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Ease Versus Noise: Long-Run Changes in the Value of Transport (Dis)amenities

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E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Abstract
For a complete cost-benefit analysis of durable infrastructures, it is important to understand how the value of non-market goods such as transit time and environmental quality changes as incomes rise in the long-run. We use difference-in-differences and spatial differencing to estimate the land price capitalization effects of metro rail in Berlin, Germany today and a century ago. Over this period, the negative effect of rail noise tripled in percentage terms. Our results imply long-run income elasticities of the value of noise reduction and transport access of 2.2 and 1.4, substantially exceeding cross-sectional contingent valuation estimates.

Key words: accessibility, spatial differencing, noise, difference-in-differences, income elasticity, land price
JEL Codes: R12; R14; R41; N73; N74

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1 Introduction

Understanding how the values of locational amenities and disamenities change as incomes rise is crucial for optimal decisions regarding investments with long-term consequences. A typical example are investments in transport infrastructure, which are often undertaken publicly following cost-benefit analyses (CBA). The evidence from cross-sectional survey-based contingent valuation research suggests that the income elasticity of the value of noise reduction is positive, but less than unity (Wardman et al. 2005). The value of travel time is typically set to a fraction of the wage rate (Anderson 2014; Parry & Small 2009), which implies a unity income elasticity, but a lower elasticity has been recently suggested (Börjesson et al. 2012). It is not clear, however, whether these estimated short-run elasticities generalize to long-run comparisons. Intuitively, the intertemporal income elasticity should be larger than unity if locational amenities and disamenities are non-necessities as typically conjectured in the literature (Brueckner et al. 1999; Glaeser et al. 2001). As real incomes rise, (dis)amenity values should then rise more than proportionately, implying that in appraisals of durable infrastructures costs and benefits need to be inflated rather than deflated to reflect demand by future generations. To date, there is little evidence to substantiate this intuition. There is at best indirect evidence in that public spending tends to increase more than proportionately in GDP, suggesting that public services, broadly defined, are luxury goods (Wagner's law, see Lamartina & Zaghini 2011; Ram 1987; Wagner 1890).

In this paper, we take a step towards filling this gap by providing the first long-run comparison of transport amenity and disamenity capitalization effects in land prices over a period as long as a century. Theoretically, besides the amenity of offering improved access, there are a range of transport-related disamenities, including congestion, pollution, and noise, which can affect outcomes such as productivity, health, and annoyance levels (Navrud, 2002). Our focus on accessibility and noise effects is driven by the empirical setting we exploit. We choose to evaluate land price capitalization effects of metro rail (*U-Bahn*) in Berlin, Germany, due to the availability of historical and contemporary property data and a transport technology that has remained approximately constant since the system's inauguration in 1902. The system is fully electrified and has exclusive right-of-way, so that the effects on pollution and road congestions are rather negligible. We find little evidence for a negative view effect, so that noise from the elevated parts of the system is arguably the primary disamenity. Our property data covers commercial and residential property; therefore, our estimated capitalization effects reflect productivity and (dis)utility effects. They likely exclude health effects given that the public awareness of noise-induced health impacts is limited (Navrud, 2002). In line with the worldwide trend, real income in Germany has increased at a rate of 2% per year since 1900, accumulating to an overall increase of about 650%.[1] Our setting, thus, allows us to compare the valuation of rail access and rail noise on real estate markets in a historical low-income scenario and a contemporary high-income scenario.

[1] Own calculations using data from the Maddison Project (Bolt & van Zanden 2014). The 2% annual growth generalizes to the mean across a sample of 170 countries. See appendix section 3.1 for details.

Our contribution is facilitated by a rather unique combination of suitable micro-geographic data at the turns of the 19th (1881-1914) and the 20th centuries (1990-2012). For our analyses, we digitize a series of historical maps, compiled by the chartered surveyor Gustav Müller, which provide information on land prices as detailed as to the level of individual parcels.[2] We complement these historical data with a confidential contemporary micro data set covering a complete record of property transactions. With these data at hand, we estimate that over the course of the 20th century, the land price capitalization effect of a 10-decibel decrease in rail noise increased from 4.2% to 13.0%. Accounting for the increase in the share of land in the value of housing over the same period, we infer a capitalization effect in house-price terms that increased from 1% to 4%. The land price capitalization effect of a one-kilometer reduction in distance from the nearest metro rail station, a measure that captures the value of the associated walking time (Gibbons & Machin 2005), decreased from 20.2% to15.5%. However, because the land share increased substantially over the same period, this decrease implies a sizable increase, from 3.6% to 5.0%, in terms of house-price capitalization.

These results suggest that the value attached to rail access and even more so to the disamenity from rail noise has increased over time. One interpretation is that access and a quiet environment are luxury goods on which recent generations are willing to spend more as they are richer. Making admittedly strong assumptions, we use our estimated capitalization effects to derive novel estimates of the long-run income elasticities of the amenity value of accessibility and the disamenity value of noise of 1.4 and 2.2, respectively. While we acknowledge that significant uncertainty surrounds these estimates, on balance, they likely represent lower bounds.

On top of these main insights, we contribute to the literature in several more specific respects. First, we contribute to a vast literature in the tradition of Oates (1969) that has inferred the value of non-marketed goods from house price capitalization, including clean air (Chay & Greenstone 2005; Hanna 2007), health risk (Currie et al. 2015; Davis 2004), proximity to hazardous waste sites (Greenstone & Gallagher 2008) or nuclear power plants (Tanaka & Zabel 2018), crime risk (Linden & Rockoff 2008), public school quality (Cellini et al. 2010), energy efficiency (Walls et al. 2017), aircraft noise (Boes & Nüesch 2011; Ahlfeldt & Maennig 2015), road noise (Graevenitz, 2018), wind farms (Gibbons 2015) or transport access (Gibbons & Machin 2005). We add to this literature by showing that within the same spatial context, capitalization effects of the same (dis)amenities can vary sizably in the long-run due to changes in consumer preferences.

[2] To our knowledge, the only comparable historic data are from Olcott's land values blue book of Chicago and suburbs, published regularly by G. C. Olcott's & Co., Inc. from the 1910s to the 1990s. The construction of the core of Chicago's metro rail system (the L), however, precedes this period.

Second, we enrich a literature on rail access capitalization effects that has recently shifted from the use of cross-sectional variation to the use of variation over time to improve identification (see Dubé et al. 2013 and appendix section 2 for a review). We expand on this line of research by proposing a novel weighted difference-in-differences (DD) estimator, which minimizes the conditional correlation between pre-announcement trends in the outcome variable (land prices) and multiple continuous treatment variables (proximity to the station and rail noise). Consequently, we minimize the risk that unobserved *trends* in property prices correlated with station access or rail noise confound our estimates.

Third, we also add to a literature on noise capitalization effects that, with few exceptions concerning the analysis of aircraft noise (Ahlfeldt & Maennig 2015; Boes & Nüesch 2011), has employed cross-sectional designs. The literature on rail noise effects is particularly underdeveloped (see Navrud 2002 and appendix section 2 for a review). Our spatially highly disaggregated, micro-geographic data sets allow us to exploit the relatively sharp change in rail noise that arises where a track enters a tunnel to vanish beneath the surface, a source of variation that has not been previously exploited in the literature. The spatial differencing (SD) approach used to assess the causal effect of noise on the price of adjacent land parcels in our contemporary analyses represent an improvement in terms of identification compared to the extant literature. Our novel estimate of the effect of a one-decibel increase in rail noise on house prices of -0.4% is close to recent estimates pointing to an aircraft noise effect of -0.5% to -0.6% (Ahlfeldt & Maennig 2015; Boes & Nüesch 2011) and a road noise effect of -0.1% to -1.4% (Graevenitz, 2018; J. P. Nelson, 2008 reports a central estimate of -0.57%).

Fourth, we explicitly disentangle the positive effects of rail access from the negative effects of rail noise in a causal analysis of rail capitalization effects. Therefore, we go beyond most of the existing work that typically focuses on the aggregate (or net) effect of countervailing rail externalities. In doing so, we also examine the degree of bias that arises when accessibility effects are estimated without controlling for noise effects and vice versa.

Fifth, we provide one of the few analyses of rail capitalization effects into land prices (e.g. Ahlfeldt, Moeller, et al. 2015; Coffman & Gregson 1998), whereas most previous studies have looked at price responses of properties or housing units. The analysis of land prices comes with the advantage of not having to control for structural characteristics. In addition, because land is scarce in an urban context and provided (almost) inelastically, adjustments in land prices can be assumed to be purely driven by demand. The analysis of house price effects, in contrast, may be mitigated by supply responses if the demand curve is locally downward sloping because of imperfect mobility and idiosyncratic location preferences (Hilber & Vermeulen 2015).

Last but not least, we provide a case study which illustrates that, due to the increase in noise aversion, the case for the construction of underground metro rail as opposed to elevated metro rail is much stronger today than in the past. In doing so, we also provide novel auxiliary findings that are interesting in their own right. We estimate the per-kilometer cost of an underground metro line at the beginning of the 20th century to be three times that of an elevated line, which is substantially larger than the contemporary rule-of-thumb factor of two. We also find that, over a period of about 130 years, the average annual nominal land price growth rate was about 5% in Berlin and, therefore, typically within the range of the opportunity cost of capital (central bank interest rates).

The remainder of the paper is organized as follows. In Section 2, we discuss the context of our study, present our data, and introduce a simple theoretical framework that will guide the interpretation of the parameters we estimate. Section 3 presents the historical analysis, followed by the contemporary analysis in Section 4. In Section 5 we relate the historical and contemporary estimates to each other and discuss policy implications. Finally, Section 6 provides our conclusions.

2 Empirical and theoretical context

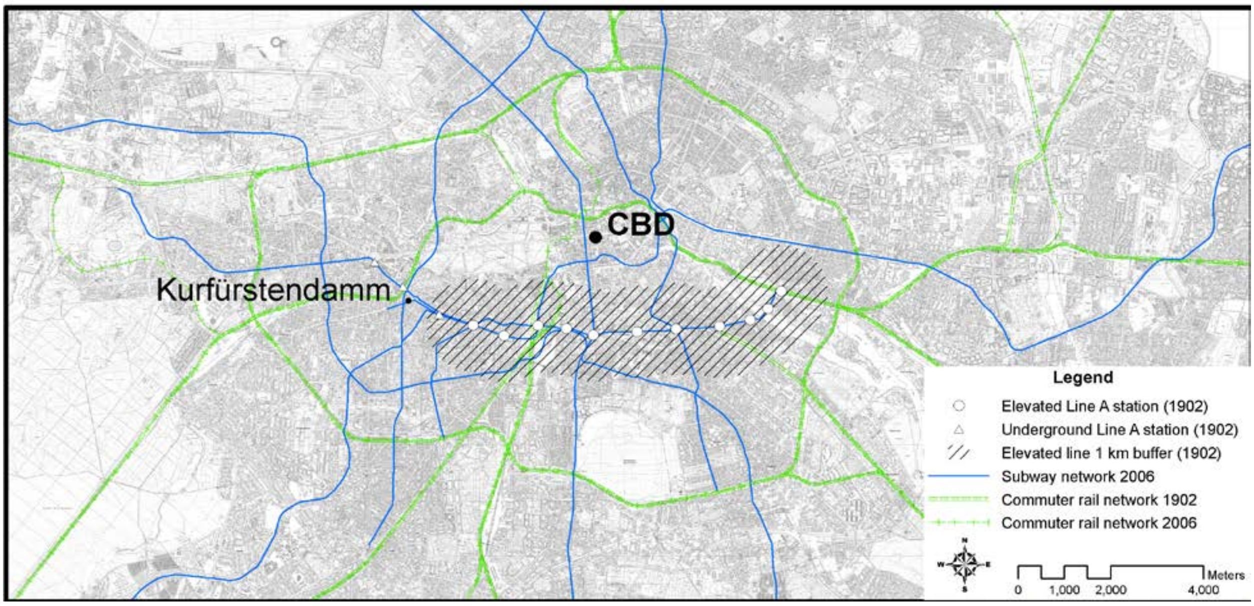
2.1 Metro rail in Berlin

In 1879, the German founder and inventor Werner von Siemens presented the first fully electrified experimental railway at the internationally renowned trade and industrial exhibition (*Gewerbeausstellung*) in Berlin. By 1891, the company Siemens & Halske had proposed a dense network of various lines to connect the inner core of "old Berlin" with its then surrounding municipalities. According to initial plans, the network was to be built entirely on elevated tracks, mainly because of strict regulation of underground activities due to construction works on the new canalization system led by James Hobrecht. In 1895, a concession was granted for the first line, which was to connect the eastern parts of Berlin, at the station Warschauer Brücke, and the wealthy western city of Charlottenburg, at the station Zoologischer Garten, running exclusively on elevated tracks. Built along one of Berlin's major boulevards this routing did not require major acquisitions of land or fundamental changes to the building structure. In 1897 (only five years before the inauguration of the line), Siemens & Halske founded the Elevated Railway Company (*Hochbahngesellschaft*) in cooperation with the Deutsche Bank to guarantee the funding.

The construction began immediately, starting from the eastern parts. However, Berlin residents increasingly expressed concerns about a viaduct's potentially unpleasant appearance. Also, Berlin's municipal planning and building control office, with its newly appointed head Friedrich Krause, was no longer generally opposed to plans for the construction of underground lines. As a result, the city of Charlottenburg managed to ensure, in a last-minute move, that the tracks ran beneath the street surface once the line reached its city boundaries. Eventually, the line was inaugurated in 1902 and called "Line A" (*Linie A* or *Stammstrecke*). The final routing negotiated between various stakeholders such as Deutsche Bank and the city of Charlottenburg was later described by historians as an outcome of agreements and accidents (Bousset 1935). The elevated section of the line consists of 11 stations, while the entire line (including the underground section) consists of 14 stations with a total length of about 10 km.

As evident from Figure 1, Line A complemented a commuter rail network consisting of various suburban lines as well as a circular line (*Ringbahn*) and an east-west connection through the CBD (*Stadtbahn*). This network was operated entirely on ground-level tracks or elevated tracks. It is comparable to today's commuter rail (*S-Bahn*) network, but the technology was different as trains were powered by steam and electrification did not start before 1924. Over time, the subway (*U-Bahn*) network was continuously expanded. Since the re-unification of the city, the combined subway and commuter rail networks comprise 475 rail km and 275 stations.

Fig. 1. Historical and contemporary geography of Berlin's metro rail network



Notes: Own illustration using the Urban Environmental Information System of the Berlin Senate Department (Senatsverwaltung für Stadtentwicklung Berlin 2006). CBD is the central business district. Kurfürstendamm is a major sub-centre.

2.2 Historical Land Prices and Contemporary Property Prices

Our main variable of interest are land prices which are extracted from various editions (1881, 1890, 1896, 1900, 1904, 1910, and 1914) of assessed land value maps for Berlin created by the renowned technician Gustav Müller in cooperation with official planning authorities. Müller's maps provide data at a remarkably disaggregated level of individual plots. The stated objective was to provide official and representative guides for both private and public investors participating in Berlin's real estate market. While Müller himself did not describe in detail the exact procedure of land valuation, the imperial valuation law (*Reichsbewertungsgesetz*) of the German Reich contained a strict order to use capital values for the assessment of commercial plots based on fair market prices. In line with the valuation laws for commercial land, Müller claims that his assessment refers to the pure value of land, which is adjusted for all building and even garden characteristics. He also corrected values for specific location characteristics such as single and double corner lots, subsoil and courtyard properties.

Müller's maps are by now an established data source. They have been used, among others, by Ahlfeldt, Moeller, et al. (2015), who also provide an extensive data appendix that describes in detail the nature of the data. More notably, the data are directly comparable to the more recent Berlin land price data (1928, 1936, 1986, 2006) used by Ahlfeldt, Redding, et al. (2015); they also share many similarities to Olcott's Chicago land values, which have been used in studies such as Ahlfeldt and McMillen (2018), Berry (1976), Kau and Sirmans (1979), McDonald and Bowman (1979), McMillen (1996), McMillen and McDonald (2002), Mills (1969), and Yeates (1965).

In contrast to previous analyses based on Müller's data, we exploit its full spatial detail at the parcel level. To preserve the highly-disaggregated nature of the original data, we digitize every single data point within a one-kilometer buffer around the newly built elevated tracks within a geographical information system (GIS) environment. After creating a balanced panel for the final analyses, this leaves us with a total of about 38,000 observations for seven points in time.

For the contemporary analyses we utilize a confidential data set, which is the same as in Ahlfeldt & Maennig (2015), containing detailed information on more than 70,000 transactions of buildings (single-family and multi-family) and the corresponding land parcels and including features such as price, transaction date, location, and a set of parameters describing building/plot characteristics. The data were obtained from the Committee of Valuation Experts Berlin (*Gutachterausschuss Berlin*). The transactions are geo-referenced (addresses and x/y coordinates), which allows them to be integrated into a GIS environment. The building characteristics include floor space, parcel area, age, land use, quality of the building stock, location within a block of houses (e.g., a corner lot), and several other amenities like basements, elevators, etc.

2.3 Rail noise

To translate the typically volatile levels of rail noise into a standardized summary statistic, engineers compute the equivalent continuous sound level, which is essentially a sophisticated mean over the varying noise levels observed during a given period. We use a highly disaggregated map, containing 2007 estimates of the continuous sound level by the source of noise (including rail) at a 10x10-meter grid from Berlin's Senate Department for Urban Development and the

Environment (2013). The noise measure reflects the weighted average noise exposure over one year and all times of a day (L_{den}) at a reception point of four meters above the ground. Following the rules defined by the EU Environmental Noise Directive, the micro-geographic noise map is the result of a simulation using a 3D model that is fit to actual noise measurements. The model incorporates features of the track design (e.g. speed, squeaking noises in curves, the presence of lubrication facilities) and the terrain geography (e.g. elevation of the track, built-up structure, bridges) that affect noise dissemination. Summarizing existing research, Navrud (2002) concludes that "*[…] the elimination of noise annoyance occurs at 37-40 db*". Thus, we measure rail noise in terms of decibels exceeding 40 decibels, i.e. 45, 50, and 55 decibels correspond to 5, 10, and 15 excess decibels. As we illustrate in an auxiliary analysis presented in appendix section 3.2, our rail noise measure sharply declines with distance from the track, is higher where trains run faster, and disproportionately affects the first row of buildings facing the track.

For our historical episode, estimates of the rail noise level unfortunately do not exist as the measurement technology had not been developed (Ampel & Uzzle 1993). However, regarding the transferability of the contemporary noise measure, we note that the building footprint remained largely the same within the affected area, despite significant damage during World War II, as documented on detailed ground plans published by the Berlin Senate Department (Senatsverwaltung für Stadtentwicklung Berlin 2000).[3] Therefore, it seems reasonable to assume that contemporary rail noise levels also reflect the dissemination of sound about 100 years ago in relative terms. Moreover, the service operator was contractually required to serve all stations in at least five-minute intervals during day time, a frequency that corresponds to the current service (Lemke & Poppel 1996). Historical and contemporary timetables also reveal that the average speed remained constant over time (Ahlfeldt, Redding, et al. 2015). This is consistent with a rolling stock technology that did not change fundamentally. As discussed above, Line A was the first electrified subway system in Germany. The trains (type A1/A2) as well as the track design represented a revolutionary technology. In comparison, the subsequent improvements that came with the introduction of new trains in the 1960s (type A3, still the backbone of the fleet) were evolutionary (Lemke & Poppel 1996).

The exact changes in noise levels from the first to the second generation are not documented, but it seems likely that technological progress even within a similar technology at constant speed and frequency has resulted in an at a least moderate reduction of noise levels. New generations of rolling stock tend to reduce noise levels of inter-city trains by about 10 decibels (Clausen et al. 2012;

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3 Note that for very few plots, where the building structure changed, we impute historic noise levels using adjacent plots.

Murphy & King 2014), although a smaller reduction is expected for urban rail since trains operate at lower speeds. Moreover, less tree coverage in the past may have implied less noise mitigation. Importantly, passive noise insulation was probably weaker in the past, although the characteristic wooden double box windows (*Doppelkastenfenster*) from the late 19th century have remained popular in Berlin. All in all, it seems reasonable to assume that our contemporary noise measure represents a lower-bound estimate of the noise levels experienced in the early 20th century.

2.4 Visual disamenity

In addition to a noise disamenity, an elevated line may cause a visual disamenity. The routing of Line A follows major roads which were sufficiently wide to accommodate a viaduct in the middle of the sides. Because the elevated line generally does not obstruct views of open spaces such as parks or lakes, the visual disamenity is less obvious than the noise disamenity in the present case. Moreover, addressing the concerns raised by Berlin residents mentioned above, the elevated tracks and stations were eventually executed with some attention to architecture (Bohle-Heintzenberg 1980). To empirically disentangle the effects from the noise disamenity and the visual disamenity, we create a dummy variable that takes the value of one if a parcel has a direct view of the elevated track and zero otherwise. Moreover, subways cause vibrations that potentially transmit to nearby buildings, where they can be perceived as a disamenity (Kurzweil 1979). Because the effects are highly localized and normally reach no further than to the first row of houses (Melke 1988), a potential disamenity effect should also be captured by the view dummy. Previewing our results, we do not find evidence for a direct view effect conditional on the noise effect and find similar noise effects when excluding parcels with a direct view from the analysis. We therefore generally interpret our noise estimates as originating purely from noise.

2.5 Other spatial data

We utilize the complete transport network data for post-unification Berlin processed by Ahlfeldt, Redding, et al. (2015). The network data consists of electronic maps (shapefiles) of streets (used for walking and driving), buses, trams, subway (*U-Bahn*) and commuter rail (*S-Bahn*). In addition, we digitize the underground and elevated sections of Line A as well as the other historical transportation networks, including horse-powered buses, horse-powered trams (one line), steam-powered trams (one line), electrified trams (the great majority of tram lines), and commuter rail (powered by steam). To compile the historical network data (and the associated speeds) we combine the contemporary transport networks with historical network plans.[4] An illustration of the historical and contemporary transport networks is in appendix section 3.3.

We complement our key data sets (property, access, noise) with several spatial characteristics, which we merge in GIS, including contemporary measures of distance from the central business district (still at the historical location), distance from the Kurfürstendamm sub-center, distance from nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street, and street noise (excluding rail noise).

2.6 Interpretation of estimated implicit prices

Our historical and contemporary analyses utilize different types of data. In our historical analysis, we exploit the spatiotemporal distribution of land prices. In our contemporary analysis, the dependent variable is the ratio of transaction price of a parcel of land, including the structure, over the parcel size. To theoretically link the estimated coefficients from these distinct models to each other as well as to a vast literature analyzing house prices, it is useful to assume a Cobb-Douglas housing production function and a competitive construction sector (Epple et al. 2010).

Assume that housing services H are produced using the inputs capital K and land L as follows: $H = K^{\delta} L^{1-\delta}$. Housing space is rented out at bid-rent ψ while land is acquired at land rent Ω. Combining the first order condition $K/L = \delta/(1-\delta)\,\Omega$ (where the price of capital is the numeraire) and the non-profit condition $\psi H = K + \Omega L$ gives $\psi H/L = 1/(1-\delta)\Omega$. Log-linearization yields a relationship with a slope of one, which implies that estimated parameters from our historical models (in which the dependent variable corresponds to $\ln(\Omega)$) and our contemporary models (in which the dependent variable corresponds to $\ln(\psi H/L)$) are directly comparable. From the first-order condition and the non-profit condition, it is further immediate that $\ln(\psi) = (1-\delta)\ln(\Omega) + c$, where c is a constant that cancels out in first-differences, i.e., $\Delta\ln(\psi) = (1-\delta)\Delta\ln(\Omega) = (1-\delta)\Delta\ln(\psi H/L)$. In log terms, it is, therefore, possible to translate the capitalization effects from our historical and contemporary models into a floor space price capitalization effect, by multiplying the former by a land share parameter.

It is important to note that housing services as defined by Epple et al. (2010) are not identical to housing space. Units of housing services can be thought of as bundles of features, including hous-

[4] Network plans are also available online; see, for instance, http://www.berlineruntergrundbahn.de and http://www.berliner-verkehr.de.

ing space, the quality of materials, sophistication of design, and access to communal and private exterior space, that generate equivalent consumption utility. Especially in places where building volumes are subject to binding regulations, such as in central Berlin, supply of housing services can be elastic (at a price the elasticity $dln(H/L)/dln(\psi) = \delta/(1-\delta) > 0$) even if supply of housing space is not, because developers choose to invest in housing quality (better materials and designs require more K/L) to achieve higher rents ψ. In fact, the building fabric in the study area is still dominated by the late19th century stock and where the buildings have been replaced, the quantity of housing space has been regulated by floor area ratio limits. Yet, H has increased over time as the historic building capital has been upgraded, e.g. by retrofitting central heating, private bathrooms, modern kitchens, or balconies (Hämer 1990). In appendix section 6.1, we show that $\psi H/L$ is correlated with various observable features of building capital, conditional on housing space. There, we also show that various features that are presumably correlated with housing capital and housing services, including housing space, decrease significantly in station distance and rail noise, as predicted for disamenities.

The Cobb-Douglas formulation of the production function implies that the elasticity of substitution between land and capital is unity at any given point in time, such that as the price of land increases, developers invest in capital (via maintenance, upgrades, or replacements) at rates that ensure constant factor shares. It does not preclude that the land share and the price elasticity of housing services change over time due to factors that are exogenous to developers' decisions on factor inputs. As discussed by Ahlfeldt and McMillen (2018), the intensity of capital use varies over time as the structure of demand, regulation, or construction technology change. To account for such trends, we borrow separate historical (1900) and the contemporary (2000) estimates of the share of land in total housing value in Germany of $1-\delta_{1900} = 0.18$ and $1-\delta_{2000} = 0.32$ from Knoll, Schularick, and Steger (2017).

3 Historical estimates

3.1 Empirical strategy

Our baseline empirical strategy for the estimation of historical capitalization effects combines hedonic (Rosen 1974) and difference-in-differences (DD) methods (Ashenfelter & Card 1985). We employ the hedonic approach to express the price of a parcel of land as a function of various attributes, including rail noise and rail access, and their implicit prices. The DD method then allows us to identify a treatment effect (e.g., of rail access or rail noise) by differentiating across space (with different degrees of exposure) and time (before and after exposure). Our baseline empirical specification takes the following form:

$$\ln(P_{it}) = f(S_i, N_i, t) + \mu_i + \theta_t + \varepsilon_{it}, \tag{1}$$

where P_{it} is the land price of a parcel i at time t, μ_i is a parcel fixed effect controlling for unobserved time-invariant locational amenities such as pollution, onto which we cluster standard errors (Bertrand et al. 2004), and θ_t is a year fixed effect controlling for common macroeconomic shocks. $f(S_i, N_i, t)$ is a treatment function that expresses the effects of the metro line as a function of the straight-line distance to the nearest station S_i, the emitted noise N_i, and time t.

While the opening date of the line (1902) is known a priori, the exact temporal structure of the capitalization of the effects of the line into land prices is not. Capitalization will occur gradually rather than immediately if the service is an experience good and it takes some time before transit riders adjust their behavior to take full advantage of the new option. If the semi-strong (or strong) efficient market hypothesis (Fama 1970) holds, markets will respond to all information made publicly available, which can result in anticipation effects as soon as the new line is announced. In setting up our DD model, we begin by estimating a series of time-varying treatment effects that reveal the temporal adjustment path in a flexible manner:

$$f(S_i, N_i, t) = \sum_{z=1890,1896,\ldots}^{1914} [\alpha_z^S S_i \times I(t = z)_t + \alpha_z^N N_i \times I(t = z)_t], \tag{2}$$

where $I(t = z)_t$ is an indicator variable, which takes the value of one if the condition is met and zero otherwise. Parameters α_z^S and α_z^N each represent an individual DD parameter reflecting how land prices for parcels exposed differently to noise and accessibility effects (first differences) changed from 1881 to year z (second differences).

We note that, because there was no metro rail noise prior to the elevated rail line, our noise measure reflects the increase in noise due to the elevated rail line (such that $N_i = \Delta N_i$, where ΔN_i is the before-after change in noise). Therefore, α_z^N provides a first-difference estimate of the effect of rail noise on land prices that can be interpreted as a hedonic implicit price. In contrast, α_z^S gives the change in the hedonic implicit price of distance to station locations from year 1881 to year z, i.e. $\alpha_z^S = \vartheta_z^S - \vartheta_{1881}^S$, where ϑ_z^S is the hedonic implicit price in given year z. α_z^S can still be interpreted as the hedonic implicit price of proximity to a station ϑ_z^S since in 1881 the stations could not be anticipated and, thus, $\vartheta_{1881}^S = 0$.

Informed by this analysis, we then estimate an extended DD model which provides a before-and-after comparison, controlling for the effects during an identified adjustment period:

$$f(S_i, N_i, t) = \alpha^S[S_i \times I(t > 1902)_t] + \alpha^N[N_i \times I(t > 1902)_t] + \sum_A [\alpha_A^D S_i \times I(t = A) + \alpha_A^N N_i \times I(t = A)], \quad (3)$$

where $I(t > 1902)_t$ is an indicator variable taking the value of one for years after the line opening and $I(t = A)_t$ is the same for a vector of years A during which land prices appear to be adjusting to a new equilibrium. Note that compared to dropping those years, controlling for adjustment effects offers the advantage of processing more information for identification of covariate effects (introduced in robustness checks) and fixed effects (μ_i, θ_t).

The critical and essentially untestable assumption of any DD analysis is that, in the absence of a treatment, all subjects (irrespectively of the intensity of treatment) would have followed the same trend. A selection problem exists if the treated and the non-treated subjects differ in observable or unobservable dimensions, and these differences imply heterogeneous responses to common shocks. In the context of the analysis of transport infrastructure effects, it is a notorious concern that the placement may be endogenous to location characteristics which may be correlated with trends. A variety of techniques have emerged to address selection problems, many of which aim at weighting observations in such a way that the treatment assignment becomes orthogonal to observable covariates. Examples include the inverse probability weighting (Hernán et al. 2001) and the special case of entropy balancing (Hainmueller 2012), the propensity score matching (Rosenbaum & Rubin 1983), or the synthetic control method (Abadie & Gardeazabal 2003). The problem with the application of these tools to the present case is that they serve the purpose of evaluating singular treatments and not multiple correlated treatments.

In the absence of a suitable off-the-shelf matching technique, we use a simple sledgehammer approach to defining parcel weights that minimize the conditional correlations between both treatment variables and the 1881-1890 trend in land prices, a period for which we are confident that the line has not been anticipated. We note that this is the first application of this weighted parallel trends (WPT) DD approach. To save space, we relegate a more technical discussion, including a Monte-Carlo evaluation of the small-sample properties of the estimator, to a companion paper (Ahlfeldt 2018).[5] In line with other weighting-based matching techniques, we view the 1881-1890 trend in land prices as a covariate to be balanced; however, balancing must be achieved with respect to two correlated treatment assignments, noise and station distance. Under the identifying

5 The companion paper cites an earlier working paper version of this paper.

assumption that the correlation between treatments and unobserved factors that interact with time are time-invariant, successful elimination of treatment-trend correlations during the pre-treatment period implies that non-parallel trends are also removed in potential outcome trends during the post-treatment period. To achieve this purpose, we define the following parcel weights:

$$W_i = \frac{w_i}{\sum_i w_i}, w_i = \sum\nolimits_m q_m K\left(\lambda_m, M_{i,m}\right), \tag{4}$$

where, $Q(q_1, \dots, q_m)$ are parameters to be identified. $M_{i,m}$, is one of m variables capturing observable time-invariant parcel characteristics that enters the weights in a Gaussian transformation:

$$K(\lambda_m, H_{i,m}) = \frac{1}{\lambda_m \sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{M_{i,m} - \bar{M}_m}{\lambda_m}\right)^2\right), \tag{5}$$

where the bandwidths λ_m are set according to the Silverman (1986) rule and the upper bar indicates the mean of a distribution. We use the Gaussian transformation because we presume that parcels that are more "normal" with respect to a plot characteristic $M_{i,m}$ are more likely to be on a similar trend. Furthermore, we presume that parcels that are representative with respect to different characteristics $M_{i,m}$ are likely on different trends. This approach has been chosen so as to mix these different trends in a way that ensures that the average trend in the weighted sample is orthogonal to the treatments. A positive collateral of the Gaussian transformation is that all $K_{i,m} = K(\lambda_m, M_{i,m})$ are positive and in the same dimension. In the baseline, we use distance from the CBD, distance from a sub-centre, and 1881-1890 price growth as parcel characteristics M_m in the algorithm. In searching for a vector Q that minimises the objective function, we search over a parameter space defined by $q_1 = 0, 0.01, 0.02, \dots, 1$, $q_2 = 0, 0.01, 0.02, \dots, 1$, $q_3 = 0, 0.01, 0.02, \dots, 1$, which equates to 101^3=1,030,301 combinations. We select Q that minimizes the sum of squared partial correlations between our treatment measures (rail noise and station access) and the land price growth over the 1881 to 1890 period.[6]

To overidentify our parcel weights, we use information that did not enter the weights construction. We have two more pre-opening periods in our data set (1890-1896, 1896-1900) which we use to evaluate whether the common trends assumption holds within the weighted sample. We have experimented with alternative sets of parcel characteristics and objective functions and our

6 To this end, we run r regressions of the form $\Delta\ln(P_{i,1890}) = c_r^0 + c_r^S \tilde{S}_i + c_r^N \tilde{N}_i + \varepsilon_{ri}$, where $\Delta\ln(P_{i,1890})$ is the change in log land price from 1881 to 1890 and tilde denotes normalization by standard deviation. In each regression, observations are weighted by W_i, which depends on the vector $(q_1, \dots, q_m)$. We select the combination of parameters that minimizes $\sum_{V=(S,N)} \left(\widehat{c_r^V}\right)^2$.

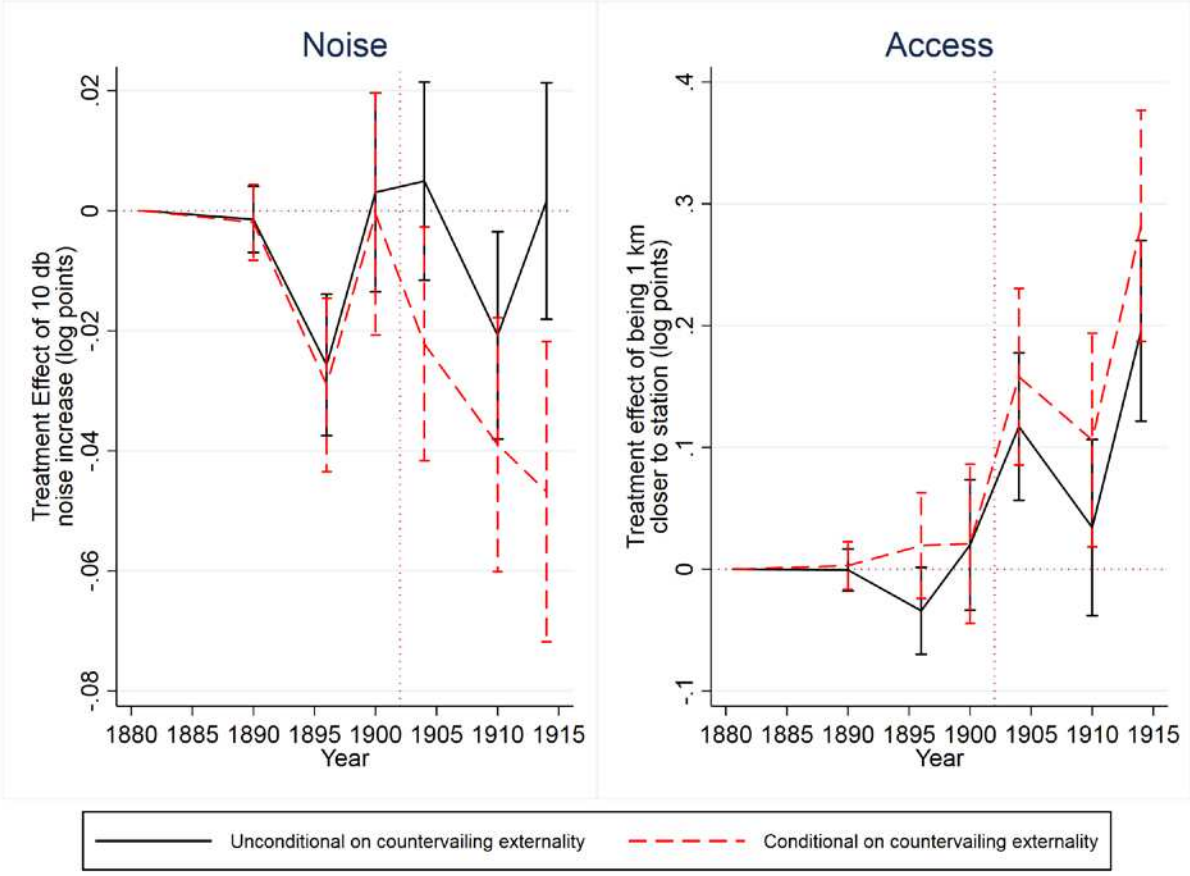
choices are based on their performance in the overidentification test reported in appendix section 4. There, we also evaluate whether the weighting changes the composition of the sample with respect to observable parcel characteristics. The weighted sample resembles the unweighted sample in terms of observable characteristics (see appendix section 4.1). While every weighted analysis results in a local estimate, in our case it is at least not obvious that the weighted DD effects are identified from parcels with very particular characteristics that would impede generalizability within our sample.

3.2 Baseline results

In Figure 2, we illustrate the time-varying treatment effects, estimated according to the DD model (1) using the treatment function (2) and the weights defined in (4) and (5). We report rail noise and station distance effects, estimated unconditional (solid lines) and conditional (dotted lines) on each other. Estimated station distance effects are multiplied by -1 to ensure that positive numbers mean normatively positive effects. Our weighted estimation approach achieves its purpose of eliminating pre-trends, i.e., there is no significant correlation between the 1881-1890 land price trend on the one hand and proximity to stations or exposure to rail noise on the other. Proximity effects are insignificant in 1896 and 1900 and the noise effect is insignificant in 1900 (years that were not used in the construction of the weights), indicating that the common trends assumption holds within the weighted sample.

Station distance effects remain insignificant during all years prior to the opening of the line and become significantly positive afterwards, with a tendency to increase over time. The absence of anticipation effects in combination with the gradual adjustment after the opening of the line are consistent with an interpretation that the line represents a novel mode of transportation whose benefits were yet to be experienced. Controlling for rail noise, a one-kilometer decrease in distance from the station increases land prices in the long-run by some notable 0.3 log points (35%).

Fig. 2. Difference-in-differences: Time-varying treatment effects (WPT models)



Note: Time-varying treatment effects (α_z^S and α_z^N) based on baseline DD equation (1) and treatment function (2). WPT models use weights constructed to minimize the conditional correlations between noise and the 1881-1890 land price trend as well as access (distance from station) and the 1881-1890 land price trend. Access parameters (effects of distance from station) multiplied by -1 so that positive shifts indicate positive economic effects. Vertical error bars indicate the 95% confidence interval based on standard errors that are clustered on parcels. Solid vertical lines denote the year of opening of the metro line (1902).

The estimated weighted rail noise effects also display an intuitive pattern. Controlling for station distance effects, a 10-decibel increase in rail noise is associated with a reduction in land prices by slightly more than 4% in the long-run. In contrast to our results for station distance effects, we find notable anticipation effects of rail noise for 1896. This finding is plausible in light of the intense public debate about the aesthetic appeal of elevated rail lines. The conflict was settled after the announcement to improve the architectural design of the stations and the viaduct and the decision to build an underground line within the boundaries of the city of Charlottenburg, explaining why the anticipation effect disappears in 1900. In keeping with intuition, estimated station distance effects increase by about one third if rail noise effects are controlled for. The effect of controlling for station distance effects on rail noise effects is even larger.

Informed by Figure 2, we now proceed to estimating parametric before-after DD effects, using our baseline specification (1), the treatment function (3), and, again, the weights defined in (4) and (5). The results are reported in Table 1. For comparison, we present weighted DD estimates of station distance effects not controlling for rail noise effects (columns 1-2) and rail noise effects not controlling for station distance effects (columns 3-4). In columns (5-6) of the table, we then report our preferred station distance and rail noise effects estimated conditional on each other. We control for anticipation effects in 1896 and 1900 as indicated.

When we do not control for rail noise effects, our estimation results indicate that the price of a parcel located right at a station increases by 12.7% (=exp(0.120)-1) after the opening of the line, compared to a parcel one kilometer away from a station. Rail noise effects are close to zero and statistically insignificant if station accessibility is ignored. Controlling for anticipation effects in either case has a minor impact on the estimated rail effects. A comparison of these results to columns (5-6) highlights the importance of jointly identifying a transportation infrastructure's amenity and disamenity effects. As shown in column (6), the station distance effect increases to 20.2% in our preferred model. Moreover, in line with Figure 3, the (negative) rail noise effect is now statistically significant. The point estimates indicate that a 10-decibel increase in rail noise causes a relative decline in land prices by 3.7%. Comparing our estimates across the different specifications, the bias that results from ignoring countervailing (dis)amenity effects amounts to as much as about 35% ($[0.184 - 0.119]/0.184$) in station distance effects and to about 85% in rail noise effects. In this context, it is worth noting that consistent with the insignificant noise effect in columns (3-4), our preferred estimates in column (6) suggest that positive accessibility effects about offset the negative noise effect for the parcels exposed to the highest levels of noise (see appendix section 4.2 for details).

The treatment effects reported in Table 1 are derived from a comparison of the mean land price at the parcel level in the periods 1881-1890 and 1904-1914. Since this model ignores price trends after the opening of the line, the effects are smaller than the 1914 treatment effects reported in Figure 2. These parametric estimates, however, are closer to the standard approach in the literature, therefore providing a more reasonable starting point for a comparison of our quantitative results to contemporary estimates in the literature.

Tab. 1. Noise and distance effects: Historical weighted difference-in-differences estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln land price (1881-1914)					
Distance (km) x after	-0.120***	-0.119***			-0.173***	-0.184***
$(S_i \times (t > 1902)_t)$	(0.025)	(0.032)			(0.031)	(0.040)
Noise (10 db) x after			0.001	-0.004	-0.029***	-0.036***
$(N_i \times (t > 1902)_t)$			(0.006)	(0.008)	(0.007)	(0.010)
Parcel effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Anticipation effects	-	Yes	-	Yes	-	Yes
N	37,933	37,933	37,933	37,933	37,933	37,933
r2	.93	.93	.93	.93	.93	.93

Notes: Weighted models use weights constructed to minimize the conditional correlations between noise and the 1881-1890 land price trend as well as access (distance from station) and the 1881-1890 land price trend. After is a dummy variable indicating years after the line opening (1902). Announcement effects are distance and noise variables interacted with 1896 and 1900 effects. Balanced panel of repeated parcel observations for 1881, 1890, 1896, 1900, 1904, 1910, 1914. Standard errors in parentheses are clustered on parcels. * $p <$ 0.10, ** $p < 0.05$, *** $p < 0.01$.

3.3 Robustness checks and complementary analyses

We have performed a number of perturbations of the baseline model reported in column (6) of Table 1 to address various concerns. For instance, we obtain similar results when we use different covariates and objective functions in the weights-generating algorithm. We also find that the baseline results are reasonably robust to allowing for time-varying implicit prices of various location characteristics (captured by controls × year effects interactions). Allowing for interactions of noise and distance variables with separate time trends before and after the opening of Line A results in cumulated effects after 10 years that are very close to the baseline estimates. Adding a dummy variable indicating parcels with an unobstructed view of the elevated line does not significantly affect the noise (or the distance) effect. Similarly, the results hardly change if all parcels with a direct view of the elevated line are excluded. A view effect is only significant if the noise measure is excluded from the model. Not controlling for noise, parcels with a direct view experienced a relative decrease in the land price of 4.4%, which is substantially less than implied by the noise effect at the same location (about -9.5%; see previous paragraph). It is, therefore, unlikely that our noise estimates are confounded by a view disamenity effect or a disamenity from subway vibrations (as both effects should be highly correlated). We have also evaluated the spatial decay in the distance effect using a series of dummies denoting parcels in mutually exclusive 100-meter station distance bins. We find that the distance effect is largely confined to the first 400 meters, with no evidence for negative congestion effects at close distances. Comparing the effect in the innermost ring versus the outermost residual category results in an effect that is almost identical to the one-kilometer distance effect from the baseline model. We have also evaluated the stability of the hedonic function (Kuminoff and Pope, 2014) around the opening dates by comparing marginal effects of other spatial attributes over time and experimented with varying levels of spatial clustering. These robustness tests and complementary analyses are presented and discussed in detail in appendix section 4, where we also present the results of an unweighted OLS analyses for the interested reader. As a final and particularly powerful robustness check, we also evaluate the noise effect exploiting a discontinuity in noise at the tunnel entrance close to Nollendorfplatz, finding qualitatively and quantitatively similar results. This analysis is presented in appendix section 5.

4 Contemporary estimates

4.1 Empirical strategy

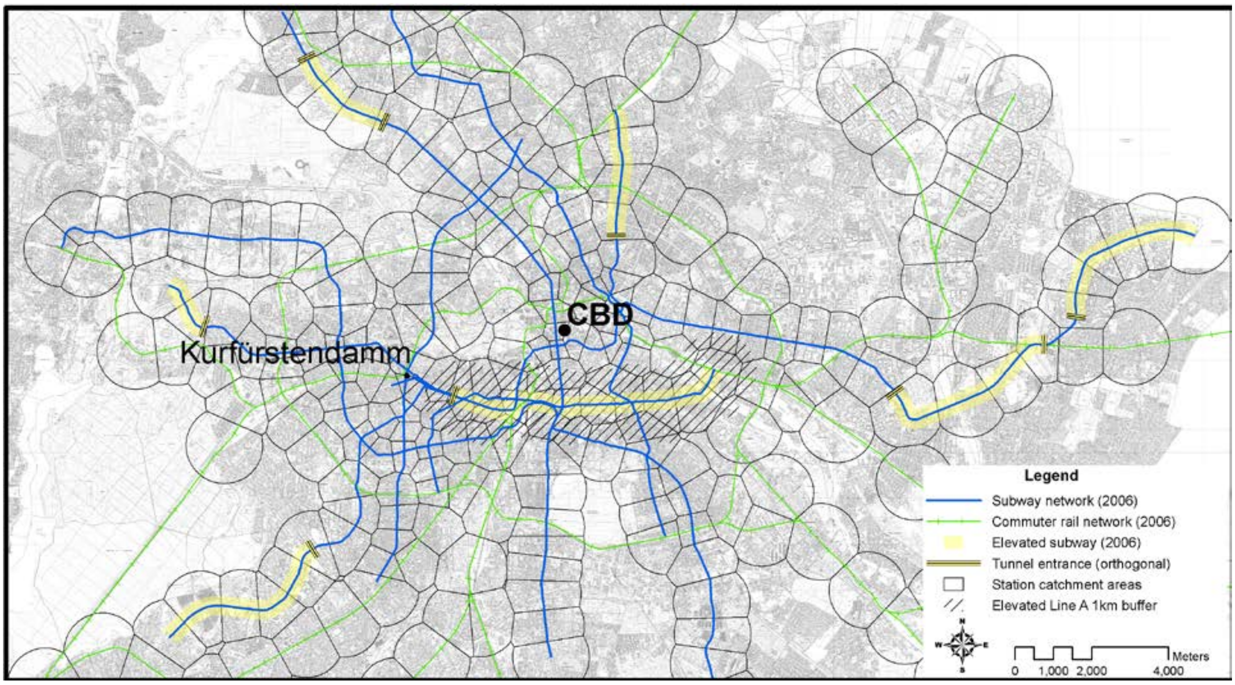
In the absence of variation over time in the metro rail network during the contemporary study period (1990-2012), we estimate a cross-sectional model. To improve the identification of noise effects, we restrict the identifying variation to the sharp change in noise that arises at nine tunnel entrances where elevated lines turn into underground lines. The reasons for the transition and the selection of the location of the tunnel entrances are often specific to the line (Bohle-Heintzenberg, 1980). In particular, we estimate models of the form:

$$\ln\left(p_{jtce}\right) = \alpha^S S_j + \alpha^N N_j + Y_{jt} b + (\rho_c \times \theta_t) + (\varsigma_e \times \theta_t) + \varepsilon_{jst}, \tag{6}$$

where p_{jtce} is the property transaction price normalized by the lot size of a property j selling at time t within the catchment area of station c and within a network corridor e. As discussed in section 2.6, this specification accounts for endogenous housing quality and yields marginal effects of rail noise and rail access that are directly comparable to the historic land price effects estimated in section 3. In contrast to conventional hedonic analyses using sales prices (corresponding to ψH in notations of section 2.6), housing attributes like the number of bathrooms or bedrooms must not be controlled for. $p \mathrel{\widehat{=}} \psi H/L$ is directly observed in the data and theoretically only depends on factors that affect the land price, i.e. locational characteristics. In contrast to the theoretical framework outlined in section 2.6, however, housing is durable such that the actual building capital does not necessarily correspond to the equilibrium value since capital depreciates (see appendix section 6.1 for estimates of the depreciation rate). Therefore, we control for age in the vector Y_{jt}, which also contains a host of locational control variables.

The variables S and N are our respective measures of station distance and rail noise as before, ρ_c is a fixed effect for station catchment areas and θ_t is a year fixed effect. Since subway and commuter rail use a similar technology in the contemporary period, we treat both types of stations as perfect substitutes. Station catchment areas are, therefore, defined for groups of properties sharing the same nearest station. In our baseline specification, we restrict the sample to areas within one kilometer of the nearest station. As evident from Figure 3, the density of stations is relatively high within the central parts of Berlin, further reducing the size of a catchment area. The mean catchment area is just 1.3 square kilometers (about 0.8 square miles) as opposed to more than three square kilometers implied by a circle with a one-kilometer radius. With the interaction effects $\rho_c \times \theta_t$, we, thus, provide a strong control for unobserved location characteristics such as pollution, changes in locational characteristics and changes in the implicit prices of location characteristics.

Fig. 3. Contemporary rail network and station catchment areas



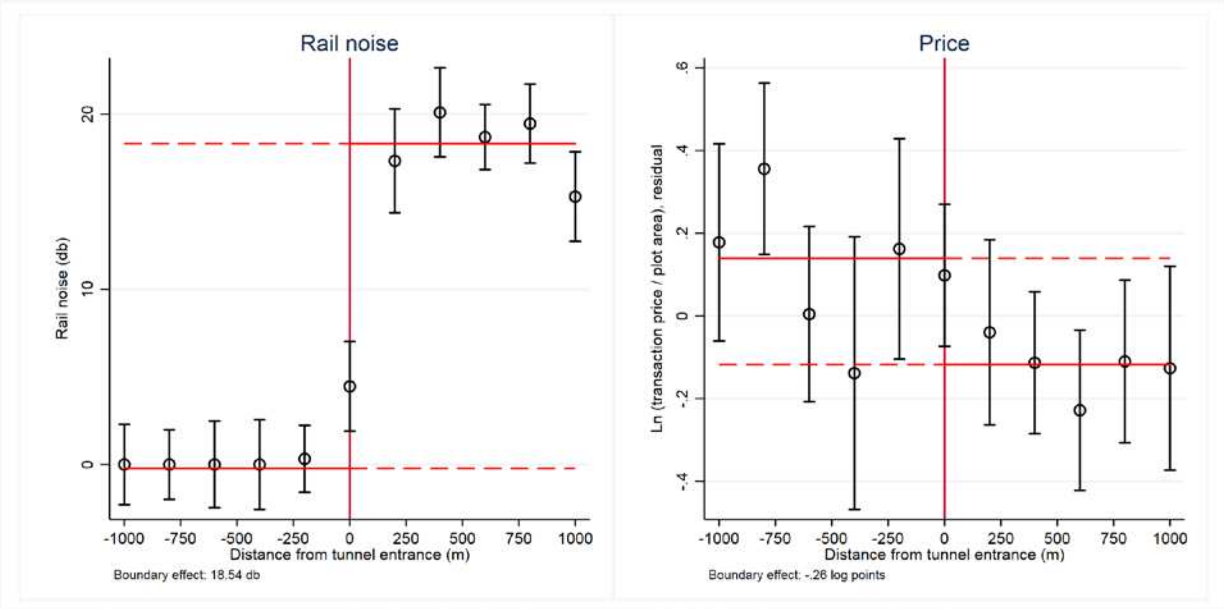
Notes: Own illustration using the Urban Environmental Information System of the Berlin Senate Department (Senatsverwaltung für Stadtentwicklung Berlin 2006).

Critical for the identification of the noise effect, ς_e is a set of fixed effect for rail corridors. Each corridor is centered on the intersection of the rail network and one of the nine tunnel entrances indicated by the orthogonals in Figure 3. We use corridors defined based on a track distance of 100 meters and a distance from the orthogonal of 1000 meters. The interaction fixed effects ($\varsigma_e \times \theta_t$) capture arbitrary shocks to any of these corridors. We define an auxiliary running variable D_{je} that takes the distance from the nearest tunnel entrance (negative distances in the tunnel section) within a corridor e and a value of zero elsewhere. We then use a dummy variable indicating the elevated parts of those corridors $I(D_{je} > 0) \times K_e$ (K_e is one within any of the corridors) as an instrument for noise to restrict the identification to the difference in noise across elevated and underground segments within corridors.

4.2 Baseline results

Figure 4 illustrates rail noise and contemporary property prices along the rail corridors and tunnel entrances. We present mean values of outcomes within 100-meter bins and confidence intervals that summarize whether the within-bin mean is significantly different (at the 90% level) from the mean across all observations within a corridor on the other side of a tunnel entrance.

Fig. 4. Contemporary spatial differences in noise and property prices



Notes. Each circle illustrates the mean value of a dependent variable within a grid cell. One dimension of the grid cells are 200-m bins defined based on the distance from the tunnel entrance. The other dimension is a 100-m-distance buffer around the track. Negative distances from the tunnel refer to the underground section. Solid horizontal lines indicate the means (weighted by the number of observations) within the underground (negative distance) and elevated (positive distance) segments. Error bars are the 90% confidence intervals based on robust standard errors from separate parcel-level regressions (within the buffer). For each outcome, we run one regression of the outcome against dummies indicating positive distance (≥ 0) bins, and another regression of the outcome against dummies indicating negative distance (<0) bins. For each bin, the error bar represents a test if the mean within the bin is different from the spatial counterfactual (the dashed line). The boundary effect corresponds to the difference between the two horizontal lines. Transaction prices are the residuals plus the block fixed effect component from regressions of the natural log of the transaction price normalized by lot size against a host of hedonic controls, year effects, and block fixed effects, several distance variables, including distance from the central business district, distance from the nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street, street noise (excluding rail noise).

Within these rail corridors, the levels of rail noise along the elevated segments exceed that of the underground segments by about 18 decibels. The additional noise comes with a discount on land prices of -0.26 log points. Four out of five high noise bins (elevated section) have mean prices that are significantly lower than the mean price within the low noise (underground) section and four out of six low noise (underground section) bins have mean prices that are significantly higher than the mean price within the high noise (elevated) section. The implied price effect of a 10-decibel increase in rail noise is about -0.14 log points, more than three times the land price capitalization effect in the historical period.

Table 2 reports the estimates for several variants of equation (6). In columns (1-3), we present, for comparison, the results of a conventional hedonic model, which excludes all corridor-related variables and does not use the instrument. Our preferred SD specifications for the noise effects identification are tabulated in columns (4-6). For both variants, we report results of models that exclude (1 and 4) and include (2 and 5) station catchment × year effects as well as models that use all transactions (1-2 and 4-5) or samples restricted to properties within one kilometer of the nearest station (3 and 6).

The estimated station distance effects are relatively stable across all specifications. Our preferred estimate of the per-kilometer station distance effect is the $(\exp[-0.144]-1)/100=-15.4\%$ estimate from column (3), for several reasons. In model (3), station catchment × year effects control for arbitrary shocks at a relatively local level. Moreover, the restriction to a one-kilometer station radius further increases the strength of this control and makes the results more comparable to our historical analysis. Importantly, the model controls for noise along all elevated segments of the network whereas in the SD specification much of the variation in noise is intentionally wiped out by the instrument.

The SD models consistently point to relatively large and negative noise effects. The most conservative estimate suggests that a 10-decibel increase in noise reduces the property price per land unit (and under the assumptions made in section 2.6 also the land price) by about 11.5%. Given the geography of the Berlin rail network, it is intuitive that the hedonic models in columns (1-3) yield smaller estimates. The subway network often follows major boulevards that were laid out in the 1862 Hobrecht-Plan (Bernet 2004), which borrowed many features from Haussmann's designs for Paris (de Moncan 2009). These boulevards provide the necessary space for the construction of viaducts for elevated lines or facilitate the cost-effective open construction of tunnels. Such boulevards, however, also possess desirable features such as distinctive architecture, tree coverage, shops, boutiques and restaurants, which are not observed in the data. If these features are empirically confounded with rail noise, the noise disamenity will be underestimated.

Tab. 2. Contemporary analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln property transaction price / lot size					
Distance (km)	-0.128***	-0.126***	-0.144***	-0.127***	-0.126***	-0.152***
	(0.003)	(0.007)	(0.021)	(0.003)	(0.007)	(0.022)
Rail noise (10 decibel)	0.050***	-0.021	-0.032**	-0.166***	-0.143***	-0.122**
	(0.011)	(0.015)	(0.015)	(0.032)	(0.049)	(0.049)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	-	-	Yes	-	-
Station x year effects	-	Yes	Yes	-	Yes	Yes
Corridor x year effects				Yes	Yes	Yes
Noise instrument				Yes	Yes	Yes
Sample	All	All	Station distance < 1 km	All	All	Station distance < 1 km
N	71,313	71,313	46,143	71,313	71,313	46,143
r2	.259	.584	.608	.261	.586	.61

Notes: Unit of analysis is property transaction. Controls include structure age, dummies for location within a block (corner lot, street front, backyard, etc.), dummies for building condition (poor, good), distance from nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street, street noise (excluding rail noise). Station effects identify groups of properties which have the same nearest rail station. Corridor effects identify groups of properties within 100-meter buffers along a rail line, spreading 1,000 meter in both directions from a tunnel entrance. Noise instrument is a dummy variable taking the value of one with the elevated segment of any rail corridor and zero otherwise in models (4-6). Standard errors in parentheses are robust in (1) and (4), clustered station x year effects in all other models. * p < 0.10, ** p < 0.05, *** p < 0.01.

4.3 Robustness checks and complementary analyses

We have expanded the analysis of contemporary property price effects in several directions. We have evaluated the ancillary prediction from the theoretical framework in Section 2.6 that increases in land values due to locational amenities should be accompanied by investments in building capital and a larger quantity of housing services. We find that increases in station distance by one kilometer and increases in rail noise by 10 decibels reduce the supply of floor space per land unit by more than 20% and about 10%, respectively. There is also a negative effect on building conditions as well as the propensity of buildings with features such as elevators, basements, or underground parking. To allow for a more explicit comparison to the historical analysis, we estimate distance and noise effects within the one-kilometer buffer surrounding the elevated part of Line A depicted in Figure 1. The amenity and disamenity effects within the buffer are very similar to the rest of the city area. If anything, the distance effect appears to be somewhat larger (-19.3% per kilometer), although the difference between the effects in both areas is not significant. With a similar aim, we estimate the distance effect for the subway (*U-Bahn*) and commuter rail (*S-Bahn*) network separately. The distance effect for the subway network of 21.9% per kilometer is, again, somewhat larger than in the baseline. In robustness checks, we analyze the sensitivity of the results to variations in the definition of the rail corridor and different attempts to achieve a more local identification in a reduced-form framework (using the noise instrument as an explanatory variable). Narrower definitions of the rail corridor (75 or 50 meters) result in similar point estimates, but larger standard errors. Further restricting the identification to variation closer to the tunnel entrance by weighting observations by distance or adding distance trends results in larger noise estimates. A complementary analysis of non-linear distance effects reveals that the distance effects largely capitalize within the first 500 meters, with no evidence for negative congestion effects at close distances. The peak capitalization effect close to the station relative to the one-kilometer station distance margin, at about 20%, is somewhat larger than implied by the baseline estimate. We also find that conditional on controls the difference in road noise within elevated and underground segments of our rail corridors is close to and not statistically distinguishable from zero. Thus, with the chosen research design, road noise is unlikely a potential confounder for rail noise effects, and so are other disamenities such as pollution that are likely correlated with road noise. A more complete presentation and discussion of the extensions and robustness checks is in appendix section 6.

5 Interpretation

5.1 Comparison of historical and contemporary estimates

Thus far, we have provided contemporary and historical estimates of capitalization effects of noise and rail access into land prices. Using the theoretical framework discussed in Section 2.6, it is possible to retrieve the implied house price capitalization effects. To obtain estimates of the long-run income elasticities of (dis)amenity values of noise and access, we make some further assumptions. In particular, we assume that, within each period (historic and contemporary), (i) preferences for all goods (including noise and access) are homogeneous, and so are expenditure shares on housing and land shares in the production of housing (this does not preclude differences across periods); (ii) real incomes grow at a constant rate for all population groups (this does not preclude level-differences across groups); and (iii) the estimated marginal effects of noise and access are causal and constant across the distributions (for noise this concerns values exceeding 40 decibels). We can then define the willingness to pay (WTP) for a unit amenity increase in period t as the product of the capitalization effect in house price terms $(1-\delta_t)\alpha_t$ ($1-\delta$ is the land share as defined in section 2.6), income I_t, and the expenditure share on housing η_t: $WTP_t = (1-\delta)\alpha_t \times I_t \times \eta_t$. Taking log-differences and rearranging the WTP equation gives the income elasticity of the amenity value:

$$\frac{\Delta \ln WTP}{\Delta \ln I} = 1 + \frac{\Delta \ln(\alpha)}{\Delta \ln I} + \frac{\Delta \ln(1-\delta)}{\Delta \ln I} + \frac{\Delta \ln \eta}{\Delta \ln I}, \tag{7}$$

Of course, the assumptions made are disputable and are subject to a critical assessment in appendix section 7, where we also provide a detailed discussion of the calibrated values for $\Delta \ln(1-\delta)$, $\Delta \ln \eta$ and $\Delta \ln I$. Acknowledging that considerable uncertainty surrounds our estimates of both long-run income elasticities, we provide a summary of our main takeaways below.

5.1.1 Noise

Over a period of about 100 years, the effect of a 10-decibel increase in noise on land prices roughly tripled from -4.2% (Table 2, column 3) to -13.0% (Table 3, column 6). Under the assumptions made, this corresponds to an increase in the per-decibel house price capitalization effect from - 0.1% to - 0.4%, the latter being within the range of contemporary estimates of aircraft noise (Boes and Nüesch, 2011 report - 0.5% per decibel) and road noise effects (Graevenitz, 2018 reports a range of - 0.1% to - 1.4% per decibel). The implied income elasticity of the noise disamenity value is 2.2. This long-run income elasticity estimate is without precedent, but complements cross-sectional stated-preference estimates that point to an income elasticity of the marginal cost of noise below unity (Wardman et al. 2005 cite a central estimate of 0.5).

One possible concern with the inter-temporal comparison we make is that we do not observe historic rail noise. For the reasons discussed in section 2.3, contemporary rail noise levels likely understate historical noise levels, implying that our historical noise estimates are upwardly biased and the long-run income elasticity of the noise disamenity value is likely larger than the value we infer. Another concern is that, in the past, road noise levels were likely lower due to the absence of affordable mass-produced cars. This will be a potential problem if we relax the assumption of a constant marginal effect of noise. If the disamenity effects of rail and road noise were mutually reinforcing, an increase in road noise over time would lead to a higher noise capitalization effect even in the absence of a change in noise aversion. However, in an ancillary analysis, we find that the rail noise capitalization effect decreases in the presence of higher levels of road noise, i.e. rail noise matters less if there is already a lot of road noise. So, without a presumed increase in road noise levels over time, the rail capitalization effect today would likely be even greater, implying, again, a larger income elasticity. If we relax the assumption of homogeneous preferences, it seems reasonable to expect that after 100 years of sorting most noise sensitive households will have left the noisiest areas (Kuminoff and Pope, 2014). This, again, mutes the contemporary noise capitalization effect and increases the implied income elasticity. However, the overall increase in noise levels across the city could also lead to the marginal buyer in a noisy area being more noise sensitive, so that the net effect of sorting is ambiguous. Importantly, rapid rail transit in Berlin was relatively more popular among wealthy people in the past since fares where relatively higher and, in the absence of cars, rapid transit was the fastest mode. So, likely, average income in the study area increased at a rate lower than calibrated, implying a likely downward bias in our income elasticity estimate. Thus, on balance, we believe that 2.2 is a lower-bound estimate of the income elasticity of the noise disamenity value.

5.1.2 Access

According to our estimates, the land price capitalization effect of a one-kilometer reduction in distance from the nearest metro station (treating subway and commuter rail as substitutes) declined from about 20.2% to 15.5%. Because of the increase in the share of land in the value of housing this decrease in the land price capitalization effect corresponds to an increase in the house price capitalization effect from 3.6% to 5.0%. This is within the range of recent difference-in-difference estimates such as by Gibbons & Machin (2005), who report a 1.5% to 5% range, or Dubé et al. (2013), whose estimates imply a per-kilometer effect of 7%. The implied income elasticity of the access amenity value is 1.4. Because the distance-from-station capitalization effect captures the value of the associated walking time (Gibbons & Machin 2005), the income elasticity of the value of station access should generalize to the value of time. It is therefore notable that our estimates are significantly larger than the cross-sectional estimates of the income elasticity of travel time value in the literature, which tend to be below unity (Börjesson et al. 2012 report a central estimate of 0.6-0.7).

One concern regarding the comparability of the historic and contemporary estimates is that rail transit was relatively more valuable in the past since mass-produced cars were not yet available as affordable substitutes. At the same time, the metro rail network has expanded substantially over time, now offering connections to a greater variety of locations, which should increase its value. In a network analysis, we find that the two offsetting effects are likely of comparable magnitude. The effects of sorting with respect to the access amenity go, again, both ways. Preference-based sorting over a century makes it more likely that households with large preferences for rail transit locate close to stations. However, the expansion of the network makes it more likely that the marginal buyer in a well-connected area today has a relatively lower preference for rail access than in the past. Given that income sorting likely leads to us using an exaggerated value for income growth near metro stations, we tentatively conclude that 1.4 is a lower-bound estimate of the income elasticity of the rail access amenity value.

5.2 Fiscal case for underground metro lines

Building an underground line is significantly more expensive than building an elevated line. Underground lines, conversely, avoid sizable disamenities. In this section, we provide some simple back-of-the-envelope calculations to evaluate how long it takes to refinance the extra costs via property tax revenues. To this end, we estimate the extra cost of a hypothetical underground Line A, the extra property value generated in this counterfactual, and the associated extra tax revenues.

5.2.1 Extra cost

Bousset (1935) reports the per-kilometer construction costs for 31 segments of the Berlin metro rail network opened by 1930, including per-kilometer cost of about two million Reichsmark (RM) for a five-kilometers long sub segment of the elevated part of Line A. Multiplying the per-kilometer cost by the total length of the elevated section of eight kilometers yields construction costs of about 16 million RM. To approximate the extra cost associated with a hypothetical underground section, we run an auxiliary regression of the natural log of per-kilometer construction costs against a dummy indicating underground sections, controlling for track width and period (five years) effects. The results, reported in Section 8 in the appendix, indicate that building an underground section in the early 20th century in Berlin was about three times as expensive as building an elevated section. Multiplying the estimated construction cost of Line A by this factor yields a counterfactual construction cost of about 50 million RM and an extra cost for the underground line of about 34 million RM. It is noteworthy that the current rule of thumb suggests costs of an underground line are about twice the cost of an elevated line (Flyvbjerg et al. 2008). So, the extra cost for the construction of underground lines have declined over time.

5.2.2 Extra property value

To compare the extra cost of construction to the aggregated effect on property values, we aggregate the plot-level land price observations to a 50×50-meter grid, which allows for rich spatial variation in rail noise and, at the same time, ensures that we cover the entire built-up area. Under the assumptions made in section 2.6, the noise-induced change in property value in each grid cell is $d\psi H = \psi H(\partial \ln \psi / \partial N) dN$, where dN is noise level attributable to Line A and $\partial \ln \psi / \partial N = (1-\delta)\partial \ln \Omega / \partial N$ is the relative house price capitalization effect of a one-decibel increase in noise. Since the Cobb-Douglas housing production function implies that $\psi H = 1/(1-\delta)\Omega L$, we can express the impact on property value as a function of the estimated house price capitalization effects and the aggregate land value:

$$d\psi H = \frac{1}{(1-\delta)} \Omega L \frac{\partial \ln \psi}{\partial N} dN, \tag{8}$$

Intuitively, in equation (8), we hold the capital stock constant such that the value of the property increases due to an increase in the value of the underlying land, exclusively. This way, we only account for the incidence on the immobile factor, i.e. we avoid the problem that a policy-induced increase in the quantity of housing stock at one location displaces demand in other areas. The resulting land price effects by grid cell are illustrated in the appendix (section 9). In this context, it is worth emphasizing that our plots include all types of land uses; the aggregate land value effect, therefore, reflects both changes in utility and productivity.

Table 3 provides a comparison of the extra cost for an underground variant of Line A and the aggregated impact on building values that would result from the associated noise reduction. We provide the comparison for the actual historical scenario (using our historical land price capitalization estimates) and a counterfactual scenario in which we apply the contemporary estimate of the land price capitalization effect $\tilde{\alpha}_{1900}^{N}$. This counterfactual land price capitalization effect inflates the estimated contemporary land price capitalization effect α_{2000}^{N} by the ratios of the contemporary over the historical land $(1-\delta)$ and housing expenditure (η) shares to reflect that the same willingness to pay with lower share parameters implies a larger percentage land price capitalization effect: $\tilde{\alpha}_{1900}^{N} = \alpha_{2000}^{N} \frac{(1-\delta_{2000})\eta_{2000}}{(1-\delta_{1900})\eta_{1900}}$.

Based on our historical noise estimates, the aggregate increase in property values in a counterfactual scenario with an underground Line A amounts to slightly more than one half of the extra cost of going underground (18.6 million RM). It is important to note that these results do not reject a welfare case for an underground Line A since positive health benefits are likely important, but unlikely to fully capitalize into property prices due to lack of public awareness (Navrud, 2002). Also, an underground line relative to an elevated line generates wider benefits to other than local residents and firms (e.g., to visitors and tourists). Yet, applying the counterfactual contemporary land price capitalization effect, the generated property value alone already more than offsets the extra costs of going underground. In theory, local landlords would be able to bear the extra cost for an underground line without making losses.

5.2.3 Extra tax revenues

While land value capture schemes are often difficult to implement in practice, the increase in the property tax base mechanically generates revenues and, therefore, may be a less controversial means of refinancing in the long-run. In Germany, the property tax is determined as the product of the tax base (the assessed value of the property, the so called *Einheitswert*), a tax rate (*Grundsteuermesszahl*) and a tax factor (*Hebesatz*). Since the *Einheitswert* is fixed at a historic value, property tax revenues are insensitive to changes in locational (dis)amenities. However, property transaction taxes respond immediately as they are levied on actual transaction prices. To approximate the yearly tax revenues resulting from noise-induced changes in property value, we consider the 6% property transaction tax rate currently applicable in Berlin as well as a historic (pre-1998) rate of 3.5%. Moreover, we consider 5% and 10% probabilities of any property being transacted in a given year since empirical evidence points to average holding periods between 10 and 20 years (Collett et al., 2000: Fisher et al, 2004). In appendix section 11, we discuss the German property tax environment in greater detail and show that in more conventional property tax settings similar fiscal revenues would be generated.

In a further set of auxiliary regressions of the natural log of land price on location fixed effects and a year trend, we find that annual land price appreciation rates tended to fluctuate around 5% in Berlin from the late 19th century to the early 21st century, which is close to the mean interest rate across years in the same period. Moreover, there is a positive correlation between the two variables (see section 10 in the appendix). Thus, it seems reasonable to make the simplifying assumption that in the long-run land prices grow at a rate that equates to the opportunity cost of capital.

Tab. 3. The fiscal case for an underground line

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Noise preference	Historic					Contemporary		
Rail noise capitalization effect on hsoue prices	0.41%	0.41%	0.41%	0.41%	3.32%	3.32%	3.32%	3.32%
Estimated total cost (million 1900 RM)	15.94							
Estimated underground extra cost (1900 RM)	34.36							
Aggregated noise effect building value (million RM)	18.6	18.6	18.6	18.6	151	151	151	151
Transaction tax rate	0.04	0.04	0.06	0.06	0.04	0.04	0.06	0.06
Transaction probability	0.05	0.10	0.05	0.10	0.05	0.10	0.05	0.10
Yearly tax revenue (million 1900 RM)	0.03	0.07	0.06	0.11	0.26	0.53	0.45	0.91
Years to recover underground extra costs	1056	528	616	308	130	65	76	38

Notes: Contemporary land price effect adjusted for changes in land share and housing expenditure share (land price capitalization effect inflated by the ratio of contemporary over historic shares). Cost estimates based on Bousset (1935). Estimated total cost result from multiplying the reported 1902 per km costs of over elevated sections by 8 km (the length of the elevated sections of the Line A). The estimated underground extra cost result multiplying the total cost by the percentage extra costs for underground segments obtained from an auxiliary regression reported in Section 5 of the appendix. Years to recover extra costs are calculated under the assumption that property values grow at a rate similar to cost of capital (see appendix 9 for a justification).

Under the assumptions made, it turns out that based on our estimates of the historical land price capitalization effects, it would have taken hundreds of years to recover the extra costs via property taxes. Therefore, it is perhaps no surprise that Line A was built as an elevated line and that it took major protests and political pressure to force the line underground within the boundaries of Charlottenburg. In contrast, under the counterfactual contemporary capitalization effect, tax-revenues, depending on the assumed tax rate and transaction probability, would have refinanced the extra cost for an underground line within 38 to 130 years and, thus, likely within the past lifetime of Line A.

6 Conclusions

We use difference-in-differences and spatial differences designs to estimate the land price capitalization effects of the contemporary metro rail network in Berlin and Germany's first electrified metro rail line, Line A, which opened more than a century ago. We find that the land price (implied house price) capitalization effect of a 10-decibel reduction in rail noise increased from 4.2% to 13.0% (1% to 4%). The effect of a one-kilometer reduction in distance from the nearest station decreased (increased) from 20.2% to 15.5% (3.6% to 5.0%.). From these estimates, we infer novel estimates of the long-run income elasticities of the value of noise reduction and transport access of 2.2 and 1.4. While significant uncertainty surrounds these elasticity estimates, we view them as likely lower-bound estimates. Thus, our tentative conclusion is that the long-run income elasticities of transport (dis)amenity values likely exceed their short-run counterparts which have been estimated at below-unity values.

This finding has important implications for transport infrastructure appraisals as it suggests that time and environmental quality are luxury goods whose values will likely increase in absolute and relative terms as incomes rise. While the existing below-unity cross-sectional income elasticity estimates are certainly relevant for the assessment of the distributional consequences of investments within generations, larger values may be required for the assessment of distributional consequences across generations. As we demonstrate, using Berlin's Line A as a case in point, the welfare case for constructing underground rail lines is much stronger today than a century ago because the value of a quiet environment has increased more than proportionately to income. In anticipation of likely increases in real incomes, infrastructure appraisals that seek to fully capture net-benefits to future generations, should inflate rather than deflate contemporary (dis)amenity values.

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Online Appendix to Ease vs. noise: Long-run changes in the value of transport (dis)amenities

Version: June, 2019

1 Introduction

This appendix complements the main paper by providing additional information and complementary results not reported in the main paper for brevity. We begin with a short review of the related capitalization literature in Section 2. In Section 3, we provide additional detail regarding the data used. Section 4 adds to the historical difference-in-differences analysis, providing additional detail on the construction and distribution of weights, robustness checks, and complementary analyses. Sections 5 provides a complementary analysis of the historical noise capitalization effect using a spatial differences approach. Section 6 complements the contemporary spatial differences analyses. Section 7 describes in detail how we compute the income elasticities and the station accessibility measures discussed in section 5.1 in the main paper. Section 8 explains how we estimate the extra costs for constructing an underground line instead of an elevated line, followed by an analysis of the aggregate effect of the reduction in noise emission on land values in Section 9. In Section 10, we examine the long-run change in land prices in Berlin. Finally, Section 11 provides additional background material on our calculations of property taxation.

2 Review of related capitalization research

A vast literature has inferred the value of non-marketed goods such as clean air (Chay and Greenstone, 2005), health risk (Currie et al., 2015; Davis, 2004), proximity to hazardous waste sites (Greenstone and Gallagher, 2008), crime risk (Linden and Rockoff, 2008), public school quality (Cellini et al., 2010; Gibbons et al., 2013), high-speed broadband (Ahlfeldt, Koutroumpis, et al.,

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2016) or building externalities related to design and maintenance (Ahlfeldt and Holman, 2017; Rossi-Hansberg et al., 2010) from spatial variation in property prices. This approach is derived from the spatial equilibrium assumption in bid-rent theory, one of the workhorse tools in urban economics (Alonso, 1964; Mills, 1967; Muth, 1969). Essentially, it is argued that the value of (urban) land must offset all utility and productivity enhancing or depreciating factors, including noise and accessibility, if households are mobile and markets are competitive. The revealed preference approach is a popular tool in social cost-benefit analyses, which are, in many settings, the preferred method to evaluate welfare effects of public policies (Osborne and Turner, 2010).

Reviewing the literature, a number of studies have analyzed the property price effects of transportation infrastructure (e.g. Bajic, 1983; Baum-Snow and Kahn, 2000; Bowes and Ihlanfeldt, 2001; Damm et al., 1980; Dewees, 1976; McDonald and Osuji, 1995; Voith, 1993). Recent applications focus, in particular, on the property price effects of transport innovations, e.g. improvements of a road or rail network, to achieve better identification (Ahlfeldt, Moeller, et al., 2015; Billings, 2011; Gibbons and Machin, 2005; Hurst and West, 2014; McMillen and McDonald, 2004; Xu et al., 2015). The literature is surveyed in, among others, Mohammad et al. (2013), Bartholomew and Ewing (2011), Debrezion, Pels, and Rietveld (2007), Gibbons and Machin (2008), and Wrigley and Wyatt (2001). Overall, the findings suggest that transport infrastructures (and railways in particular) are typically associated with an increase in local property values. Quantitatively, the results in the literature are more heterogeneous, but based on the more robust evidence (exploiting variation over time) it seems fair to conclude that a one-kilometer reduction in station distance tends to increase house prices by about 2-7%. Cross-sectional hedonic estimates tend to be larger.

On transport-related disamenity effects, there is cross-sectional evidence that aircraft noise depreciates property prices (see J. P. Nelson, 2004 for a meta-analysis). Recent studies have also made use of quasi-experimental methods to identify aircraft noise effects (Ahlfeldt and Maennig, 2015; Boes and Nüesch, 2011; J. P. Nelson, 2004; Pope, 2008). The consensus in this literature is that a one-decibel increase in aircraft noise depreciates house prices by 0.5-0.6%. This is somewhat less than the mean of 0.92 % (median 0.74 %) across 24 earlier cross-sectional studies reviewed by J. P. Nelson (2008). As for road noise, Graevenitz (2018) reports that a one-decibel increase in noise above 55 db leads to a reduction in house prices in the range of 0.1 to 1.4 %. These results are similar to what Day et al. (2007) find. J. P. Nelson (2008) concludes that across 25 reviewed studies, the mean estimate for the effect of a one-decibel increase in house prices was -0.57 %. The evidence on other noise sources and, in particular, rail noise (A. C. Nelson, 1992) is somewhat less complete and robust (Navrud, 2002). Still, there is some evidence suggesting that railway lines may have negative property price effects at a highly localized level, possibly due to noise (e.g. Al-Mosaind et al., 1993; Debrezion et al., 2010; A. C. Nelson, 1992). Other dimensions of environmental quality, e.g., clean air or water, are typically associated with positive capitalization effects (Harrison and Rubinfeld, 1978; Leggett and Bockstael, 2000; J. P. Nelson, 1978), as are unspoilt natural spaces (Gibbons, 2015; Tyrväinen and Miettinen, 2000).

3 Background and data

3.1 Real GDP growth

In modern industrial economies, steady economic growth subject to some cyclicality has become the norm. As a result, an average consumer today can spend a budget that is more than seven times as large as that of their ancestors a century ago. This rise in income has important implications for consumer demand. With an income elasticity of demand below unity, the US consumer expenditure share on the necessities food and clothing has declined from 56.6% in 1900 to 17.3% in 2000 (U S Department of Labor 2006). At the same time, the historical increase in real income has more than proportionately freed up budget for the consumption of non-necessities. For some goods, including a clean, quiet or safe environment, quick access to jobs, or consumption amenities such as retail and entertainment, consumers pay indirectly via the cost of housing. It is, thus, no surprise that the consumer expenditure share on housing has increased by about 50% (from 23.3% to 32.8%) over the 20th century (U S Department of Labor 2006).

These changes are in line with a steady increase in real GDP per capita in the United States, Western Europe and the world as a whole. We compute the rate at which real GDP grew using the 2013 version of the Maddison Project data set (Bolt and van Zanden, 2014).[1] The data set represents a unique collection of real GDP per capita indices by country and world regions, brought together by a group of scholars who continue Angus Maddison´s work on measuring economic performance for different regions and time periods.

Because the data set is an unbalanced panel, it is empirically convenient to estimate the average annual growth rate by regressing the natural logarithm of real GDP per capita against a yearly trend variable. In Table A1, we show the results of such regressions for different countries and world regions. In column (2), we conduct a panel analysis to estimate the average annual growth rate across about 170 countries and world regions. In each case, we include all available years

[1] To access the data set, visit http://www.ggdc.net/maddison/maddison-project/home.htm.

since 1900. For the world as an aggregate unit of observation, we find an average annual growth rate of about 2%. The average annual growth rate across all available countries is only marginally smaller. This is about the rate at which the US, Western Europe, and Germany grew. Other world regions such as Latin America, Africa and Asia had slightly lower growth rates of about 1%-1.5% per year.

Tab A1. Real GDP per capita growth since 1900

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln real GDP per capita (index)							
Year	0.019***	0.018***	0.020***	0.021***	-0.021***	0.015***	0.009***	0.016**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Country effects	-	Yes	-	-	-	-	-	Yes
Unit	World	Coun-tries	US	Western Europe	Germany	Latin America	Africa	Western Asia, Eastern Asia
N	63	11,856	111	111	111	63	62	129
r2	.973	.898	.969	.954	.907	.944	.819	.856

Notes: The data set is an unbalanced panel of country year observations covering the years from 1900 to 2010 from the Maddison Project. “World”, “Western Europe”, “Latin America”, “Africa”, “Eastern Asia” and “Western Asia” are aggregated series provided in the data set. Standard errors robust or clustered on countries where fixed effects included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 Rail noise diffusion

As discussed in the main paper, we use a highly disaggregated map, containing 2007 estimates of the continuous sound level by the source of noise at a 10×10 meter grid from the Berlin Senate Department for Urban Development and the Environment (2013). The noise measure reflects the weighted average noise exposure over one year and all times of a day (L_{den}) at a reception point of four meters above the ground. Following the rules defined by the EU Environmental Noise Directive, the micro geographic noise map is the result of a simulation using a 3D model that is fit to actual noise measurements. The model incorporates features of the track design (e.g. speed, squeaking noises in curves, the presence of lubrication facilities) and the terrain geography (e.g. elevation of the track, built-up structure, bridges) that affect noise dissemination. We note that the data are provided for rail corridors extending 300 meters in either direction from an elevated rail line. Outside these corridors, data are missing as noise levels are deemed generally too low to be relevant. To avoid missing values, we expand the coverage by gradually deflating noise levels outside the corridors using a regression-based extrapolation approach. With this approach, we estimate the noise decay in track distance within the noise corridors and, using the estimated rate of decay, predict the noise levels outside the corridors. Because the noise levels at the margin of the noise corridors are generally low, this manipulation hardly affects the data as we measure noise in terms of decibel exceeding 40 decibels.

In Table A2, we analyze the spatial pattern of rail noise dissemination. The results in the first column reveal that a 0/1 dummy indexing parcels that immediately face the elevated rail line (those with an unobstructed view) already explains more than half of the spatial variation in rail noise (in excess of 40 decibels). In line with intuition, rail noise is highly localized within an area close to the viaduct. In the second column, we replace the view dummy with two sets of distance dummies. The first set consists of dummy variables that index mutually exclusive buffer areas drawn around the elevated rail line. We define the size of these buffers progressively, i.e. we increase the size as we move further away from the line (where there is less variation in noise). The second set consists of a similarly defined set of indicator variables indexing distance from station rings.

Relative to the residual category (800-1000 meters, where excess noise is essentially zero), rail noise levels increase by up to 22.7 db within the first 25 m buffer. Noise levels then decline steeply in distance from the track so that beyond 200 m, noise levels are economically marginal and beyond 400 meters statistically indistinguishable from the residual category. Conditional on the orthogonal diffusion from the track, there is also some variation along the track. Noise levels are significantly lower very close to stations, in line with the low speeds with which trains enter and exit stations. Adding the view dummy to the model in column (3) reveals some variation within the first distance-from-track categories, but has otherwise little impact. In columns (4) and (5), we distinguish between straight and curved line segments. Within the former, there is no conditional front-row effect, which is the expected result given that a 25-meter buffer along a straight section normally covers just about exactly those parcels (see Figure 2 in the main paper). In contrast, along the curved sections where the building structure is less regular, there is a sizable front-row effect conditional on distance, revealing that buildings represent significant obstacles to noise diffusion and protect areas in the background.

Overall, our analysis confirms that the empirically calibrated 3D noise model employed by the Senate Department for Urban Development and the Environment (2013) produces significant and plausible spatial variation in noise.

Tab A2. Noise diffusion along Line A

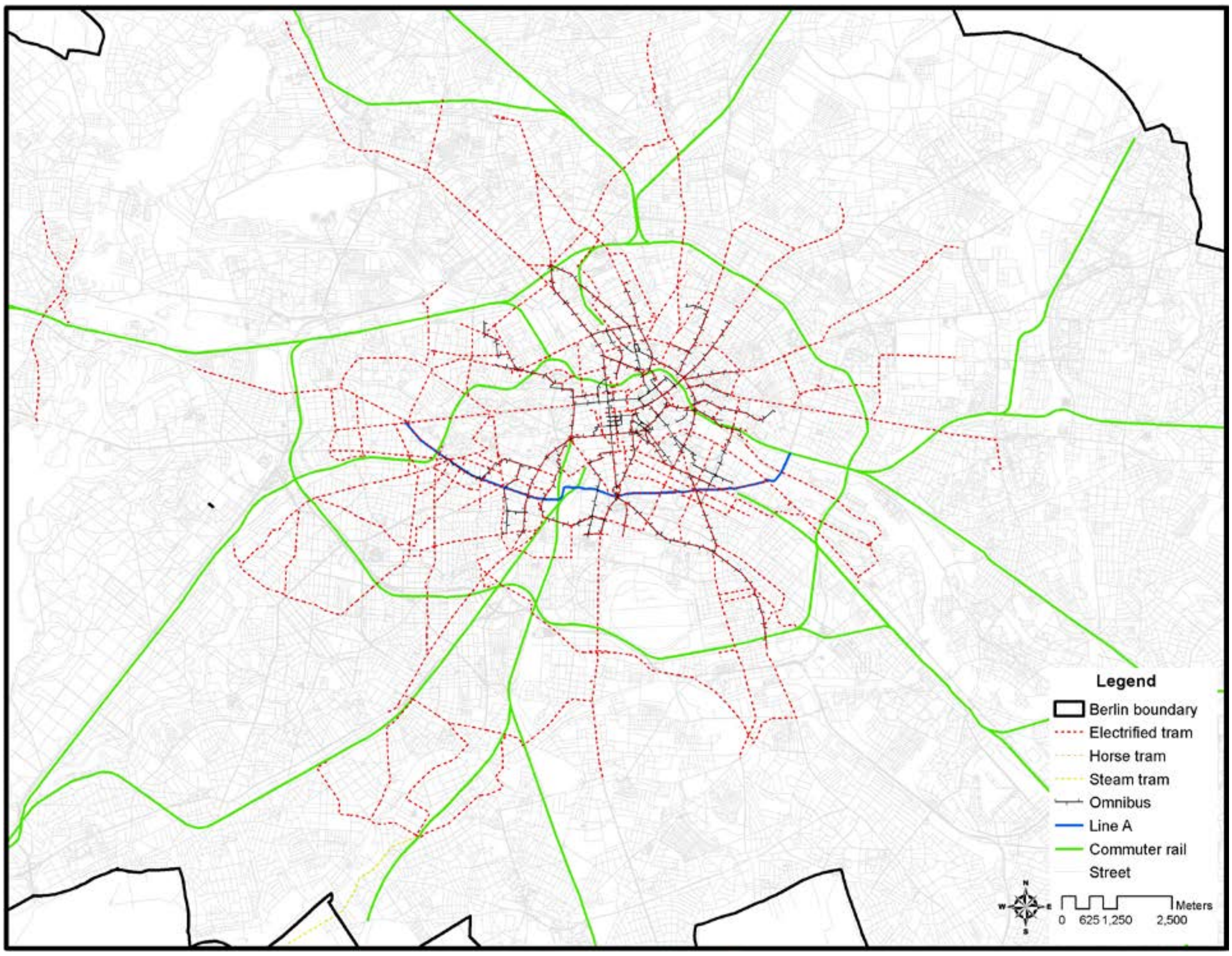
	(1)	(2)	(3)	(4)	(5)
	Noise (decibels) exceeding 40 decibels				
View (dummy)	19.664***		4.308***	0.243	5.415***
	(0.311)		(0.693)	(1.338)	(0.742)
0 m < Track distance <= 25 m		22.792***	18.763***	24.510***	17.091***
		(0.489)	(0.884)	(1.417)	(1.074)
25 m < Track distance <= 50 m		20.901***	17.941***	21.539***	17.291***
		(0.465)	(0.723)	(1.151)	(0.891)
50 m < Track distance <= 100 m		12.525***	11.778***	11.269***	12.102***
		(0.458)	(0.483)	(0.851)	(0.579)
100 m < Track distance <= 200 m		4.063***	4.096***	3.110***	4.819***
		(0.254)	(0.254)	(0.429)	(0.321)
200 m < Track distance <= 400 m		0.833***	0.834***	1.266***	0.655***
		(0.095)	(0.095)	(0.197)	(0.096)
400 m < Track distance <= 800 m		0.007	0.004	-0.000	0.004
		(0.014)	(0.014)	(0.000)	(0.018)
0 m < Station distance <= 25 m		-5.007***	-5.287***	-7.953***	-2.756
		(1.900)	(1.893)	(1.175)	(4.828)
25 m < Station distance <= 50 m		-3.293***	-3.427***	-5.578***	-3.557**
		(1.271)	(1.194)	(1.410)	(1.576)
50 m < Station distance <= 100 m		-1.344**	-1.456**	-5.030***	-0.771
		(0.639)	(0.627)	(1.275)	(0.694)
100 m < Station distance <= 200 m		-0.055	-0.175	0.122	-0.588
		(0.331)	(0.325)	(0.627)	(0.389)
200 m < Station distance <= 400 m		0.237*	0.233*	-0.264	0.374***
		(0.127)	(0.127)	(0.299)	(0.120)
400 m < Station distance <= 800 m		-0.010	-0.007	0.000	-0.011
		(0.013)	(0.013)	(0.000)	(0.016)
Constant	1.439***	-0.002	-0.001	0.000	-0.001
	(0.058)	(0.003)	(0.003)	(0.000)	(0.005)
Sample	All	All	All	Straight	Curved
N	5,456	5,456	5,456	1,651	3,805
r2	.554	.786	.793	.837	.783

Notes: Straight and curved distinguish between parcels along straight or curved line segments. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

3.3 Transport networks

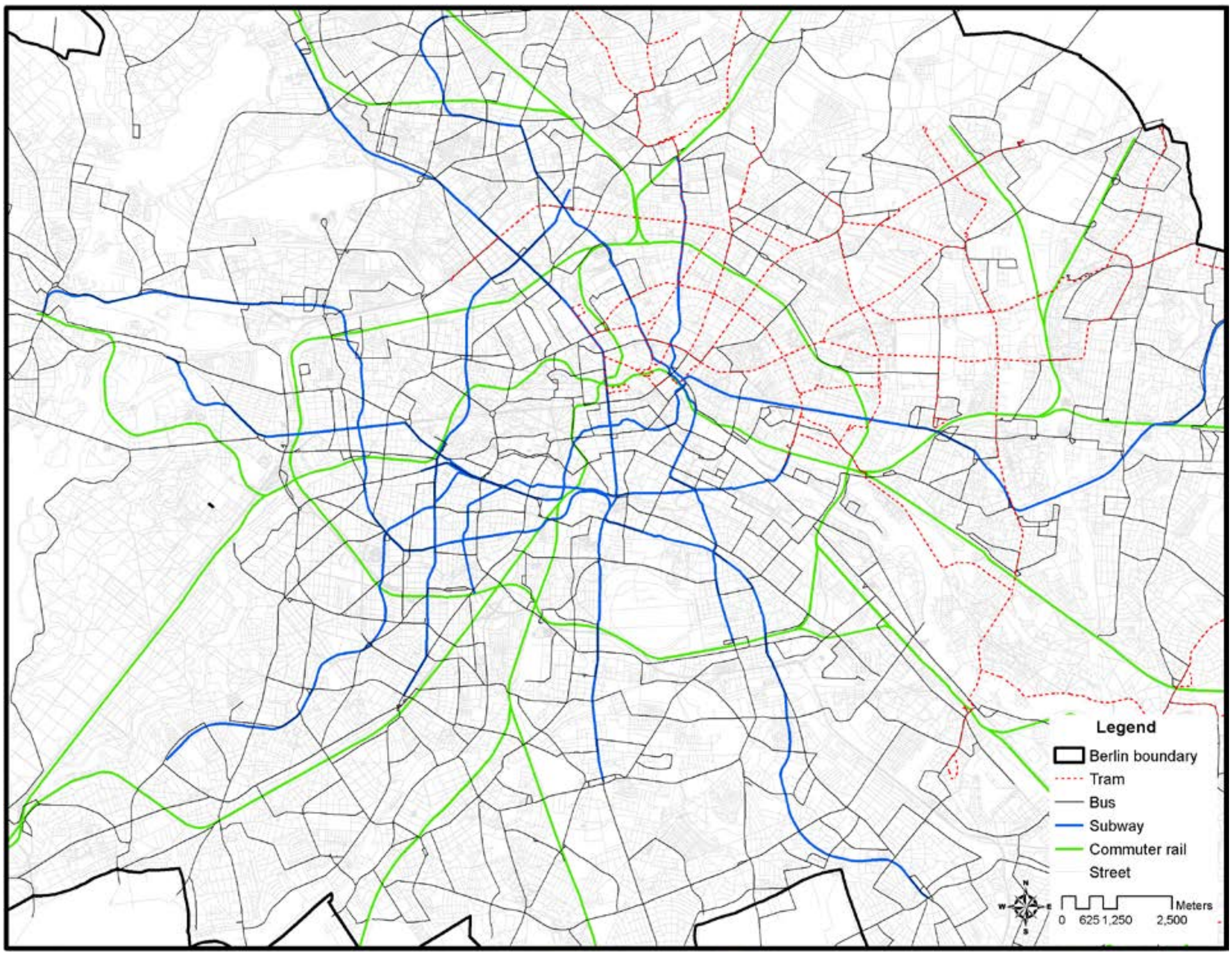
In the figures below, we illustrate the historical and contemporary transport geography of Berlin. The networks and modes illustrated are those which underlie the construction of the transport accessibility measures discussed in section 7.2 of this appendix. The figures show how the commuter rail network, despite significant technological upgrades (e.g. electrification from 1924 onwards) has remained roughly constant in terms of its coverage. In contrast, the subway network has since the opening of Line A developed into one of the densest networks in Europe. In line with the general settlement pattern, there was a dense network of complementary transport modes such as various tram systems and omnibuses within the central city around 1900, but the coverage was less complete in the suburbs. In contrast, the contemporary bus and tram (almost exclusively in the area of former East Berlin) networks cover a much broader area, reflecting the typical 20th century process of urban decentralization.

Fig A1. 1902 Transport geography



Notes: Own data collection. Own illustration based on Senatsverwaltung für Stadtentwicklung Berlin (2006).

Fig A2. 2006 Transport geography



Notes: Own illustration. Data from Ahlfeldt, Redding, et al. (2015) and Senatsverwaltung für Stadtentwicklung Berlin (2006).

4 Historical difference-in-differences models

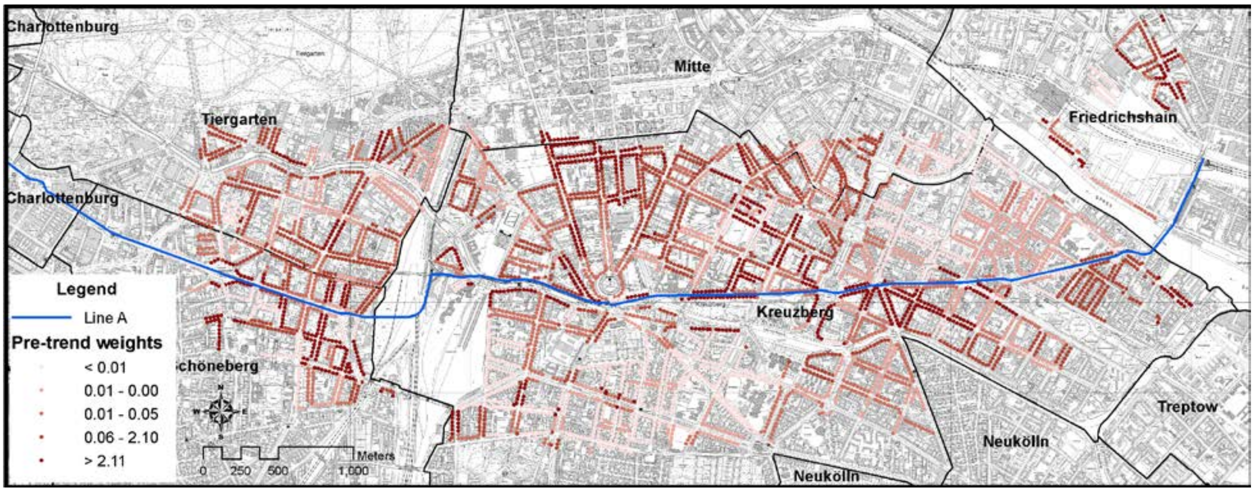
4.1 Weighted-parallel-trends difference-in-differences

It is well known that causal inference using difference-in-differences models relies on the untestable assumption of parallel counterfactual trends. The idea of the weighted estimator discussed in Section 3.2 of the main paper is to reweight observations in a way that one or multiple treatment measures become orthogonal to observable trends in an outcome over the pre-treatment period. The implicit assumption underlying the estimator is that if the weighting removes non-parallel trends successfully during the pre-treatment period (which can be tested), it will likely mitigate a potential non-parallel trends problem during the post-treatment periods (which cannot be tested). For a more formal introduction and evaluation of the estimator in the context of a Monte Carlo study, we refer to a companion paper (Ahlfeldt, 2018). For better accessibility, there is some overlap between the material presented in this appendix and in the companion paper.

4.2 Distribution of DD weights

The algorithm described in Section 3.2 of the main paper finds a vector of parcel weights, which ensures that the partial correlations between our two treatment measures, noise and station distance, with the 1881 to 1890 property price trend are minimized. The resulting weights are plotted in Figure A3. Overall, parcels with relatively high weights are distributed relatively evenly across the study area. The most notable finding are areas with relatively low parcel weights in the central southern section and the north-eastern section of the study area.

Fig A3. Spatial distribution of pre-trend weights



Notes: Classes defined based on quintiles. Own illustration using the Urban Environmental Information System of the Berlin Senate Department (Senatsverwaltung für Stadtentwicklung Berlin, 2006).

Table A3 compares descriptive statistics of the weighted sample to the unweighted parcel population. The distributions are fairly similar. In line with Figure A3, the mean parcel in the weighted sample is somewhat closer to the CBD (Stadtmitte, in the north) and the sub-centre (Kurfürstendamm in the west). But, overall, the weights inspection suggests that the results in the weighted DD will not be driven by a small number of non-representative parcels, so the estimates are hopefully not too far from average effects. Most likely, the DD will have greater internal validity than the historical spatial differences estimate, which is identified from a small number of parcels around the tunnel entrance.

Tab A3. Descriptive statistics in weighted vs. non-weighted sample

	Non-weighted			Weighted		
	Mean	Median	S.D.	Mean	Median	S.D.
Ln land price 1881	4.213	4.094	0.605	4.388	4.094	0.615
Ln land price 1914	5.854	5.768	0.521	6.058	5.991	0.591
Station distance (km)	0.502	0.491	0.237	0.467	0.486	0.226
Noise (10 db)	0.229	0.010	0.553	0.321	0.013	0.665
Distance from CBD	2.018	2.061	0.797	1.764	1.733	1.033
Distance from sub-centre	4.212	4.258	1.725	3.999	3.703	1.712
Distance from Line A track	0.543	0.517	0.265	0.559	0.503	0.310

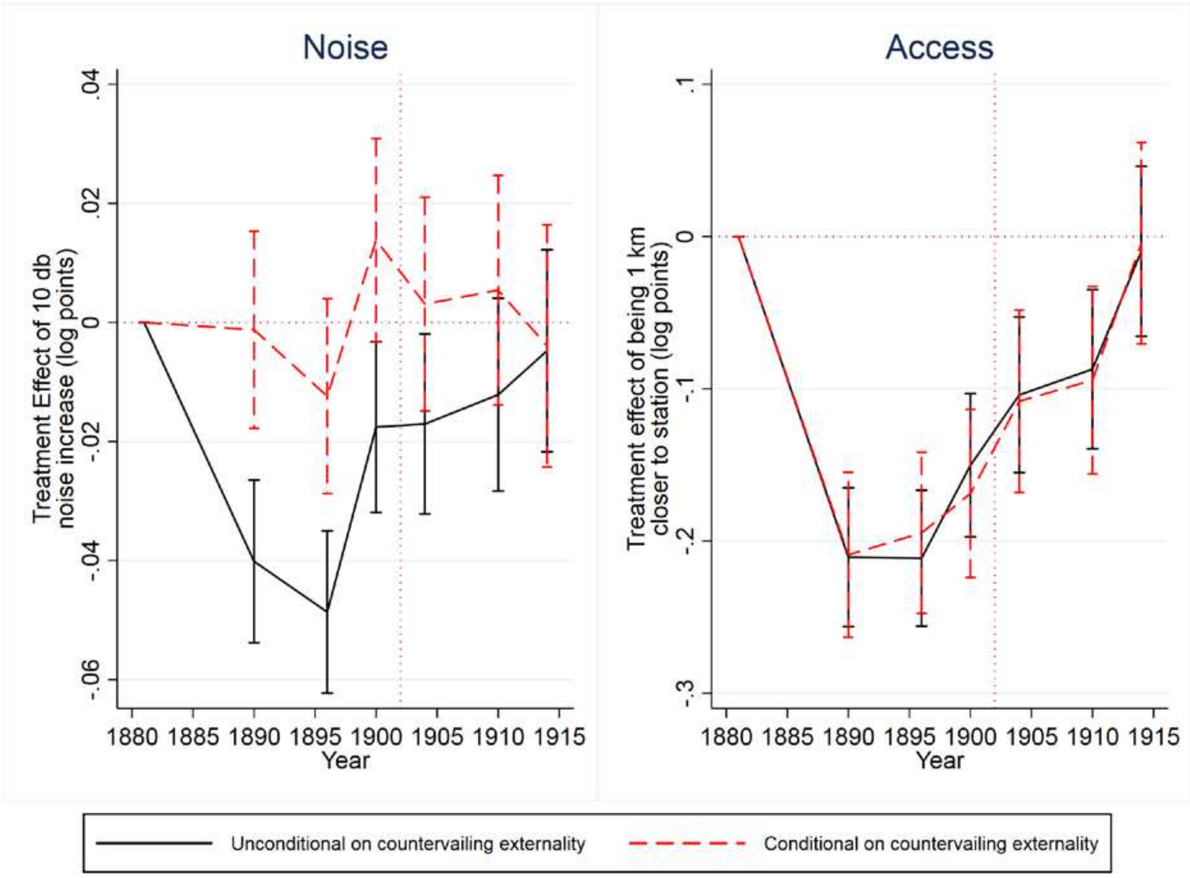
Notes: Source: Ahlfeldt (2018). Weights are constructed using the algorithm described in section 3.2 in the main paper and a Gaussian transformation of the mean 1881 to 1890 land price growth, the distance from the CBD and the distance from the most important sub-centre.

4.3 Time-varying OLS estimates

In section 3.2 of the main paper, we focus on our preferred weighted-parallel-trend (WPT) models. For comparison, we present the OLS-equivalent to Figure 1 below. The OLS results turn out to be somewhat difficult to interpret. According to our estimates, parcels located closer to to-be-opened stations experienced significantly lower land price growth, which points to a violation of the common trend assumption. As shown, the trend is flat from 1890 to 1896 and positive afterwards. To infer the effect of the rail line, a judgement has to be made on a baseline period that provides a counterfactual trend. Because the relative trends are flat, it may be tempting to choose the 1890 to 1896 trend as a baseline, implying a price effect of a one-kilometer change in station distance of about 0.2 log points over the subsequent 20 years. However, given that the concession for the line was granted in 1895, it is possible that the change in trend between 1881-1890 and 1890-1896 is attributable to the rail line, in which case the rail effect would be considerably larger. Another, not particularly conclusive feature of the estimated OLS station effects is the insensitivity of the point estimates to controlling for rail noise effects.

The estimated OLS rail noise effects are even less conclusive. Not controlling for station distance effects, parcels which later become exposed to rail noise experience a relative decline in prices up until 1896, when, shortly after the concession was granted, the trend reverses. Controlling for station distance effects, the land price trends do not seem to depend on the degree to which parcels become exposed to rail noise. This pattern is not in line with rail noise being a disamenity. If anything, the unconditional OLS estimates suggest that rail noise is an amenity.

Fig A4. Difference-in-differences: Time-varying treatment effects (OLS models)



Note: Time-varying treatment effects (α_Z^S and α_Z^N) based on baseline DD equation (1) and treatment function (2)in the main paper. Access parameters (effects of distance from station) multiplied by -1 so that positive shifts indicate positive economic effects. Vertical error bars indicate the 95% confidence interval based on standard errors that are clustered on parcels. Solid vertical lines denote the year of opening of the metro line (1902).

4.4 Alternative covariates and objective functions

In the models reported in section 3.2 in the main paper, the DD weights are constructed as a mix of parcels that are normal with respect to distance from the CBD, distance from the sub-centre, and land price growth over the 1881 to 1890 period. Ideally, weighted DD results will be replicable using different sets of uncorrelated weights as this suggests that identification is not driven by a limited number of units receiving high weights. Therefore, we have generated two alternative set of weights, which we use in Table A4 throughout models (3) to (6) (columns (1) and (2) replicate the baseline model for comparison). We stress that the weights in (5) and (6), which use distance from the Line A rail track instead of the 1881-1890 land price growth as a covariate, are virtually uncorrelated with the baseline weights used in Table 1 in the main paper (correlation coefficient: 0.076). Given this, it is reassuring that the estimates remain within the same ballpark.

Tab A4. Weighted DD: Varying predictors

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln land price (1881-1914)					
Distance x (km) x (t > 1900)	-0.174***	-0.191***	-0.183***	-0.214***	-0.256***	-0.315***
	(0.030)	(0.039)	(0.031)	(0.040)	(0.044)	(0.061)
Noise (10 db) x (t > 1900)	-0.034***	-0.046***	-0.039***	-0.051***	-0.018*	-0.037***
	(0.008)	(0.011)	(0.008)	(0.011)	(0.010)	(0.014)
Parcel effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Anticipation effects	-	Yes	-	Yes	-	Yes
Predictors	Land price growth, distance from CBD, distance from sub-centre	Land price growth, distance from CBD, distance from sub-centre	Land price growth, distance from station, rail noise	Land price growth, distance from station, rail noise	Distance from rail track, distance from CBD, distance from sub-centre	Distance from rail track, distance from CBD, distance from sub-centre
N	37,933	37,933	37,898	37,898	38,192	38,192
r2	.931	.931	.929	.93	.915	.916

Notes: Source: Ahlfeldt (2018). Unit of observation is parcel-year (balanced panel). Weighted DD models use weights constructed to minimise the conditional correlations between noise and the 1881–1890 land price trend as well as access (distance from station) and the 1881–1890 land price trend. Weights are constructed using the algorithm described in section 2.4.1 and a Gaussian transformation of the listed covariates. Land price growth is the deviation from the mean 1881 to 1890 land price growth. Announcement effects are distance and noise variables interacted with 1896 and 1900 effects. Balanced panel of repeated parcel observations for 1881, 1890, 1896, 1900, 1904, 1910 and 1914. Standard errors in parentheses clustered in parcels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We similarly evaluate the sensitivity of the weighted DD estimates to using alternative objective functions in the weight-generating algorithm. As described in the main paper, we search over a parameter space defined by $q_1 = 0, 0.01, 0.02, \dots ,1$, $q_2 = 0, 0.01, 0.02, \dots ,1$, $q_3 = 0, 0.01, 0.02, \dots ,1$ to identiy the parameter vector $Q(q_1, \dots, q_m)$ in equation (4) in the main paper. To this end, we run r regressions of the form $\Delta \ln(P_{i,1890}) = c_r^0 + c_r^S \tilde{S}_i + c_r^N \widetilde{N}_i + \varepsilon_{ri}$, where $\Delta \ln(P_{i,1890})$ is the change in log land price from 1881 to 1890 and tilde denotes normalization by standard deviation. In each regression, observations are weighted by W_i, which depends on the vector $Q(q_1, \dots, q_m)$. In the baseline approach, we select the combination of parameters that minimizes the additive objective function $\sum_{V=(S,N)} \left(\widehat{c_r^V}\right)^2$. As alternatives, we consider a function $\max\left(|\widehat{c_s^1}|, |\widehat{c_s^2}|\right)$, to which we refer as min-max objective function, and a multiplicative function $\prod_{=(S,N)} \left(\widehat{c_m^q}\right)^2$.

In Table A5, we evaluate how the weighted DD estimates change as we alter the objective function in the algorithm. Evidently, the results are not particularly sensitive to the choice of the selection criterion.

Tab A5. Weighted DD: Varying objective functions

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln land price (1881-1914)					
Distance x (km) x (t > 1900)	-0.174***	-0.191***	-0.182***	-0.211***	-0.175***	-0.194***
	(0.030)	(0.039)	(0.031)	(0.040)	(0.030)	(0.039)
Noise (10 db) x (t > 1900)	-0.034***	-0.046***	-0.038***	-0.050***	-0.034***	-0.047***
	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)
Parcel effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Anticipation effects	-	Yes	-	Yes	-	Yes
Objective function	Additive	Additive	Multipli-cative	Multipli-cative	Min-max	Min-max
N	37933	37933	38052	38052	37933	37933
r2	.931	.931	.93	.93	.93	.93

Notes: Source: Ahlfeldt (2018). Unit of observation is parcel-year (balanced panel). Weighted models use weights constructed to minimise the conditional correlations between noise and the 1881–1890 land price trend as well as access (distance from station) and the 1881–1890 land price trend. Weights are constructed using a Gaussian transformation of the 1881 to 1890 land price growth, the distance from the CBD and the distance from the most important sub-centre. Announcement effects are distance and noise variables interacted with 1896 and 1900 effects. Balanced panel of repeated parcel observations for 1881, 1890, 1896, 1900, 1904, 1910 and 1914. Standard errors in parentheses clustered in parcels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We note that we have selected the covariates and the objective function used in our baseline approach following an inspection of how the weights address the non-parallel-trends problem during the pre-treatment period. In Table A6, we provide two tests of the conditional correlations between the treatment variables and pre-treatment outcome trends. Models (1–6) regress the change in ln land price over the 1881–1890 period (the period targeted by the algorithm) against both treatment variables. Models (7–12) replicate the exercise using the change in ln land price over the 1890–1900 period as a dependent variable. This (non-targeted) pre-treatment period has not been used in the computation of the weights, so it can be used in an overidentification test.

Models (1) and (7) present OLS estimation results. There is a significant correlation between station distance and land price growth over the targeted period. Compared to prices right next to a to-be-constructed station, prices at a 1km distance grow at a 0.221 log points higher rate (24%). There is also a significant correlation during the non-targeted period, however, with the opposite sign, suggesting the presence of unobserved effects that interact non-linearly with time. Conditional on the station-distance effect, the noise effect is insignificant. However, station distance and noise are correlated, which explains why the unconditional correlation between noise and the change in price is significant (to keep the presentation compact, we do not report the results of formal tests). The main takeaway from these results is that the parallel-trends assumption is violated during the pre-treatment period, thus, it seems likely that it does not hold during the post-treatment period.

The remaining models use weights to address this problem, which are constructed using different algorithms, objective functions and covariates. All approaches succeed in achieving their formal objective of reducing the correlation among treatments and trends during the targeted period (models 2–6). In several instances, the effects of both treatment variables are close to and not statistically distinguishable from zero. The models using the Gaussian transformation of land price growth as a covariate perform best in terms of the overidentification tests reported throughout models (8–12). Apparently, the treatment-trend correlation is low among parcels that experienced "normal" growth over the targeted period.

Tab A6. Marginal treatment effects on pre-outcome trends (placebos)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln land price 1890 – ln land price 1881 (targeted period)					
Distance (km)	0.221***	-0.007	-0.024***	-0.006	-0.022**	-0.009
	(0.028)	(0.010)	(0.009)	(0.076)	(0.009)	(0.010)
Noise (db)	0.008	-0.004	0.001	-0.036**	0.000	-0.004
	(0.009)	(0.004)	(0.003)	(0.015)	(0.003)	(0.003)
r2	.0146	.0005	.0051	.0071	.0031	.0004
	(7)	(8)	(9)	(10)	(11)	(12)
	Ln land price 1900 – ln land price 1890 (not targeted period)					
Distance (km)	-0.052***	-0.038	-0.054	-0.172***	-0.051	-0.040
	(0.015)	(0.033)	(0.033)	(0.058)	(0.033)	(0.033)
Noise (db)	0.007	-0.011	-0.014	-0.012	-0.014	-0.011
	(0.006)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
r2	.0045	.0011	.0023	.0120	.0021	.0013
Objective	-	Additive	Additive	Additive	Multi.	Min-max
Covariates	-	Land price growth, distance from CBD, distance from sub-centre	Land price growth, distance from station, rail noise	Distance from rail track, distance from CBD, distance from subcentre	Land price growth, distance from CBD, distance from sub-centre	Land price growth, distance from CBD, distance from sub-centre
N	5,456	5,456	5,456	5,456	5,456	5,456

Notes: Ahlfeldt (2018). Unit of observation is parcel. Columns (1) and (7) show results of separate OLS regressions of land price growth over the first (1) and second (2) period in the data against the treatment measures. The subsequent columns show results of weighted regressions, where the weights are recovered using objective functions, and a Gaussian transformation of the covariates indicated in the bottom of the table. Robust standard errors in parentheses. Additive minimises/multi./min-max minimises the sum/product/the largest of squared standardised coefficients on distance and noise. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

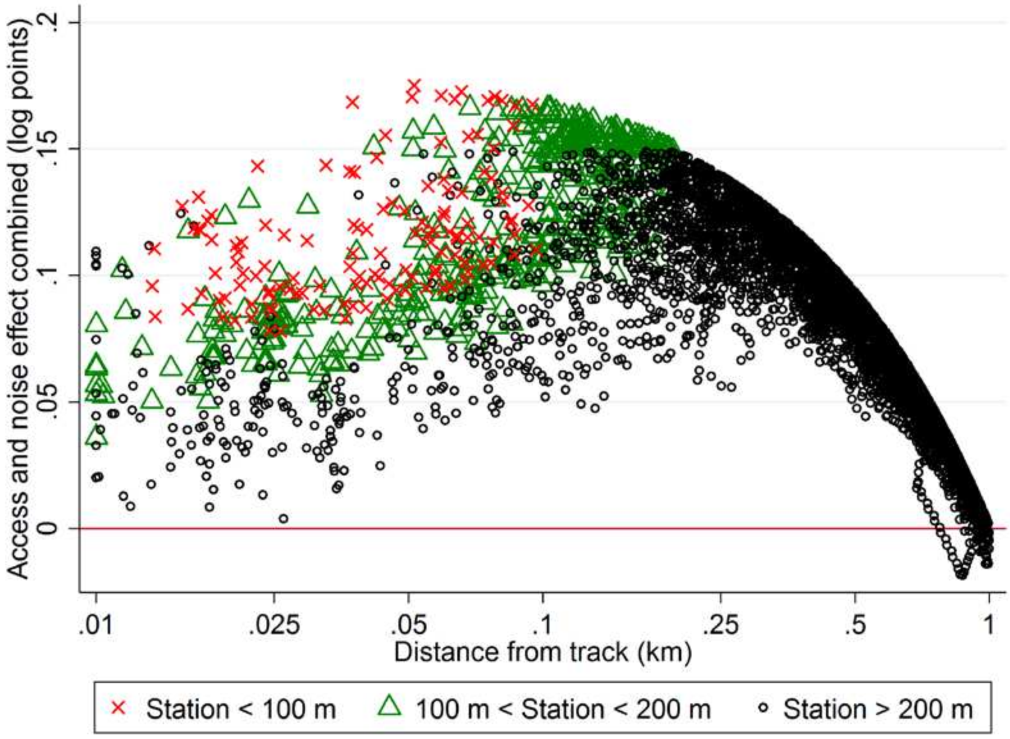
The weights used in models (2) and (8) are the most promising in terms of addressing non-parallel trends in the data, as they minimise the treatment variables' effects on outcome trends over the targeted and the non-targeted period. This is why we use these weights in the main paper.

4.5 Countervailing externalities

In the figure below, we explore the countervailing nature of rail externalities. To illustrate the net benefit from locating close to the elevated rail line, we plot the predicted joint station access and rail noise effect ($\hat{\alpha}^S S_i + \hat{\alpha}^N N_i$) from model (6) in Table 1 in the main paper against the straight-line distance from the elevated track. The figure illustrates that, for the clear majority of parcels, being located closer to the elevated line is associated with net benefits relative to locations at the outer margin of our study area. Beyond 100 m, the rail effect tends to be positive as reflected by the expected negative relationship between rail effect and track distance. At shorter distances, the net proximity effect tends to be negative, reflecting an increasing noise disamenity. This inverse U-shaped relationship is the expected pattern for a densely-developed area where noise tends to be highly localized. Some further interesting features of the countervailing nature of rail externalities are evident from the figure. As long as a location is sufficiently close to a station, the net effect of the line is positive, suggesting that the benefits from access to the line are relatively large. Land prices of parcels within 100 m of a station increase by at least 5% relative to those located at the margin of our study area. For parcels within a 100-200 m distance to a station, the effect is about half the size. Among the parcels further away from the nearest station, there are at least a handful for which the negative rail noise effect exceeds the positive station access effect.

As a plausibility check, we illustrate this negative net effect with a numerical example. The largest distance between two stations along the elevated line is about 1 km, implying that a parcel can be located at most 500 m from a station while still being located directly at the track. At 500 m, the benefit from rail access compared to the outer margin of the study area amounts to some $(0.5 \times 1.84 =)0.092$ log points. At this location, a parcel will be exposed to a very high noise level. Multiplying the 99th percentile in the distribution of rail noise (exceeding 50 db) of 26.1 db by the per-decibel noise effect of (-0.036/10) yields an effect of -0.93 log points, which indeed more than compensates for the accessibility effect.

Fig A5. Net benefit of proximity to elevated rail line



Notes: Figure illustrates the joint effects of station distance and rail noise predicted by model (6) in Table (1), formally: $\hat{\alpha}^S S_i + \hat{\alpha}^N N_i$. All effects are expressed relative to the outer margin of our study area. Therefore, we do a normalization by the mean across the predicted effects within the outmost 50 meters. Station indicates distance from the nearest station.

4.6 Time-varying implicit prices and treatment trends

In table A7, we provide a number of robustness checks on our preferred empirical model, reported in column (6) of Table 1. We begin by estimating an extended version of specification (1), allowing for time-varying implicit prices for various characteristics throughout columns (1-5). The interaction between time-invariant covariates and year effects are demanding controls, creating concerns of over-controlling. Some changes in implicit prices, e.g., distance from CBD or distance from the Kurfürstendamm, could be caused by the elevated line, implying a potential bad control problem (Angrist and Pischke, 2009). Yet, the station distance effect remains significant throughout all models, although it is reduced considerably. The noise effect becomes insignificant once we allow for time-varying effects for distance from rivers, lakes, or canals. Since the elevated track was partially built along a canal, however, it is difficult to separately identify the time-invariant effect of time-varying noise and the time-varying effect of time-invariant distance from rivers, lakes, or canals.

Tab A7. Weighted DD estimates: Robustness I

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln land price (1881-1914)					
Distance (km) × after	-0.130***	-0.094**	-0.129***	-0.114***	-0.073**	-0.097**
$(S_i \times (t > 1902)_t)$	(0.040)	(0.039)	(0.033)	(0.033)	(0.032)	(0.040)
Noise (10 db) × after	-0.036***	-0.030***	0.010	-0.007	-0.004	-0.014
$(N_i \times (t > 1902)_t)$	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)
Distance × (year – 1902)						-0.000
						(0.001)
Distance × (year – 1902) x						-0.010***
$(t > 1902)$						(0.003)
Noise × (year – 1902)						-0.000
						(0.000)
Noise × (year – 1902) ×						-0.002**
$(t > 1902)$						(0.001)
Parcel effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Anticipation effects	Yes	Yes	Yes	Yes	Yes	Yes
Distance from CBD effects	Yes	Yes	Yes	Yes	Yes	-
Distance from Kudamm effects	-	Yes	Yes	Yes	Yes	-
Distance from water body effects	-	-	Yes	Yes	Yes	-
Distance from main street effects	-	-	-	Yes	Yes	-
Tram density effects	-	-	-	-	Yes	-
N	37,933	37,933	37,933	37,933	37,933	37,933
r2	0.934	0.936	0.942	0.944	0.944	0.931

Notes: Weighted DD models use weights constructed to minimize the conditional correlations between rail noise and the 1881-1890 land price trend as well as station distance and the 1881-1890 land price trend. After is a dummy variable indicating years after the line opening (1902). Announcement effects are distance and noise variables interacted with 1896 and 1900 effects. All other effects are time-invariant covariates interacted with year effects. Distance from CBD is defined as distance from the underground station "Stadtmitte" (downtown). Distance from Kudamm (slang for Kurfürstendamm) is defined as distance from Breitscheidplatz. Tram density is defined as kernel smoothed density of tram tracks within 2 km (bandwidth according to Silverman (1986)). Data is a balanced panel of repeated parcel observations for 1881, 1890, 1896, 1900, 1904, 1910, 1914. Standard errors in parentheses are clustered on parcels. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In column (6), we add interaction terms between our treatment measures and time trends (year – 1902) and the same interacted with an after-period dummy ($t > 1902$). With this specification, we test for an effect of the treatments on levels and trends in land prices. The near to zero and insignificant pre-trend effects [Distance × (year – 1902) and Noise × (year – 1902)], once again, confirm that the weights achieve their purpose of eliminating the conditional correlations between pre-intervention price trends on the one hand and rail noise and station access on the other. The estimated station distance effect on land price levels $(S_i \times (t > 1902)_t)$ about halves in magnitude compared to the benchmark specification (column 6 of Table 1), but remains significant. The post-intervention trend in the distance treatment effect [Distance x (year – 1902) x after], however, reveals that ten years after the opening of the line the treatment effect has increased to some $-0.097 - 10 \times 0.01 = -0.197$ log points, which is remarkably close to the baseline effect reported in column (6) of Table 1. The post-intervention noise level [Noise × (year – 1902)] and trend [Noise × (year – 1902) × ($t > 1902$)] effects are both negative as expected, though not individually significant. The cumulated effect of -0.037 after ten years, however, is not only close to the baseline estimate, but also statistically significant at the 1% level.[2]

4.7 View effects and semi-parametric station distance effects

In table A8, we further investigate the spatial pattern of the effect of the opening of Line A on nearby land prices. For comparison, column (1) replicates the baseline model from Table 1, column (6) in the main paper. In column (2), we replace the noise variable with a dummy indexing parcels with an unobstructed view on the elevated line. This dummy variable should also capture disamenity effects from rail vibrations as these tend to be highly localized. There is a negative effect associated with a direct view, however, at about -4.5%, the effect is significantly smaller than the noise effect implied by the baseline model for parcels exposed to very high noise levels (-9.3%, see discussion in section 4.4 in this appendix). The station distance effect is also substantially reduced, possibly because of the confounding effects of unobserved rail disamenities. Compared to the noise measure, the view dummy appears to be a less efficient disamenity measure. In column (3), we estimate the view effect conditional on the noise effect. The noise effect remains close to the baseline model, but the view effect is close to and statistically indistinguishable from zero. Because noise is highly localized, our noise and view measures are highly correlated, raising concerns about the separability of the effects in a multivariate analysis. To address this concern, we replicate the baseline model (including the noise measure, excluding the view measure) restricting the sample to parcels that do not offer a direct view on the elevated line because the view is obstructed by other buildings in column (4). In this model, we identify the noise effect excluding the parcels exposed to the highest noise levels. Yet, the noise effect remains close to the baseline model. Together, the evidence suggests that the disamenity effect of the rail line is primarily driven by noise and not by an unpleasant view.

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2 The standard error is computed as follows: $\exp\left(var\left(\widehat{\alpha^N}\right) + 10^2 \times \mathrm{var}(\widehat{\alpha^{NT}}) + 2 \times (10) \times \mathrm{cov}(\widehat{\alpha_A^N}, \widehat{\alpha_A^{NT}})\right) - 1$, where $\widehat{\alpha^N}$ is the estimated noise treatment level effect (as defined in equation (3) and $\widehat{\alpha^{NT}}$ is estimated trend effect [Noise × (year – 1902) × ($t > 1902$)].

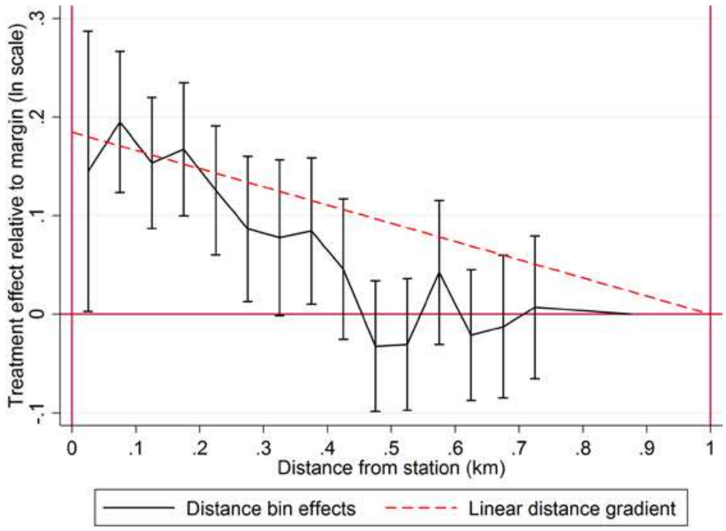
Tab A8. Difference-in-differences estimates: Robustness II

	(1) Ln land price	(2) Ln land price	(3) Ln land price	(4) Ln land price	(5) Ln land price	(6) Ln land price
Dist (km) x Post	-0.184***	-0.138***	-0.203***	-0.194***		
	(0.040)	(0.034)	(0.040)	(0.042)		
Noise (10 db) x Post	-0.036***		-0.039***	-0.040***	-0.060***	-0.064***
	(0.010)		(0.012)	(0.014)	(0.009)	(0.011)
View (0,1) x Post		-0.044***	0.001			0.009
		(0.016)	(0.021)			(0.021)
0 m < Station distance <= 50					0.145**	0.147**
					(0.072)	(0.073)
50 m < Station distance <= 100					0.195***	0.199***
					(0.036)	(0.037)
100 m < Station distance <= 150					0.153***	0.156***
					(0.034)	(0.034)
150 m < Station distance <= 200					0.167***	0.171***
					(0.034)	(0.035)
200 m < Station distance <= 250					0.125***	0.130***
					(0.033)	(0.034)
250 m < Station distance <= 300					0.087**	0.090**
					(0.038)	(0.038)
300 m < Station distance <= 350					0.078*	0.081**
					(0.040)	(0.041)
350 m < Station distance <= 400					0.085**	0.092**
					(0.038)	(0.038)
400 m < Station distance <= 450					0.046	0.065*
					(0.036)	(0.036)
450 m < Station distance <= 500					-0.032	-0.018
					(0.034)	(0.036)
500 m < Station distance <= 550					-0.031	-0.041
					(0.034)	(0.040)
550 m < Station distance <= 600					0.042	0.018
					(0.037)	(0.039)
600 m < Station distance <= 650					-0.021	-0.036
					(0.034)	(0.036)
650 m < Station distance <= 700					-0.012	-0.033
					(0.037)	(0.038)
700 m < Station distance <= 750					0.007	0.005
					(0.037)	(0.038)
Parcel effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Anticipation effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	Excluding direct view	All	All
N	37,933	37,933	37,933	37,933	37,933	37,933
r2	.93	.93	.93	.93	.932	.931

Notes: Model (1) is the baseline model. Weighted DD models use weights constructed to minimize the conditional correlations between the treatment variables and the 1881-1890 land price trend. Weights are constructed specifically for each combination of treatment variables (distance, noise, view). Announcement effects are distance and noise variables interacted with 1896 and 1900 effects. Balanced panel of repeated parcel observations for 1881, 1890, 1896, 1900, 1904, 1910, 1914. Standard errors clustered on parcels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In column (5) we address the question of whether the accessibility effect is sufficiently localized to justify a restriction to 1 km distance buffer. Therefore, we replace the linear distance measure with a set of distance bin dummies defined for mutually exclusive 50-meter rings up to 750 meters. The remaining distances are the residual category. We find that the station effect decays quickly, flattening out already at about 400-500m. Compared to the baseline category, the land prices within the innermost rings increased by about 0.19 log points, which is very close to the effect implied by the linear distance gradient estimate for a 1 km change in station distance. A graphical comparison is provided in the figure below. The results support the baseline model in that they suggest that there are unlikely station effects beyond one kilometer and that the one-kilometer distance effect is in line with a less parametric specification. In column (6), we add the view dummy to the model from column (5). Once more, we do not find evidence for a view effect.

Fig A6. Historical PTW-DD models: Distance from station gradient vs. distance bin effects



Notes: Figure compares the linear distance effect from the baseline model (Table A8, column 1) to the distance bin effects estimated in Table A8, column 5. Distance bins are dummy variables indicating mutually exclusive 50-meter rings defined for 0-50, ..., 700-750 meters. The residual category is 750-1000 meters. Error bars indicate the 95% confidence interval.

4.8 Stability of the hedonic price function

The interpretation of our difference-in-difference parameters as hedonic implicit prices hinges on the assumption that the hedonic function remained approximately constant over the study period (Kuminoff and Pope, 2014). In table A9, we provide a series of cross-sectional estimates of a simple hedonic model in which the land price is expressed as a function of some of the arguably most conventional location attributes in the hedonic literature. We find that the marginal effect of distance from the CBD remained approximately constant over the period from 1896 to 1910. The marginal effect of distance from the nearest park remained approximately constant from 1890 to 1910. In contrast, there is more variation in the effect of distance from rivers and canals, reflecting an increasing discount on the price of land close to waterways. However, it is likely that the variation in the water proximity effect is driven by an actual increase in proximity cost rather than a change in the hedonic implicit price of a time-invariant location factor. During our historical period, Berlin experienced sizable economic growth and a doubling of its population. Economic growth was fueled by rapidly increasing domestic cargo shipping, facilitated by significant investments into the regional waterway infrastructure. Between 1880 and 1914, several new canals (Oder-Spree-Kanal, Teltowkanal, Neuköllner Schifffahrtskanal, Hohenzollernkanals) and harbors (Urbanhafen, Südhafen Spandau, Tegeler Hafen, Osthafen, Hafen Britz, Tempelhofer Hafen, Steglitzer Hafen, Hafen Lichterfelde, Nordhafen Spandau, Westhafen) were constructed and a sizable fraction of the Spree river (Unterspree) was channeled. Moreover, in 1900, a large power plant (Heizkraftwerk Charlottenburg) opened at the Spree River shore close to our study area which was supplied with coal via the river (Natschka, 1971). Naturally, the growing traffic generated noise and pollution, rationalizing a land price discount close to waterways at a constant implicit price for amenities. Thus, overall, we view the evidence provided in the below table as supportive of a stable hedonic function around the years when Line A opened (1902).

Tab A9. Hedonic estimates by year

	(1) Ln land price	(2) Ln land price	(3) Ln land price	(4) Ln land price	(5) Ln land price	(6) Ln land price	(7) Ln land price
Distance from the CBD (km)	-0.381^{***}	-0.353^{***}	-0.319^{***}	-0.298^{***}	-0.276^{***}	-0.272^{***}	-0.234^{***}
	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
Distance from parks (km)	-0.092^{***}	-0.146^{***}	-0.135^{***}	-0.142^{***}	-0.160^{***}	-0.163^{***}	-0.190^{***}
	(0.007)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Distance from rivers and canals (km)	-0.043^{**}	0.057^{***}	0.138^{***}	0.205^{***}	0.247^{***}	0.288^{***}	0.314^{***}
	(0.021)	(0.015)	(0.015)	(0.014)	(0.015)	(0.017)	(0.017)
Year	1881	1890	1896	1900	1904	1910	1914
N	5456	5456	5456	5456	5456	5456	5456
r2	.373	.662	.61	.574	.559	.505	.483

Notes: Standard errors in parentheses. Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.9 Varying levels of spatial clustering

It is conventional to address serial autocorrelation by clustering standard errors (Bertrand, Duflo, Mullainathan, 2004). Following the convention, we cluster standard errors at the level of parcels, the unit at which we repeatedly observe our outcome of interest, throughout our empirical analyses. Here, we evaluate the effects of accounting for a spatial structure in the error term by clustering at higher spatial levels. To this end, we generate grids based on geographic coordinates of varying grid size. Table A10 presents the results of our baseline model when clustering standard errors at the level of those grid cells. We find that the estimated noise and distance effects remain significant when clustering up to the level of 200x200 meter grid cells. That said, we note that we already control for unobserved spatial heterogeneity at the finest possible level by means of parcel fixed effects. We have complete coverage of parcels within our study area, so we do not expect a spatial clustering problem in the sampling. And we have a parcel-specific assignment to treatment. Therefore, following Abadie, Athey, Imbens, and Wooldridge (2017), we keep the parcel-clustered model as our baseline.

Tab A10. Difference-in-differences estimates: Varying levels of spatial clustering

	(1) Ln land price	(2) Ln land price	(3) Ln land price	(4) Ln land price	(5) Ln land price	(6) Ln land price
Dist (km) x Post	-0.171***	-0.171***	-0.171***	-0.171**	-0.171**	-0.171*
	(0.031)	(0.050)	(0.065)	(0.078)	(0.085)	(0.093)
Noise (10 db) x Post	-0.028***	-0.028***	-0.028**	-0.028*	-0.028*	-0.028
	(0.008)	(0.010)	(0.014)	(0.016)	(0.017)	(0.018)
Parcel effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustering grid (in m)	25 x 25	50 x 50	100 x 100	150 x 150	200 x 200	250 x 250
N	37933	37933	37933	37933	37933	37933
r2	.93	.93	.93	.93	.93	.93

Notes: Pre-trend weighted (PTW) models use weights constructed to minimize the conditional correlations between noise and the 1881-1890 land price trend as well as access (distance from station) and the 1881-1890 land price trend. Balanced panel of repeated parcel observations for 1881, 1890, 1896, 1900, 1904, 1910, 1914. Standard errors clustered on spatial grid cells as indicated in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Historical spatial differences models

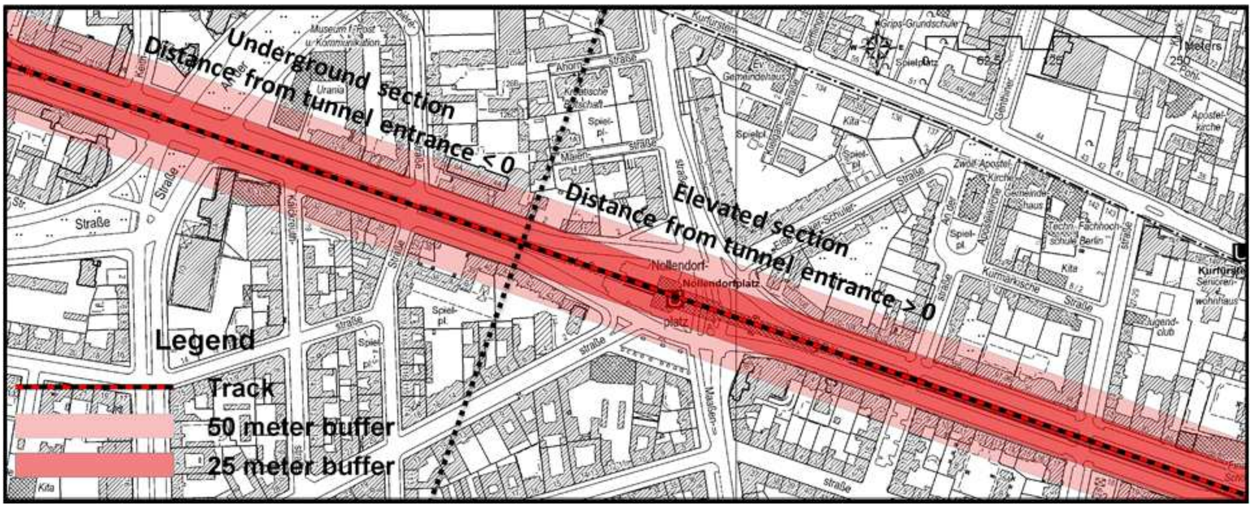
5.1 Empirical strategy

The specific character of Line A, in combination with the spatially highly disaggregated data available to us, enables us to identify the effect of the noise disamenity using a relatively sharp change in the spatial distribution of rail noise at the tunnel entrance where the line switches from being elevated to running underground and vice versa. Our SD approach to exploiting this feature is inspired by the regression discontinuity designs, in particular the fuzzy version (Hahn et al. 2001).

We note that the agreement to construct the line as an underground line within the boundaries of the city of Charlottenburg, whose authorities opposed the erection of an elevated line, was reached not earlier than three years before the inauguration. Therefore, for the change in noise at the tunnel entrance, anticipatory effects are unlikely. The idea of our SD approach is to wash out any effect of accessibility and other location characteristics that can be assumed to be similar within a very small area, thereby generating a precise estimate of the pure rail noise effect. Most notably, our land price data allows us to identify the effect using very small spatial windows from the rail track and the tunnel entrance. The figure below illustrates the micro geography around the tunnel entrance, which is right at the intersection of the two dotted lines. Evidently, a 50-

meter buffer drawn around the track comfortably covers the boulevard under which the line is routed as well as the front rows of buildings framing the boulevard.

Fig A7. Micro geography at tunnel entrance



Notes: Dotted line is the orthogonal intersecting with the track at the tunnel entrance. Own illustration using the Urban Environmental Information System of the Berlin Senate Department (Senatsverwaltung für Stadtentwicklung Berlin 2006).

Our baseline SD specification takes the following form:

$$\Delta \ln(P_{ic}) = \alpha^N \Delta N_i + \rho K_c + X_i b + \varepsilon_i,$$

where $\Delta \ln P$ is the change in ln land price from 1900 to 1904, ΔN_i is a measure of change in rail noise (equal to N_i as the rail noise level in the initial period is zero), and K_c is a dummy variable indexing parcels within a spatial window from the track and the orthogonal that intersects with the track at the tunnel entrance (the black dotted line in the above figure). In our baseline specification, we set the window to 50 meters from the track and 500 meters from the orthogonal. The noise effect is then identified conditional on all unobserved effects on levels and trends that are common to this corridor. Notably, the corridor excludes the boundary between Berlin and Charlottenburg to the west of the tunnel entrance, so administrative boundary effects do not interfere with the within-corridor identification of noise effects. In the spirit of the regression discontinuity literature, we define a running variable D_i, which is the distance from the orthogonal, taking negative values within the underground section (to the left of the dashed orthogonal in the above figure) and positive values within the elevated section (to the right of the dashed orthogonal).

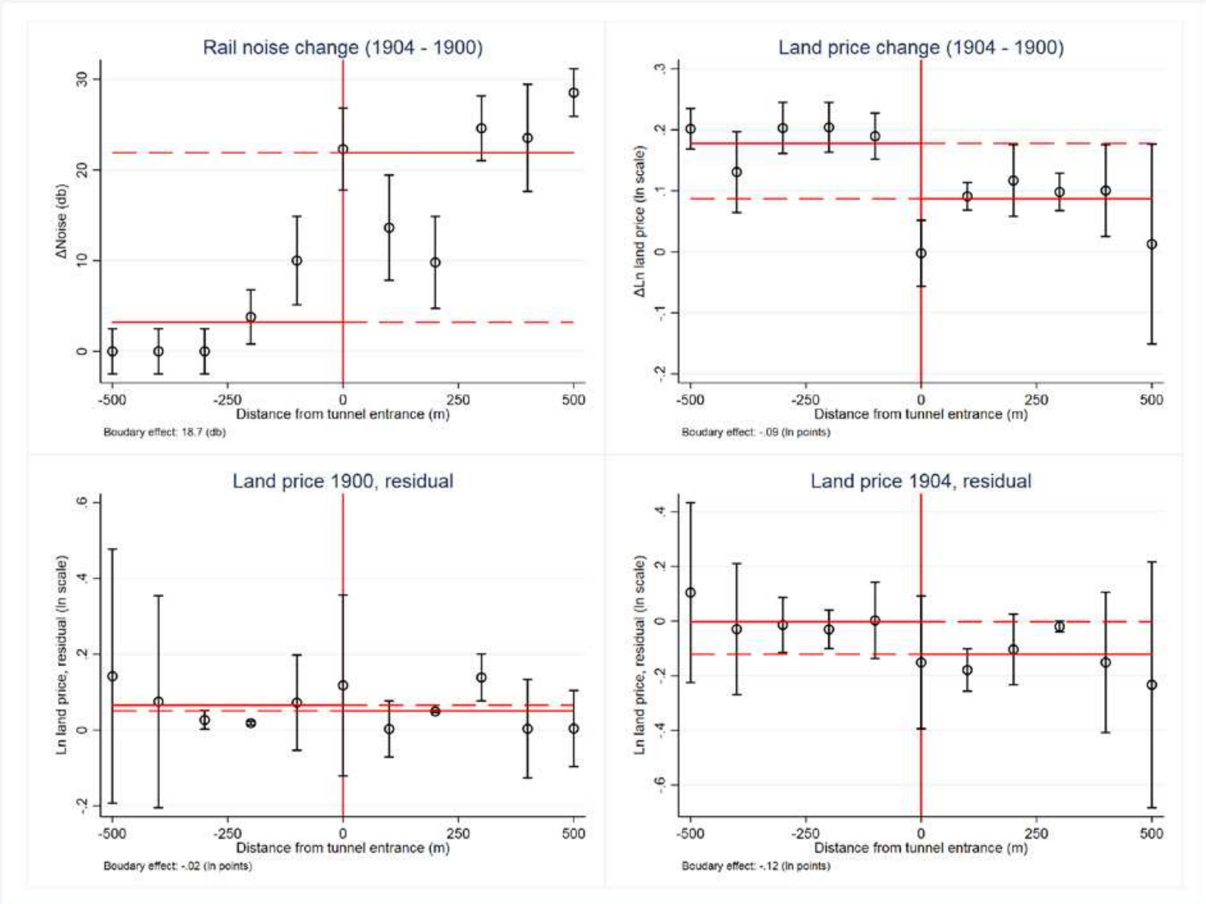
While we observe large variation in noise levels over a short distance around the tunnel entrance, the variation is not discrete in space since noise dissipates gradually in space. The positive noise values along a fraction of the underground segment of Line A correspond to non-compliers in a fuzzy discontinuity design. We use the interaction term $(D > 0)_i \times K_c$ as an instrumental variable for N_i, where $(D > 0)_i$ is a dummy variable that takes the value of one if the condition is true. The model is then estimated using 2SLS. To further strengthen the identification, we add a vector of control variables X_i, which captures trend heterogeneity with respect to observable characteristics. The coefficient of interest is α^N and provides a causal estimate of the extent to which the exposure of noise emitted by an elevated rail depreciates land prices under the identifying assumption that the conditional counterfactual trends are homogenous within the corridor (indexed by K_c).

5.2 Baseline results

The tunnel entrance between the stations Nollendorfplatz and Wittenbergplatz, where Line A turns from an elevated line into an underground line, provides a source of sharp variation in rail disamenities. In the figure below, we illustrate the distributions of rail noise emitted by Line A around the tunnel entrance, as well as the distributions of land prices in levels and changes (1900-1904, the line opened in 1902). We restrict the sample to plots within close proximity to the track (50 meters), because this is where the noise disamenity of an elevated line is concentrated in this densely developed urban setting. We group parcels into 100-m-bins for which we then illustrate the mean value of an outcome as circles. The error bars allow for a quick evaluation of whether or not a within-bin mean is statistically different (at the 90% level) from the mean across all observations on the other side of the tunnel entrance.

Considering a rail corridor covering 500 meters in either direction of the tunnel entrance, the noise level (in excess of 40 decibels) along the elevated sections exceeds the noise level along the underground section by about 18 decibels on average (upper-left panel). Average noise levels are relatively low at about 100-200 meters from the tunnel entrance within the elevated section because parcels are somewhat further away from the track at the square *Nollendorfplatz*. There are some noise spillover effects onto the underground section of the line within the first 200 meters of the tunnel entrance, which is intuitive given that the rail line vanishes underneath a boulevard and there are no structures that would impede diffusion along the track. The average land price growth along the elevated section is 0.09 log points lower, implying a 5% noise effect for a 10-decibel increase that appears quite stable and significant (upper right panel). The bottom panels show that, controlling for other factors, a significant difference in land price levels exists after the opening of Line A, but not before, which serves as a useful placebo test. A positive outlier in 1904 land prices at 300 meters (bottom-right panel) is also present in 1900 (bottom left panel) and, therefore, disappears in the time differenced SD model (upper right panel). The models in changes (upper right) and levels (bottom right) produce boundary effects that are similar (-0.09 vs. 0.12), suggesting that the noise estimates discussed here are comparable to the contemporary SD estimates in section 4 of the main paper.

Fig A8. Historical spatial differences in noise and land prices



Notes: Each circle illustrates the mean value of a dependent variable within a grid cell. One dimension of the grid cells are 100-m bins defined based on the distance from the orthogonal line intersecting with the track at the tunnel entrance (the dotted line in Figure A7). The other dimension is a 50-m-distance buffer around the track. Negative distances from the tunnel refer to the underground section. Solid horizontal lines indicate the means (weighted by the number of observations) within the underground (negative distance) and elevated (positive distance) segments. Error bars are the 90% confidence intervals based on robust standard errors from separate parcel-level regressions (within the buffer). For each outcome, we run one regression of the outcome against dummies indicating positive distance (≥ 0) bins, and another regression of the outcome against dummies indicating negative distance (<0) bins. For each bin, the error bar represents a test if the mean within the bin is different from the spatial counterfactual (the dashed line). The boundary effect corresponds to the difference between the two horizontal lines. Rail noise change from 1900 to 1904 is approximated by rail noise in 2007 (in excess of 40 db) since there was no rail noise in the study area prior to Line A (this assumes that noise levels did not change over time, see Section 2.3 for a discussion). Residual land prices (in the bottom panels) are from regressions of ln land prices against locational characteristics (distance from the CBD, Kurfürstendamm, the nearest major road, the nearest river, canal or lake, 1900 tram density, 1900 to 1904 change in tram density, dummies for residential land use and commercial land use) and lagged ln land prices (1890 and 1896).

In the table below, we report parametric estimates of the noise effect. For comparison, we begin with a parsimonious specification where we compare 1900-1904 land price growth rates across all parcels within the underground section and the elevated section of the line, i.e. there is no restriction to a specific source of variation in noise changes. As shown in column (1), there is a significantly negative noise effect of just about one fifth of the boundary effect displayed in the figure above. Once we implement the restriction of the identification to the difference in noise within the Line A corridor, however, the effects are well within the same range (columns 2 and 3). The model controlling for noise spillover effects on the underground section (column 3) yields a noise effect on land prices (-4.1% for 10-decibel increase) that is very close to the weighted DD estimate from Table 1, column (6) in the main paper. This finding is particularly reassuring because this model is closest to the weighted DD specification as it controls for unobserved heterogeneity in levels, but not in trends. In the next columns (4-5), the models become even more demanding by including kitchen sink controls that capture heterogeneity in land price trends with respect to observables. For instance, in the final column, we add lagged land prices (1890 and 1896) to control for the effect of unobserved characteristics on land prices in levels and trends. These extensions moderately increase the magnitude of the estimated noise effect.

Tab A11. Noise effects: Historical boundary discontinuity models

	(1)	(2)	(3)	(4)	(5)	(6)
			Ln land price 1904 - ln land price 1900			
Noise (10 decibel)	-0.012***	-0.052***	-0.041***	-0.062***	-0.052***	-0.049***
	(0.003)	(0.014)	(0.012)	(0.015)	(0.013)	(0.013)
Noise spillover effect	-	-	Yes	-	Yes	Yes
Corridor effect	-	Yes	Yes	Yes	Yes	Yes
Controls	-	-	-	Yes	Yes	Yes
Lagged ln land prices	-	-	-	-	-	Yes
Noise IV	-	Yes	Yes	Yes	Yes	Yes
N	7,869	7,869	7,869	7,869	7,869	7,869
r2	.0019	-	-	-	-	-

Notes: Corridor effect is a dummy variable taking the value of one for parcels within a tunnel distance of 500 m (either side of the entrance) and track distance of <= 50 m, and zero otherwise. Noise instrument is a dummy variable taking a value of one for parcels along the elevated section of the corridor and zero otherwise. Noise spillover effect is a dummy variable taking the value of one for parcels within the corridor and within the first 250 m from the entrance along the underground section. Controls include distance from the CBD, distance from Kurfürstendamm (sub-centre), distance from canal, river or lake, distance from main street, distance from 1904 station, 1900 tram density, and change in tram density from 1900 to 1904. IV models estimated using 2SLS. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To substantiate these findings, we have conducted several robustness tests. First, we replicate the analysis of the simplest and least demanding SD specification for two periods before (1890-1896 and 1896-1890) and two periods after (1904-1910 and 1910-1914) the actual opening period of the line (1900-1904). In all four “placebo” models the point estimates of the noise effect are close to and statistically indistinguishable from zero (precisely estimated zeros), further indicating that our SD estimates reported in Table 2 are not driven by unobserved trends. Next, we estimate a reduced-form version of the SD model (using the instrument as explanatory variable), weight observations by their distance from the tunnel entrance, and add controls for spatial trends in the distance from the tunnel entrance. In another sensitivity analysis, we experiment with various combinations of track distances and tunnel entrance distances that define the rail corridor as well as different polynomial orders of distance trend controls. The results, presented and discussed in more detail in the next sub-sections, support our baseline findings.

5.3 Placebo treatment periods

In the table below, we replicate the SD model from Table A11, column (2) using land price growth during periods before and after the intervention as dependent variables. We find economically marginal and statistically insignificant effects for all periods, suggesting that the noise disamenity effect around the tunnel entrance capitalized into land prices within a relatively short period of time. Also, the absence of similar effects in the other periods makes it unlikely that the noise effects found in section 3 in the main paper are driven by unobserved trends that are correlated with, but unrelated to, the noise disamenity. In this context, we note that we use model (2) from Table A11 as the baseline model because it is the least demanding specification, presumably generating small standard errors. This imposes a harder hurdle for a falsification test, making the statistical insignificance of the estimates reported in the table below more meaningful.

Tab A12. Discontinuity in differences estimates: Placebo periods

	(1)	(2)	(3)	(4)
	Log land price 1896 - log land price 1890	Log land price 1900 - log land price 1896	Log land price 1910 - log land price 1904	Log land price 1914 - log land price 1910
Noise (10 db)	-0.006	-0.007	-0.003	-0.001
	(0.004)	(0.008)	(0.016)	(0.020)
Corridor effect	Yes	Yes	Yes	Yes
Noise IV	Yes	Yes	Yes	Yes
N	11,353	11,353	11,353	11,353
r2	-	-	-	-

Notes: 2SLS estimates. Corridor effect is a dummy variable taking the value of one for parcels within a tunnel distance of 500 meters (either side of the entrance) and track distance of <= 50 meters, and zero otherwise. Noise instrument is a dummy variable taking a value of one for parcels along the elevated section of the corridor and zero otherwise. Noise instrument is a dummy variable taking a value of one for parcels along the elevated section of the corridor and zero otherwise. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

5.4 Reduced-form analysis and local identification

In the table below, we alter the SD baseline specification in that we report reduced-form estimates using the dummy variable indexing the elevated segment of the rail corridor (the instrument K_c in the baseline model) as the explanatory variable. We apply this model to explain the spatial variation in noise as well as land price growth in columns (1) and (2). In line with Figure A8, we find noise levels are, on average, 17.5 decibels higher within the elevated segment of the rail corridor while land prices are 0.09 log points lower. Because column (1) reports the first stage of the model reported in Table A11, column (2), the noise effect implied by columns (1) and (2) in Table A13 (-0.09/1.75=-0.051) is mechanically the same as the result in Table A11, column (2).

In the next columns, we estimate the change in ln land price as one moves from the underground to the elevated section of the rail corridor, restricting the identification to observations that are closer to the tunnel entrance using a similar approach as in e.g. Ahlfeldt, Maennig, et al. (2016) and Ahlfeldt and Holman (2017). In columns (3-4), we assign weights TW to observations that decline in distance from the tunnel entrance TD as determined by a Gaussian kernel function:

$$TW_i = \frac{1}{\lambda_T\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{TD_i}{\lambda_T}\right)^2\right),$$

where λ_T is a bandwidth that determines the degree of smoothing. We set the optimal bandwidth of $\lambda_T = 133$ meters in column (3) per the Silverman (1986) rule.[3] In column (4), we use half the optimal bandwidth, which improves the local fit at the expense of a greater variance. In columns (5-6), we employ an alternative approach to estimating the discontinuity at the boundary using the following model:

$$\ln(\Delta P_{ic}) = \beta(D_i > 0)_i + \sum_o \vartheta^o D_i^o + \sum_o \gamma^o((D > 0)_i \times D_i)^o + \varepsilon_i,$$

where ΔP is the change in ln land price from 1900 to 1904 and D_i is the distance from the tunnel entrance (the orthogonal) as in section 3.3 in the main paper (with negative values within the underground segment). $(D_i > 0)_i$ is a dummy variable that is one if the condition is true (within the elevated segment) and zero otherwise. This specification allows for separate distance trends on either side of the tunnel entrance of polynomial order O and provides an estimate of the change in land prices right at the tunnel entrance. We use a linear trend specification in column (5) and a quadratic trend specification in column (6). The estimated boundary effects in land prices across

[3] Formally, the bandwidth is chosen as $\lambda = 1.06 \times \sigma N^{-1/5}$.

columns (3-6) are consistently close to the baseline model in column (2). If anything, further narrowing the identification to variation close to the tunnel entrance marginally increases the boundary effect.

We note that the models in Table A13 differ from those in Table A11 in that we restrict the sample to the rail corridor rather than controlling for the rail corridor and using the full sample. In Table A11, we opt for the latter option because the additional observations help with the identification of the effects of the various control variables that we add in Table A11, columns (5-6). Here, we opt for the former option without any cost to keep the models simple and transparent. A similar control for distance trends within the rail corridor would otherwise require a full set of interactions between the rail corridor dummy and all distance variables (and their interactions with the elevated segment dummy).

Tab A13. SD in differences estimates: Reduced form estimates

	(1) Noise (10 decibels)	(2) Ln land price 1904 - ln land price 1900	(3) Ln land price 1904 - ln land price 1900	(4) Ln land price 1904 - ln land price 1900	(5) Ln land price 1904 - ln land price 1900	(6) Ln land price 1904 - ln land price 1900
Elevated track (Distance from tunnel > 0)	1.746***	-0.090***	-0.108***	-0.093**	-0.093*	-0.104*
	(0.192)	(0.024)	(0.033)	(0.043)	(0.048)	(0.054)
Track buffer (m)	500	500	500	500	500	500
Tunnel buffer (m)	50	50	50	50	50	50
Distance weights	-	-	Yes	Yes	-	-
Bandwidth	-	-	Optimal	1/2 x opt.	-	-
Linear distance trends	-	-	-	-	Yes	-
Quadratic distance trends	-	-	-	-	-	Yes
N	84	84	84	84	84	84
r2	.508	.157	.213	.167	.174	.26

Notes: Track buffer defines the sample of parcels included in terms of distance from the track. Tunnel buffer defines the sample of parcels included in terms of distance to the orthogonal intersecting with the track at the tunnel entrance (the vertical line in Figure 5 in the main paper). Distance weights decline in distance from the tunnel entrance and are constructed using a Gaussian kernel. Optimal bandwidth (133 meters) set per the Silverman (1986) rule. Linear trends are distance from the orthogonal and distance from the orthogonal interacted with being on the elevated section of the track. Quadratic trends are the same and the same variables squared. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.5 Sensitivity to corridor definition

Throughout the results reported above and in the main paper we focus on a rail corridor that covers 50 meters from the track and 500 meters from the tunnel entrance. The chosen threshold distances are preferred because they contain a reasonable number of observations (87) while, at the same time, ensuring that the included parcels are within the narrow (potential) noise impact area and sufficiently close to each other so that other locational factors can be reasonably assumed to be similar. In the table below, we present the results of a sensitivity analysis in which we experiment with different values for the two distance thresholds. We consider all combinations of 25 / 50 / 100 meters from the track, 250 / 500 / 1000 meters from the tunnel entrance excluding distance trends as well as controlling for linear and quadratic trends on each side of the tunnel entrance.

The pattern of results is generally comprehensive and reassuring. Excluding distance trends, we consistently find results within a relatively close range of our benchmark estimates. Including distance trends, the results become more volatile. With linear trends, we tend to find relatively larger effects when using shorter distance bands, and insignificant effects with the largest distance from track band. This is in line with the linear functional form being too restrictive to account for the trends around the tunnel entrance if the sample becomes too wide. With quadratic trends, we find the opposite pattern. This is in line with quadratic trends being a too flexible functional form if limited observations (shorter distance from tunnel entrance) are available. Because we allow the slopes of the trend to vary across both sides of the tunnel entrance, it is not surprising that higher order polynomials lead to somewhat instable results, either overestimating or underestimating the true discontinuity. Reassuringly, despite the increase in volatility of the estimate, the mean across the estimates conditional on linear as well as quadratic trends is very close to our benchmark results.

Tab A14. Discontinuity estimates: Sensitivity analysis

Distance	Distance from	No trends		Linear trends		Quadratic trends	
from track	tunnel entrance	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
25	250	-0.18***	0.04	-0.16***	0.06	0.03	0.04
50	250	-0.11***	0.03	-0.07	0.05	-0.03	0.05
100	250	-0.10***	0.03	-0.06	0.06	0.00	0.06
25	500	-0.07**	0.03	-0.19***	0.04	-0.08	0.06
50	500	-0.09***	0.02	-0.09*	0.05	-0.10*	0.05
100	500	-0.04	0.02	-0.15***	0.05	-0.07	0.07
25	1000	-0.12***	0.03	-0.04	0.04	-0.22***	0.05
50	1000	-0.13***	0.02	-0.03	0.03	-0.16***	0.04
100	1000	-0.07***	0.02	0.01	0.03	-0.18***	0.05
Mean		-0.10		-0.09		-0.09	

Notes: Table summarizes results of variants of the column (2, no trends), (5, linear trends), (6, quadratic trends) in Table A11 (the baseline models are within the dotted lines). * / ** / *** denotes significance at the 10% / 5% / 1% level.

6 Contemporary spatial differences models

6.1 Housing capital

The theoretical framework outlined in Section 2.6 in the main paper implies that building capital is a linear transformation of housing value per land unit $K/L = \delta\psi H/L$. It follows, that the latter should be positively correlated with observable features of capital. Moreover, such features should be negatively correlated with station distance and rail noise since these are disamenties. In Tables A15 and A16, we put these predictions to an empirical test.

In Table A15 we stick to the natural log of the ratio of the transaction price over the parcel area as the dependent variable. Given the Cobb-Douglas production function, this variable in log terms is proportionate to the building capital per land unit. We regress this dependent variable against various observable features of building capital, controlling for space-time fixed effects and focusing on distinct parts of the study area. We find that the price per land unit is positively correlated with housing space. Conditional on housing space, the price per land unit is positively correlated with the quality of the housing stock, which we measure as two indicator variables encoded for buildings in good and poor condition. These variables are encoded by members of the committee of valuation experts who maintain the official transaction records and conduct onsite examinations where indicated. The price per land unit is also positively correlated with features of the building such as an elevator, a basement, or an underground car park. In line with intuition, building capital depreciates as a building ages, albeit at a relatively low rate of about 0.2% per year. This is in line with an old fabric in Berlin (median construction year in the sample is 1935) that is being maintained through regular investments into building capital.

Tab A15. Capital density vs. housing features

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (transaction price / parcel area)					
Transaction year - construction year	-0.002***	-0.003***	-0.001***	-0.002***	-0.004***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln (floor space / parcel area)	0.571***	0.582***	0.814***	0.553***	0.561***	0.896***
	(0.002)	(0.004)	(0.014)	(0.007)	(0.006)	(0.031)
Building is in good condition (dummy)	0.414***	0.360***	0.566***	0.417***	0.269***	0.432***
	(0.005)	(0.007)	(0.024)	(0.013)	(0.008)	(0.036)
Building is in poor condition (dummy)	-0.480***	-0.324***	-0.220***	-0.336***	-0.357***	-0.227***
	(0.006)	(0.008)	(0.011)	(0.014)	(0.012)	(0.022)
Building has an elevator (dummy)	0.212***	0.017	0.094***	0.025	-0.073	0.103***
	(0.011)	(0.016)	(0.022)	(0.027)	(0.049)	(0.035)
Building has a basement (dummy)	0.191***	0.113***	0.003	0.154***	0.097***	-0.051
	(0.006)	(0.007)	(0.019)	(0.014)	(0.009)	(0.049)
Building has an underground car park (dummy)	0.262***	0.198***	0.214	0.235*	0.108*	0.550**
	(0.057)	(0.063)	(0.132)	(0.140)	(0.064)	(0.234)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Station x year effects	-	Yes	Yes	Yes	Yes	Yes
Sample	All	Berlin	Distance from CBD < 5 km	5km < distance from CBD < 10 km	Distance from CBD > 10 km	1 km elevated Line A buffer
N	71,231	70,584	14,462	20,539	35,321	3,228
r2	0.648	0.768	0.658	0.747	0.694	0.680

Notes: Unit of analysis is property transaction. Line A buffer is a dummy variable indexing properties within the one-kilometer (elevated) Line A buffer used in the historical DD analysis. Standard errors robust in (1) and clustered on station year effects in all other models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table A16, we use various variables that capture observable features of building capital in a specification that is otherwise identical to the baseline model in column (6) in Table 3 in the main paper. We find that that the density of housing space decreases in distance from the nearest station and in rail noise. The marginal effects are roughly within the range of the estimated effects on prices per land unit. This is in line with the theoretical framework in Section 2.6 of the main paper, which predicts $dln\left(\frac{K}{L}\right) = dln\left(\psi\frac{H}{L}\right)$.

Other features of building capital follow similar trends. The propensity of a building being in good condition decreases in station distance, while the propensity of a building being in poor condition increases in rail noise. Buildings further away from stations are less likely to have an elevator or a basement while buildings in areas with higher noise levels are less likely to have underground car parking.

Tab A16. Contemporary analysis: Other outcomes

	(1) Ln (floor space / parcel area)	(2) Building is in good condition (dummy)	(3) Building is in poor condition (dummy)	(4) Building has an elevator (dummy)	(5) Building has a basement (dummy)	(6) Building has an under-ground parking (dummy)
Distance (km)	-0.218***	-0.020*	0.011	-0.021***	-0.004	-0.000
	(0.024)	(0.012)	(0.011)	(0.006)	(0.010)	(0.001)
Rail noise (10 db)	-0.096**	-0.005	0.071**	-0.016	0.035	-0.006*
	(0.043)	(0.027)	(0.036)	(0.012)	(0.023)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	-	-	-	-	-	-
Station x year effects	Yes	Yes	Yes	Yes	Yes	Yes
Corridor x year effects	Yes	Yes	Yes	Yes	Yes	Yes
Corridor x running variable	Yes	Yes	Yes	Yes	Yes	Yes
Noise instrument	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Station distance < 1 km	Station distance < 1 km	Station distance < 1 km	Station distance < 1 km	Station distance < 1 km	Station distance < 1 km
N	46,089	46,143	46,143	46,143	46,143	46,143
r2	.815	.414	.336	.403	.72	.255

Notes: Unit of analysis is property transaction. Controls include structure age, dummies for location within a block (corner lot, street front, backyard, etc.), distance from nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street, street noise (excluding rail noise). Station effects identify groups of properties which have the same nearest rail station. Corridor effects identify groups of properties within 100-meter buffers along a rail line, spreading 1000 meter in both directions from a tunnel entrance. Running variable is distance from the tunnel entrance, taking negative values within the underground section (as in Figure 7). Noise instrument is a dummy variable taking the value of one with the elevated segment of any rail corridor and zero otherwise in models (4-6). Standard errors in parentheses are robust in (1) and (4), clustered station x year effects in all other models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.2 Rail effects within one kilometer of elevated Line A segment

The spatial scope of the contemporary analysis is not consistent with the historical analysis as we focus on a particular – newly constructed – rail line segment in the former, but cover the entire metro rail network in the latter period. To allow for a better comparability with the historical estimates, we interact the contemporary rail noise and station distance measures with a dummy variable denoting locations within a one-kilometer buffer from the elevated section of Line A. Summing over the baseline noise and distance effects and the respective interaction effects then gives the marginal effects within the buffer area.

In the table below, we replicate all models from Table 3 in the main paper in the same order, adding the interactions with the historical study area buffer. Once we control for station × year effects, none of the interaction effects is significant, i.e. contemporary rail amenity and disamenity effects within the area covered in the historical analysis are not significantly different from the rest of the city area. The interaction effects are also economically small. Our preferred noise (-

0.125 vs. -0.122) and station distance (-0.177 vs. 0.144) estimates within the historical study area are marginally larger than the city-wide effects reported in Table 3 in the main paper.

Tab A17. Contemporary analysis: Line A buffer interactions

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln property transaction price / lot size					
Distance (km)	-0.125***	-0.125***	-0.141***	-0.146***	-0.140***	-0.150***
	(0.003)	(0.007)	(0.021)	(0.006)	(0.009)	(0.022)
Rail noise (10 db)	0.010	-0.025	-0.034**	-0.206***	-0.136***	-0.118**
	(0.011)	(0.015)	(0.015)	(0.043)	(0.051)	(0.051)
Noise x Line A buffer	-0.005***	0.000	0.001	-0.026**	-0.013	-0.007
	(0.001)	(0.001)	(0.001)	(0.013)	(0.016)	(0.015)
Distance x Line A buffer	-0.366***	-0.113	-0.035	-0.320***	-0.096	-0.016
	(0.057)	(0.072)	(0.074)	(0.057)	(0.072)	(0.074)
Dist. effect within buffer	-.49	-.239	-.177	-.466	-.237	-.166
Noise effect within buffer	.005	-.024	-.033	-.232	-.149	-.125
Line A buffer	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	-	-	Yes	-	-
Station x year effects	-	Yes	Yes	-	Yes	Yes
Corridor x year effects	-	-	-	Yes	Yes	Yes
Noise instrument	-	-	-	Yes	Yes	Yes
Sample	All	All	Station distance < 1 km	All	All	Station distance < 1 km
N	71,313	71,313	46,143	71,313	71,313	46,143
r2	.268	.584	.608	.272	.586	.61

Notes: Unit of analysis is property transaction. Line A buffer is a dummy variable indexing properties within the one-kilometer (elevated) Line A buffer used in the historical DD analysis. Controls include structure age, dummies for location within a block (corner lot, street front, backyard, etc.), dummies for building condition (poor, good), distance from nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street, street noise (excluding rail noise). Station effects identify groups of properties which have the same nearest rail station. Corridor effects identify groups of properties within 100-meter buffers along a rail line, spreading 1000 meters in both directions from a tunnel entrance. Running variable is distance from the tunnel entrance, taking negative values within the underground section (as in Figure 6). Instruments for noise and noise x Line A buffer are a dummy variable taking the value of one with the elevated segment of any rail corridor and zero otherwise in models and the same interacted Line A buffer. Standard errors in parentheses are robust in (1) and (4), clustered station x year effects in all other models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.3 Distance effects by rail system

In the historical analysis, we focus on the analysis of the opening of the first subway in Berlin, Line A, which represented a sizable transport innovation. The empirical design used in the historical analysis implies that we hold the effects of existing commuter rail network constant, i.e. we estimate a pure subway accessibility effect. As discussed in section 2 in the main paper, the commuter rail network, which was largely developed before the inauguration of Line A, used an older technology (steam trains). Because both networks, today, are comparable in terms of technology (all electrified metro rail), speed and frequency (at least in the central sections), we treat subway and commuter rail stations as perfect substitutes in our baseline analysis.

To distinguish the subway effect from the commuter rail accessibility effect in the contemporary analysis, we allow for an interaction effect between station distance and a dummy variable denoting whether a station belongs to the commuter rail network exclusively, i.e. does not offer access to subway services, in the table below. The non-interacted baseline distance term then reveals the distance effect for stations that belong to the subway network. As with Table A17, we replicate all models from Table 3 in the main paper adding the interaction.

In all models using the full sample of observations, there is an increase in magnitude of the baseline station distance effect (capturing subway effects) and a positive S-Bahn interaction effect, suggesting that a commuter rail station adds less value than a station that (also) offers access to the subway network. A pure subway station still offers sizable positive accessibility effects. In all models including station catchment area × year effects, the sum of the base line (Distance) and the interaction distance (Distance × S-Bahn) points to an effect of a station distance reduction by one kilometer of about 10%. Once we restrict station catchment areas to not exceed one kilometer, the differential distance effect of commuter rail stations is substantially reduced. Likely, the interaction effect is driven by station catchment areas that are, on average, larger for commuter rail stations because these are more frequently located in peripheral parts of the city (see Figure 3 in the main paper). Yet, even in our preferred model for the interpretation of the distance effect (column 3), the magnitude of the subway station distance effect, at -0.198, is larger than in the respective model of Table 3 in the main paper (-0.144). The baseline station distance effect reported in Table A18 (subway stations, including stations that also are served by commuter rail) makes for an interesting comparison to the historical analysis because Line A also included stations that offered access to commuter rail services (e.g. Warschauer Brücke). While these results suggest that our baseline station distance effect may be a lower bound estimate, they do not necessarily violate our assumption of subway and commuter rail stations being perfect substitutes because the sample of subway stations includes stations that offer access to both subway and commuter rail services and these stations are presumably particularly valuable.

Tab A18. Contemporary analysis: Distance effects by system

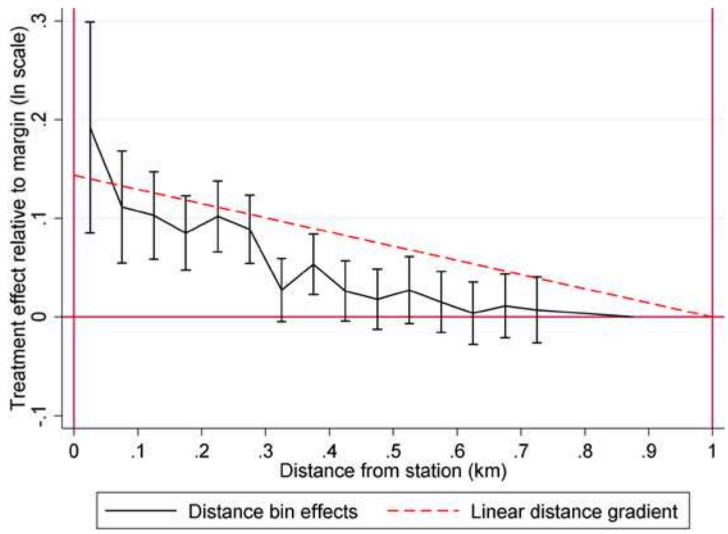
	(1)	(2)	(3)	(4)	(5)	(6)
	Ln property transaction price / lot size					
Distance (km)	-0.291***	-0.238***	-0.198***	-0.294***	-0.242***	-0.221***
	(0.006)	(0.016)	(0.029)	(0.006)	(0.016)	(0.032)
Rail noise (10 db)	-0.051***	-0.035**	-0.037**	-0.167***	-0.140***	-0.121**
	(0.011)	(0.015)	(0.015)	(0.032)	(0.049)	(0.049)
Distance x S-Bahn	0.231***	0.141***	0.097**	0.235***	0.146***	0.124***
	(0.006)	(0.017)	(0.040)	(0.006)	(0.017)	(0.043)
S-Bahn	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	-	-	Yes	-	-
Station x year effects	-	Yes	Yes	-	Yes	Yes
Corridor x year effects				Yes	Yes	Yes
Noise instrument				Yes	Yes	Yes
Sample	All	All	Station distance < 1 km	All	All	Station distance < 1 km
N	71,313	71,313	46,143	71,313	71,313	46,143
r2	.296	.586	.608	.299	.588	.61

Notes: Unit of analysis is property transaction. S-Bahn is a dummy variable indexing properties whose nearest station offers access to commuter rail (S-Bahn) exclusively. Controls include structure age, dummies for location within a block (corner lot, street front, backyard, etc.), dummies for building condition (poor, good), distance from nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street, street noise (excluding rail noise). Station effects identify groups of properties which have the same nearest rail station. Corridor effects identify groups of properties within 100-meter buffers along a rail line, spreading 1000 meter in both directions from a tunnel entrance. Running variable is distance from the tunnel entrance, taking negative values within the underground section (as in Figure 7). Noise instrument is a dummy variable taking the value of one with the elevated segment of any rail corridor and zero otherwise in models (4-6). Standard errors in parentheses are robust in (1) and (4), clustered station x year effects in all other models. * p < 0.10, ** p < 0.05, *** p < 0.01.

6.4 Semi-parametric station distance effects

To investigate the station distance effect in a more flexible manner, we replace the linear distance variable in Table 3, column (3) in the main paper with a set of dummy variables denoting mutually exclusive 50-meter distance rings up to 750 meters. The remaining distances are the residual category. The results are illustrated in Figure A9 using a similar format as in Figure A6 (which presents a similar analysis based on the historical weighted DD models). The station effect decays quickly, flattening out already at about 400-500 meters. The results support the baseline model in that they suggest that there are unlikely station effects beyond one kilometer and that the one-kilometer distance effect is in line with a less parametric specification. Compared to the baseline category, however, the land prices within the innermost rings increased by about 0.19 log points, which is somewhat more than implied by the linear distance gradient estimate for a one-kilometer change in station distance. This effect is close to the maximum relative capitalization effect near stations found in the historical analysis (see Figure A6).

**Fig A9. Contemporary hedonics models:
Distance from station gradient vs. distance bin effects**



Notes: Figure compares the linear distance effect from the baseline model (Table 3, column 3) to distance bin effects. Distance bin effects are estimated using a model in which we replace the linear distance variable by a set of dummy variables indexing mutually exclusive distance rings defined for 0-50m, ..., 700-750m. The residual category is 750-1000m. Error bars indicate the 95% confidence interval.

6.5 Reduced-form analysis: Varying corridor width

Compared to the historical analysis, we have increased the width of the rail corridor segments from 50 to 100 meters because the density of transactions in the contemporary period is smaller than the density of parcels in the historical analysis. In the table below, we evaluate the sensitivity of the results to a restriction to narrower rail corridors using a reduced-form version of the baseline empirical specification (we use the instrument as the explanatory variable). In columns (1) and (2), we estimate the conditional difference in noise and property prices per land unit between the underground and elevated segments of the rail corridors. Since the model in column (1) is the first stage of Table 3, column (6) model, the implied noise effect by columns (1) and (2) in the table below of $-0.177/1.445 = -0.122$ is mechanically the same as in the 2SLS baseline model. In columns (3-6) we reduce the width of the buffer to 75 (3-4) and 50 (5-6) meters. The implied noise effects remain within the same range, although the point estimates are somewhat smaller. The standard errors increase, resulting in insignificant price effects. These results substantiate the impression that the contemporary transactions data requires a slightly more generous definition of the rail corridor than the historical parcel data.

Tab A19. Reduced-form analysis with varying corridor width

	(1) Rail noise (10 decibels)	(2) Ln property transaction price / lot size	(3) Rail noise (10 decibels)	(4) Ln property transaction price / lot size	(5) Rail noise (10 decibels)	(6) Ln property transaction price / lot size
Elevated corridor segment (dummy)	1.821*** (0.097)	-0.177** (0.071)	1.960*** (0.103)	-0.119 (0.092)	2.088*** (0.113)	-0.154 (0.107)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Station x year effects	Yes	Yes	Yes	Yes	Yes	Yes
Corridor x year effects	Yes	Yes	Yes	Yes	Yes	Yes
Corridor width	100 m	100 m	75 m	75 m	50 m	50 m
Sample	Station distance < 1 km					
N	46143	46143	46143	46143	46143	46143
r2	.664	.61	.664	.61	.663	.61

Notes: Unit of analysis is property transaction. Controls include station distance, structure age, dummies for location within a block (corner lot, street front, backyard, etc.), dummies for building condition (poor, good), distance from nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street, street noise (excluding rail noise). Station effects identify groups of properties which have the same nearest rail station. Corridor effects identify groups of properties within 100-meter buffers along a rail line, spreading 1000 meter in both directions from a tunnel entrance. Running variable is distance from the tunnel entrance, taking negative values within the underground section (as in Figure 7). Noise instrument is a dummy variable taking the value of one with the elevated segment of any rail corridor and zero otherwise in models (4-6). Standard errors in parentheses are robust in (1) and (4), clustered station x year effects in all other models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.6 Local identification

In columns (1) and (2) of table A20, we further narrow the identification of the noise effect to properties closer to the tunnel entrances. We weight observations by their distance from the respective tunnel entrance using a similar approach as in section 5.4 in this appendix. To ensure that we use all observations for the identification of the effects of the various control variables we use a two-step estimation procedure. We first create adjusted property prices as the residuals plus the block fixed effect component from regressions of the natural log of the transaction price per land unit against a host of hedonic controls, year effects, and block fixed effects. Next, we run a weighted regression using the adjusted property prices as dependent variable, keeping observations within the rail corridors exclusively.

In an alternative approach, we add distance from the tunnel entrance trends (taking negative values within the underground section) interacted with a dummy indicating all rail corridors (columns 3 and 4). These models estimate a discontinuity in property prices conditional on a continuous spatial trend. In a further alteration, we allow for separate trends on both sides of the tunnel entrances by also interacting the trends with a dummy variable denoting the elevated parts of the rail corridors (column 5 and 6). These models estimate the change in property prices right at the tunnel entrance.

These different approaches to further restricting the identification to properties close to the tunnel entrances result in significantly larger property price effects, supporting the presence of a price discontinuity. The results suggest that our baseline model produces a rather conservative contemporary noise effect (see for comparison the 0.28 log points difference in the right panel of Figure 4 in the main paper).

Tab A20. Contemporary analysis: Reduced-form analysis

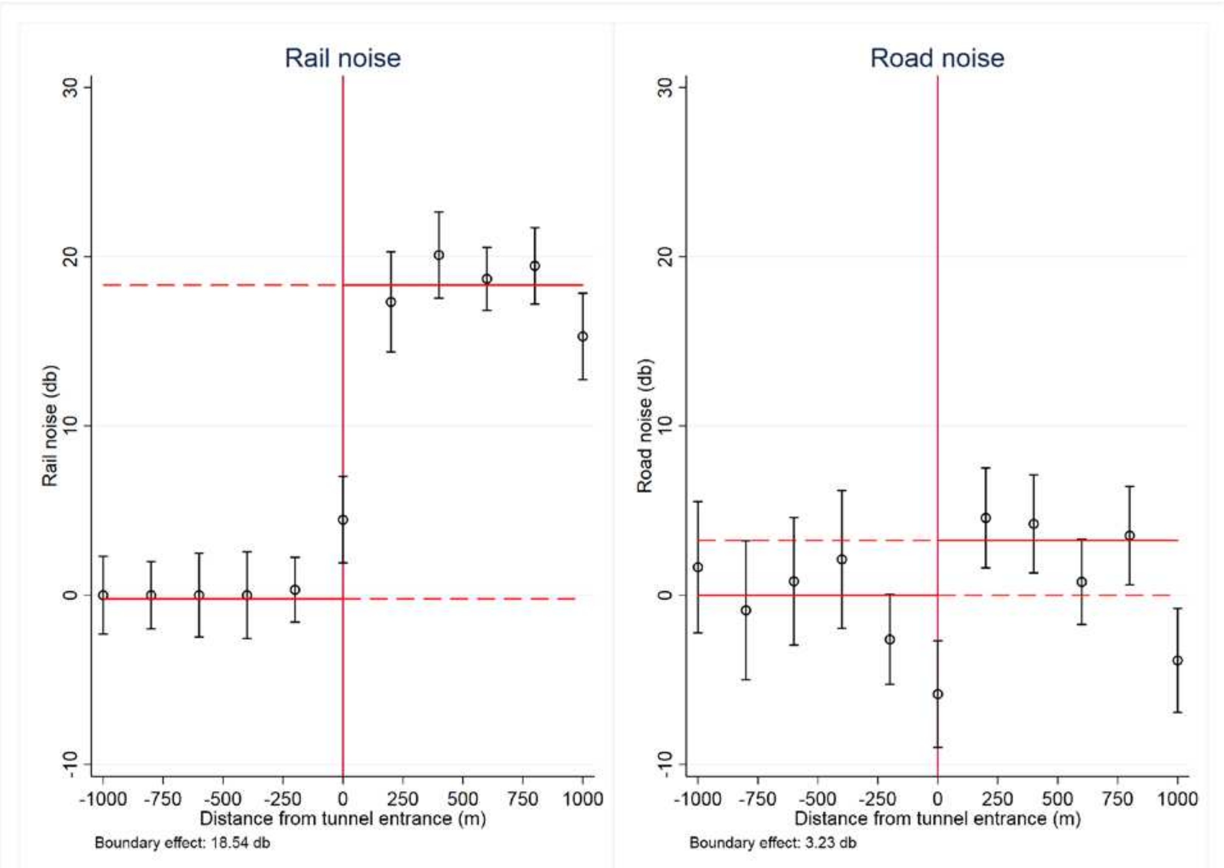
	(1)	(2)	(3)	(4)	(5)	(6)
	Adjusted ln property price / lot size	Adjusted ln property price / lot size	Ln property transaction price / lot size	Ln property transaction price / lot size	Ln property transaction price / lot size	Ln property transaction price / lot size
Elevated corridor segment (dummy)	-0.631*** (0.221)	-0.612** (0.245)	-0.333** (0.138)	-0.537*** (0.171)	-0.334** (0.138)	-0.333** (0.138)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Station x year effects	Yes	Yes	Yes	Yes	Yes	Yes
Corridor x year effects	Yes	Yes	Yes	Yes	Yes	Yes
Corridor x trends	-	-	Linear	Quadratic	Linear continuous	Quadratic continuous
Distance weights	Optimal bandwidth 182 m	1/2 optimal band-bandwidth 91 m	-	-	-	-
Sample			Station distance < 1 km			
N	463	463	46143	46143	46143	46143
r2	.851	.882	.61	.61	.61	.61

Notes: Unit of analysis is property transaction. Adjusted property prices are the residuals plus the block fixed effect component from regressions of the natural log of the transaction price normalized by lot size against a host of hedonic controls, year effects, and block fixed effects. Controls include station distance, structure age, dummies for location within a block (corner lot, street front, backyard, etc.), dummies for building condition (poor, good), distance from nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street, street noise (excluding rail noise). Station effects identify groups of properties which have the same nearest rail station. Corridor effects identify groups of properties within 100-meter buffers along a rail line, spreading 1000 meter in both directions from a tunnel entrance. Trends are based on the running variable, which is the distance from the tunnel entrance, taking negative values within the underground section (as in Figure 7). Common trends polynomial trends in the running variable of given order. Separate trends are the same, adding an interaction between trends and a dummy denoting the elevated section. Standard errors in parentheses are clustered station x year effects in all other models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.7 Variation of road noise within rail corridors

One natural concern with the spatial difference design we employ is that factors other than rail noise may change at the tunnel entrance. A natural candidate is road noise. While we control for road noise when estimating the effect of rail noise on contemporary property prices, it is still interesting to evaluate how road noise changes as we cross the spatial boundary. If there was a large difference in road noise between the two sides of the tunnel entrance, this might indicate that other factors such as pollution, congestion, etc. that are difficult to control for, could also differ. Figure A10 compares the change in rail noise at the tunnel entrance to the change in road noise. While road noise, on average, is higher along the elevated section (positive distance) than the underground section (negative distance), the difference is just a fraction (about one sixth) of the respective difference in rail noise. In table A21, we estimate the boundary effect conditional on observables, linear corridor-specific distance trends, and corridor-specific time effects. The boundary effect in rail noise remains within close range of the unconditional effect in Figure 4 and is highly statistically significant. In contrast, the boundary effect in road noise drops by about two thirds and is not statistically significant. These results substantiate our interpretation that our spatial difference strategy reveals a capitalization effect of rail noise that is not confounded by road noise effects.

Fig A10. Contemporary spatial differences in rail and road noise



Notes. Each circle illustrates the mean value of a dependent variable within a grid cell. One dimension of the grid cells are 200-m bins defined based on the distance from the tunnel entrance. The other dimension is a 100-m-distance buffer around the track. Negative distances from the tunnel refer to the underground section. Solid horizontal lines indicate the means (weighted by the number of observations) within the underground (negative distance) and elevated (positive distance) segments. Error bars are the 90% confidence intervals based on robust standard errors from separate parcel-level regressions (within the buffer). For each outcome, we run one regression of the outcome against dummies indicating positive distance (≥ 0) bins, and another regression of the outcome against dummies indicating negative distance (<0) bins. For each bin, the error bar represents a test if the mean within the bin is different from the spatial counterfactual (the dashed line). The boundary effect corresponds to the difference between the two horizontal lines.

Tab A21. Contemporary analysis: Conditional boundary effect in rail noise and road noise

	(1) Rail noise (1 db)		(2) Road noise (1 db)	
Elevated segment corridor (dummy)	18.332***	(0.631)	-1.163	(0.855)
Controls	Yes		Yes	
Year effects	Yes		Yes	
Corridor x year effects	Yes		Yes	
Corridor x running variable	Yes		Yes	
N	71,313		71,313	
r2	.241		.301	

Notes: Unit of analysis is property transaction. Controls include structure age, dummies for location within a block (corner lot, street front, backyard, etc.), dummies for building condition (poor, good), distance from nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street, street noise (in model 1), and rail noise (in model 2). Station effects identify groups of properties which have the same nearest rail station. Corridor effects identify groups of properties within 100-meter buffers along a rail line, spreading 1000 meter in both directions from a tunnel entrance. Running variable is distance from the tunnel entrance, taking negative values within the underground section (as in Figure 7). Noise instrument is a dummy variable taking the value of one with the elevated segment of any rail corridor and zero otherwise in models (4-6). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Comparison of historical to contemporary estimates

7.1 Income elasticities

In section 5.1 of the main paper, we define the willingness to pay (*WTP*) for a noise reduction of a representative individual at period t as the product of the percentage noise capitalisation effect in house price terms $(1-\delta_t)\alpha_t^N$ ($1-\delta_t$ is the land share as defined in section 2.6 of the main paper), the average income I_t, and the expenditure share on housing η_t:

$$WTP_t^N = -(1-\delta_t)\alpha_t^N \times I_t \times \eta_t$$

Taking log-differences and rearranging the equation we obtain the longitudinal income elasticity of the marginal cost of noise:

$$\frac{\Delta \ln WTP^N}{\Delta \ln I} = 1 + \frac{\Delta \ln(-\alpha^N)}{\Delta \ln I} + \frac{\Delta \ln(1-\delta)}{\Delta \ln I} + \frac{\Delta \ln \eta}{\Delta \ln I}$$

We use our baseline estimates from sections 3.2 (Table 1, column 3) and 4.2 (Table 3, column 6) in the main paper transformed into percentage terms to compute $\ln(-\alpha_{2000}^N) - \ln(-\alpha_{1900}^N)$. For the change in real income $\ln I_{2000} - \ln I_{1900}$ we use the German index of real GDP per capita from the Maddison Project (Bolt and van Zanden, 2014). As discussed in section 3.1 of this appendix, real GDP per capita in Germany since 1900 grew at rates of about 2% per year, in line with the general trend in the world. This corresponds to an aggregated increase by about 650%.

To account for changes in the land share in the value of housing, we make use of estimates reported by Knoll et al. (2017). Accordingly, the share of land at the total value of housing in Germany increased from 0.18 to 0.32 over the period from 1900 to 2000, which, in levels, is roughly in line with recent contemporary estimates of 0.25 for Berlin (Ahlfeldt, Redding, et al., 2015). For the expenditure share on housing we consider contemporary data from the Federal Statistical Office of Germany (2013) and historical data from Hoffmann (1965 [2006]). To obtain a consistently defined category in both periods, we define housing expenditures as the sum of expenditures on rent, utilities, and furniture. This expenditure share increased from 0.21 to 0.30 over the period from 1900 to 2000. This increase by about 50% is in line with the average increase across 14 countries over the same period reported in the working paper version of Knoll et al. (2014) and the increase in the respective U.S. share from 0.23 to 0.33 over the same period (U.S. Department of Labor, 2006). The longitudinal income elasticity of the marginal cost of noise is:

$$\frac{\Delta \ln(WTP^N)}{\Delta \ln I} = 1 + \frac{\ln 0.122 - \ln 0.036}{\ln 634 - \ln 100} + \frac{\ln 0.32 - \ln 0.18}{\ln 634 - \ln 100} + \frac{\ln 0.30 - \ln 0.21}{\ln 634 - \ln 100} = 2.2,$$

where the first term captures the effect of the change in land price capitalization effects, the second term captures the effect of the change in land share, and the last term captures the effect of the change in housing expenditure share. If we were to assume constant share parameters ($\Delta \ln(1-\delta) = \Delta \ln \eta = 0$), the pure effect originating from the change in land price capitalization would imply an income elasticity of 1.61, still greater than unity.

In the same way, we can compute the willingness to pay for a reduction in station distance and the respective long-run income elasticity using our baseline estimates of the station distance effect from Table 1, column (6) and Table 3, column (3):

$$\frac{\Delta \ln(WTP^S)}{\Delta \ln I} = 1 + \frac{\ln 0.144 - 0.184}{\ln 634 - \ln 100} + \frac{\ln 0.32 - \ln 0.18}{\ln 634 - \ln 100} + \frac{\ln 0.30 - \ln 0.21}{\ln 634 - \ln 100} = 1.4$$

We note that the income elasticity increases to 1.5 if we assume, as suggested by several robustness checks in section 6, a contemporary land price capitalization effect that equates to the historical land price capitalization effect.

In the per-capita accounting above, we have implicitly assumed that the value of non-marketed goods is the same to all members of a household. It is theoretically possible that the willingness to accept higher rents is skewed towards the valuation by selected household members, e.g. adults or wage earners. In an extreme scenario, a household's willingness to pay will be driven by the head of household alone. This scenario potentially leads to a different income elasticity because households have become smaller over time, so income has increased less in head-of-household terms than in per-capita terms. The average head-of-household willingness to pay for an amenity A is defined as:

$$HWTP_t^{A,} = (1 - \delta_t)\alpha_t^A \times \eta_t \times I_t \times n_t,$$

where n_t is the average number of persons per household and $I_t \times n_t$ is the real average head-of-household income. Since the log-change in head-of-household income is $\Delta \ln I + \Delta \ln n$, the income elasticity is defined as:

$$\frac{\Delta \ln HWTP^A}{\Delta \ln I + \Delta \ln n} = 1 + \frac{\Delta \ln(\alpha^A) + \Delta \ln(1 - \delta) + \Delta \ln \eta}{\Delta \ln I + \Delta \ln n}$$

Household size in Germany decreased from 2.0 in 1900 (Hoffmann, (1965 [2006])) to 1.5 in 2000 (Federal Statistical Office of Germany, 2017). In per head-of-household terms the longitudinal income elasticity of the marginal cost of noise increases to 3.1. The long-run income elasticity of the value of access increases to 1.7.

7.2 Interaction of rail and road noise

One of the limitations of our data is that we do not observe road noise – the predominant noise type in cities – during the historical period. Theoretically, it is possible that road noise and rail noise are mutually reinforcing, or the marginal disutility of rail noise might be lower if another noise source is present. Given that road noise was likely lower a century ago due to the absence of mass-produced cars, this can have important implications for the long run comparison of rail noise capitalization effects we conduct. If the noise sources were mutually reinforcing in their disutility effects, the increase in the capitalization effect of rail noise over time could be rationalized with the presence of higher levels of baseline road noise in the contemporary period. However, in the table below, we find evidence for the opposite. Higher levels of road noise are associated with lower rail noise capitalization effects. One way to interpret the interaction effect quantitatively is that if we reduce the level of road noise by 10 db, the marginal effect rail noise doubles. The implication is that in the absence of the presumably increased road noise, contemporary rail noise capitalization effects would be higher.

Tab A22. Contemporary analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln property transaction price / lot size					
Distance (km)	-0.050***	-0.096***	-0.130***	-0.052***	-0.097***	-0.141***
	(0.003)	(0.007)	(0.021)	(0.003)	(0.007)	(0.020)
Rail noise (10 decibel)	-0.019*	-0.029*	-0.041***	-0.167***	-0.185***	-0.160***
	(0.011)	(0.015)	(0.015)	(0.033)	(0.049)	(0.048)
Road noise (10 decibel)	-0.029***	0.005	0.002	-0.027***	0.004	0.000
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)
Rail noise x road noise	0.057***	0.018	0.019	0.121***	0.169***	0.159***
	(0.012)	(0.013)	(0.014)	(0.033)	(0.043)	(0.042)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	-	Yes	-	-
Station x year effects	-	Yes	Yes	-	Yes	Yes
Corridor x year effects				Yes	Yes	Yes
Rail noise instruments				Yes	Yes	Yes
Sample	All	All	Station distance < 1 km	All	All	Station distance < 1 km
N	71,313	71,313	46,143	71,313	70,665	45,364
r2	.377	.586	.609	.378	.106	.0538

Notes: Unit of analysis is property transaction. Controls include structure age, dummies for location within a block (corner lot, street front, backyard, etc.), dummies for building condition (poor, good), distance from nearest lake, river or canal, distance from nearest park or forest, distance from nearest landmark building, distance from nearest playground, distance from nearest main street. Station effects identify groups of properties which have the same nearest rail station. Corridor effects identify groups of properties within 100-meter buffers along a rail line, spreading 1000 meter in both directions from a tunnel entrance. Road noise re-scaled to have a zero mean before generating the rail noise x road noise interaction. Instruments for rail noise and rail noise interacted with road noise are a dummy variable taking the value of one with the elevated segment of any rail corridor and zero otherwise and the same interacted with road noise. Standard errors in parentheses are robust in (1) and (4), clustered station x year effects in all other models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7.3 Network accessibility

In section 5.1 of the main paper, we provide a discussion of the effective accessibility that the stations analysed in the historical and contemporary periods offer. This is an important consideration because the station distance effects will not be comparable if the considered stations differ substantially in the connectivity offered. For this purpose, we compare the effective accessibility at a station location in the actual historical and contemporary scenario to the counterfactual scenarios that we establish in our empirical models, i.e. the absence of the considered stations.

To assess the loss of effective accessibility in either counterfactual, we compute a measure of accessibility for each station *s*, in every period *t,* and scenario *z* (actual vs. counterfactual). Following Ahlfeldt, Redding, et al. (2015), we aggregate the population (*POP*) at all potential destinations *j* that can be accessed from a station weighted by the bilateral transport cost c_{sjz} to create a measure of effective accessibility:

$$A_{stz} = \sum_j POP_{jt} e^{-\tau c_{sjtz}},$$

where c_{sjtz} is the mean of the travel times by automobile c_{sjtz}^{CAR} and public transport c_{sjtz}^{PUB}, weighted by the bilateral mode share of the car χ_{sjtz}:

$$c_{sjtz} = \chi_{sjtz} c_{sjtz}^{CAR} + \left(1 - \chi_{sjtz}\right) c_{sjtz}^{PUB}$$

For the historical period, we set $\chi_{sjtz} = 0$ because the automobile was virtually non-existent in 1900. For the contemporary period, we model the car share as a logit function of the relative travel time advantage of the automobile $\Delta c_{sjtz} = c_{sjtz}^{PUB} - c_{sjtz}^{CAR}$.

$$\ln\left(\frac{\chi_{sjtz}}{1-\chi_{sjtz}}\right) = \zeta_1 + \zeta_2 \Delta c_{sjtz} <=> \chi_{sjtz} = \frac{\exp\left(\zeta_1 + \zeta_2 \Delta c_{sjtz}\right)}{1 + \exp\left(\zeta_1 + \zeta_2 \Delta c_{sjtz}\right)}$$

In computing c_{sjtz} we consider station locations as origins (s) and the geographic centroids of 93 historical city districts (*Ortsteile*) as potential destinations (j). These city districts are the smallest geographic unit for which 1900 population data are available. We compute the least-cost connections in terms of travel time between all origins and destinations taking into account the entire transport geography and all available public transit modes in GIS. As discussed in section 2 of the main paper, these modes include walking, buses, trams, subway (*U-Bahn*) and commuter rail (*S-Bahn*) in the contemporary period, as well as walking, horse-powered buses, horse-powered trams (one line), steam-powered trams (one line), electrified trams (the great majority of tram lines), and commuter rail (powered by steam) in the historical period. For the contemporary period, we also compute travel times by car. In each case, travel times are computed as the sum over the products of network segment lengths and mode-specific speed parameters along the fastest given route.

All contemporary speed parameters as well as the model parameters τ, ζ_1 and ζ_2 are borrowed from Ahlfeldt, Redding, et al. (2015). All historical transport cost parameters are average velocities derived from the study of historical timetables. The effective accessibility premium a station s offers in a period t is then simply defined as:

$$A_{st} = A_{s,t,z=actual} - A_{s,t,z=counterfactual},$$

where in the counterfactual we exclude the respective line segments (Line A in the historical period, the entire rail network in the contemporary period) when computing c_{sjtz}.

In the table below, we summarize the distribution of station accessibility premiums by period. We also provide an accessibility measure in which we aggregate the shares of the population of the 93

Ortsteile at the total population in a procedure that is otherwise identical to the one laid out above. We find that the 11 elevated Line A stations in the historical period (first panel), in their effective accessibility effect, resembled the 275 subway and commuter rail stations of the contemporary network (second panel). While the distributions of absolute premiums in terms of accessible population are very similar, the relative premiums in terms of accessible population shares are somewhat larger in the historical period. This is intuitive given that the population of Berlin in 1900 was smaller than today (approx. 2m vs. 3.5m). If we focus on the segment of the contemporary rail network that belonged to the elevated Line A, the accessibility premia are somewhat larger, reflecting the central position of this segment within the contemporary network. This is in line with the somewhat larger than average point estimate of the station distance effect in this area reported in section 6.1 of this appendix.

Tab A23. Station accessibility premium

Variable	Obs.	Mean	Std. Dev.	Min	Max
Historical: Elevated Line A stations					
Accessibility premium: Population	11	100,134	78,217	17,146	234,579
Accessibility premium: Share of population	11	0.0389	0.0304	0.007	0.0911
Contemporary: All stations					
Accessibility premium: Population	275	100,564	47,551	13,139	234,374
Accessibility premium: Share of population	275	0.0302	0.0143	0.004	0.0703
Contemporary: Elevated Line A stations					
Accessibility premium: Population	10	174,694	43,043	104,116	234,374
Accessibility premium: Share of population	10	0.0524	0.0129	0.0312	0.0703

Notes: Accessibility premium is the accessibility index in the actual scenario minus the accessibility index in the counterfactual scenario. Accessibility index is either the transport cost weighted sum of population or of population shares across potential destinations. Actual scenario includes the entire network. Counterfactual scenario excludes Line A in the historical period and the whole metro rail network in the contemporary period.

7.4 Sorting

Sorting is a well-known phenomenon within cities. Different types of household live spatially segregated because they demand different types of locational amenities. For our long-run comparison it is critical to understand how the incomes of the marginal renter driving our capitalization results compare to the average renter.[4] The change in income of the average renter will be a reasonable approximation for our purposes if the marginal renter is representative for their cohort in both periods (historical and contemporary) or if they rank similarly within the distribution of incomes in both periods. Otherwise, the change in real income of the average renter will underes-

[4] Land prices are determined by the willingness-to-pay of renters and home buyers. For simplicity, and because the Berlin housing market has been dominated by renter occupiers, we refer to renters here.

timate or overestimate the change in real income of the marginal renter. It is generally difficult to observe the income of the marginal renter. Historical data of this kind are virtually impossible to collect. To understand how the relative incomes of the relevant marginal renters have changed over time, we rely on indirect evidence.

It is likely that the renters who drive rents and ultimately land prices close to metro rail stations are frequent users of the system. To understand how the incomes of metro rail users compare to those of car users and public transit users more generally, we analyze the 2008 edition of the German micro commuting survey.[5] From this representative survey, we use information on slightly more than 8,000 trips within Berlin in 2008 for which we know the modes used, the distance travelled, the household income as well as the origin and destination city district (*Bezirk*) of the trip. In Figure A11, we summarize the distribution of income by mode. In keeping with intuition, the main takeaway is that those with higher incomes tend to travel by car more often.

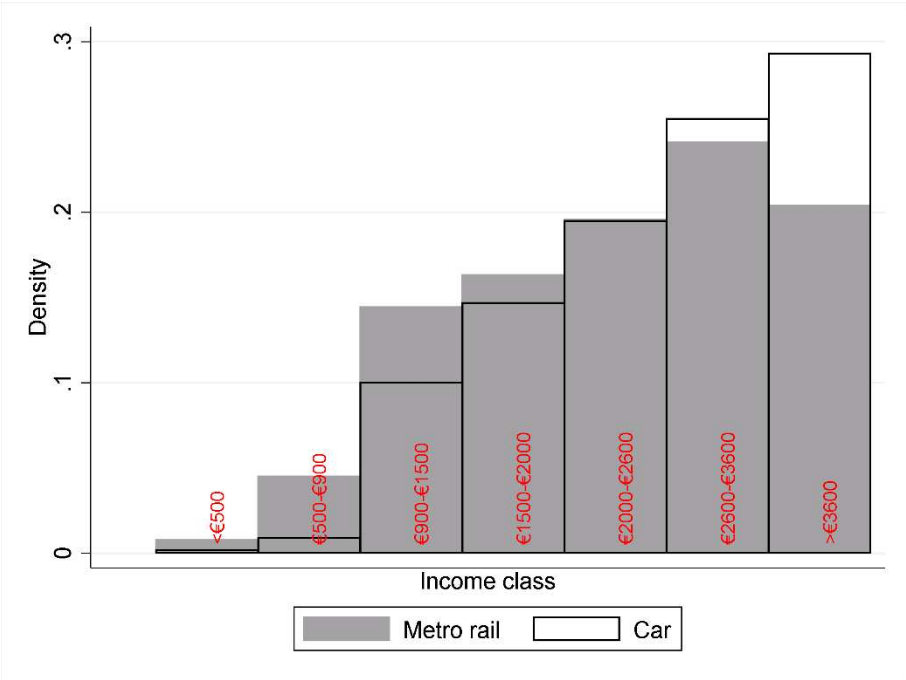
As with most surveys, income in this data set is given by category. For an econometric analysis, we construct a continuous income variable that, for each of the seven income categories reported in Figure A11, takes the value that corresponds to the mean over the category bounds. For the highest category, we assign the mean over the minimum value and twice the minimum value because no upper limit is given. The results of a Logit regression analysis reported in Table A24 confirms that users of the urban rail system, on average, belong to lower income groups. Controlling for trip length and origin and destination effects, the probability of using metro rail for a trip decreases by 0.276% for a one-percent increase in net-household income (column 2).

The results in Table A24 also confirm the strong intuition that the negative correlation between income and the use of public transport is driven by the availability of an attractive, but somewhat pricy alternative, the automobile. Before World War II, cars played a subordinate role as a means of transportation in Berlin. In relative terms, metro rail, therefore, was more attractive to higher-income groups as it was by far the fastest available mode of urban transportation (Leyden, 1933). To tailor to the needs of wealthier income groups, the historical trains operated on Line A featured special coaches that offered higher comfort at higher rates (Schmiedeke, 1997). More generally, some trains operated on several lines of the emerging metro rail network were casually referred to as banker trains ("*Bankierzüge*") due to their popularity among wealthy commuters

[5] See for details, http://daten.clearingstelle-verkehr.de/224/1/Staedtepegel_SrV2008.pdf.

(Reinhardt, 2015). Overall, it seems fair to conclude that metro rail users during the historical period were, on average and in relative terms, likely richer than metro rail users today.

Fig A11. Distribution by of trips by income category and transport mode



Notes: Income class refers to the net monthly household income. Metro rail includes trips where part of the journey is taken by U-Bahn (subway) or S-Bahn (suburban railway). Car includes trip where part of the journey is taken by car. Raw data are micro survey data from Ahrens et al. (2009).

Tab A24. Mode choice analysis

	(1) Metro rail for part of the trip (0,1)	(2) Metro rail for part of the trip (0,1)	(3) Car for part of the trip (0,1)	(4) Car for part of the trip (0,1)	(5) Other modes (no car and no metro rail) (0,1)	(6) Other modes (no car and no metro rail) (0,1)
Net income (€/month)	-0.093*** (0.017)	-0.129*** (0.019)	0.168*** (0.015)	0.170*** (0.016)	-0.080*** (0.015)	-0.071*** (0.017)
Distance travelled (km)		0.118*** (0.004)		0.029*** (0.003)		-0.178*** (0.006)
Mode elasticity	-.199	-.276	.31	.312	-.151	-.133
Origin effects	-	Yes	-	Yes	-	Yes
Destination effects	-	Yes	-	Yes	-	Yes
N	8,043	8,043	8,043	8,043	8,043	8,043

Notes: Unit of analysis is individual response in survey. Data from a 2008 representative travel survey Ahrens et al. (2009). Results from Logit estimations. Mode elasticity is the elasticity of the probability of selecting a model (over all alternatives) with respect to income, computed at the means of the distributions. Origin and destination effects are at the Bezirke level (12 city districts). Other modes include walking, cycling, bus, tram, and other shared transport. Robust standard errors. * p < 0.10, ** p < 0.05, *** p < 0.01

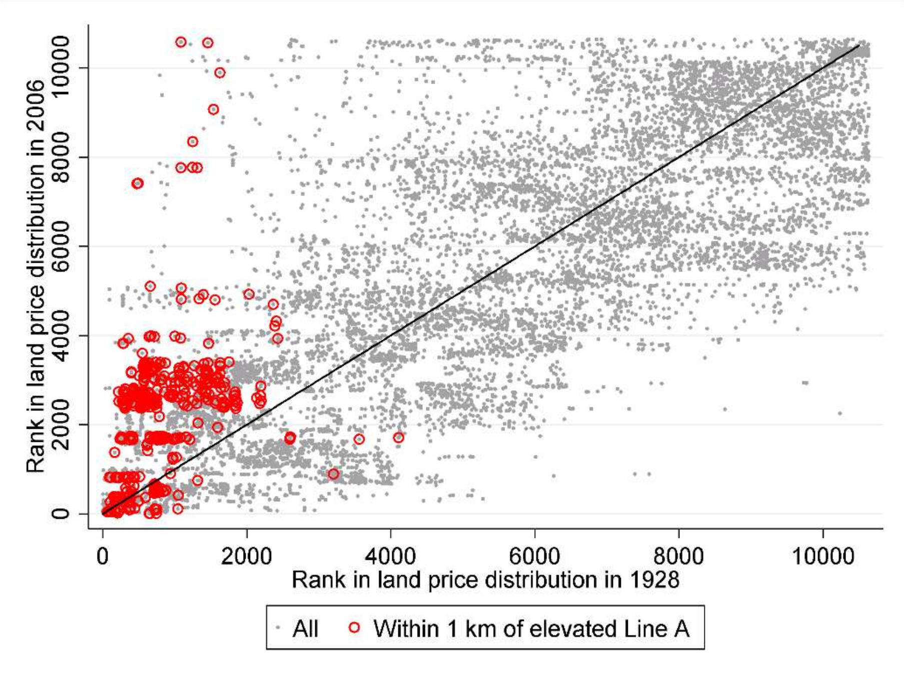
Income patterns within metro areas can vary substantially in space and time, following major trends such as suburbanization, white flight and gentrification. It is therefore possible that the residents living near metro stations today, in relative terms, are more or less wealthy than one hundred years ago, irrespectively of the mode of transportation they choose. Unfortunately, spatially disaggregated income data is not available for the historical period. Therefore, we cannot directly assess if the incomes of residents living near the areas considered in our capitalization studies increased above or below the average rate. As an imperfect approximation, we consider the change in land prices over time. Given that the built-up structure remained similar within the central parts of the city (where Line A is routed through), we would expect relative trends in land prices to be correlated with relative trends in incomes. To gain insights into differential trends, we compare land prices within the 1-km buffer around the elevated part of Line A relative to the rest of the city during the historical as well as the contemporary period. While in our contemporary capitalization study we also include other parts of the network, we have shown in Section 6.1 that the capitalization effects within a 1-km buffer around the elevated part of Line A are roughly representative for the capitalization effects along all elevated parts of the subway network.

The historical land price data from the Müller maps we use in our capitalization studies are available for the central parts of the city only. The first summary of land prices for approximately the entire area within today's city boundaries is available for 1928 (Kalweit, 1929). Using the land price data set compiled by Ahlfeldt, Redding, et al. (2015), we focus on a comparison of 1928 to 2006. In Figure A12, we compare the rank a block occupies in the distribution of land prices in 1928 to its rank in 2006 distribution, where rank one refers to the block with the highest land price. Both rank measures are positively correlated, revealing some degree of persistency in the internal structure of the city. Most of the blocks within the Line A buffer, however, have a high rank (low number, high land price) in 1928, but a low rank (high number, low land price) in 2006. In relative terms, these blocks are perceived as being less attractive during the contemporary period.

In Table A25, we subject the descriptive evidence to some simple econometric tests. We begin by regressing the long-difference in log land prices against a dummy variable that indicates the Line A buffer (column 1). To rule out that changes in land prices are driven by changes in economic density instead of locational attractiveness we control for long-differences in log population, log employment, and log floor area ratio (the ratio of total floor space over land lot size) in column (2). In column (3), we control, in addition, for a range of lagged variables in levels to control for correlated long-run trends. In columns (4-6), we estimate similar models using long-differences in the rank measure introduced in Figure A12 as a dependent variable. The estimates confirm the descriptive evidence from Figure A12. Our preferred estimate from column (2) suggests that in relative terms, land prices in the buffer area decreased by more than 60% (=exp(-0.953)-1).

One interpretation is that this area close to Line A came out as a loser from the long-run cycle of sub-urbanization and gentrification that has been typical for many cities during the 20th century (McMillen, 1996). An alternative explanation is that the area has not yet recovered from the potentially detrimental effects of being close to the former Berlin Wall during the division period. In any case, it seems likely that such a remarkable decrease in the relative price of land is associated with a decrease in the relative income of the local population.

Fig A12. Ranks in the distributions of land prices in the historical vs. the contemporary period



Note: Unit of analysis is housing blocks. Data from Ahlfeldt, Redding, et al. (2015). Rank one corresponds to the highest land price within a period. Sample restricted to a balanced panel.

Tab A25. Long-run change in relative land price close to elevated Line A

	(1) Ln 2006 land price - ln 1928 land price	(2) Ln 2006 land price - ln 1928 land price	(3) Ln 2006 land price - ln 1928 land price	(4) Rank 2006 - Rank 1928	(5) Rank 2006 - Rank 1928	(6) Rank 2006 - Rank 1928
Within 1 km of elevated Line A (0,1)	-1.262*** (0.031)	-0.953*** (0.033)	-0.290*** (0.032)	1463.820*** (72.271)	401.594*** (68.061)	192.957*** (67.693)
Difference controls	-	Yes	Yes	-	Yes	Yes
Level controls	-	-	Yes	-	Yes	Yes
N	10641	10641	10641	10641	10641	10641

Notes: Unit of analysis is housing blocks. Data from Ahlfeldt, Redding, et al. (2015). Differenced controls are change in ln floor area ratio (FAR) from 1928 to 2006, change in population from 1936 to 2006, and change in employment from 1936 to 2006. Level controls are ln land price in 1928, ln FAR in 1928, ln population in 1936, ln employment in 1936, distance from the CBD, distance from the nearest lake, river, or canal, and distance from the nearest park. Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Briefly summarized, the indirect evidence presented in this section suggests that the marginal renter driving our estimated capitalization effects were, in relative terms (within their cohorts), richer during the historical period than during the contemporary period. The change in real income of the average renter, thus, overestimates the change in real income of the marginal renter, suggesting that the income elasticities we infer from the capitalization studies are lower-bound estimates.

8 Extra cost for underground sections

For the back-of-the-envelope calculations reported in Section 4.5 of the main paper, we require an estimate of the extra cost associated with an underground line (as opposed to an elevated line). To obtain such an estimate, we make use of data compiled by Bousset (1935), who reports per kilometer construction costs for 31 segments of the Berlin underground network opened until 1930. In the table below, we present results of regressions of the natural log of per-kilometer construction costs against a dummy indicating underground sections. In column (1), we control for the opening year using a linear trend. In column (2), we replace this trend by five-year period effects. In column (3), we additionally control for the track width. The results are reasonably consistent across specifications. According to our preferred estimate in column (3), an underground section in the early 20th century in Berlin was about three times as expensive as an elevated section. A collateral finding from column (1) is that per-kilometer metro rail construction costs in Berlin increased by about 4% per year from 1900 to 1930.

Tab A26. Underground extra costs

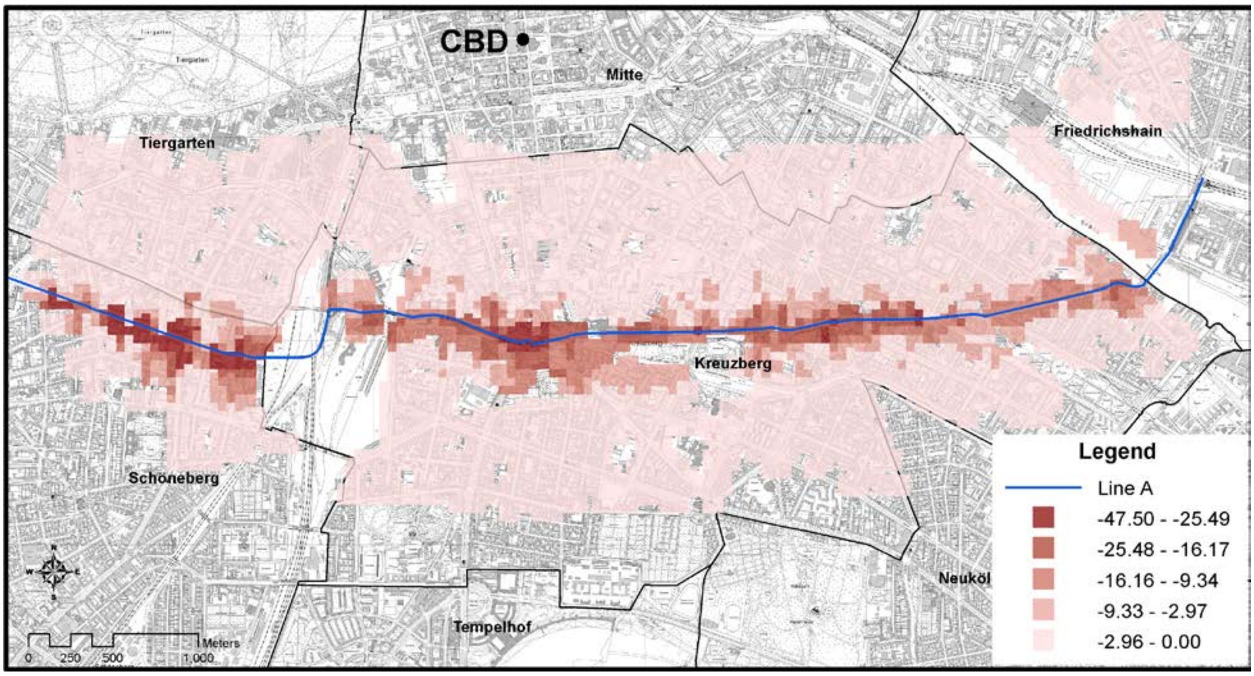
	(1)		(2)		(3)	
	Ln cost per km (million RM)					
Underground section (dummy)	0.985***	(0.264)	1.190***	(0.184)	1.149**	(0.333)
Opening year	0.039***	(0.009)				
Broad gouge (dummy)					0.064	(0.335)
Percent extra underground cost	168		229		216	
Period effect (five years)	-		Yes		Yes	
N	31		31		31	
r2	0.598		0.664		0.664	

Note: Standard errors (in parenthesis) are robust in (1) and clustered on year bins in (2) and (3). * p < 0.1, ** p < 0.05, *** p < 0.01

9 Aggregate land price effects

As described in the main paper, we aggregate parcels (the unit of observation in our regressions) to 50×50-meter grid cells before computing the aggregate effect of rail noise on land prices. The grid size is chosen to ensure that we cover all developed areas and allow for sufficient spatial detail to account for the localized nature of noise emissions. Below, we illustrate the resulting noise effects by grid cells. Figure A13 shows how we only cover parts of the city that were developed in 1900. Figure A13 is also reflective of the typical features of noise emission. Noise is contained to relatively narrow corridors in densely developed areas, but spreads further along open spaces.

Fig A13. Estimated noise effects and land prices



Notes: Plots are aggregated to 50x50 m grid cells. Noise estimate $\widehat{\alpha^N}$ from Table 1 column (1) in the main paper. The noise effect per grid cell g is $P_{g,1900}\left(1-\exp\left(\widehat{\alpha^N}\times N_{g1904}\right)\right)$, where P_g and N_g indicates the average land price and rail noise within a grid cell. The background map shows the situation in 2006, which corresponds to the situation in 1900 in most, but not all areas. Own illustration using the Urban Environmental Information System of the Berlin Senate Department (Senatsverwaltung für Stadtentwicklung Berlin, 2006).

10 Land price appreciation vs. interest rates

In this section, we compare long-run land price growth rates and central bank interest rates to support the back-of-the-envelope calculations presented in Section 5.2 of the main paper. To our knowledge, no price index tracking real estate prices over the 19th and 20th century exists for Berlin. Therefore, we combine our data with a data set on block-level land values in Berlin compiled by Ahlfeldt, Redding, et al. (2015). Consistently using the one-kilometer buffer around Line A as a study area, we regress the log of nominal land prices against block fixed effects and a year trend to obtain an estimate of the average yearly price appreciation during several historical periods. We note that in the results reported in Table A27 we exclude the 1914-1928 period because of the hyperinflation in the aftermath of WWI which complicates the comparison of nominal prices. For the later currency reforms (reichsmark to Deutsche Mark, 1948 and Deutsche Mark to euro, 1998) we apply the official conversion factors (10:1 and 1.95583:1).

As evident from Table A27, growth rates in nominal land prices fluctuate around 5%, with peaks during the major economic boom periods such as the "*Gründerzeit*" (2) and the post-WWII (pre-unification) period (4 and 5). These rates are in line with Knoll et al. (2017) who report a long-run average growth rate of 4% for Germany (4.3% and 3.7% for the post-WWII and the pre-WWII periods).

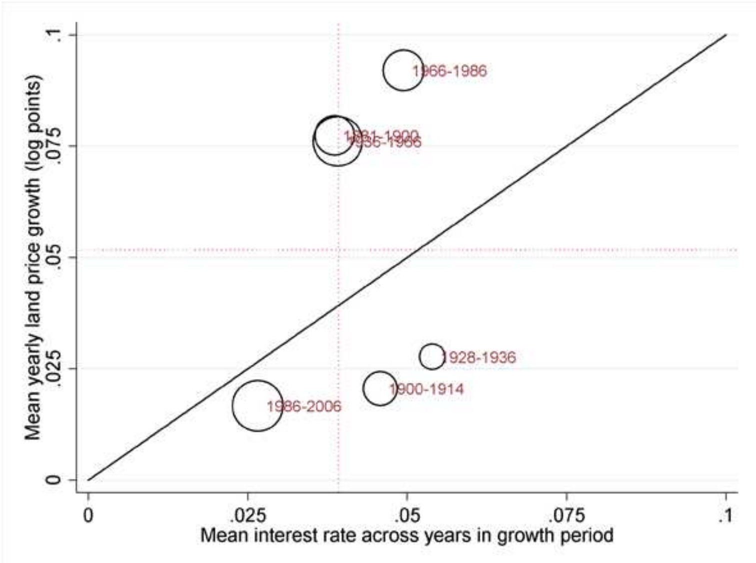
In Figure A14, we compare the estimated land price growth rates to interest rates (central bank discount and base rates). We find that the weighted (by year) average growth rates and interest rates over the period from 1881 to 2006 are roughly within the same range (about 4-5%). The correlation between the two variables is positive, with half of the observations being located above the 45-degree line and the other half below. It seems fair to conclude that over the course of about 130 years, nominal land prices in Berlin appreciated roughly at a rate that reflects the opportunity cost of capital.

Tab A27. Land price appreciation

	(1) Ln land price	(2) Ln land price	(3) Ln land price	(4) Ln land price	(5) Ln land price	(6) Ln land price
Year	0.077***	0.021***	0.028***	0.076***	0.092***	0.017***
	(0.001)	(0.001)	(0.006)	(0.002)	(0.002)	(0.003)
Fixed effect	Blocks	Blocks	Blocks	Blocks	Blocks	Blocks
Period	1881-1900 (4 years)	1900-1914 (4 years)	1928-1936 (2 years)	1936-1966 (2 years)	1966-1986 (2 years)	1986-2006 (2 years)
Area	1 km from Line A	1 km from Line A	1 km from Line A	1 km from Line A	1 km from Line A	1 km from Line A
N	1,348	1,348	614	584	562	576
r2	0.924	0.951	0.845	0.949	0.970	0.757

Notes: Sample are is a 1 km buffer drawn around Line A. Standard errors (in parenthesis) are clustered on fixed effects level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Fig A14. Land price appreciation vs. central bank interest rate



Notes: Mean yearly land price growth are the estimated year effects in Table A14. Interest rate is the central bank discount rate from 1881 to 1998, the base rate as per Discount Rate Transition Act from 1999 to 2002, and the base rate as per civil code thereafter as published by Rahlf (2015) and the Deutsche Bundesbank (interest statistics). Dotted lines are weighted (by year) averages. The black solid line is the 45-degree line.

11 Property taxation

In the back-of-the envelope calculations reported in Table 4 in the main paper, we consider fiscal revenues from property transaction taxes. Here, we provide a comparison in terms of revenues from property taxes, which are internationally more popular..

11.1 Real property tax rates in Germany

In Germany, the property tax is determined as the product of the tax base (the assessed value of the property, the so called *Einheitswert*), a tax rate (*Grundsteuermesszahl*) and a tax factor (*Hebesatz*). The tax rate depends on the property type (e.g. single family houses) while the tax factor varies across federal states. One specific feature of the German property tax system is that the *Einheitswert* is based on an assessment that took place as early as in 1961 (in the states belonging to the former German Democratic Republic, the *Einheitswert* refers to 1935). The *Einheitswert*, thus, substantially underestimates the current market value of a property. The legal tax rate (*Grundsteuermesszahl*), therefore, does not directly correspond to a real property tax rate.

To approximate the real property tax rate in Table A28, we first compute the ratio of the *Einheitswert* over the market value as the inverse of a factor that captures the price inflation over fifty years since 1961. We get to this factor using the weighted (by year) average of the yearly land price growth rates from 1966 to 1986 and 1986 to 2006 reported in the Table A27 (columns 5 and 6). This appreciation rate implies that the *Einheitswert* after 50 years, on average, corresponds to 10.55% of the market value. For the tax rate, we consider values of 0.27%, which applies to single-family houses, and a rate of 0.35% which applies to larger structures. For the tax factor, we consider values of 333% (Hesse, the lowest in Germany), 410% (the German average) and 810% (Berlin, the highest in Germany), reported by the Federal Statistical office (Statistisches Bundesamt Fachserie 14 Reihe 10.1 – 2010).

Under the assumptions made, it is then straightforward to approximate a real property tax rate for the different scenarios by multiplying the ratio of the *Einheitswert* over market value by the tax rate and the tax factor. The typical tax rate in central Berlin is 0.35% (non-single-family houses) and the tax factor is 810%, thus the real property tax is 0.3%. In other parts of Germany, the real property tax rate is likely to be lower because the tax factors are much lower. Moreover, property price appreciation was, on average, higher at 7%, implying a ratio of *Einheitswert* over market value of just about 5% (Bundesministerium der Finanzen, 2011).

The real property tax rate that we estimate for Berlin is low by international standards. According to a Property Tax Comparison Study by the Minnesota Center for Fiscal Excellence (2014), the average property tax in US urban areas was 1.5%. Across urban areas, tax rates vary from 0.61% (Columnia, SC) to 4.1% (Bridgeport, CT).

Tab A28. Real property tax in Germany and Berlin

	(1)	(2)	(3)	(4)	(5)	(6)
Long-run yearly price inflation				4.6%		
Ratio "Einheitswert" / market value				10.55%		
Tax rate (Grundsteuermesszahl)	0.27%	0.35%	0.27%	0.35%	0.27%	0.35%
Tax factor (Hebesatz)	333%	333%	410%	410%	810%	810%
Real property tax	0.09%	0.12%	0.12%	0.15%	0.23%	0.30%

Notes: The yearly price inflation is from an auxiliary regression of the natural log of 1966-2006 (Berlin) land price on block fixed effects and a year trend. The ratio of the “Einheitswert” over the market value is the inverse of a factor that captures the price inflation over fifty years since 1961 (the year of the “Einheitswert” assessment). A tax rate (Grundsteuermesszahl) of 0.27% applies to single-family houses whereas a rate of 0.35% applies larger structures. The “Hebesatz” values are from the Federal Statistical Office (Statistisches Bundesamt Fachserie 14 Reihe 10.1 – 2010) and refer to Hesse (333%, the lowest in Germany), the German average (410%) and Berlin (810%, the highest in Germany). The real property tax is obtained by multiplying the ratio of "Einheitswert" / market value (a measure of the undervaluation of the tax base) by the Grundsteuermesszahl (the tax rate) and the Hebesatz (the tax factor).

11.2 Property tax vs. property transaction tax revenues

In the context of the back-of-the-envelope calculations reported in Table 4 in the main paper, it is noteworthy that, in reality, a public investment will not refinance via the property tax in Berlin because, as described above, the tax base is fixed to 1961 (or 1935) assessed values (the *Einheitswert*). However, as summarized below in Table A29, revenues from property taxes (*Grundsteuer*) and property transaction taxes (*Grunderwerbssteuer*) tend to be within the same range in Berlin. Unlike property taxes, property transaction taxes are based on actual transaction prices and are responsive to increases in real estate prices. The fiscal returns listed in Table 4 can, thus, be thought of being incurred via property taxes instead of property transaction taxes in Berlin, leaving all interpretations and conclusions unaffected. For comparison, we replicate Table 4 for a hypothetical and internationally more conventional scenario – in which the cost of an underground line are recovered in terms of property taxes. Given the results from A28, it is no surprise that the results are similar.

Tab A29. Property transaction tax revenues vs. property tax revenues in Berlin

	2012	2013	2014	2015	Mean
Property transaction tax (million)	578.0	735.4	796.0	960.0	767.3
Property tax (million)	756.7	763.7	776.9	780.8	769.5

Notes: Data are from the State Statistical Office Berlin (available from the website of Berlin Senate Department (https://www.berlin.de/sen/finanzen/steuern/steuereinnahmen/)

Tab A30. The fiscal case for an underground line

	(1)	(2)	(3)	(4)	(5)	(6)
Noise preferences		Historic			Contemporary	
Noise effect on land price (per decibel)	0.41%	0.41%	0.41%	3.32%	3.32%	3.32%
Property tax rate	0.25%	0.75%	1.5%	0.25%	0.75%	1.5%
Estimated total cost (million 1900 RM)			15.94			
Estimated underground extra cost (million 1900 RM)			34.36			
Aggregated noise effect on land value (million 1900 RM)	18.6	18.6	18.6	151	151	151
Yearly tax revenue (million 1900 RM)	0.05	0.14	0.28	0.38	1.13	2.26
Years to recover underground extra costs	738	246	123	91	30	15

Notes: Contemporary land price effect adjusted for changes in land share and housing expenditure share (land price capitalization effect inflated by the ratio of contemporary over historical shares). Cost estimates based on Bousset (1935). Estimated total cost result from multiplying the reported 1902 per km costs of over elevated sections by 8 km (the length of the elevated sections of the Line A). The estimated underground extra cost result multiplying the total cost by the percentage extra costs for underground segments obtained from an auxiliary regression reported in Section 5 of the appendix. Years to recover extra costs are calculated under the assumption that land values grow at a rate similar to cost of capital (see appendix 9 for a justification).

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