either driven by firm or residential demand/supply. Land use data and results are explained and interpreted in greater detail in the appendix. The distinction by land use confirms a co-development between land values and transport, too. The strong positive transport response to land value shocks in the core can partly be explained by the firms located in the CBD. However, in the periphery transport follows high priced areas as well. The location of transport is therefore neither determined by only firms nor by only residents. It is the location of firms and residents that matters.

An alternative robustness check involved a Granger causality test of the causality direction between transport and population/land values in a single equation set-up with dynamic panel data. This rather ad hoc approach involves estimating the models once with the transport variable as dependent variable and then a second time reversing them by having the urban development indicator on the left hand side. The Granger causality test is closely related to Levinson (2008) and has also been used by Cervero and Hansen (2002) as a robustness check. The idea is that a variable x has a Granger causal effect on y if a model for y performs better when the lags of y and x are included than only past values of y. We follow Arellano and Bond (1991) in the estimation process. The estimates generally support our aforementioned results and are moved to the appendix.

These mixed findings require are careful interpretation: Population as well as land values react to transport shocks. The transport sector leads the urban development process, especially the population one. Conversely, transport reacts only to land values but not to population. We have seen that rail stations (densities) are rather located in core than peripheral areas as indicated by the strong response to high land values and the spatial pattern of the effect.

Public transport lines are generally built for commuting, i.e. linking the two types of economic agents in a city. If we assume transport companies being private enterprises the routing of a new line must be planned under the consideration of future returns.[11] These investments require a lot of capital and above all a critical mass of potential passengers. The estimates illustrate that new lines are therefore not built into undeveloped areas. An increase in land values reflects an upgrade in land use; transport follows into developing areas. In fact, commuting requires the lines to be connected to employment centres.

Going back to the history of Berlin (top map in Figure 2.1) we observe that all initial railways originate in the core and then leave radially into the periphery. There is, however, no transport line which runs only through the periphery. Prominent examples are today's underground lines U1 and U2. They were the first underground lines in Berlin and initially planned for public transport. The two

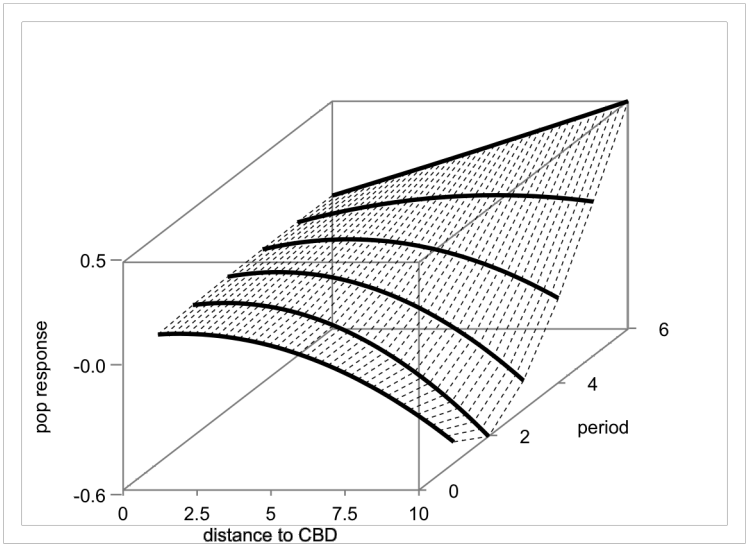
[11] Even subsidised enterprises will follow profit maximisation.

lines were opened between 1902 and 1914 and run through the historic CBD with stations like “Stadtmitte” (“city centre”, opened in 1908) and to a secondary economic centre which developed itself around Kurfürstendamm in the west of the historic CBD (Bousset 1935, Ahlfeldt, Nitsch et al. 2011).

The interaction between transport and population is only supply side driven. But in consideration of the land value models we conclude that the provision of transport infrastructure is not completely exogenous. Lines are not built in the middle of nowhere but need to connect developed areas in order to generate returns. Nevertheless, new lines have highly influenced the structuring and the development of Berlin.

Our impulse responses have a time as well as a spatial component (distance to CBD). Figure 4.13 illustrates the individual impulses for each period interacted with distance to CBD. The graphs allow us to see how the shocks spatially diffuse over time. Even though the main model, the IRF results as well as the predictions, yield a population increase in the periphery as response to a transport shock, we can see from the figure (top graph) that this response varies over time. In the short-run population reacts negatively with greater distance to the CBD. It takes more than four periods until the effect is positive in the periphery. The middle graph illustrates the land value response to transport shocks over time and space. The effect is stronger in the periphery but positive throughout the entire city as also suggested by the IRFs above. Overall, the spatial and time response can be considered to be relatively homogeneous. Finally, the transport response to shocks to land values is positive in the first periods in the core and negative in the periphery (bottom graph). This relation swops around over time but declines in power.

Based on these observations, land values spatially diffuse quicker than population does. This result is not surprising as land values result from demand and supply and are thus rather are theoretic concept. Population, however, is a physical good and responds inertially to shocks. This exercise enables the planner to get a more distinct picture of how transport and development interact over time and space. Shocks can be amplified or dampened. However, it would be interesting to repeat this task for other cities to see whether common patterns exist or are individual to each city.



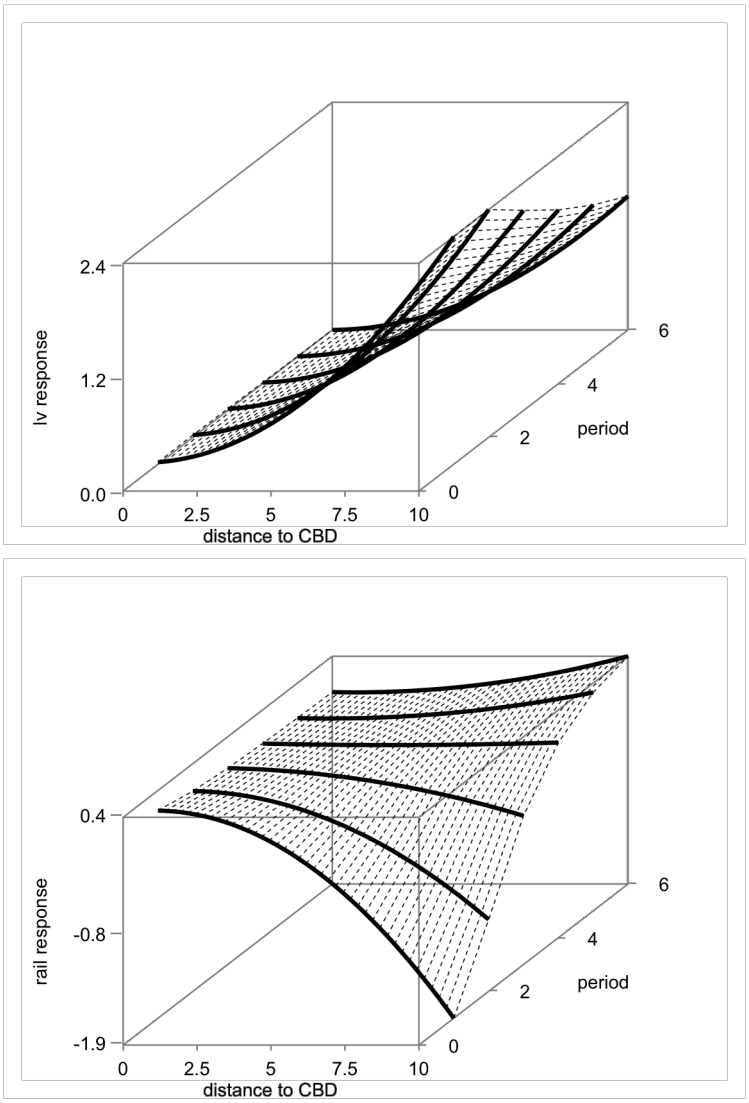


Figure 4.13: Impulse responses over time and space.

4. Conclusion

The intention of this paper has been to provide a new and purely empirical perspective on the chicken-and-egg-problem of transport economics. We have argued that either transport leads urban development (supply side driven) or conversely that transport follows development (demand side driven). Alternatively, transport and land development could also follow a co-development process. We propose a panel VAR approach employing a unique data set for historic Berlin between 1870 and 1936. We argue that it is of a planner's interest to not only incorporate the supply side driven relationship but also the demand sided one. Our atheoretical approach is based on the assumption that an in practice it becomes rather difficult to construct a comprehensive model that fully reflects all mutual interactions and turn the chicken-and-egg-problem into a purely empirical question. The PVAR treats all variables endogenously and allows us to estimate the underlying adjustment processes simultaneously. Not only looking at the effect of/on population, we extend recent literature by additionally investigating the interaction between transport and land values. As information about new transport lines could directly enter the market we additionally estimate a price anticipation model using announced rail station density instead of actual one. The population

and the two land value models combined allow us to derive a more distinct picture of economic agents' reactions to changes in the transport network and thus the effect on urban development. Moreover, we find the a priori and time invariant determination of a core area to be problematic and suggest a rather flexible distinction.

Our estimates yield a supply side driven relationship between transport improvement and population. While in the CBD increased rail density drives people out, they are attracted by better commuting possibilities in the periphery. Land values and transport are characterised by a positive reciprocal relation where land values influence transport more strongly than vice versa.

We conclude that the provision of transport infrastructure is not exogenous. On the one hand, new lines fostered and structured the development of Berlin but on the other hand, lines were not built in the middle of nowhere. We justify these results by the fact that commuting involves the connection to at least one employment centre by definition. Therefore transport lines are always somehow connected to developed areas characterised by high land values. Moreover, we observe only small price anticipation effects. Rail developers are not fully risk-loving. We finally illustrate the time as well the spatial pattern of the different shock induced impulses. We note that this exercise enables the planner to get a more distinct picture of how transport and development interact over time and space.

Our results do not reject theoretical or empirical models which reflect only the supply or only the demand side driven relationship between transport and development. It adds to the literature by filling a lack of studies investigating the two circular causative effects simultaneously. It would be interesting to repeat this task for other cities to see whether common patterns exist or are individual to each city.

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