Public transport, noise complaints, and housing: Evidence from sentiment analysis in Singapore

Yi Fan | Ho Pin Teo | Wayne X. Wan

1Department of Real Estate, National University of Singapore, Singapore, Singapore
2Department of Building, National University of Singapore, Singapore, Singapore
3Department of Land Economy, The University of Cambridge, Cambridge, UK

Abstract
This paper investigates the effect of a new bus route on noise complaints of residents and the influence of noise on housing price. To overcome the challenge of mapping noise data with subjective emotion, we use a novel data source—text-based noise complaint records from residents in a town in Singapore—and apply natural language processing tools to conduct sentiment analysis. To address the endogeneity concern regarding the bus route, we use a hypothetical least cost path as an instrument for the existing bus route. We find that living closer to the bus route for every 100 m increases noise complaints by around 10 percentage points, and the effect is more severe on medium floor levels (5th–8th floors) and near bus stops (within 100 m). We further link noise with housing price and discover a price reduction of 3% with a 1-scale-point increase in noise complaints. This implies that bus noise offsets 17.8% of the benefit from convenience, which sheds light on the importance of noise insulation in transit-oriented developments.

Keywords
housing, noise, public transport, sentiment analysis
1 | INTRODUCTION

Public transport is an important service for improving accessibility and addressing congestion in cities (Anderson, 2014). Better accessibility to public transport results in higher housing price and provides more social welfare of residents (Chalak et al., 2016; Cohen & Paul, 2007; Holmgren, 2014; Monchambert & De Palma, 2014). Meanwhile, public transport also constitutes a significant proportion of road transportation, which is one of the major sources of noise pollution in urban environments (Chui et al., 2004; Monica et al., 2018). Noise pollution has significant impacts on physical and mental health (Weinhold, 2013; WHO, 2016). Excessive noise also leads to social issues such as violence and generates economic losses (Cohen & Coughlin, 2008; De Borger & Proost, 2013; Jamir et al., 2014). With rapid urbanization, the problem of urban noise pollution has been attracting increasingly more attention from governors, scholars, and the public. However, only a few studies have differentiated the transportation accessibility benefits and negative environmental externalities for housing price, especially from the noise of public transport (Chasco & Le Gallo, 2015; Higgins et al., 2019).

In this paper, we use a natural experiment with a newly launched bus route across a dense residential area in Singapore to examine the impact of public transport on noise complaints and its influence on housing price. As one of the world’s most densely populated city-states, Singapore has always faced a severe issue of urban noise pollution (Lam et al., 2013). More than 80% of its citizens live in public housing, with short distances between buildings. Around 70,000 complaints of excessive noise are made to government agencies every year (Wan, 2016). Our study covers the entire 2032 noise complaint records from 142 public housing blocks in three planning subzones of the Bukit Panjang area in Northwest Singapore from March 2010 to February 2018.

One of the major challenges for past studies on noise pollution and housing is the lack of real-time measurement of noise pollution at the building level (Friedt & Cohen, 2020; Segura-Garcia et al., 2014). To overcome this challenge, we propose a novel sentiment analysis method to study residents’ perception of noise pollution from their noise complaints.1 Our sentiment analysis method has two advantages: First, government agencies in many major cities worldwide encourage the residents to report noise incidents, so the database of noise complaint records naturally exists, such as the Noise Complaints Open Data in New York City. In other words, this method is not only applicable in Singapore, but also externally valid. Second, our sentiment analysis method captures the subjective perceptions of noise pollution, which is found to better explain the impact of noise on housing price than the objective measurements (Boyle & Kiel, 2001; Chasco & Le Gallo, 2013, 2015). Different from past studies using surveys (Weinhold, 2013), this method captures a quasi-real-time measurement of the noise sentiment intensity and is powerful for baselining the subjectivity of individual responses.

Another major challenge in past studies is the problem of endogeneity due to omitted variables (Cropper & Gordon, 1991; Higgins et al., 2018). Singapore’s public housing and the public bus enhancement program provides an ideal context to address the endogeneity problem. Our study area is a representative public housing satellite town in Singapore. The buildings were almost all constructed during the period when the town was initially planned, and few further developments have been carried out after that. Public housing blocks, which accommodate more than 80% of Singapore residents, have uniform building plans, room layouts, and construction materials. Demographics such as nationality and ethnicity are controlled for to be evenly distributed based on the nation’s “Ethnic Integration Policy and Permanent Resident Quota” system. As part of Singapore’s public bus enhancement program, a new regional bus service, Route no. 972, was launched in November 2013, and no other bus routes were introduced in this region during the same period. This allows us to apply a difference-in-differences (DID) strategy to examine the causal noise impact from the launch of the bus service.

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1This sentiment analysis method originates in the field of natural language processing (NLP). SentimentR, which is based on a sentiment dictionary containing approximately 6800 ranked positive and negative sentiment words, is used in this study (Hu and Liu, 2004; Lam, 2016; Rinker, 2016). Details of the toolkit are discussed in Appendix A.
In addition, following the strategy of Faber (2014) and Jedwab et al. (2017), we use the hypothetical least cost route as the instrumental variable (IV) to consistently estimate the causal effect of the new bus on noise complaints. The main IV in the estimation is the Euclidean cost path (ECP), which is the shortest linear distance connecting all of the bus stops along the bus service route. The other IV used in the robustness check is the least cost path (LCP), which is the shortest driving route connecting the points at which the bus enters and exits the study area. Furthermore, to alleviate the concern that unobserved changes in accessibility may correlate with both the noise sentiment and housing price, we include an explicit control for the change in accessibility before and after the new bus service when we estimate the impact of noise on housing price.

Our empirical results reveal that at an individual level, the new bus service has worsened the sentiment of noise complaints from residents living near the bus route (within 100 m) by 10.9 percentage points compared to those living between 100 and 200 m. If the distance between the housing unit and the bus route decreases by 100 m, the sentiment increases by 9.5 percentage points. These results remain robust if we change the cut-off distance to 90 or 110 m, include controls for the noise sentiment in the previous year and the complaint time, use aggregated sentiment scores at building level, or use alternative theoretically shortest paths as IVs.

The adverse effect also exhibits heterogeneity across floor height and distance to bus stops. For units on the 1st–4th floors and on 9th floor or above, this adverse effect is not statistically significant, probably due to noise insulation infrastructure on the ground and attenuation of noise on higher floors. On medium floors (5th–8th levels), however, this adverse effect has doubled in comparison with the average: Living near the bus route (within 100 m) increases the sentiment by 21.4 percentage points, and a decrease of distance by 100 m increases the sentiment by 24.3 percentage points. The noise effect from the new bus has also shown a larger magnitude on buildings closer to bus stops, which implies that the introduction of visitors is a major source of noise annoyance.

Finally, we conduct cost and benefit analysis on the impact of public transport on housing price, using resale transaction data in the study area from 2010 to 2018. By explicitly controlling for the change in accessibility before and after the new bus, we find that an increase of 1 scale point in noise sentiment is associated with a 3% decrease in housing price. This implies that, for properties closer to the bus route by 100 m, noise generated by buses leads to an implicit 0.29% decrease in property value. Using the same transaction data, we also find that, after the new bus service launches, the prices of properties closer to the bus route by 100 m has increased by 1.34%. Therefore, our empirical results estimate that over 17.79% of the benefit from improved accessibility brought by the new bus is offset by the negative externality from its noise pollution.

Our paper contributes to the literature from both conceptual and methodological perspectives. First, we isolate the negative impact of noise pollution on housing price apart from the accessibility convenience by launching a new public bus route. It is closely related to the studies of transportation and land use policies for the transit-oriented developments (TOD) and for addressing the last-mile connectivity issue, which is trending not only in Singapore but also in many other congested cities worldwide (Xie et al., 2010). Improving the accessibility to the mass public transport involves a significant amount of government investment, while the associated increases in land values are also expected to sustain the future TOD. Prior literature intensively examines the overall impact of public transport on housing price (Baum-Snow & Kahn, 2000; McMillen & McDonald, 2004; Xu et al., 2015), but a few studies present empirical evidence on cost-benefit analysis considering the environmental externalities (Chasco & Le Gallo, 2015; Higgins et al., 2019), possibly because of the costly real-time measures of noise intensity and the complexity of the public transport system. Taking advantage of the clean setting of the public bus system in Singapore’s context, we advance current understanding by weighing the advantages and disadvantages of public transport for housing price. It thus provides empirical evidence for policy makers to minimize the noise exposure in TOD and maximize the land values.

Second, as Segura-Garcia et al. (2014) document, current noise map data in the major cities worldwide are estimations based on sparse measurements and mathematical propagation models, while measuring noise at the building level in the dense urban environments is costly. We propose a novel methodology to measure the quasi real-time noise sentiment at finer detailed level using the noise complaints data, which naturally exists with the
government agencies in many major cities (Friedt & Cohen, 2020). In addition, different from measuring noise incidents by counting frequency through surveys (Tamura et al., 2017; Weinhold, 2013), our methodology of sentiment analysis also contributes to the literature on understanding residential noise pollution based on subjective perception, which is proved to show a pattern that is complementary to that in previous literature (Boyle & Kiel, 2001; Chasco & Le Gallo, 2013; Dzhambov & Dimitrova, 2014).

The rest of the paper is structured as follows. Section 2 reviews the literature and Section 3 introduces the institutional background. Section 4 presents the empirical specifications, and Section 5 describes the data. Results are summarized in Section 6, followed by cost-benefit analysis in Section 7 and Section 8 concludes.

2 | LITERATURE REVIEW

Noise pollution is harmful for human life and activities. According to the WHO, noise exposure is responsible for a wide range of negative public health issues, such as heart disease, cognitive impairment in children, and stress-related mental health risks (WHO, 2016). Exposure to residential road traffic noise is also associated with a higher risk of diabetes and cardiovascular disease (Münzel et al., 2018; Sørensen et al., 2013). From a social perspective, community noise pollution increases violent behavior and crime rates and lowers the birth rate and newborn weights (Jamir et al., 2014; Nieuwenhuijsen et al., 2017). Total socioeconomic loss from road noise pollution in the UK is similar to the loss from road accidents, and it exceeds the loss from climate change (DEFRA, 2013).

It has been widely acknowledged that better accessibility to public transport results in higher housing price and the intensification of its service increases the social welfare of residents (Chalak et al., 2016; Cohen & Paul, 2007; Holmgren, 2014; Monchambert & De Palma, 2014). At the individual level, better accessibility enables participation in social activities and is associated with positive health outcomes (De Vos et al., 2013; Lucas, 2012). However, the elevation of service frequency also introduces traffic noise, possibly aggravates environmental pollution (Bilger & Carrieri, 2013; Nega et al., 2013), and imposes negative externalities on housing price (Ossokina & Verweij, 2015). Cohen and Coughlin (2008) find that houses under the interruption of airport noise sell for 20.8% less, and the spatial spill-over effect magnifies this negative price impact. Chasco and Le Gallo (2015) estimate the households' willingness to pay for properties with less noise, using the households' subjective perceptions of noise from the census data. Diao et al. (2016) document that the removal of train noise externalities increases housing prices in the affected area by 13.7%. Higgins et al. (2019) find the accessibility benefits of the new highways are offset by the environmental costs of air pollution, specifically for the housing units with high accessibility and high exposure to pollution. However, there still lacks empirical studies about the accessibility benefit and noise cost of public bus, which is one of the common solutions to address the trending last-mile connectivity issues in many global cities (Xie et al., 2010).

The real-time measurement of noise can be very costly at individual building levels in the dense urban environments (Segura-Garcia et al., 2014), which has been a major challenge for past studies. Although several cities around the world are providing the city-level noise maps, only sparse measurements of noise samples at the district or regional level are taken, and noise contours are estimated using propagation models (Mircea et al., 2008; Swoboda et al., 2015). To overcome this challenge, one branch of research focuses on improving noise-measurement instruments or building empirical mathematical models to simulate real-time sound environments and noise distribution (Alam et al., 2010; Mak et al., 2010; Rana et al., 2010). However, these studies usually cover a limited number of buildings and the results may not be generalized. Other studies propose to use in-house surveys to construct residents' noise perception index as a proxy for actual noise levels (Brown & Lam, 1987; Jakovljevic et al., 2009; Park et al., 2016). Nevertheless, the survey method suffers from a number of drawbacks, such as memory error and retrospective bias in responses (Taylor et al., 2013). Furthermore, most previous studies in this stream focus on the frequency of troublesome cases, possibly because it is

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2Examples of the city-level noise maps include the US National Transportation Noise Map (https://www.transportation.gov/highlights/national-transportation-noise-map), and the London Road Traffic Noise Map (http://www.londonnoisemap.com/).
difficult to address subjectivity when measuring the severity of noise incidents (Weinhold, 2013). Recent studies also exploit the frequency of residents’ noise complaints as an alternative measure of noise pollution (Friedt & Cohen, 2020). However, incidence and intensity are two distinct dimensions, and are expected to have different patterns (Figure 1).

The concept of sentiment analysis that we use to measure noise annoyance in this study was introduced in the early 2000s, when computer scientists tried to extract polarized opinions (either positive or negative) from customer reviews of commercial goods or movies (Pang et al., 2002; Turney, 2002). It has since been applied in various empirical studies involving human perceptions (Cambria et al., 2013). Tetlock (2007) finds that the frequency of negative words in Wall Street Journal articles predicts stock returns, and Garcia (2013) finds that this predictive power is stronger during recessions. Using search results from Google, Zheng et al. (2016) conclude that investor confidence is a determinant of China’s housing price.

In addition, past literature has also discussed the challenge that unobserved factors may be simultaneously associated with public transport and the perception of urban noise, which undermines the reliability of empirical results (Cropper & Gordon, 1991; Higgins et al., 2018). For instance, the intensification of public transport services may be an ex post action by the government to address the growing population in the area, while the higher resident density also induces more noise. Residents’ unobserved personal attributes may also threaten the estimation, as residents who are sensitive to noise are likely to choose quieter locations and are less tolerant of a sudden increase in noise. One of the main empirical approaches to address this challenge is to develop IVs that are highly correlated with the actual route of the transportation service but are intended to affect noise output only through this correlation (Redding & Turner, 2015). In the literature, commonly applied instruments include the initially planned route (Baum-Snow, 2007; Donaldson, 2018; Michaels et al., 2012), the historical route

![FIGURE 1 Map of noise complaint frequency and sentiment severity in Singapore’s Bukit Panjang Area during 2010-2018. (a) Complaint frequency and (b) sentiment severity [Color figure can be viewed at wileyonlinelibrary.com]](image-url)
Institutional Background

3.1 Public housing and residential noise in Singapore

The issue of residential noise pollution is serious in densely populated modern cities such as Singapore. According to the Straits Times, “over 7,000 residents are living in each square kilometer of land in Singapore,” and “more than 85 percent of its residents live in the nation’s public housing flats with very close distance to roads, constructions or other building blocks.” Around 70,000 complaints are made to various government agencies each year about excessive noise in Singapore (Wan, 2016). To manage noise pollution in public housing, the local public housing authority—the Housing Development Board (HDB)—has promoted the Neighborliness Campaign among residents, which encourages them to respect the neighborhood by avoiding producing excessive noise. The National Environment Agency (NEA) has also established regulations to control for noise origins, such as setting maximum permissible noise levels for factories and construction work, a no-work rule during certain periods of the day, and maximum noise emission limits for air conditioning and mechanical ventilation systems in buildings. In case of excessive noise, residents can also call or email the hotlines located in individual town centers.

Public housing in Singapore provides an ideal setting to study urban residential noise pollution. As one of the world’s most successful public housing schemes, new units are sold to citizens and permanent residents by the government at prices much lower than the market price. Owners are also allowed to resell their public housing units to other eligible buyers at the market price. On the one hand, residential noise pollution in public housing is much more serious than in private estates, which leads to policy incentives for social equality. Due to concerns about land and construction cost, most public housing is densely constructed using economical materials, which provide limited performance in noise insulation. Since residents living in public housing have stronger demand for public transport, most public housing is located closer to transportation hubs or major roads. This leads to more exposure to traffic noise. On the other hand, different building and urban attributes, such as building typology and floor level, will have significant noisescapes influence (Lam et al., 2013; Mak et al., 2010). This makes it challenging to control for these noise-related variables in a complex urban context. In Singapore, however, public housing has undergone around four waves of morphological changes, and the buildings constructed in each era have uniform morphology (Pow, 2009). This makes it feasible to largely exclude the impact from variant morphology in this study.

3.2 Study area and the new bus service

Our study covers 142 HDB blocks in the subzones of Fajar, Jelebu, and Bungkit of Bukit Panjang District in Northwest Singapore, which accommodate around 100 households per building. The district of Bukit Panjang is one of the oldest residential suburban towns in Singapore. To meet demand stemming from the population surge after the nation’s independence, the development of public housing in the town began in the early 1980s. Most of the HDB development was completed by the mid-1990s, and only a few new residential projects or redevelopments have been completed since then. As a result, the morphology of HDB blocks in the study area mostly follows the two standard prototypes for HDB buildings in that generation: 132 Slab Blocks and 8 Point Blocks (Appendix Figure B1). Slab Blocks are between 12 and 14 stories, and Point Blocks are all 25 stories. Only two blocks have been redeveloped in recent years, for which a new building typology was adopted. HDB buildings from the same generation are also constructed using standard materials, and layouts of the units and the number of rooms

(Duranton & Turner, 2011; Hsu & Zhang, 2014; Martincus et al., 2017), and other related hypothetical routes (Banerjee et al., 2020; Faber, 2014; Jedwab et al., 2017; Tsivanidis, 2019).
are almost the same. Like any other public housing in Singapore, regular repainting and upgrading programs are also conducted in this district every 5–7 years. Therefore, the maintenance of these buildings is also kept at a similar level.

Sales of HDB blocks are restricted to Singapore citizens or permanent residents, and there is a quota for noncitizen owners in each building. The nation's Ethnic Integration Policy requires that the proportion of owners' ethnicity in each individual building strictly follows the national average proportions of Singapore's three major races (Chinese, Malay, and Indian). If the number of owners from one race hits the threshold, owners from this race can only sell the unit to buyers of the same race. Therefore, on the aggregate block level, the distributions of residents' ethnicities are relatively uniform. According to the population surveys in 2010 and 2015, the distributions of residents' gender and age groups are also relatively stable in our study area (DOS, 2019).

The road network in the area follows a typical town planning hierarchy in Singapore. The north and east sides of the site are enclosed by the two highest standard expressways, and on the other side of the expressways are reserved forest land with limited urban development. One major road (Bukit Panjang Road) cuts through the site to connect with the expressways, and a secondary ring road forms a loop to direct traffic to the major road. All other minor roads in the community are connected to the ring road loop. Since 1999, there has been a light rail train (LRT) line looping in the district, which connects to the nearby Choa Chu Kang mass rapid transit (MRT) station on the North-East Line. The Bukit Panjang MRT station—the terminal station of the Downtown Line—also connects to this LRT line in the district; it started operations on December 27, 2015.

Like many other major cities worldwide, the Singapore government aims to address the trending last-mile connectivity issue in the city by improving the service coverage and frequency of its public buses (Xie et al., 2010). Public buses are the most frequently used transportation mode (41.3%) by the population traveling to work in Singapore (GHS, 2015). Singapore's Ministry of Transport aims to increase the peak-hour public transport mode share to 75% by 2030, and it launched the Bus Service Enhancement Programme (BSEP) to expand the bus fleet by 35% before 2017.

As part of the BSEP program, a new regional bus service, Route no. 972, was launched in November 2013 in our study area (Figure 2). It operates daily from 6 a.m. to 11:30 p.m. The service frequency is every 4–5 min during the peak hours and every 8–10 min during the nonpeak hours. Our study site has an area of 1.2 km², and the segment of the bus route in our site is over 2.5 km long with six bus stops. The bus stops are sequentially allocated along the road at intervals of about 300–400 m. Unlike buses intended to connect the community with other districts in the city, this bus is designed to improve last-mile connectivity within the community. Therefore, instead of driving on the fastest path along major roads, this bus zigzags along minor community roads to ensure that most of the blocks are within 200 m of its service cover. Apart from Route no. 972, no other buses were introduced along a similar route during our study period, and the service frequencies of existing buses have not been changed since the introduction of bus no. 972. The new route was announced only 11 days before launching the service, and there were no other government documents disclosing the new bus route in our study area before the announcement. Therefore, the anticipation effect is likely minimal.

4 | EMPIRICAL STRATEGY

A standard DID strategy estimates the net impact of proximity to new public transport services on housing prices (Diao et al., 2017). However, it is not able to differentiate the benefit of accessibility and the cost of environmental externalities, because both the benefit and the cost correlate with the closeness to public transport. Therefore, we apply a two-step strategy to specifically estimate the negative impact of noise from public transport on housing price. First, we apply a DID strategy to estimate the impact of closeness to the new bus route on noise sentiment. Second, we estimate the impact of lagged noise sentiment on subsequent
housing price, by explicitly controlling for the change in accessibility. Combining the results from the two steps, we interpolate the negative impact of closeness to the bus route on housing price due to the noise. Finally, we compare the net impact of public transport on housing price and its negative impact due to noise, and we estimate how much benefit of accessibility is offset by the noise externalities. The following part of this section explains our empirical specifications in detail.

4.1 Public bus and noise complaints: Baseline estimation

The baseline estimation uses complaint records from March 2010 to February 2018 with intact floor and unit information. The following DID specification is applied:

$$S_{ij}^t = \beta_1 \text{Near}_i + \beta_2 \text{Launch}_i + \beta_3 \text{Launch}_i \times \text{Near}_i + X\theta + U\mu + \varphi_i + \omega_j + \varepsilon_{ij},$$  

(1)

where $S_{ij}^t$ is the sentiment score from a complaint made at time $t$ by a resident living in building $i$ and unit $j$. $\text{Launch}_i$ is a dummy variable, and it is one if complaint time $t$ is later than the launch of bus service. Otherwise, it equals to zero. $\text{Near}_i$ is a dummy variable indicating whether block $i$ is within 100 m of the actual bus route. In other words, the treatment group includes buildings within 100 m and the control group includes buildings within 100–200 m. Therefore, the coefficient of the interaction between $\text{Launch}_i$ and $\text{Near}_i$ is the estimate of the causal impact of the new bus route on noise complaints. We use proximity to the bus route

![FIGURE 2](https://wileyonlinelibrary.com)
rather than the closest bus stop in our identification strategy, because noise can be generated both from bus stops and along the road (Diao et al., 2016). Since the bus stops are located along the bus route, using this strategy also facilitates the investigation of the heterogeneous impact across distance to bus stops (Appendix Figure B2).

In addition, we further allow variation in the distance from each building to the new bus as the measure for the linear attenuation of noise pollution. We specify Distance$_i$, a continuous variable as an alternative to Near$_i$, in Equation (2).

\[
SI_{ij} = \beta_1 \text{Distance}_i + \beta_2 \text{Launch}_i + \beta_3 \text{Launch}_i \times \text{Distance}_i + X_i \theta + U_j \mu + \varphi_t + \omega_i + \varepsilon_{ij}.
\]

$X_i$ is a vector controlling for building $i$'s physical properties, which include the morphology of the building (slab block, point block, or new HDB block), age of the block, existence of residential community (RC) centers, and its distance to MRT/LRT stations, the LRT viaduct line, bus stops, expressways, and major roads. These factors are common sources of residential noise. $U_j$ is the vector controlling for unit-specific properties, including the floor level and its squared form, and the gender of the complainant. $\varphi_t$ is the year times month fixed effect, and $\omega_i$ is the block fixed effect. $\varepsilon_{ij}$ is the error term. Standard errors are clustered by building blocks.

4.2 Hypothetical LCP

The ordinary least square (OLS) estimates from Equations (1) and (2) are likely to be biased if the design of the bus service route is not random. To address this concern, we construct a hypothetical least cost bus route, and use the distance to the least cost route as the instrumental variable for distance to the actual bus route, following the IV construction strategies from Faber (2014) and Jedwab et al. (2017). We define two such theoretically shortest paths. The first one, following the strategy of Faber (2014), assumes that the original bus stops along the service route are the fixed nodes and uses Euclidean straight lines to connect these nodes as the shortest path. This path is denoted as the ECP and is presented in Figure 2a. In the second construction, we consider actual travel time as the cost indicator. By fixing only the bus's entrance and exit points in the site, we use Google Map to calculate the shortest-time commuting path connecting these two points. This path is denoted as the LCP and is drawn in Figure 2b. Distances from buildings to these paths are calculated using ArcGIS. We use the ECP as the main IV and include the LCP in the robustness check.

These theoretically shortest paths are valid instruments because of their relevance and exclusion restrictions (Redding & Turner, 2015). On one hand, the actual bus route deviates from the theoretically shortest route to cover more residential areas, but it is not likely to deviate too far from the theoretical path. This is because bus service must also compete with alternative travel modes, such as trains and private driving, and must take passengers' total commuting time into consideration. Thus, the actual bus route is expected to be highly correlated with the theoretically shortest route.

On the other hand, the theoretical path is considered to be uncorrelated with noise annoyance beyond its correlation with the actual bus service. In particular, two unobserved trends may be present that potentially threaten our estimations. First, the government may design the new bus route to serve some specific areas (e.g., buildings with higher population density), where there might be more neighborhood noise. The theoretically shortest paths are not expected to correlate with these unobserved trends in neighborhood features along the actual bus route. Second, residents who are more sensitive to noise may self-sort into units that are farther from streets. Nevertheless, our ECP instrument is a hypothetical path, so it is unlikely to correlate with any residential sorting trends along the real roads.
4.3 Noise complaints and housing price

Further, we examine the impact of residents’ noise sentiment on housing price. We test this effect from the yearly aggregated noise sentiment in each block. The empirical specification is as follows:

\[
\log(\text{Price}_{it}) = \beta S_{i,t-1} + X_i \theta + U_{ijt} \mu + \lambda M_t + \varphi_t + \omega_i + \varepsilon_{it},
\]

where \(\log(\text{Price}_{it})\) is the log form of the transaction price for unit \(j\) in block \(i\) sold at time \(t\). \(S_{i,t-1}\) is the average noise sentiment in block \(i\) during the 12 months before transaction time \(t\). The coefficient \(\beta\) is thus the estimate of the effect of the noise sentiment on housing price. \(X_i\) is the same vector controlling for characteristics of building block \(i\) as in Equations (1) and (2). \(U_{ijt}\) controls the properties of the housing unit, including its size and floor level. \(M_t\) represents the macroeconomic index and equals the prime lending rate for bank mortgages at time \(t\). \(\varphi_t\) is year times quarter fixed effect, while \(\omega_i\) is the block fixed effect. \(\varepsilon_{it}\) denotes the error term. Standard errors are clustered by building blocks.

The OLS estimate of coefficient \(\beta\) in Equation (3) is likely biased upward due to endogeneity and may serve as an upper bound of the true negative effect of noise pollution on housing price (i.e., a lower bound in magnitude). It is because the variable of noise sentiment \(S_{i,t-1}\) may positively pick up the benefit brought by unobserved factors, such as the changes in accessibility. To estimate the exact economic costs of noise pollution on housing price, we further include an explicit control for accessibility before and after the launch of bus no. 972. Specifically, we use distance to the nearest bus stop connecting to the Central Business District (CBD) of Singapore as a proxy for change in accessibility. As illustrated in Appendix Figure B3a, the new bus route (no. 972), which zigzags within the RC, aims to solve the problem of last-mile connectivity to the CBD. Before the launch of bus no. 972, the only bus connecting the site and the CBD was route no. 190, which operates along a major road (Appendix Figure B3b). Therefore, before the launch of the new bus route, the nearest bus stop connecting to the CBD only lies on the route of no. 190. After the treatment, it will be on either bus route no. 190 or bus route no. 972.

5 DATA

In Singapore, residents in public housing report their noise complaints to the local government through hotlines, email, or other written notices. These records are then centralized by local Community Development Councils (CDC) for further action. The data in our study are provided by the local government and cover all noise complaints made by HDB residents in the study area from March 2010 to February 2018. We collected the entire 2032 records on noise complaints in all 142 buildings. The number of complaints per building at the 25th percentile, the median, and the 75th percentile are 6, 11.5, and 17, respectively. For each complaint, the incident date, time, and complaint content are recorded by the agency that receives the complaint.

A cleansing process is applied before calculation of sentiment scores. Specifically, we manually corrected the grammatical errors and typos in the complaint records. In addition, when complaint data were recorded, the registrar used a number of abbreviations, such as “plz” for “please.” These abbreviations are also manually revised. The sentiment score of each individual noise report is then calculated by running the SentimentR tool on the cleaned complaint contents. Results are winsorized to the top and bottom 1% of the distribution to remove the impact of outliers. This is followed by a normalization of scores to the range from zero to one, which represents the most low-key and the most severe emotions, respectively.

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3Noise compliant records are too scarce to map onto individual housing transactions.

4After the treatment, 63 out of the 142 blocks in our study area have the nearest bus stop connecting to the CBD on the new route no. 972.
A subset of 593 records in the database contain the complainant’s full unit number and floor. The maximum distance from the building to the new bus route is 198.5 m. There are 328 complaints within 100 to 200 m of the bus route (the control group), and 265 complaints within the 100-m boundary (the treatment group). The parallel trend between treatment group and control group is also verified (Appendix Figure B4). The average difference between the distance from the building to the ECP and the distance from the building to the bus route is 46 m, which equals 41% of the average distance to bus route. The average difference between the distance to the LCP and the distance to the bus route is 75 m, which equals 67% of the average distance to bus route. Distributions on demographics and the physical features of buildings are consistent with the standard for Singapore’s public housing (GHS, 2015). When the complainant calls the hotline, the registrar will usually record the complainant’s title (Mr., Ms., etc.) so that information on their gender can be obtained, which yields 527 records from 96 buildings. We use these 527 records as our main sample in the baseline regressions. There are 227 cases before the launch of the bus and 300 cases after. The gender distribution remains stable in the pretreatment (46.70%) and posttreatment periods (46.67%). In total, 80 out of the 96 buildings (83.3%) have complaint records both before and after the new bus service, and the geographic distributions of buildings with noise complaints are similar before and after launching the new bus (Appendix Figure B5).

Geo-referenced information on the site’s administrative boundary is obtained from the Singapore government’s online public data portal, while information on building blocks, road networks, MRT and LRT lines, and bus stops are downloaded from OpenStreetMap. We also code the morphological classification of the buildings and the locations of RC centers. The list of shopping centers in the study area is from the OneMap of Singapore’s Urban Redevelopment Authority. The age of each building block is from the HDB website. The distance from each building block to roads, bus stations, or other public facilities is calculated using ArcGIS. The LRT line in our study area operates on a viaduct, which causes noise exposure, so the distance from buildings to the viaduct is also calculated. Table 1 presents summary statistics for these complaint cases. The average distances to train stations, bus stops, and expressways are 212.5, 120.2, and 428.1 m, respectively.

Data on housing transactions, including transaction price, date, floor, and size of the unit, are also obtained from the government’s online public data portal. In our study period, there are 1450 resale transactions from 131 out of 142 buildings in our study area, and the information is also summarized in Table 1. The averaged transacted housing price is 375,207 SGD, which is equivalent to approximately 278,365 USD. The dwelling size is 104 m² on average, with a mean floor level of 6.7. This is similar to the national average statistics, so our sample is also representative of public housing transactions in Singapore (GHS, 2015). Of these transactions, 893 can be matched with noise complaints in the same building 12 months before the transaction date, and we use them as our regression sample. The prime lending rate for bank mortgages is directly retrieved from the Monetary Authority of Singapore (MAS).

6 | EFFECTS OF PUBLIC TRANSPORT ON NOISE COMPLAINTS

6.1 | Baseline estimation results

Table 2 reports first-stage IV regression results for the effects of bus routes on noise complaints at the individual level. Columns (1) and (2) examine the binary indicator of closeness to the bus route, as specified in Equation (1), using ECP and the combination of ECP and LCP as the instrument(s), respectively. Columns (3) and (4) include the numerical distance to the bus route instead, as specified in Equation (2), and also apply ECP and the combination of ECP and LCP as the

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5 We also conduct the robustness test at building level to address the issue of missing unit information for individual cases.

6 We use distance from the main entrance of building to the road as the proxy for the distance from each unit to the road, due to a lack of information on the floor plan. Since most of the buildings in our study area are slab type and a majority of units are located along the corridor parallel to the road, the distances from the units to the road are roughly the same within buildings. Linear distance to roads is used because noise propagates linearly. We also use the linear distance to amenities as the proxy for measuring walking accessibility, because the first floors of Singapore’s public housing buildings are empty (i.e., the “void deck”), and pedestrians are free to pass through the buildings.
|                      | Total (100–200 m) | Near = 0 (100–200 m) | Near = 1 (within 100 m) | Diff ((5)–(8)) |
|----------------------|-------------------|----------------------|------------------------|----------------|
|                      | N     | Mean   | SD    | N     | Mean   | SD    | N     | Mean   | SD    | t-test |
| Noise sentiment      | 593   | 0.409  | 0.165 | 328   | 0.416  | 0.170 | 265   | 0.399  | 0.159 | 0.017  |
| Distance (100 m)     | 593   | 1.111  | 0.493 | 328   | 1.483  | 0.317 | 265   | 0.650  | 0.187 | 0.833**|
| LCP (100 m)          | 593   | 1.737  | 1.323 | 328   | 2.136  | 1.349 | 265   | 1.243  | 1.108 | 0.893**|
| ECP (100 m)          | 593   | 1.068  | 0.794 | 328   | 1.516  | 0.649 | 265   | 0.514  | 0.578 | 1.001**|
| Launch (after = 1)   | 593   | 0.575  | 0.495 | 328   | 0.512  | 0.501 | 265   | 0.653  | 0.477 | -0.141***|
| Near (within 100 m = 1) | 593   | 0.447  | 0.498 | 328   | 0.0671 | 0.251 | 265   | 0.072  | 0.258 | -0.005  |
| RC center (with = 1) | 593   | 0.069  | 0.254 | 328   | 0.0671 | 0.251 | 265   | 0.072  | 0.258 | -0.005  |
| Building age         | 593   | 29.022 | 2.267 | 328   | 28.902 | 2.584 | 265   | 29.170 | 1.794 | -0.267  |
| Floor level          | 593   | 6.408  | 3.960 | 328   | 6.479  | 3.976 | 265   | 6.321  | 3.946 | 0.158   |
| Morphology           | 593   | 2.926  | 0.293 | 328   | 2.878  | 0.371 | 265   | 2.985  | 0.122 | -0.107***|
| Gender (Male = 1)    | 527   | 0.467  | 0.499 | 300   | 0.503  | 0.501 | 227   | 0.419  | 0.494 | 0.085* |
| To train station (100 m) | 593   | 2.125  | 1.155 | 328   | 2.435  | 1.224 | 265   | 1.741  | 0.933 | 0.693***|
| To LRT line (100 m)  | 593   | 1.531  | 1.154 | 328   | 1.884  | 1.155 | 265   | 1.093  | 0.994 | 0.790** |
| To bus stop (100 m)  | 593   | 1.202  | 0.501 | 328   | 1.335  | 0.548 | 265   | 1.038  | 0.377 | 0.233***|
| To expressway (100 m) | 593   | 4.281  | 2.030 | 328   | 4.553  | 2.357 | 265   | 3.945  | 1.468 | 0.608***|
| To major road (100 m) | 593   | 1.217  | 0.816 | 328   | 1.359  | 0.758 | 265   | 1.041  | 0.851 | 0.318***|
| To shopping center (100 m) | 593   | 5.302  | 2.863 | 328   | 5.181  | 3.154 | 265   | 5.452  | 2.467 | -0.271 |
| Price (thousand SGD) | 1450  | 375.207| 73.564| 1003  | 364.924| 69.114| 447   | 398.282| 77.968| -33.359***|

(Continues)
|                  | Total        | Near = 0 (100–200 m) | Near = 1 (within 100 m) | Diff ((5)–(8)) |
|------------------|--------------|-----------------------|-------------------------|---------------|
|                  | N  | Mean | SD   | N  | Mean | SD   | N  | Mean | SD   | t-test |
| Floor            | 1450| 6.710| 3.630| 1003| 6.671| 3.588| 447| 6.799| 3.724| -0.128 |
| Area (m²)        | 1450| 103.595| 20.399| 1003| 99.984| 19.56 | 447| 111.696| 19.928| -11.712 *** |

Note: Morphology equals to 1 if the block follows the new generation building layout, 2 if it follows the point block layout, or 3 if it follows the slab block layout.

Abbreviations: ECP, Euclidean cost path; LCP, least cost path; LRT, light rail train.

*p < 0.1.
**p < 0.05.
***p < 0.01.
TABLE 2  First-stage IV estimation results of the effects of bus route on noise complaints at individual level

|                      | (1) Launch × ECP | (2) Launch × ECP | (3) Launch × Distance | (4) Launch × Distance |
|----------------------|------------------|------------------|----------------------|----------------------|
|                      | -0.3653***       | -0.3306***       | 0.4184***            | 0.4025***            |
|                      | (0.0546)         | (0.0615)         | (0.0520)             | (0.0602)             |
| ECP                  | 0.0190           | 0.0367           | -0.0070              | -0.0491              |
|                      | (0.0419)         | (0.0451)         | (0.0364)             | (0.0395)             |
| Launch × LCP         | -0.0787**        | 0.0491           |                      |                      |
|                      | (0.0360)         |                  |                      |                      |
| LCP                  | -0.0790          | 0.1558**         |                      |                      |
|                      | (0.0651)         |                  |                      |                      |
| Launch               | 0.7781***        | 0.8410***        | 0.8278***            | 0.7932***            |
|                      | (0.2049)         | (0.2067)         | (0.2051)             | (0.2057)             |
| Building age         | -0.0040          | -0.0023          | -0.0117              | -0.0158              |
|                      | (0.0119)         | (0.0119)         | (0.0104)             | (0.0102)             |
| Floor                | 0.0007           | -0.0000          | 0.0029               | 0.0033               |
|                      | (0.0123)         | (0.0126)         | (0.0102)             | (0.0105)             |
| Floor squared        | 0.0005           | 0.0005           | -0.0008              | -0.0008              |
|                      | (0.0007)         | (0.0007)         | (0.0006)             | (0.0006)             |
| Point block          | 0.0401           | 0.0605           | 0.3776**             | 0.3339**             |
|                      | (0.1951)         | (0.1908)         | (0.1789)             | (0.1692)             |
| Slab block           | 0.0943           | 0.1315           | 0.1492               | 0.0789               |
|                      | (0.1448)         | (0.1457)         | (0.1397)             | (0.1330)             |
| Male                 | -0.0402          | -0.0405          | 0.0156               | 0.0149               |
|                      | (0.0299)         | (0.0286)         | (0.0239)             | (0.0228)             |
| RC center            | -0.0094          | -0.0105          | -0.0135              | -0.0083              |
|                      | (0.0796)         | (0.0803)         | (0.0684)             | (0.0692)             |
| Block and time fixed effect | Y            | Y                | Y                    | Y                    |
| First-stage F-Stats  | 22.69            | 26.81            | 32.67                | 38.07                |
| J-Statistics (p value) | 0.2787         |                  |                      | 0.2235               |
| Observations         | 527              | 527              | 527                  | 527                  |

Note: Columns (1) and (2) report results for the binary closeness indicator. Columns (3) and (4) report results for the continuous distance variable. Columns (1) and (3) use the ECP, the Euclidean straight lines connecting bus stops, as the instrument. Columns (2) and (4) use both ECP and LCP, the least travel time path, as the instrument. Unreported control variables include distance to train stations, LRT viaduct line, bus stops, expressways, major roads, and shopping centers. Standard errors are clustered by building blocks. Robust standard errors in parentheses.

Abbreviations: ECP, Euclidean cost path; LCP, least cost path.

*p < 0.1.

**p < 0.05.

***p < 0.01.
| Noise sentiment | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------|-----|-----|-----|-----|-----|-----|
|                 | OLS | ECP IV | Both IVs | OLS | ECP IV | Both IVs |
| Launch × Near   | 0.0496 | 0.1090** | 0.1118** | (0.0324) | (0.0459) | (0.0437) |
| Near            | -0.0136 | -0.0105 | -0.0300 | (0.0303) | (0.0529) | (0.0476) |
| Launch × Distance | -0.0405 | -0.0953** | -0.0965** | (0.0338) | (0.0430) | (0.0422) |
| Distance        | 0.0074 | 0.0125 | 0.0301 | (0.0328) | (0.0462) | (0.0423) |
| Launch          | -0.1123 | -0.1330 | -0.1365 | -0.0400 | 0.0319 | 0.0333 |
| (0.1217) | (0.1069) | (0.1054) | (0.1167) | (0.1140) | (0.1114) |
| Building age    | -0.0016 | -0.0011 | -0.0015 | -0.0019 | -0.0024 | -0.0022 |
| (0.0048) | (0.0044) | (0.0044) | (0.0048) | (0.0044) | (0.0043) |
| Floor           | -0.0130* | -0.0126** | -0.0128** | -0.0128* | -0.0122* | -0.0125** |
| (0.0070) | (0.0063) | (0.0063) | (0.0071) | (0.0063) | (0.0063) |
| Floor squared   | 0.0008* | 0.0007* | 0.0007* | 0.0008* | 0.0007* | 0.0007* |
| (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Point block     | -0.0487 | -0.0764 | -0.0593 | -0.0423 | -0.0457 | -0.0415 |
| (0.0811) | (0.0786) | (0.0786) | (0.0792) | (0.0739) | (0.0728) |
| Slab block      | -0.0429 | -0.0675 | -0.0505 | -0.0409 | -0.0484 | -0.0393 |
| (0.0543) | (0.0549) | (0.0554) | (0.0508) | (0.0475) | (0.0480) |
| Male            | 0.0181 | 0.0195 | 0.0186 | 0.0171 | 0.0166 | 0.0156 |
| (0.0201) | (0.0188) | (0.0186) | (0.0199) | (0.0187) | (0.0186) |
| RC center       | 0.0484* | 0.0448* | 0.0501** | 0.0453* | 0.0420* | 0.0463* |
| (0.0269) | (0.0251) | (0.0251) | (0.0260) | (0.0236) | (0.0239) |
| Block and time fixed effect | Y | Y | Y | Y | Y | Y |
| Observations    | 527 | 527 | 527 | 527 | 527 | 527 |
| R²              | 0.214 | 0.203 | 0.207 | 0.213 | 0.206 | 0.208 |

Note: Columns (1)–(3) report results for the binary closeness indicator and Columns (4)–(6) report results for the continuous distance variable. Columns (1) and (4) are OLS estimation results. Columns (2) and (5) use the ECP, the Euclidean straight lines connecting bus stops, as the instrument. Columns (3) and (6) use both ECP and LCP, the least travel time path, as the instrument. Unreported control variables include distance to train stations, LRT viaduct line, bus stops, expressways, major roads, and shopping centers. Standard errors are clustered by building blocks. Robust standard errors in parentheses.

* p < 0.1.
** p < 0.05.
*** p < 0.01.
First-stage results reveal that both ECP and the combination of ECP and LCP are strongly and statistically significantly correlated with the actual bus service route, controlling for the physical features, gender of the complainants, and the fixed effect from time and building. The F-statistics in all specifications are around 20–30, mitigating concerns about weak instruments. For estimations with more instrumental variables than endogenous variables (Columns (2) and (4)), the J-statistics for over-identification test are 0.2787 and 0.2235, respectively.

Table 3 presents OLS and second-stage IV estimation results. Column (1) presents OLS estimates from Equation (1), while Columns (2) and (3) display IV estimates using ECP and the combination of ECP and LCP, respectively. Columns (4)–(6) show corresponding estimates from Equation (2). The OLS estimate is positive, though with no statistical significance, in Column (1), and it is likely contaminated by unobserved factors. For example, residents who are less sensitive to noise will choose to live in units closer to roads and will also make less noise complaints. Therefore, the OLS estimate of the noise effect will be downward biased in magnitude. Using ECP as an instrument, being close to the bus service route (within 100 m) results in a higher negative sentiment score of 0.109 (Column (2)) and 0.112 (Column (3)) using both ECP and LCP as IVs. Both of the two IV estimates are statistically significant at the 5% level. Since the sentiment score is normalized to the range of 0 to 1, this indicates that intensification of public transport services worsens the noise sentiment in surrounding public housing by approximately 11 percentage points. The continuous distance effect is estimated to be −0.095 (Column (5)) using ECP as the IV, or −0.097 (Column (6)) using the combined IVs. Both estimates are statistically significant at the 5% level. Consistent with previous findings using a binary indicator of closeness, the distance estimates reveal that by living closer to road traffic by 100 m, the negative noise sentiment will increase by around 10 percentage points on average.

One assumption in the interpretations above is that the intensification of the bus service is the only source of changing noise levels along the bus route. A possible concern about the validity of this assumption is that with the newly opened bus route, increased bus traffic will change the traffic patterns of other vehicles on the route. For instance, commuters using private vehicles instead of public buses may choose other routes to avoid congestion. However, under this scenario, the traffic volume from other vehicles is expected to decrease after the treatment, and the measured increase in noise sentiment in buildings near the bus route will be smaller than the real increase due to the new bus. In other words, the real impact of closeness to the new bus service on noise sentiment is likely larger than our estimates.

6.2 Robustness checks

We first examine the robustness of our baseline results by setting different cut-off distances for the treatment and control groups in the DID estimations. Since the maximum distance to the bus route for buildings in our sample is 198.5 m, we set the cut-off distance to be 100 m in the baseline estimation to balance sample size in each group. This 100 m boundary for road traffic noise insulation is also supported by the acoustics literature (Avsar & Gonullu, 2005; Martin & Hothersall, 2002). As robustness checks, we follow the same empirical strategy as Equation (1) but change the cut-off distances to 110 or 90 m. The corresponding estimation results are reported in Appendix Table C1. The estimates are very close to those in our baseline results, for both the magnitude and statistical significance.

Another possible concern about the baseline estimation result is that an individual’s sentiment about a new noise incident is dependent on previous exposure to noise. If the surrounding environment has been noisy for years, residents may not notice additional noise incidents, while residents living in quiet housing units may be less tolerant of a sudden increase in the noise level. To alleviate this concern, the average sentiment score of noise complaints made in the same building with a 1-year lag is included as an additional control. Results are reported in Appendix Table C2. The estimates remain robust in magnitude and level of significance.

In addition, the occurrence time of noise incidents may impact the noise sentiment, because residents may be disrupted more easily at night. Therefore, we use the report time of the noise complaints as a proxy for the occurrence
time of the noise incidents and include it as an additional control in the baseline model. Specifically, we denote the complaints made between 7 p.m. and 7 a.m. as the complaints made at night and denote the rest of the complaints as the ones made in the daytime. Appendix Table C3 reports the corresponding estimation results. As we expect, it reveals that complaints made at night have stronger adverse sentiments by around 10 percentage points. Living closer to the bus route by 100 m is estimated to have stronger noise sentiments by 10.4–10.5 percentage points, and the estimates are statistically significant at 5% level and 1% level, respectively. This indicates that our baseline estimation results remain robust.

Moreover, we address potential self-selection in the complaint samples. At the building level, to ensure that the composition of the sampled buildings is homogeneous, we conduct a robustness check by including only the buildings that have complaints both before and after the new bus service. The estimation results are reported in Appendix Table C4. Our results remain robust. On the individual level, if some residents are sorted to the areas near the bus route after the new bus service, they are expected to have gained ex ante knowledge of the new traffic noise when they inspected the houses before movement. Thus, it is possible that these new residents, who choose to live in a noisy area, report less severe complaints than those original residents who used to live in a quiet area and are now exposed to more noise. In that case, our estimated impact of closeness to the new bus service on noise sentiment is likely to provide a lower bound estimate of the true impact. In other words, the magnitude of the true impact of the new bus service on noise sentiment will be even larger than our estimation.

Further, to address potential selection by excluding individual cases without unit-level information and potential measurement error in the distance between each unit and the bus route, we further conduct the analysis at an aggregated building level. Within each building block, the sentiment of complaints in the past 12 months is averaged to construct the aggregate building-level sentiment index. In this way, records without full floor, unit, or demographic information can then be included in the analysis. Specifically, using a 12-month window before and after the opening of the new bus route, we investigate the impact of bus service on average noise sentiment within buildings. This specification follows the empirical strategies applied by Faber (2014):
with an interval of 350 m, which is the average distance between bus stops in Singapore (Lim, 2016). Then we use the distance to the alternative ECP as the instrument for the distance to the actual bus route, and the estimation results are reported in Appendix Table C7. Second, previous studies construct a cost function to calculate the theoretically shortest path, using factors such as land use, slope gradients and the existence of built areas (Faber, 2014; Jedwab et al., 2017; Tsivanidis, 2019). Our method for constructing the LCP in the baseline result is similar, since we assume that the cost of driving in the built area (except for roads) is infinitely large and the cost of driving on the road is the travel time. As a robustness test, we relax this restriction of the built area in the cost function and construct an alternative theoretical path that can "pass through" the built area. Specifically, we use the geographic slope gradient as the cost of moving in the district. Appendix D presents the details of the calculation and the corresponding estimation results. Our findings are robust under these two alternative IV strategies.

6.3 Heterogeneous effects across floor levels and distance to bus stops

Transmission of sound differs across height and sound insulation at various levels. To explore the heterogeneous noise effects of the bus service on noise complaints from different floor levels, we classify the samples into several categories and include the subsamples in separate regressions. Since the majority of buildings in our study areas are 12 stories, we naturally divide the samples into three categories: low floor (1st–4th floor), medium floor (5th–8th floor) and high floor (above 8th floor). Results are presented in Panel A of Table 4 using ECP as the IV. The empirical specification follows Equations (1) and (2). R² values in the estimations have improved significantly from the baseline specification, indicating that the heterogeneous floor effect is strong. For the low floor range and high floor range, the noise effect from the bus service is statistically insignificant. However, the noise effect on the medium floor range has doubled in comparison with the baseline estimation. The effect of binary closeness is about 0.214 (Column (2)), and the continuous distance effect for 100 m is estimated as −0.243 (Column (5)).

There are several plausible explanations for the strong noise impact on the medium floors. First, both the real noise data and the simulation results in literature support that residents living on medium floors may suffer the most from traffic noise exposure, due to the reflection of noise from the road surface and the natural attenuation of noise on higher floors (Barclay et al., 2012; Chew, 1991; Mak et al., 2010; Walerian et al., 2001). Specifically, Walerian et al. (2001) use simulated noise data and document that the noise of road transport peaks at the 5th and 6th floors of the surrounding parallel buildings with a width of approximately 40 m in between, which is very similar to the urban form in our study area. Second, it is also probably due to the common practice of sound insulation along community roads. Using landscaping and noise barriers along the major roads (expressways) to reduce transport noise is common in many global cities (DEFRA, 2019), but there usually lacks policy regulation for noise insulation along community roads and across different floors. Specifically, in the public housing of Singapore, there is no soundproofing design across different floors. Noise insulation infrastructures are only installed along rail tracks and expressways, but not along the community roads in our study area (LTA, 2015). As a result, only the shade trees along the roads and some noise tolerant buildings (e.g., multiple-floor car parks) may serve as the natural noise barriers (Bin et al., 2019). Based on our field study, most of these natural barriers are around three to four stories in height. Third, it may be explained by the existing occupants at lower floors, because elderly people who are more likely to be hearing impaired may also prefer to live on the lower floors. In summary, our result implies the need for further investigation to improve urban noise prevention for medium floor units in Singapore’s public housing as well as in the urban context of other cities beyond.

In addition, we examine how distance to a bus stop impacts noise complaints, as bus stops are special nodes on the entire bus route. Samples within 100 m of a bus stop are separated from those outside the 100-m radius in

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8Our result that the noise impact is stronger on medium floors remains robust if we further divide the samples into four categories (i.e., 1st–3rd floor, 4th–6th floor, 7th–9th floor, and above 9th floor).
estimations, using ECP as IV. Results are presented in Panel B of Table 4. Columns (1) and (2) show estimates using the dummy variable measuring closeness, while Columns (3) and (4) present estimates using distance variations. The effects at buildings within 100 m of a bus stop show larger magnitude (0.511 for the binary closeness variable and −0.288 for the continuous distance variable), with statistical significance at the 1% level. This indicates that the noise effect from bus service is more severe around bus drop-off points. A possible explanation is the influx of visitors around bus stops. Also, it is possible that buses generate more noise when they stop at or leave from the

| Panel A: Noise sentiment across floor levels | (1) | (2) | (3) | (4) | (5) | (6) |
|-------------------------------------------|-----|-----|-----|-----|-----|-----|
| 1–4 Storey  | 0.0738 | 0.2141*** | −0.0290 | 0.0674 | (0.0799) | (0.0802) |
| 5–8 Storey  | (0.0802) | | | | | |
| Above 8 Storey | | | | | | |

| Launch × Near | 0.0738 | 0.2141*** | −0.0290 | 0.0674 | (0.0799) | (0.0802) |
|----------------|-------|-----------|---------|-------|-------------|-------------|
| Launch × Distance | −0.0552 | −0.2428*** | 0.0282 | (0.0527) | (0.0820) | (0.0608) |

| Block and time fixed effect | Y | Y | Y | Y | Y | Y |

| First-stage F-stats | 14.83 | 18.11 | 7.85 | 32.74 | 20.66 | 11.65 |
|----------------------|-------|-------|-------|-------|-------|-------|
| Observations | 221 | 144 | 162 | 221 | 144 | 162 |
| R² | 0.477 | 0.605 | 0.544 | 0.479 | 0.598 | 0.564 |

| Panel B: Noise sentiment with different distance to bus stops | (1) | (2) | (3) | (4) |
|-------------------------------------------------------------|-----|-----|-----|-----|
| Within 100 m | 0.5114*** | 0.1315* | −0.2875*** | −0.1330** |
| (0.1924) | (0.0739) | (0.0853) | (0.0607) |
| Out of 100 m | 0.1315* | 0.1330** | 0.0993 | 0.0984 |
| (0.0739) | (0.0607) | (0.0548) | (0.0548) |

| Block and time fixed effect | Y | Y | Y | Y |

| First-stage F-stats | 17.24 | 21.35 | 38.59 | 26.27 |
|----------------------|-------|-------|-------|-------|
| Observations | 179 | 348 | 179 | 348 |
| R² | 0.447 | 0.274 | 0.590 | 0.314 |

Note: Columns (1)–(3) of Panel A report results for the binary closeness indicator. Columns (4)–(6) of Panel A report results for the continuous distance variable. Columns (1) and (2) of Panel B report results for the binary closeness indicator. Columns (3) and (4) of Panel B report results for the continuous distance variable. All estimations use ECP, the Euclidean straight lines connecting bus stops, as the instrument. Unreported control variables include building age, floor and floor squared, gender, morphology, RC center, and distance to train stations, LRT viaduct line, bus stops, expressways, major roads, and shopping centers. Standard errors are clustered by building blocks. Robust standard errors in parentheses. *p < 0.1. **p < 0.05. ***p < 0.01.
## Table 5  Net effects of the new bus service on housing price

|                                | (1) log (price) | (2) log (price) |
|--------------------------------|-----------------|-----------------|
| Launch × Near                  | 0.0129**        | −0.0134***      |
|                                | (0.0054)        | (0.0050)        |
| Near                           | −0.0097**       |                |
|                                | (0.0038)        |                |
| Launch × Distance              | −0.0134***      |                |
|                                | (0.0050)        |                |
| Distance                       | 0.0104***       | 0.0104***       |
|                                | (0.0037)        | (0.0037)        |
| Launch                         | 0.0101          | 0.0299***       |
|                                | (0.0077)        | (0.0094)        |
| Prime lending rate             | −2.8766***      | −2.8815***      |
|                                | (0.3558)        | (0.3563)        |
| Floor                          | 0.0070***       | 0.0070***       |
|                                | (0.0003)        | (0.0003)        |
| Area                           | 0.0030***       | 0.0030***       |
|                                | (0.0008)        | (0.0008)        |
| Building age                   | −0.0009         | −0.0009         |
|                                | (0.0006)        | (0.0006)        |
| Distance to train station      | −0.0035**       | −0.0036**       |
|                                | (0.0015)        | (0.0015)        |
| Distance to bus stop           | −0.0042         | −0.0046         |
|                                | (0.0031)        | (0.0032)        |
| Distance to expressway         | 0.0025***       | 0.0024***       |
|                                | (0.0008)        | (0.0008)        |
| Distance to major road         | −0.0014         | −0.0010         |
|                                | (0.0016)        | (0.0017)        |
| Distance to shopping center    | 0.0037***       | 0.0037***       |
|                                | (0.0009)        | (0.0009)        |
| Block and time fixed effect    | Y               | Y               |
| Observations                   | 1450            | 1450            |
| $R^2$                          | 0.941           | 0.941           |

Note: Column (1) reports results for the binary closeness indicator and column (2) reports results for the continuous distance variable. Unreported control variables include building morphology and RC center. Standard errors clustered by building blocks. Robust standard errors in parentheses.

*p < 0.1.

**p < 0.05

***p < 0.01.
bus stops. In addition, with frequent visual exposure to noise sources at bus stops, subjective feelings of annoyance by surrounding residents may be intensified.

7 | COST-BENEFIT ANALYSIS: PUBLIC TRANSPORT AND HOUSING PRICE

Public transport offers convenience to surrounding residents, and thus raises housing price in the neighborhood (Chalak et al., 2016; Cohen & Paul, 2007; Holmgren, 2014; Monchambert & De Palma, 2014). Nonetheless, it also generates noise pollution, which exerts a negative impact on the housing price (Diao et al., 2016). To implement a cost-benefit analysis, we start with an estimation on the overall impact of the new bus route on housing price. Specifically, we follow the same specification in Equations (1) and (2), but replace the dependent variable of noise sentiment with housing price (Diao et al., 2017):

\[
\log(\text{Price}_{ij}) = \beta_1 \text{Near}_{ij} + \beta_2 \text{Launch}_{ij} + \beta_3 \text{Launch}_{ij} \times \text{Near}_{ij} + X'_{ij} \vartheta + U_i \mu + \varphi_t + \omega_i + \varepsilon_{ij}. \tag{6}
\]

\[
\log(\text{Price}_{ij}) = \beta_1 \text{Distance}_{ij} + \beta_2 \text{Launch}_{ij} + \beta_3 \text{Launch}_{ij} \times \text{Distance}_{ij} + X'_{ij} \vartheta + U_i \mu + \varphi_t + \omega_i + \varepsilon_{ij}. \tag{7}
\]
The definitions for the other variables are the same as in Equations (1) and (2). Table 5 displays the corresponding results using all of the resale transaction data in our study area from 2010 to 2018. Column (1) reveals that before the bus starts operation, the housing prices within 100 m of the route are 0.97% lower than those farther away (100–200 m). This is probably because the route is designed along the community road, generating traffic noise but offering limited convenience before the new bus service begins. After the introduction of bus service, the housing price within 100 m of the bus route increases by 1.3% compared to units within 100–200 m of the bus route. A similar conclusion can be drawn if we use a continuous variable of distance to estimate the benefit from the convenience of public transport (Column (2)). The prices for units closer to the new bus route by 100 m increase by 1.34%. The estimate is statistically significant at the 1% level.

Nevertheless, this explicit benefit is likely to be offset by an implicit decrease in housing price due to the noise generated by the new bus route. We thus examine the negative effect of noise sentiment on housing price using the same set of resale transaction records. Column (1) in Table 6 presents the corresponding OLS regression results of Equation (3). We include all the transaction records in our study area which can be matched with the lagged noise sentiment. To estimate the exact economic costs of noise pollution on housing price, we also control for the distance to the nearest bus stop connecting the CBD before and after the launch of bus no. 972. It reveals that a 1-scale-point increase in noise sentiment over the past 12 months is correlated with a 3% decrease in housing price. This estimate is statistically significant at the 5% level.

Finally, we analyze the cost and benefit for intensifying public transport on housing price. Since living closer to the new bus service route by 100 m has caused the noise sentiment score to increase by around 9.53% (Column (5) in Table 3), the negative effect of its noise on housing price can be interpolated as approximately 0.29% per 100-m distance to the bus route. Taking the explicit 1.34% increase in housing price per 100 m closer to the new bus route, we estimate that the implicit effect of traffic noise on housing value has offset around 17.79% of the economic benefit brought by the improvement of public transport.

We also investigate the heterogeneous impact of noise from the new bus route on housing price across floor levels in two steps. First, we examine the heterogeneous impact of the new bus service on noise sentiment on low, medium, and high floors. We find that the noise nuisance from the new bus service is positive and statistically significant on medium floors only, as reported in Table 4. Second, we estimate the impact of sentiment from general noise on housing price across floor levels. Specifically, we modify Equation (3) by interacting $S_{i,t-1}$ with a dummy variable denoting the units on the low and high floors. The estimation results are reported in Column (2), Table 6. We find that if the 1-year lagged noise sentiment increases by 1 scale point, the housing price on medium floors decreases by 2.62%. This estimate is statistically significant at the 5% level. In addition, the overall impact of a 1-scale-point increase in sentiment from general noise on housing price is similar across housing units on low/high floors and on medium floors, which is reflected by the statistically insignificant coefficient for the interaction term between the lagged noise sentiment and the dummy variable for units on low/high floors.

Combining the results from these two steps, we conclude that for units on medium floors, a decrease of distance to the bus route by 100 meters increases the noise sentiment by 24.3 percentage points (Column (5) in Panel A, Table 4), which translates to a 0.64% drop in housing price, or equivalently, a loss of around 2401 SGD (1766 USD) per housing unit. In comparison, for units on high/low floors, as the impact of the new bus service on noise sentiment is statistically insignificant (Columns (4) and (6) in Panel A, Table 4), the direct impact of noise from the new bus on housing price is likely small.

The results remain robust if we use the noise sentiment over the past 6 months instead. The estimation results are reported in Appendix Table C8.
CONCLUSION

Public transport is supposed to raise housing price in the neighborhood because of its convenience. The byproduct of excessive noise pollution from public transport, however, may offset its benefit to the region, and such effect is considered more severe in urban areas with high density. Using the opening of a new bus route zigzagging through a public housing neighborhood in Singapore, we contribute to the literature on public transport and housing price by presenting new empirical evidence in the form of a cost-benefit analysis (Baum-Snow & Kahn, 2000; McMillen & McDonald, 2004; Xu et al., 2015). We also use the natural language processing tools to generate real-time noise sentiments, which exhibits patterns that are different from and complementary to those in the literature that counts the frequency of noise incidents in retrospective surveys (Dzhambov & Dimitrova, 2014; Weinhold, 2013).

Applying an IV estimation, we show that the intensification of public transport service significantly increases residents’ noise complaints. Individuals living within 100 m of the new bus route make more severe noise complaints to government agencies by about 11 percentage points than those living farther away. This adverse effect is more serious at median floor levels and locations near bus stops. We further link noise complaints to housing transactions. With the change in accessibility explicitly controlled for, it is estimated that traffic noise offsets 17.8% of the economic benefits brought by the improvement of public transport.

Our results shed light on urban policies to address the negative impact of noise pollution on urban economic development. Many global cities are undergoing intensification in rapid urbanization (Searle & Filion, 2011). While the congestion caused by private transport has always been an issue, economies of scale from intensified population encourages governments to intensify public transport as a solution to congestion (Goetzke, 2008). Services like public buses, which aim to ease last-mile mobility from trains or subways, better connect with residential buildings. However, as demonstrated in this paper, they may introduce adverse noise effects as well, which potentially leads to environmental inequality. The results of this paper provide an empirical basis for policy design, such as a differentiated residential noise insulation infrastructure within communities, in high-density cities like Singapore.

In addition, our study also has significant implications for land use and transportation policies. With the significant government investment into the TOD (Cervero & Dai, 2014; Kahn, 2007), the property values and land values should rise. As a result, more value can be extracted by the governments to finance additional TOD and other mass transportation infrastructures. However, our empirical evidence indicate that the noise externalities of the public transport may offset the earlier increases in property values and lead to lower tax revenues in future, which thus impair the financial sustainability of TOD. Our study emphasizes the importance of considering noise impact in coordinating TOD allocation and designing the route of public transport to minimize the amount of exposure to noise.

DATA AVAILABILITY STATEMENT

The data are not publicly available due to privacy or ethical restrictions. The data that support the findings of this study are available upon reasonable request.

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**SUPPORTING INFORMATION**

Additional Supporting Information may be found online in the supporting information tab for this article.

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