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Metro's night travel offer on the weekend and its impact on house prices

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ABSTRACT

We examine the impact of introducing a weekend metro night service on housing prices in Frankfurt, Germany. Our identification strategy combines a triple-differences design to estimate the average treatment effect on the treated (ATET). We find both statistically and economically significant ATETs. For housing units located within a 300 m distance of the night service trains, housing value experience an average 22 % increase within a one-year period following the schedule change. This is equivalent to an average increase in home value of EUR 109,835 , or a total value appreciation of the nearby housing stock of more than EUR 32 million. Further, we do not find evidence that the night service trains bring negative externalities, such as noise, for units located within 100 m of train stations.

1. Introduction

Transportation infrastructure plays a crucial role in household location choices, as it often reflects a trade-off between commuting time and house prices (Alonso, 1964; Mills, 1967; Muth, 1969). This is particularly relevant in metropolitan areas where high house prices and rents necessitate city planners to maintain affordability by considering this balance. In contrast, constrained budgets of local governments often make it challenging to construct large-scale infrastructure projects. Thus, politicians and city planners must efficiently use existing resources and optimize the utilization of existing transportation infrastructure, i.e. by adjusting their timetable of

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operation.

In December 2017, a metro night service on weekend nights was introduced on all S–Bahn (suburban train) lines, excluding S9, and two selected U-Bahn (underground railway) lines (U4 and U8) in the city of Frankfurt (Main) in Germany.[1] This implementation was part of the annual timetable adjustment that occurs every December. We leverage this quasi-experimental setting to study whether and how changes in public transportation infrastructure, i.e. increasing service intensity due to a time table expansion, exogenously affects real estate prices. Fig. 1 displays all metro stops in the city with those offering weekend night service marked in orange. Hence, selected areas of the city have gained enhanced accessibility, potentially increasing their appeal to residents.

Existing literature primarily focuses on the impact of newly constructed infrastructure on real estate prices. For example, McMillen and McDonald (2004) measure the impact of a new rapid transit line on property prices in Chicago, USA. Their findings indicate that the effect varied across the chosen time frame but was predominantly positive with a 6.89 % increase from 1986 to 1999. In a similar vein, Boucq and Papon (2008) scrutinize the impact of light rail infrastructure in the Haute-de-Seine department, France, indicating an average price surge of around 3 % from 1993 to 2004, which allows for considering anticipation and learning effects. Furthermore, Mulley and Tsai (2016) measure the impact of a bus rapid transit system in Sydney, Australia, and find that treated properties experience an approximately 11 % price increase compared to non-treated units after the commencement of the bus rapid transit in 2003 and 2004. This corresponds to an increase in average property value of AUD$ 37,841.[2] In this context, Chen et al. (2019) highlight that house prices generally decrease (increase) at the project announcement (project construction) of the Northwest Metro Line in Sydney, Australia.

Sun et al. (2016) examine the influence of a completed subway line on real estate prices in Tianjin, China. They observe a 9.9 % average price increase within a 1,000 m range from the next metro station, concluding that operational subway lines significantly affect house prices compared to those under planning. Zhou et al. (2021) assess the effect of a new subway line in Shanghai district, China, resulting in an average property price appreciation of 3.75 % from December 2006 to May 2015. Additionally, studies also find that the benefits of accessibility to metro stations are capitalized in residential and commercial land prices in Shanghai (see, e.g., Murakami and Chang, 2018; Chang and Murakami, 2019). Each of these studies utilize OLS regression for their estimates.[3]

However, OLS estimators may be biased and inconsistent due to spatial autocorrelation (Corrado and Fingleton, 2012). Thus, several studies use spatial methods to account for spatial lags and unobserved spatial heterogeneity. For instance, Dorantes et al. (2011) explore the impact of a new metro line on property values in Madrid, Spain. They find that better accessibility positively impacts prices with an appreciation effect between 2.18 and 3.18 % within a 1,000 m distance to the closest metro station in 2004, a year after the metro line starts its operation. Furthermore, Ibeas et al. (2012) use spatial methods to evaluate the influence of public transportation infrastructure on property values in Santander, Spain and Rome, Italy, with mixed findings: They find that while increased bus transport availability generally increases property values, noise disturbance from rail access can negatively impact property prices. Lastly, Efthymiou and Antoniou (2013) investigate how new transportation infrastructure affects real estate prices and rents in Athens, Greece over the period from September 2011 to January 2012. Utilizing various spatial econometric methods, they find a positive impact, with a 6.74 %–11.66 % price increase within 500 m of the nearest metro station.

Our research contributes and expands this strand of literature by examining the effect of small adjustments in public transportation infrastructure on house prices. As the introduction of nighttime metro service were not anticipated (no pre-trend) by the population of Frankfurt, the increased service intensity serves as an exogenous event for real estate prices. More specifically, in a city with lacking development space and no significant development projects, the altered time schedule is an easy way to provide an additional amenity for residents living close to metro stations. Hence, this quasi-experimental policy shock eliminates selection bias and provides an ideal setting to estimate the causal impact of intensified metro service on house prices.

This paper aims to estimate whether enhancements in existing transportation infrastructure impact real estate transaction prices. We employ both difference-in-differences (DID) and triple-differences regressions in our empirical strategy. The results from the triple-differences estimation suggest that the night service trains of U- and S-Bahn can increase the average property values located within 300 m of train stations by approximately 22 %. Moreover, we find no evidence that the night-service trains generate negative externalities in terms of noise emissions. A back-of-the-envelope estimation indicates that night train services can boost the average home value by about EUR 109,835. Compared to the estimates derived in previous studies, our causal effect of a timetable adjustment on house prices is substantially larger compared to the development of a new transit system. However, it is obvious that the former change cannot be anticipated and is implemented within a short period. In contrast, the construction work is announced well in advance, and it takes time until the mass transit line operates. Hence, the appreciation of such a measure will slowly diffuse into prices with

[1] The city of Frankfurt in Germany is equipped with two types of rapid transit systems: S-Bahn (suburban trains) and U-Bahn (underground railways). The nine S-Bahn lines (S1-9) provide access to the airport, the sports stadium, the trade fair, as well as nearby cities and small towns. Most routes run from East to West with a minimum service interval of about 15 min. There are also nine U-Bahn lines (U1-9) connecting the city to the Northern suburban districts with a service interval about 3–10 min. U-Bahn trains are in fact light rail as most lines run underground in the city center and rather run in the middle of the street in suburban areas. Besides the S- and U-Bahn transit systems, the city also provides other public and private transit modes, such as trams, bus, taxi etc., for which we control in our estimation strategy.

[2] Other studies focusing on the effect of high-speed railways on residential prices provide mixed results. For example, Chen and Haynes (2015) investigate a train connection between Beijing and Shanghai high-speed rail, whereas Anderson et al. (2010) analyze a high-speed railway connecting seven metropolitan areas in Southern Taiwan.

[3] Ingvardson and Nielsen (2018) provide an extensive literature review on the effects of rapid bus and light rail transit as well as metro and heavy rail systems on house prices.

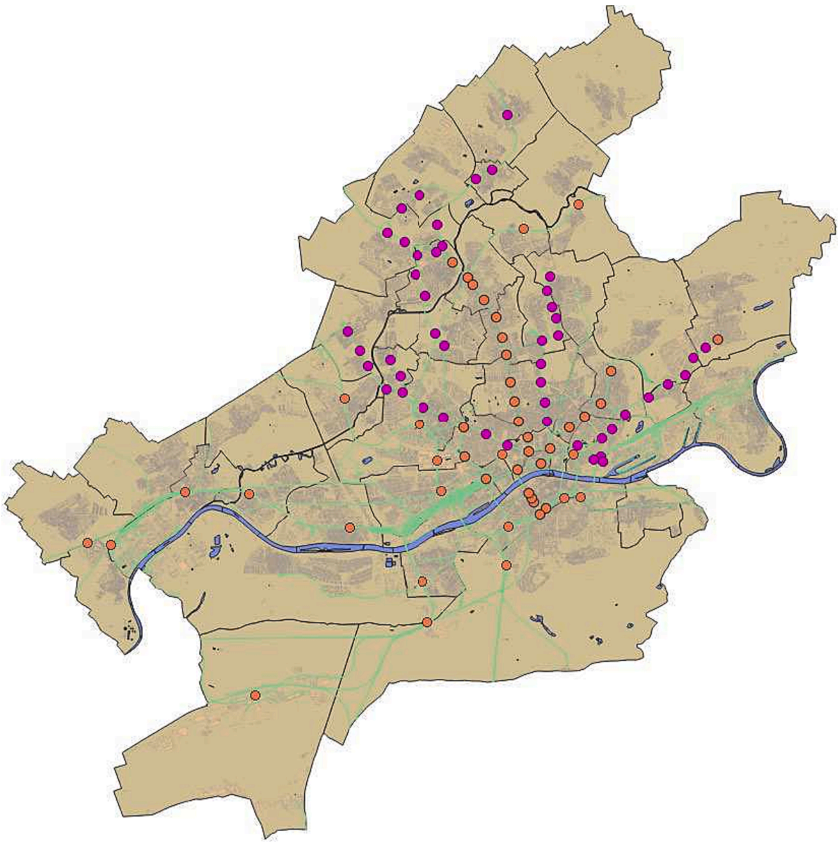

Fig. 1. City Map of Metro Stations. *Note*: This figure shows a city map of S- und U-Bahn stations in Frankfurt (Main), Germany. Stations that are accessed by night service on the weekend are displayed in orange color. Stations which are not accessed by this service are marked in purple color. Green lines indicate rail networks, while blue lines indicate water.

anticipation effects in the pre-operation period and a longer acceptance time by users.

Our results have important implications for city planners and policy makers. On the one hand, in times of limited local government budgets, availability changes of already built infrastructure (e.g., timetable adjustments) can improve or even optimize capacities. On the other hand, such public spending at low costs creates additional amenities and improves working conditions in times of flexible work arrangements, capitalizing in location values or real estate prices. Moreover, increased property values may raise local tax revenues in terms of property and real estate transfer tax. Finally, third parties involved in financing transportation infrastructure can benefit from increased profit sharing due to such changes in public transportation infrastructure.

The remainder of this paper is organized as follows. Section 2 outlines the data collection process, provides summary statistics, and reviews the filtering process. Section 3 formalizes the methodology, details the research design and the models used to estimate the causal effect of a timetable change. Section 4 provides the empirical results and Section 5 concludes.

2. Data

The real estate transaction data for the period of December 2016 until December 2018 was provided by the "Gutachterausschuss für Immobilienwerte" of the city of Frankfurt, which compiles all transactions witnessed by notaries in the city. The dataset contains the transaction price and various housing characteristics (such as the number of rooms, size in square meters, floor level, area quality, building age, property type) as well as their coordinates. These coordinates enable geocoding and establishing a variety of amenity variables in the form of distance parameters. Rather than using these variables individually, we utilize building-fixed effects to encompass a wide range of amenities. Metro noise data is published by the "Hessisches Landesamt für Naturschutz, Umwelt und Geologie" and is available in shape-file format. The noise covariate is generated based on whether an observation lies within an area affected by the respective noise source. Besides the covariates being provided with the transaction data, we control for a building-fixed effect, which accounts for all time-invariant urban amenities such as distance to schools, trams, buses, central business districts (CBDs),

Table 1
Variable Description.

Category	Abbreviation	Explanation
Dependent Variable		
Y	*lnPrice*	Transaction price in log-form
Difference-in-Difference Variables		
D_1	*After*	Binary dummy determining whether an observation is posterior to the cut-off date (10/12/2017 = statement date of RMV (Rhein-Main Verkehrsverbund))
D_2	*Dist*	Binary dummy determining whether an observation falls within the distance range to a metro station
D_3	*U_Treat*	Binary dummy, determining if the closest U-Bahn station is accessed by night transportation
D_4	*S_Treat*	Binary dummy determining if the closest S-Bahn station is accessed by night transportation
D_5	*Treat*	Binary dummy determining if the closest metro (either U-Bahn or S-Bahn) station is accessed by night transportation
D_6	*Treat* × *After*	Interaction term determining if an observation is in After and Treat group
D_7	*Dist* × *After* × *Treat*	Interaction term between After and Treat and *Dist*, determines whether an observation falls both in the treatment and the posterior group and is accessed by night transportation of metros
Housing Attributes		
X_1	*Size*	Size of property (m^2)
X_2	*Age*	Property age (years)
X_3	*Rooms*	Number of rooms (#)
X_4	*Good Area*	Categorical variable, indicates quality of area
X_5	*Type*	Categorical variable, indicates type of property
X_6	*Floor*	Categorical variable, indicates floor level
Distance Measures		
A_1	*Dist_U*	Network distance (m) to closest U-Bahn station
A_2	*Dist_S*	Network distance (m) to closest S-Bahn station
Noise Variables		
N_1	*Noise_Metro*	Binary variable determining if there is Metro noise
Time Dummies		
T_1	*MONTH*	Matrix of binary time dummy covariates

Note: This table lists and explains variables in the dataset of real estate transactions. Data on housing attributes and prices are provided by the "Gutachterausschuss für Immobilienwerte", whereas noise data is provided by the "Hessisches Landesamt für Naturschutz, Umwelt und Geologie". Differences-in-Difference Variables and distance measures are self-computed.

Table 2
Descriptive Statistics.

Variables	Full Sample		Sample within 300 Meters		Sample between 300 and 800 Meters	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Price	431,677.300	346,813.200	479,265.700	394,117.007	434,321.000	365,700.000
lnPrice	12.755	0.663	12.861	0.640	12.753	0.673
After	0.486	0.500	0.479	0.500	0.508	0.500
Dist	817.120	606.722	219.480	62.330	519.266	126.804
U_Treat	0.493	0.500	0.427	0.495	0.514	0.500
S_Treat	0.797	0.402	0.921	0.271	0.964	0.187
Treat	0.836	0.370	0.890	0.313	0.862	0.345
Size	81.061	36.350	77.805	37.329	78.249	36.088
Age	31.595	38.247	39.420	45.973	39.022	41.465
Rooms	2.801	1.124	2.655	1.082	2.765	1.162
Dist_U	1,703.601	1,900.902	218.730	57.635	521.439	127.018
Dist_S	1,591.850	1,291.403	223.787	69.386	554.296	129.526
Noise_Metro	0.050	0.217	0.125	0.330	0.032	0.177
Observations	6,591		683		3,281	

Note: This table lists descriptive statistics for numeric variables in the dataset of real estate transactions. The mean and standard deviation (St. Dev.) are listed for the full sample as well as subsamples within a cutoff-distance 300 m and a cutoff-distance between 300 and 800 m.

shops, parks, rivers, etc. Table 1 defines all variables, and Table 2 presents summary statistics.

Network distance, rather than Euclidean distances, are used to calculate the distance parameters. Network distance measures are based on a network layer, such as a city streets network, instead of a straight line.[4] The argument for using the network distances in the regression is that they are likely to have a stronger impact on people's location choice. For example, the actual walking distance between a property and the nearest metro station can vary greatly from its Euclidean distance due to the street network. Moreover, distances have been transformed to binary dummy variables where 1 indicates that an observation falls within a specific category and

[4] Empirical studies point out that Euclidean and network distance measures may differ significantly depending on the geographical context (Chang et al., 2019; Chang & Li, 2021; Diao et al., 2017).

0 otherwise.

The data is filtered according to the following process. The original dataset contained 7,137 transactions from the period of 12/12/2016 until 08/12/2018. The starting date is determined by the previous timetable change in 2016 (12/10/2016) while the end date aligns with the subsequent timetable change in 2018 (08/12/2018). The filtering process involved five steps: First, all observations without coordinates have been removed. Second, all observations with a missing number of rooms have been removed. Third, all observations with zero rooms have been removed. Fourth, observations where proper geo-coding was not possible have been removed. Finally, to make the common support assumption (CSA) to hold, (overlap) histograms and scatterplots of each variable are evaluated. Buildings older than 200 years are excluded, and only observations with 25 rooms or less are retained. Fig. 2 illustrates the spatial distribution of housing transaction during the study period.

Table 2 provides descriptive statistics for the covariates of the full sample of 6,591 observations and the subsamples within 300 m and between 300 and 800 m range from the S- and U-Bahn stations. In the subsequent part of the paper, we define the treatment group as units located within 300 m cutoff distance and the control group as units located between 300 and 800 m from train stations, respectively.[5] Therefore, we also provide summary statistics for units falling into these two ranges. For better economic understanding, the original price is displayed alongside the log-price used in later analyses.

3. Research design

3.1. Quasi-Experiment

Quasi-experimental methods are commonly employed to evaluate the impact of transportation development programs on housing values. For example, Dube et al. (2014) apply a spatial DID estimator and measure the influence of changes in public mass transit systems on house prices in Montreal, Canada. Their findings reveal a 5.2 % appreciation in property prices within 500 m of the closest metro station while houses within the area of 500 to 1000 m appreciated only by 2.3 % during the period from 1994Q1 to 2009Q4. Diao et al. (2017) use a spatial DID estimator to identify an effect of a new mass rapid transit line on real estate prices in Singapore. They identify the critical treatment cutoff distance by an LPR approach. Within a 600 m distance to the closest station, they find an 8.6 % increase in prices. However, the authors also find significant anticipation effects one year prior to the opening day. Chang and Diao (2022) estimate the effect of a high-speed railway development on housing value in Shenzhen, China. The authors find that the effect of high-speed railway can spread along the city's metro network and lead to an average 7 % increase in prices of residential houses close to metro stations from 2014 until 2016.

We refrain from using spatial econometrics for several reasons: First, our identification strategy defines areas within a certain distance to a metro line. Within these areas house prices are more homogeneous. Second, the estimates of spatial autoregressive models (SAR) only capture first-round effects, neglecting spillover and feedback effects. Third, the estimates cannot be interpreted as marginal effects. Finally, spatial autocorrelation can also arise from other exogeneous variables, i.e. not only from the spatially lagged endogenous variable. This problem is known as the reflection problem (Manski, 1993) and requires additional spatial lags.

Moreover, because pure cross-sectional OLS estimators are not likely to reveal causal relationship due to omitted variables and selection bias, an increasing number of studies have employed quasi-experimental design in program evaluation over the past decade.[6] For example, many studies have adopted the DID and regression discontinuity approaches to uncover the capitalization rate of factors like crime, environmental programs, and school quality on housing values (Chang et al., 2021; Chang and Li, 2018, 2021; Gibbons et al., 2013; Linden and Rockoff, 2008). The key identification assumption is that the shock to the local location factor is arguably exogenous to house prices.

Most existing studies typically estimate the causal impact of new transit development such as metros on property values. However, one major concern for those studies is that the new transit development project always involves the site selection, and the DID estimation may not be credible because the treatment and control groups are not very comparable. For example, public sector authorities may choose the highly densely populated area to build metro stations, where those districts may have high house prices or great growth potentials compared to other districts in far distance. In this case, comparing the price responses of housing units to new metros between districts close and faraway from metro stations may not be convincing given the selection bias, even within a DID framework. Eliminating such bias is difficult for new transit development projects. *But how can we accurately estimate the causal effect of the introduction of a new transit system on property values?*

This paper aims to identify the impact of a change in public transportation on real estate prices, i.e., to measure how the introduction of a night metro service impacts housing prices within a specific range. More precisely, we avoid the selection bias problem by utilizing the introduction of a metro night service during weekends in an existing transportation infrastructure as part of our

[5] The 300 m cut-off distance to the closest metro station is the result of a local polynomial regression (LPR) on house price developments with varying smoothing parameters. This essential identification of the cut-off point between treated and non-treated observations is outlined in Subsection 4.1. In addition to this baseline scenario, we vary the area between treated and control group in robustness tests in Subsection 4.2.

[6] Our estimates are derived from an unbalanced panel lasting over two years from December 2016 to December 2018. Hence, we cannot apply a repeat sales regression that captures property price appreciation compared to hedonic regression analysis. For instance, Kim and Lahr (2014) are one of the few studies using repeat-sales data to analyze the effect of transportation infrastructure (Hudson-Bergen Light Rail in New Jersey) on residential property prices between 1991 and 2009. However, including building fixed effects in our specification is close to utilizing a repeat sales approach.

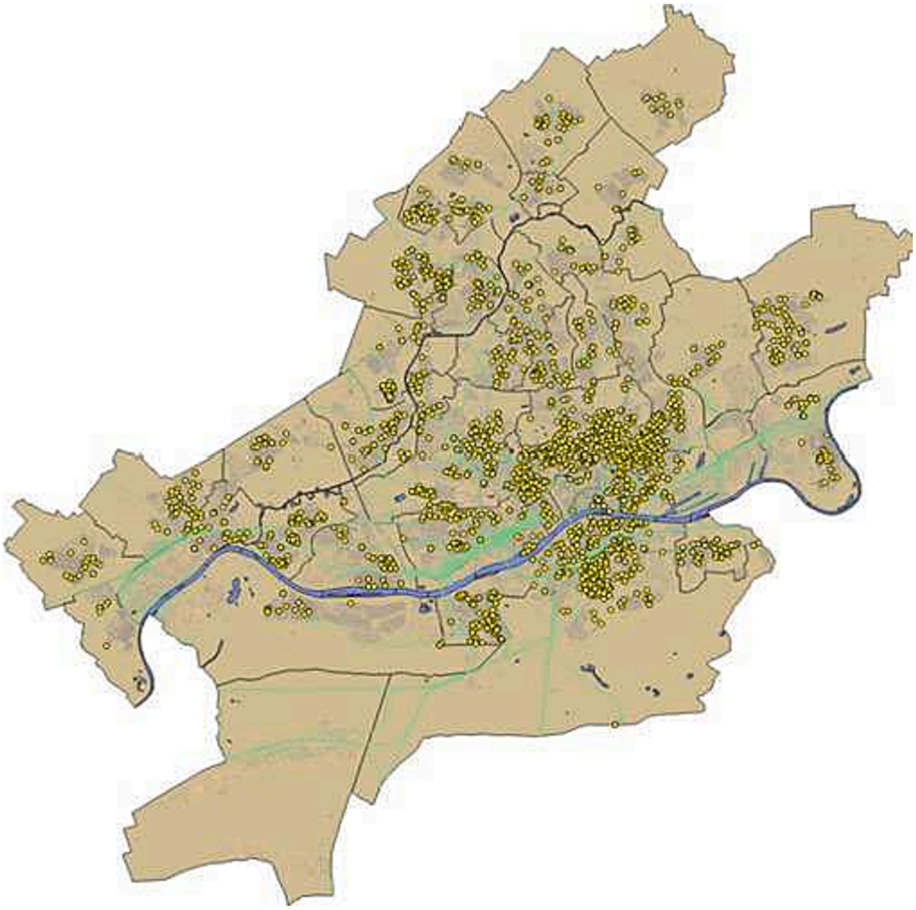

Fig. 2. City Map of Housing Transactions. *Note*: This figure shows the spatial dispersion of housing transactions in Frankfurt (Main), Germany. City districts are separated by dark lines while observations are displayed in yellow. Green lines indicate rail networks, while blue lines indicate water.

identification strategy. Therefore, it is necessary to identify a group of observations which simultaneously falls within a specific distance range from the closest metro station, where this metro station offers night services on weekend and the transaction occurred after the treatment date (10/12/2017).

We argue that the introduction of the night service train is exogenous for the following reasons: First, we find no discussions or announcements of the night service in the media prior to the introduction. It therefore seems likely that nobody anticipated the introduction of the night train service in Frankfurt before its announcement. Most people presumably expected a timetable adjustment similar to previous years. More specifically, the timetable change in December 2017 surprisingly introduced weekend night services almost 30 years after the introduction of the night bus. Second, there were no significant development projects in the city even after the introduction of the nighttime train service. This is primarily because the city lacks development space. Third, as the night train service operates only on weekends it can be interpreted not only as an additional amenity but also creates value for local residents in terms of connectivity, safety etc. Furthermore, the event study demonstrates that there was no pre-trend prior to the announcement. This suggests that the housing market did not anticipate a price wedge ex ante when the public sector made the decision. Lastly, as the control group is located close to train stations (300–800 m), any overarching regional growth expectations can be largely offset in a DID setting. In other words, it is highly improbable that any other policy could have had an effect similar to the nighttime trains, both spatially (within 300 m of all treated stations) and temporally (right after December 12, 2017).

A DID approach identifies a causal *average treatment effect on the treated* (*ATET(X)*), i.e. the impact that the timetable change has on the treatment group (see, e.g., Lechner (2010) and Froelich and Sperlich (2019)). More specifically, the idea behind the DID approach is to construct a counterfactual outcome for the treatment group (i.e., determining the outcome for the treatment group had they not been affected by the timetable change).[7] For our empirical analysis, it is necessary to extend the classic DID design to triple differences

[7] The identifying assumptions necessary to make identification possible are: *stable unit treatment value assumption* (SUTVA), *exogeneity*, the treatment itself should not have impacted the pre-treatment population in the pre-treatment period, the *common support/overlap assumption*, and specific to the DID-approach is the *common trend assumption* (CTA).

to ensure that the CTA holds. Consequently, the *ATET(X)* for this setting is given in Equation (1):

$$\boldsymbol{ATET}(\boldsymbol{X}) = \boldsymbol{E}\left[\boldsymbol{Y}^1_{t=1} - \boldsymbol{Y}^0_{t=1} | \boldsymbol{D} = 1, \boldsymbol{N} = 1, \boldsymbol{X} = \boldsymbol{x}\right], \tag{1}$$

where $E[]$ is the expectations operator, $Y^{0/1}$ indicates the observable and counterfactual outcome, respectively, $t \in \{0, 1\}$ flags the pre- and post-treatment period, and $D \in \{0, 1\}$ indicates the non-treatment and treatment. Furthermore, $N \in \{0, 1\}$ indicates whether the closest metro station to an observation is accessed by night transport in the treatment period and X describes confounders.

It is crucial to ensure that the identifying assumptions hold for the empirical part. We therefore provide some explanations for these assumptions. Our analysis aims to estimate the price effect on real estate properties depending on whether they fall within a certain distance range to a metro station offering night service. The treatment does not affect properties which do not lie within a reasonable walking distance to a metro station. Thus, the SUTVA assumption is likely to hold for this setting.[8] Moreover, we control for a wide range of covariates, which includes housing characteristics and the building block level fixed effect. Housing characteristics are clearly not affected by the treatment. In contrast, the categorical variable describing neighborhood quality may be impacted by the treatment. However, this is rather a long-term scenario, and other, more important characteristics (e.g., architectural style of buildings, access to parks, etc.) are more likely to impact the quality of an area. Amenity parameters in the form of distance measures are not impacted by the treatment and are absorbed in the fixed effects.

The binary dummy variables for noise parameters included as fixed effects are not affected by the treatment, as they only indicate whether an observation falls within the range of the noise polygon or not. The polygons measure the noise extension between 10 pm and 6am. Thus, their size is not likely to be expanded by the treatment since the night line service runs for approximately three hours between 2am and 5am. Hence, the exogeneity assumption is likely to hold.

The prerequisite of a valid DID strategy is on the CTA. Empirical studies employ the event-study method to verify whether the pre-policy common trends assumptions hold or not (Clarke and Tapia-Schythe, 2022; Freyaldenhoven et al, 2019). We employ the standard event study approach to examine the common trend assumption in the DID model. Moreover, we adopt the triple difference design which can significantly contribute to the fulfillment of the assumption.

3.2. Model specifications

The *ATET(X)* is estimated by different regression methods. A common approach is the hedonic regression (Rosen, 1974), which states that the price of a heterogeneous good can be derived from a set of implicit, or “hedonic” prices of the characteristics of the good. These implicit prices can be econometrically estimated by regressing a product’s price on its characteristics.

In our empirical analysis, we conduct a standard two-way fixed effect DID regressions for metro lines that began offering night-time service on December 10, 2017. The regression function is shown in Equation (2):

$$lnP_{ijt} = a_0 + a_1 Dist_j \times After_t + a_2 X_{it} + \mu_i + T_t + \varepsilon_{it} \tag{2}$$

where $\ln P_{ijt}$ represents the natural logarithm of housing price for units i in building j at the time t. $Dist_j$ is a dummy variable which equals to 1 if building j is close to a metro station and 0 otherwise. $Dist_j$ defines the treatment group. The catchment area of a new metro station generally ranges from 500 to 800 m in existing studies, however, the impact area of night service trains on the weekend could be smaller. Therefore, we will limit our examination for samples located within 800 m of metro stations. We change the range of $Dist_j$ from 100 to 600 m to explore the impact area of night service trains. $After_t$ is a time dummy which equals to 1 if units are transacted after December 10, 2017, and 0 otherwise. X_{it} is the housing attributes including unit size, age, number of rooms, and we add these controls in the form of natural logarithms. Other unit characteristics include floors, apartment and building types, and area quality, which are added using fixed effect. μ_i is the building-fixed effect, which capture the time-invariant factors such as local amenities. T_t is the monthly fixed effect which includes 24 monthly dummies during our study period. ε_{it} is an error term. In the following regressions, the standard errors are clustered at the building level.

The coefficient of a_1 is our research interest. Presumably, a_1 should be positive if buyers value the night train services and the associated negative externalities, such as noise, are not too large. Equation (3) can also be applied for units closer to other metro stations that do not offer night train service in Frankfurt. This examination provides a placebo test, with the hypothesis that house prices close to those conventional trains do not exhibit a detectable change after the new transit policy.

As described in the previous section, the pre-parallel trend assumption must be hold for a valid DID examination. Here we adopt the standard event study to verify the price wedge between the treatment group and control group using the T-1 (one month before the policy shock) as a reference. The formula of an event study is shown in Equation (3):

$$lnP_{ijt} = b_0 + \sum_{k=-12}^{11} \beta_k Dist_j \times 1[month_t = k] + b_1 X_{it} + \mu_i + T_t + \varepsilon_{it} \tag{3}$$

[8] Theoretically, night train service can increase housing demand for both the treatment (closer) and control (slightly farther away) groups. Practically, our results from Table 3 suggest that the impact of the night train service is largely capitalized into housing prices within a 300-m radius. For units farther away, the increased housing demand is either not strong enough to induce a price rise or there is simply not a notable change in demand beyond the 300-m catchment area. The DDD approach in Subsection 4.4 further alleviates concerns regarding potential contamination of the control group in the DID setting.

where $1[month_t = k]$ is an event study month dummy that equals to one for each pre- and lag-month before and after the night-time metro service. All other variables are the same as those used in Equation (2) for the two-way fixed DID model.

As we can estimate the house price changes for units closer to night-service trains and other trains respectively, we need to compare the differences on the house price changes for units close to the two different types of metro stations. This provides the triple difference strategy as the house price changes for units close to other conventional metro stations provide a reasonable counterfactual. The benefit from a triple difference strategy is that it captures the unobservable trends and could reduce the bias in the estimate of the policy change. The regression formula for the triple difference is summarized in the Equation (4):

$$lnP_{ijt} = c_0 + c_1 Dist_j \times After_t + c_2 Treat_j \times After_t + c_3 Dist_j \times Treat_j \times After_t + c_4 X_{it} + \mu_i + T_t + \varepsilon_{it} \quad (4)$$

where $Treat_j$ is a dummy variable which equals to 1 if the closest of metro stations to building j provides the nighttime services, and 0 otherwise. All the other variables remain the same as those shown in the Equation (2). In the standard triple difference regression, we need to add another interaction term $Dist_j \times Treat_j$. However, this interaction is time invariant and is absorbed by the building fixed effect μ_i. The coefficient c_3 reveals our research interest.

3.3. Local polynomial regression

To identify a potential treatment region, we use a local polynomial regression (LPR), i.e., we regress the distance to the closest metro station on the log-price per square meter. A similar approach has been used by Linden and Rockoff (2008) to determine the impact of sex offenders on property prices in a neighborhood. A LPR fits a flexible non-linear function by only using observations within a specific range to the current observation, i.e. training observations are only locally used (James et al., 2013). The number of observations included in each local fitting can be determined by using a smoothing parameter $\alpha < 1$, which determines the percentage of observations to be included. Further, observations used in the local fitting process get weights assigned. The weight is calculated by a tri-cubic weighting function:

$$\omega_j = \left(1 - \left(\frac{dist_j}{maxdist}\right)^3\right)^3 \quad (5)$$

with w_j being the weight assigned to observation j, $dist_j$ being the distance of observation j to observation i, and *maxdist* being the maximum distance in the local fitting area.

4. Empirical results

In this section, we first present the results of the LPR, which identifies a cutoff distance for the treatment selection. Using the cutoff distance, we estimate the results by using DID and triple differences, respectively. For better readability, regression tables contain only coefficients of covariates that are important for interpretation. However, all covariates as described in Table 1 have been included in all regressions.

4.1. Identifying cutoff distances

A key element of the empirical study is the identification of an appropriate cutoff point, which identifies observations as either treated or not. This cutoff point has been determined by finding a specific network distance point where a change in price development occurs. The LPR identifies a cutoff point at approximately 300–500 m. This makes economically sense since an assuming walking speed of 3 km/h would imply an average 6–10 min' walk to the nearest metro station. This aligns with the findings of Diao et al. (2017). Fig. 3 shows the fitted curve estimated by the LPR as well as the single points of the observations. Results are tested on robustness by varying the smoothing parameter between a range of 0.3 and 0.55. As a result, we establish the cutoff point within 300 m as the base scenario for selecting the treatment group.

4.2. Results from DID regressions

We employ Equation (2) to estimate the impact of night service trains on housing values. Initially, we group U- and S-Bahn trains together because the U-Bahn lines in Frankfurt are, in fact, light rail systems similar to S-Bahn trains. The result from local polynomial regression suggests the cutoff range from the night service trains is about 300–500 m. We vary the cutoff ranges from 100 to 600 m to explore the price responses for units located within 800 m of the closest U-Bahn or S-Bahn stations. The results are reported in Table 3.[9]

In the first column, the treated area is defined as units located within 100 m of their closest stations, and units in the control group

[9] The total sample within 800 m of the train station includes 3,964 observations (683 observations within 300 m radius plus 3,281 between 300-800 m radius). The DID model focuses only on units close to the station that introduced the night-time service, which explains the slightly reduced sample size (2,759 observations). The DDD incorporates all observations. However, some properties appear in the sample only once and will be omitted when we control for the building fixed effects.

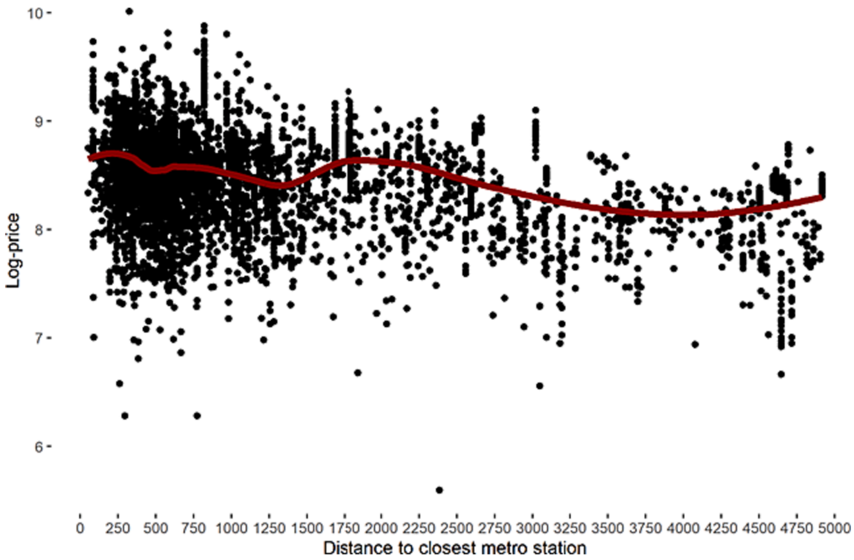

Fig. 3. Local Polynomial Regression (LPR). *Note*: This Figure shows the results for a local polynomial regression with a smoothing parameter of 0.4. More precisely, the fitted curve is displayed in red while black dots indicate single points of observations.

Table 3
Results of DID Regression.

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
	lnPrice	lnPrice	lnPrice	lnPrice	lnPrice	lnPrice
Treated Area (Meters)	<=100	<=200	<=300	<=400	<=500	<=600
Control Area (Meters)	100–800	200–800	300–800	400–800	500–800	600–800
Dist × After	0.129***	0.268***	0.155***	0.086***	0.052**	0.051*
	(0.037)	(0.095)	(0.037)	(0.028)	(0.026)	(0.029)
ln(Size)	0.939***	0.936***	0.933***	0.936***	0.937***	0.940***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)
ln(Rooms)	0.025	0.024	0.031	0.027	0.026	0.024
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
ln(Age)	0.018	0.017	−0.001	0.034	0.028	0.037
	(0.031)	(0.030)	(0.027)	(0.026)	(0.033)	(0.035)
Other Housing Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Building Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,769	2,769	2,769	2,769	2,769	2,769
R-squared	0.957	0.958	0.958	0.958	0.958	0.957

Note: This table lists results for the DID regressions for varying cutoff-distances to the closest U-Bahn or S-Bahn station. HAC-robust standard errors are reported in parentheses. ***, ** and * denote statistical significance at the 1, 5, and 10 % levels.

are those located in the range from 100 to 800 m of their closest train stations. We find the housing values in the treated area increases by about 13 % after the operation of night-service trains, compared to the housing values in the control group. The result is statistically significant at the 1 % level. In Column (2), we increase the cutoff point to 200 m, and the control area ranges from 200 to 800 m. We find the housing values increase to 26.8 %. From Columns (3) to (6), we continue to increase the cutoff range and observe coefficients that gradually become smaller and statistically less significant.

Next, we verify whether the DID estimations satisfy the pre-treatment common trends assumption. By employing Equation (3), we conduct an event study for the regression using the 300 m as the cutoff point (Column 3 in Table 3). Fig. 4 shows the results by plotting the changing trend of housing values between the treatment and control groups relative to the reference point (one month before the operation of nighttime trains). Due to other policy shocks, such as the annual train timetable adjustments that occur outside our study period, we focus on short-term effects and limit our data collection to one year. Despite its brevity, the pre-treatment period is divided into 12 intervals (months). We also assume that the insignificant results do not arise due to limited sample size. If anything, having a

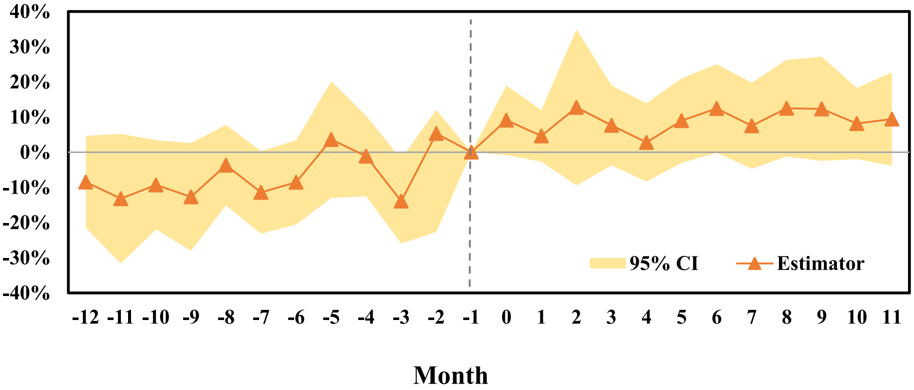

Fig. 4. Results of Event Study. *Note*: This figure shows the results of the event study with cutoff distance of 300 m (see Table 3, Column 3) by plotting the changing trend of house prices between the treatment and control groups relative to the reference point (one month before the operation of nighttime trains).

smaller sample size each month could introduce anomalies, as outliers might have a disproportionate influence. However, there is no observed increase in the price gap during the pre-treatment period. In contrast, we find that the CTA holds in the pre-treatment period.[10] Moreover, the housing price experiences a systematic increase in the post-treatment period, though most results are only weakly significant.

The results from Table 3 show that the benefits of the night service trains are capitalized in housing values, especially for units close to train stations. However, the specifications in Table 3 cannot precisely reveal the cutoff range. Therefore, we next use the same data and partition the treatment area into six 100 m bins and interact the policy time dummies with each bin. In this regression, we have six treatment groups, and the control group includes the units located from 600 to 800 m of train stations. Table 4 reports the results.

Column (1) shows that house prices increase by about 16.3 %, 51.8 %, and 13.1 % for units located in the first 100, second 100 (100–200), and the third 100 (200–300) m of train stations, respectively, compared to the housing price for units located between 600 and 800 m from the same train station.[11] All the results are statistically significant at the 1 % level. For units located beyond the 300 m cutoff, coefficients become relatively small and insignificant. In our dataset, several hundreds of units were built after 2018. One may be concerned about selection bias as those units were built after the introduction of night service trains. In Column (2), we address this by excluding these units and running the same regression, and the results do not change. In the first two columns, we aggregate the U- and S-Bahn trains. In theory, the price response from U- and S-Bahn trains can be different. In Column (3), we examine the price responses for units close to U-Bahn trains. We find the price trends are very similar to those shown in Column (1). Column (4) shows the price change trend for units close to S-Bahn trains. Although there are no transactions within the first 100 m cutoff distance, we find house price appreciations of about 96 % and 7.6 % in the range of 100–200 and 200–300 m, respectively.[12] Finally, we run a placebo test to explore the price variation for units close to other lines without the night-time services. Not surprisingly, all coefficients are relatively small and insignificant as shown in the Column (5) of Table 4.

Table 4 provides concrete evidence that both U-Bahn and S-Bahn night service trains bring a benefit for housing values within the 300 m of cutoff distance. Thus, we choose the 300 m cutoff to define the treatment group, while units located from 300 to 800 m of a train station are defined as the control group. We run DID regressions to estimate the average price response due to the operation of night service trains. Table 5 summarizes the results.

The first column presents the aggregate results by combining the U- and S-Bahn night-service trains. House prices increase about 15.5 % and the results are statistically significant at the 1 % significance level. In Column (2), we interact the U- and S-Bahn trains with policy time dummies. We find units close to U- and S-Bahn trains experience a price increase of about 15.9 % and 13.3 %, respectively. In Columns (3) and (4), we run the same regressions by analyzing the impact of the U- and S-Bahn lines separately. The resulting estimates derived in Columns (3) and (4) are very close to those from Column (2). We are reassuring that both the U- and S-Bahn night service trains bring a large benefit for nearby housing units. Lastly, Column (5) shows the results from other transit lines without a timetable adjustment, i.e. which do not provide the nighttime services. The coefficient is slightly negative, however, not significant.

[10] Any effects from previous policy shocks, i.e. the timetable change in 2016 will be accounted for in both the treatment and control groups (in DID and DDD settings). As shown in Fig. 4, the event study, which examines parallel trends after 2016 and before 2017, further indicates that the previous adjustments did not create diverging trends between the treatment and control groups.

[11] Please note that for a small bin range (100 m), the sample size is relatively small, which can lead to high estimates such as 51.8 % for the second 100 m range. However, the purpose of this test is to show that there is no effect left beyond a 300 m distance. In contrast, we rely on the average effect estimated for a range within 300 m rather than in each 100 m bins.

[12] The result of nearly doubled house prices (96 %) after the introduction of the night service train could again be triggered by the relatively small sample size within a 100 m bin.

Table 4
Results of DID Regression within a 100 Meters Range.

Dependent Variable	(1)	(2)	(3)	(4)	(5)
	U-/S-Bahn	U-/S-Bahn	U-Bahn	S-Bahn	Others (Placebo)
	lnPrice	lnPrice	lnPrice	lnPrice	lnPrice
Dist(0–100) × After	0.163***	0.159***	0.195***	–	−0.134
	(0.038)	(0.039)	(0.055)	–	(0.150)
Dist(100–200) × After	0.518***	0.501**	0.435***	0.960***	0.084
	(0.129)	(0.234)	(0.129)	(0.069)	(0.122)
Dist(200–300) × After	0.131***	0.141***	0.144**	0.076***	−0.141
	(0.040)	(0.041)	(0.062)	(0.027)	(0.090)
Dist(300–400) × After	0.019	0.015	0.007	0.047	0.076
	(0.035)	(0.036)	(0.047)	(0.110)	(0.125)
Dist(400–500) × After	0.008	0.008	0.034	−0.023	−0.101
	(0.031)	(0.031)	(0.051)	(0.044)	(0.147)
Dist(500–600) × After	0.017	0.016	0.012	0.040	−0.094
	(0.034)	(0.034)	(0.052)	(0.056)	(0.093)
Housing Attributes	Yes	Yes	Yes	Yes	Yes
Building Fixed Effect	Yes	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	2,769	2,410	1,660	1,097	398
R-squared	0.959	0.960	0.951	0.967	0.951

Note: This table lists results for the DID regressions for varying treatment groups which are sorted into six 100 m bins. HAC-robust standard errors are reported in parentheses. ***, ** and * denote statistical significance at the 1, 5, and 10 % levels.

Table 5
Results of DID Regression within a 300 Meters Cutoff Point.

Dependent Variable	(1)	(2)	(3)	(4)	(5)
	U- and S-Bahn		U-Bahn	S-Bahn	Others (Placebo)
	lnPrice	lnPrice	lnPrice	lnPrice	lnPrice
Dist × After	0.155***	–	0.159***	0.138**	−0.053
	(0.037)	–	(0.044)	(0.066)	(0.069)
Dist_U × After	–	0.159***	–	–	–
	–	(0.041)	–	–	–
Dist_S × After	–	0.133*	–	–	–
	–	(0.069)	–	–	–
Housing Attributes	Yes	Yes	Yes	Yes	Yes
Building Fixed Effect	Yes	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	2,769	2,769	1,660	1,097	398
R-squared	0.958	0.958	0.951	0.966	0.949

Note: This table lists results for DID regressions for varying treatment groups and a cutoff-distance of 300 m. HAC-robust standard errors are reported in parentheses. ***, ** and * denote statistical significance at the 1, 5, and 10 % levels.

4.3. Temporal effects on house prices

We attribute our finding of substantially larger coefficients compared to the introduction of a newly constructed transit system to the lack of anticipation effects.[13] In our setting, there is no anticipation effect due to the sudden change in the policy adjustment announced. What might seem like a long-term anticipation is the market's reaction and adjustment. Therefore, we examine the temporal effect in Table 6.

The results are consistent with our understanding of the housing market dynamics. Unlike the stock market, housing transactions take time. In the German housing market, it is typical for a transaction to span 3–6 months, encompassing bargaining, mortgaging, and contracting phases. In the first month following the night-train service announcement, we observed no price effect, as it is improbable for a housing unit to be transacted within such a short time frame. This further supports our assertion that there is no anticipation effect (or the policy is exogenous); otherwise, house prices would have risen immediately. The temporal effects indicate that the night-train service has enhanced house values.

[13] However, in the case of new developments, the anticipation effect likely plays a significant role. New developments typically go through three phases: announcement, construction, and operation. Due to the anticipation effect, the price impact of a metro's operation (or opening) tends to be smaller compared to our case. This is because house prices begin to change gradually right from the announcement as investors anticipate the effects of the new metro opening.

Table 6
Temporal Effect on House Prices.

	1 Month	2 Months	3 Months	4 Months	8 Months	12 Months
Dist × After	0.016	0.040	0.124	0.129*	0.137***	0.155***
	(0.048)	(0.037)	(0.086)	(0.069)	(0.045)	(0.037)
Housing Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Building Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,390	1,543	1,674	1,798	2,264	2,769
R-squared	0.967	0.966	0.962	0.962	0.9619	0.958

Note: This table lists results for the DID regressions for varying treatment groups and a cutoff-distance of 300 m. HAC-robust standard errors are reported in parentheses. ***, ** and * denote statistical significance at the 1, 5, and 10 % levels.

4.4. Results from triple difference regressions

The DID regressions demonstrate a positive price variation for units close to specific type of night service trains (U- or S-Bahn trains). However, the estimation may not be accurate if we do not consider the price changing trends in the absence of night-service train policy. The price responses for units close to other lines without night service trains provide an ideal counterfactual scenario. By employing Equation (4), we conduct triple difference regressions to estimate the price responses of units close to night service trains versus the price variation of units close to other lines. Table 7 summarizes the results by using a 300 m cut-off distance.

The first column combines the U- and S-Bahn trains. The coefficient is 21.9 % and the result is statistically significant at the 1 % level. Columns (2) and (3) exhibit the results for U- and S-Bahn trains individually. We find that units within 300 m of U-Bahn night service trains experience a price hike about 22.5 % within the 12-month time window. Similarly, the coefficient is 20.6 % for units within 300 m to S-Bahn trains.

4.5. Noise externalities

Table 4 shows that the price increases for units within the first 100 m of night service U-Bahn trains is smaller than the value growth for those located in 100–200 m distance range. One explanation is that the night-service trains may bring a negative externality such as noise for residential units nearby. To verify this channel, we run the DID regressions similar to the Table 4 and use data on metro noise as the dependent variable. Unreported results on varying noise levels due to night service trains show essentially zero effects. Therefore, we do not find evidence for noise externalities through night service trains, although we cannot rule out other type of externalities such as congestion and crime.

4.6. Estimating the total benefits

The night service trains seem to bring large social benefits, which are capitalized to housing values. Our estimation suggests that the averaging housing value goes up by 21.9 % for dwellings located within 300 m of night-service trains within 12 months. To estimate the total benefits, we conduct the back-of-envelope estimation.

By multiplying the selling price of units in the treatment group after the policy by the price appreciation of 21.9 %, we estimate an *average benefit* from selling one housing unit from the treatment group of EUR 109,835 (EUR 501,529 × 21.9 %). We receive the *total benefit* by multiplying the resulting average benefit by the number of units within 300 m of night service train. The total benefit (or the total house value appreciation) is about EUR 32.072 million (EUR 109,835/unit × 292 units). This result surely underestimates the total benefits as we should estimate the benefits based on the housing stock within 300 m of night service trains in Frankfurt, rather than using the number of transacted units within 1 year of the policy. The night service trains also incur costs such as labor, electricity and administrative costs etc. However, we believe these costs are relatively small especially when comparing to the costs of building a new metro line which incurs a substantial construction costs and rolling stock procurement. Nevertheless, the night service trains should bring a significant net benefit to society if the public sector can capture the housing value gains through property and capital gain tax or other value capture mechanisms.[14]

5. Conclusion

This paper aims to measure the impact of an extended metro night service at the weekend on property prices in the city of Frankfurt (Main), Germany. To do this, we regress transaction prices on a variety of covariates using a triple-differences strategy. We find the

[14] Even though we do not have a detailed breakdown of the costs and revenues of metro services in Frankfurt, the fact that metro night service on the weekend is still offered after six years, indicates its operation is most likely profitable (or at least must be breakeven). Overall, the expenses of offering additional metro night services on the weekend are far lower in comparison to the construction of a new metro line. These costs mainly consist of additional electricity, wages, and rolling stock maintenance during the weekend. Hence, a timetable change of metro services on the weekend seems to be a cost-efficient measure in comparison to other policies.

Table 7
Results of Triple Difference Regression within a 300 Meters Cutoff Point.

Dependent Variable	(1)	(2)	(3)
	U- and S-Bahn	U-Bahn	S-Bahn
	lnPrice	lnPrice	lnPrice
Dist × After × Treat	0.219***	0.225***	0.206**
	(0.079)	(0.082)	(0.097)
Dist × After	−0.064	−0.071	−0.063
	(0.071)	(0.071)	(0.068)
Treat × After	−0.012	−0.022	0.004
	(0.046)	(0.050)	(0.044)
Housing Attributes	Yes	Yes	Yes
Building Fixed Effect	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes
Observations	3,188	2,063	1,500
R-squared	0.957	0.951	0.953

Note: This table lists results for the triple difference regressions for varying treatment groups and a cutoff-distance of 300 m. HAC-robust standard errors are reported in parentheses. ***, ** and * denote statistical significance at the 1, 5, and 10 % levels.

benefits of night service trains can be capitalized to housing values for units located within 300 m of train stations with an average price appreciation of about 21.9 %. This result is equivalent to a minimum housing value appreciation of EUR 32.072 million for the city. Besides the housing value appreciation, there could be other social benefits brought by the night service trains.

In sum, city planners should be aware of the impact that relatively small changes in public transportation infrastructure can have. In this case, the impact was both statistically significant and economically substantial. Further, it is important to acknowledge that improving and optimizing existing transport infrastructure is a promising strategy in times of constrained budget resources. The results are also noteworthy for policymakers, as people tend to appreciate increased flexibility in public transportation infrastructure and are willing to pay a premium on properties. This, in turn, boosts tax revenues, making it appealing for third parties to participate in financing of such investments.

CRediT authorship contribution statement

Zheng Chang: Conceptualization, Methodology, Formal analysis, Visualization, Writing – review & editing. **Roland Füss:** Conceptualization, Methodology, Resources, Writing – original draft, Writing – review & editing. **Johannes von Möllendorff:** Conceptualization, Methodology, Formal analysis, Visualization, Writing - original draft. **Jon Olaf Olaussen:** Conceptualization, Writing – review & editing. **Alois Weigand:** Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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