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The impact of train accessibility on housing affordability: evidence from COVID-19 and the work-from-home shift

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ABSTRACT

This study examines the impact of train accessibility on housing affordability in Sydney, Australia, before, during, and after COVID-19. Using panel regression and propensity score matching (PSM) to mitigate bias from unobserved neighbourhood heterogeneity and sample selection, we compare housing affordability between train-stop and non-stop suburbs for both house and unit (apartment) markets. Our findings indicate that before COVID-19, housing affordability was worse in train-stop suburbs relative to non-stop suburbs due to an accessibility premium, particularly for houses. However, the pandemic and the shift towards remote work significantly reduced this premium, resulting in improved purchase affordability in train-stop suburbs for homeowners and investors, particularly for units. Meanwhile, rental affordability for houses in train-stop suburbs improved during and after the pandemic, but not for units. Our findings may influence the effectiveness and design of the government's Transport-Oriented Development (TOD) initiatives aimed at increasing unit/apartment supply around major train stations under changing commuting patterns and post-pandemic housing demand.

1. Introduction

Land rents in urban areas are shaped by the highest bid-rent functions across competing land uses (Alonso, 1964). Advances in transport technologies, telecommunications, and internet connectivity, coupled with the emergence of multiple mixed-use centres, have enabled greater decentralisation, contributing to urban sprawl and polycentric development patterns (Glaeser & Kahn, 2004). While agglomeration benefits remain relevant, factors such as decentralised employment, improved transport infrastructure, and increased demand for quality of life continue to erode central land values and promote outward urban expansion (Geltner et al., 2007). The COVID-19 pandemic and the widespread adoption of work-from-home (WFH) models have further accelerated these trends, weakening centrality and introducing new housing affordability challenges due to shifting residential demand and location preferences (D'Lima, 2022; Mondragon and Wieland, 2022; Gamber et al., 2023; Howard et al., 2023).

In response to Australia's deepening housing affordability crisis since the COVID-19 pandemic (National Housing Supply and Affordability Council, 2024), the Australian Government launched the National Housing Accord, which aims to deliver one million (later expanded to 1.2 million) well-located new homes over five years starting mid-2024 (Australian Government, 2022). As part of this effort, the New South Wales (NSW) Government has promoted Transport-Oriented Development (TOD), aiming to increase medium- to high-density housing near train stations, particularly in the Sydney metropolitan area (NSW Government, 2023). By

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concentrating development around transit hubs, TOD is intended to curb sprawl, reduce reliance on private vehicles, enhance public transport use, and foster vibrant, accessible neighbourhoods (Cervero, 2004).

This paper investigates the relationship between public transport accessibility and housing affordability near train stations, particularly in the context of COVID-19 and the rise of WFH models. We demonstrate that COVID-19 and WFH have significantly altered transportation needs, leading to reduced reliance on train access in urban areas. Consequently, we observe improved housing affordability in suburbs with train stations relative to those without, during and after the COVID-19 period.

Specifically, we measure housing affordability at the suburb level using three key ratios, which correspond to homeowners, investors, and renters. To assess homeownership demand and purchase affordability for homeowners, we use the price-to-income ratio, calculated as median home sale prices divided by median annual household income in the suburb. To measure investment demand and affordability for investors, we use the price-to-rent ratio, calculated as median home prices divided by median annual rents. Finally, the rent-to-income ratio, calculated as median weekly rent divided by median weekly household income, is used to evaluate rental demand and affordability for renters. These ratios are commonly used in the housing literature to reflect levels of unaffordability (Hendershott & Slemrod, 1982; Hulchanski, 1995; Himmelberg et al., 2005; Gan & Hill, 2009; Shi & Kabir, 2018; McQuinn et al., 2021; Shi et al., 2025).

We find that houses and units represent two distinct markets. For houses, prior to COVID-19, housing affordability was significantly worse in train-stop suburbs (i.e., suburbs with a train station), with price-to-rent, price-to-income, and rent-to-income ratios higher by 6.7 %, 15.5 %, and 8.0 % respectively compared to suburbs without train stops, reflecting an accessibility premium. During and after the pandemic, as more workers transitioned to WFH, affordability in train-stop suburbs improved by 3.0–3.4 % for homeowners and 2.2–2.6 % for renters, with no significant change in affordability for investors. For units, affordability for investors and homeowners showed no significant difference between train-stop and non-stop suburbs before COVID-19, while rental affordability for renters was significantly worse by 5.3 % in train-stop suburbs. During and after the pandemic, affordability in train-stop suburbs relative to non-stop suburbs substantially improved by 5.2–7.6 % for investors and 6.1–8.5 % for homeowners, but showed no improvement for renters.

Our research makes several important contributions to the existing literature. First, it offers one of the earliest empirical examinations of how public transport accessibility influences housing affordability. This is increasingly relevant in Australia, where WFH has become a “new normal” of the labour market (Beck and Hensher, 2020; Hensher et al., 2021a; Hensher et al., 2021b), contributing to persistent declines in public transport use. For example, Newman et al. (2022) reported a 15 % drop in public transport demand in Perth, while Roy Morgan (2023) found nationwide public transport use in 2023 remained over 20 % below pre-pandemic levels. Currie et al. (2021) estimate a long-term decline in Melbourne commuter volumes by 6 % overall and up to 20 % in the CBD under ongoing WFH arrangements. Most recently, Roy Morgan (2025) reported that nearly 70 % of Sydney CBD workers worked from home at least some of the time between July 2024 and June 2025, and the Victorian Government is planning to legislate a right to WFH at least two days a week (Swan, 2025). All these developments reflect a significant and enduring shift in commuting patterns and public transport demand in the post-COVID era (Hensher et al., 2024; Rüger et al., 2024; Curtis et al., 2025). By focusing on affordability, our work adds a socially and policy-relevant dimension to the post-pandemic TOD discussion.

Second, the COVID-19 pandemic and the rise of WFH created a rare quasi-natural experiment, generating behavioural and market conditions not previously available. Similar studies cannot be conducted in countries like China, where WFH has largely receded and traditional office-based work has resumed more fully in the post-pandemic period. In contrast to Dingel and Neiman (2020) and Brueckner et al. (2023), who used surveys of US workers to classify the feasibility of WFH for all occupations and to estimate the potential for remote work in each location, we do not directly measure the share of WFH in a suburb. Instead, we use reductions in train usage during and after the pandemic as a proxy for lockdowns and ongoing WFH arrangements (Independent Pricing and Regulatory Tribunal, 2024; Curtis et al., 2025), which allows us to examine how these changes altered the accessibility premium in train stop suburbs. Using the pre-COVID period as a baseline, we estimate our main regressions through the coefficients on train stop suburbs for affordability before, during, and after COVID-19. Our contribution therefore lies in linking observed and ongoing changes in transport behaviour (train usage) to housing affordability outcomes, providing a complementary perspective to studies that rely on self-reported WFH shares.

Third, methodologically, we employ a fixed effects panel regression framework combined with Propensity Score Matching (PSM) to address neighbourhood heterogeneity and improve comparability between train-stop and non-stop suburbs. We also introduce a weighted measure of train usage to capture the intensity of transport accessibility. Together, these innovations enable us to quantify how housing affordability responds to shifts in transport demand across different property types and locations.

The research has important policy implications. The COVID-19 pandemic reshaped housing markets, and WFH is likely to have enduring effects on urban form and affordability (Gallagher, 2021; Parker, 2023; Pacheco, 2024). Since purchase affordability for homeowners and investors in the unit market has been improved in train-stop suburbs relative to non-stop suburbs during and after the pandemic, while rental affordability for units has not, it is more important than ever to think carefully about how to best target TOD. Our research presents a strong case for TOD to focus on improving rental affordability, for example through the development of build-to-rent projects. New investment in neighbourhood infrastructure and amenities may be essential to enhance liveability (Cervero, 2004; Australian Housing and Urban Research Institute, 2024) and prevent TOD areas shifting towards a predominantly working-class or low-income population.

The remainder of the article is organised as follows. Section 2 reviews the relevant literature. Section 3 outlines the theoretical framework and the development of our hypotheses. Section 4 details the research design, followed by a description of the data in Section 5. Section 6 presents and discusses the empirical findings. Section 7 concludes.

2. Literature review

The relationship between public transportation and property values has long been a focus in urban economics, property markets, and transport planning. The literature suggests that proximity to public transport is positively correlated with property values, although the magnitude and direction of this relationship can vary depending on the type of transport, distance from the station, development phase, and socio-economic context. For instance, Debrezion et al. (2007) found that commercial property values benefit more from proximity to railway stations, whereas residential properties tend to benefit from being further from a railway. Armstrong and Rodríguez (2006) observed a roughly 10 % increase in property values in areas served by commuter rail stations in Massachusetts. Dai et al. (2016) found that transfer stations generated greater price impacts than non-transfer stations when studying newly opened metro stations in Beijing, showing that connectivity levels influence price outcomes. Li (2020) found that consumers are willing to pay more for access to rail transit in more congested areas of Beijing. Zhou et al. (2021) reported that the opening of a new subway line in Shanghai resulted in average house price appreciation of 3.75 % due to easier commutes to the central business district. Additionally, property prices are positively associated with ease of access to public bus or light rail routes (Mulley et al., 2016; Mulley & Tsai, 2016; Mulley et al., 2018; Yang et al., 2020). More recently, Zhou et al. (2024) found that shared bike usage reduced the subway premium in house prices, with house prices in neighbourhoods far from subways increasing with the intensity of shared bike usage. Zheng et al. (2025) suggested that accessibility affects labour market redistribution across regions in China through high-speed rail linking cities into broader urban networks, which in turn could affect local housing prices.

The impact of public transport infrastructure is dynamic and heterogeneous. Chen et al. (2019), examining the Sydney metro line, found that property prices decreased during the announcement phase but increased during the construction phase, with an average 0.037 % increase in price for every 1 % decrease in distance to the nearest metro station. Bohman (2021) showed that lower-priced segments of the housing market in Malmö, Sweden, were most affected by new railway stations, suggesting that accessibility improvements disproportionately benefit lower-income neighbourhoods. Khammo (2024) noted that rising housing costs in Australia were associated with longer commute times and a shift from private car use to public transit. In contrast, negative externalities such as noise and dust from transport infrastructure can lead to price declines, as seen in Efthymiou and Antoniou's studies (2013, 2015) in Greece. Afandizadeh et al. (2024) showed that while improved accessibility in Washington, D.C. initially increases house prices, beyond a certain threshold adverse effects arise due to reduced privacy and increased noise pollution. Collectively, these studies demonstrate that while public transport accessibility generally enhances housing values, its impact is contingent on a range of spatial, economic, and temporal factors.

Housing demand patterns have undergone substantial changes following the COVID-19 pandemic. In the United States, Mondragon and Wieland (2022) and Gamber et al. (2023) found that WFH contributed to over 50 % of the rise in national house prices since late 2019. Liu and Su (2021) reported that the pandemic reduced housing demand in dense neighbourhoods, driven by reduced need to live near workplaces and less value placed on amenities. D'Lima (2022) found that the pandemic's impact varied with population density and housing characteristics, showing a preference for larger living spaces in less crowded environments. Howard et al. (2023) further demonstrated that WFH initially drove up rents and prices due to increased housing demand, but the long-term impact may vary depending on housing supply elasticities across different regions.

Similar trends have been observed in other international contexts. In Kraków, Poland, Tomal and Marona (2021) reported rental price declines of 6–7 % and 6.25 % during the initial and subsequent phases of the pandemic, respectively. In China, Yang and Zhou (2022) examined the Yangtze River Delta region and found that housing prices rose significantly following the initial outbreak of COVID-19, although this effect gradually diminished as the pandemic progressed. Complementing this, Yang et al. (2022) explored how metro accessibility influenced housing prices during the pandemic. Their analysis revealed a modest decline in the benefit of being near metro transit on property values, suggesting that the advantages of access to public transport became less pronounced during periods of widespread remote work.

3. Theoretical framework and hypothesis development

Traditional urban land use theories suggest that land values vary spatially due to differences in transportation costs and agglomeration benefits (e.g., Park and Burgess,1925; Hoyt, 1939). These models underscore the importance of transport in shaping the spatial distribution of housing prices and population densities. Under the standard monocentric city model, the bid-rent curve (Alonso, 1964; Wheaton, 1974) declines as distance from the city centre increases, reflecting higher transportation costs faced by land users (Brueckner, 1987).

Consistent with these theories, suburbs with train stations typically command a location premium, reflected in higher property prices and rents. For a given level of suburb income,[1] this results in higher price-to-income and rent-to-income ratios, indicating reduced housing affordability in train-stop suburbs. If property prices rise disproportionately to rents in relation to train access, this further leads to a higher price-to-rent ratio. For houses, the location premium is generally more pronounced, reflecting land scarcity and the redevelopment potential of sites near train stations. For units, however, the premium is less distinct, as the uplift in land value is shared across high-density developments on the site, diluting the per-unit location premium. Therefore, we propose our first

[1] Note that residential sorting with access to rail transit in the Sydney metropolitan area was relatively limited (e.g., see discussions in Carleton et al., 2022), and changes in household income growth across suburbs were relatively small over the sample period (see Fig. 3, which presents a heatmap of suburb income changes before, during, and after COVID-19).

hypothesis:

H1: Before the COVID-19 pandemic, housing affordability was worse in suburbs with train stops compared to those without, particularly for houses.

However, the benefits of train access declined significantly during the COVID-19 pandemic due to lockdowns, avoidance of public transport, and the shift to WFH arrangements. According to the Australian Bureau of Statistics (2024), around 43–53 % of people worked from home during the pandemic in 2020 and 2021, with approximately 24–31 % working most of their hours from home—the highest levels ever recorded. In response to the pandemic, people increasingly preferred outer suburbs for their greater space and amenities (see Gamber et al., 2023). This dispersal of demand reduced population density in central locations, lowering absolute location rents (Geltner et al., 2007). Together with decreased commuting due to WFH, this should erode the accessibility premium in the centre and around train stations. As a result, property prices should come under significant downward pressure in train-stop suburbs, particularly for units, as their location premium is closely tied to demand for high-density living and proximity to transit. Meanwhile, reductions in rent in train-stop suburbs may have been more pronounced for houses than for units. Renters of higher-priced houses generally had greater financial means and mobility, enabling them to relocate to outer suburbs with larger dwellings or better amenities when the accessibility premium of train proximity declined. By contrast, demand for lower-priced units was more inelastic, as lower-income households renting lower-priced units were largely priced out of homeownership due to rising house prices (Gamber et al., 2023) and were also more reliant on public transport and less able to work remotely (Bohman, 2021). Accordingly, we propose our second hypothesis:

H2: During the COVID-19 pandemic, purchase affordability for both homeowners and investors improved in suburbs with train stops, particularly for units, while rental affordability in these suburbs was more likely to improve for houses but less so for units.

In the post-pandemic period, WFH remained a persistent feature of the Australian labour market, with approximately 36–37 % of people working from home in 2023–2024 (Australian Bureau of Statistics, 2024). This sustained WFH shift flattened the property price gradient near city centres and transit hubs, while making it steeper in outer suburbs (Brueckner et al., 2023). Consequently, purchase affordability in train-stop suburbs should continue to improve for both houses and units.

Rental affordability, however, is somewhat more ambiguous. Renting remains a critical tenure option, particularly for low-income households. Young and low-income households are especially sensitive to public transport accessibility, which may slow or even reverse gentrification trends in the centre and transit hubs (Giuliano, 2005; Glaeser et al., 2008; Brueckner & Rosenthal, 2009). At the same time, rising rental demand from immigrants and international students seeking accommodation near train stations may place additional pressure on already limited rental stock (Pawson et al., 2021). This dynamic could counteract the potential rent reductions in train-stop suburbs resulting from WFH, particularly for lower-priced units. Accordingly, we propose our third hypothesis:

H3: After the COVID-19 pandemic, purchase affordability for both homeowners and investors continued to improve in suburbs with train stops, while rental affordability was unlikely to further improve, particularly for units.

4. Empirical estimation strategy

4.1. The basic OLS models

To examine the effect of COVID-19 on housing affordability between train-stop and non-stop suburbs, we employ a panel data fixed-effects OLS regression model. This approach accounts for unobserved factors that may correlate with the explanatory variables, while also revealing how train usage influenced housing affordability in train-stop suburbs relative to non-stop suburbs across the periods before, during, and after COVID-19. The model is specified as follows:

$$\ln(Affordability_{it}) = \beta_0 + \beta_1 TrainStop_{it} + \beta_2 Covid_t + \beta_3 PostCovid_t + \beta_4 TrainStop_{it} \bullet Covid_t + \beta_5 TrainStop_{it} \bullet PostCovid_t + y_t + m_t + \alpha_i + \mu_{it} \quad (1)$$

where $Affordability_{it}$ denotes housing affordability for suburb *i* at month *t*, measured by the price-to-rent, price-to-income, and rent-to-income ratios, respectively. $TrainStop_{it}$ is a dummy variable equal to one if the suburb has at least one train stop, and zero otherwise. $Covid_t$ is a dummy variable indicating the COVID-19 period, equal to one for months between March 2020 and November 2022, and zero otherwise. $PostCovid_t$ is a dummy variable representing the post-COVID period, equal to one from December 2022 onwards, and zero otherwise. y_t captures year fixed effects, and m_t represents monthly seasonal fixed effects; α_i captures the location fixed effect within a postcode and Local Government Area (LGA) (postcode × LGA) and μ_{it} is the error term.

To test our hypotheses, we expect the following outcomes. If H1 holds, the coefficient (β_1) on the train-stop dummy variable before the pandemic should be positive and statistically significant, with a stronger effect observed for houses. If H2 is supported, the coefficient (β_4) on the interaction term between the train-stop dummy and the COVID-19 period should be negative and statistically significant, with a more pronounced effect for units. If H3 is valid, the coefficient (β_5) on the interaction between the train-stop dummy and the post-COVID-19 period should be negative and significant for ownership and investment affordability, but positive or insignificant for rental affordability, with the effect being stronger for units.

By employing fixed effects in the panel regression, we aim to produce a consistent estimator by removing unobserved time-invariant variables and effects. For instance, the location fixed effect (α_i) accounts for heterogeneity in suburb characteristics, including slowly changing demographics and unobserved locational amenities within a postcode × LGA. The year fixed effect (y_t) captures broader economic conditions across years, while the monthly seasonal fixed effect (m_t) accounts for recurring seasonal patterns across months. To mitigate concerns about omitted variables, we conduct additional checks by incorporating suburb characteristics and macroeconomic variables in Section 5.3. Lastly, to account for potential dependence among observations within the same postcode and time (year × month), standard errors are clustered by postcode and time, allowing for possible serial correlation both within each postcode and over time.

4.2. Propensity score matching (PSM)

A potential limitation of our analysis is the non-random allocation of train-accessible suburbs. To mitigate potential selection bias and ensure comparability, we employ a PSM approach, pairing suburbs with train stops to similar suburbs without them. According to Smith and Todd (2005), the reliability of PSM hinges on the selection of appropriate estimators. To address this, we incorporate all available demographic characteristics at the suburb level into the matching process. We then compare the PSM estimates from the matched sample with our basic OLS results from the full sample as a robustness check. Appendix A provides a detailed description of the PSM procedure and matching outcomes.

4.3. Potential endogeneity issues

Endogeneity issues primarily arise from the fact that placement of train stops is not exogenous. Although PSM helps mitigate bias from observable factors, it does not fully address potential endogeneity stemming from unobserved variables or reverse causality.

To best mitigate endogeneity, we first examine housing affordability in suburbs with existing train stops, which reduces concerns about reverse causality, as the infrastructure was already in place prior to the observed changes in affordability. By focusing on affordability trends before, during, and after the COVID-19 pandemic, we aim to reveal how reduced transport usage—driven by broader societal shifts such as WFH—affected housing affordability. This temporal focus helps mitigate endogeneity concerns by anchoring our analysis in structural changes rather than infrastructure decisions, such as the placement of new train stations.

Second, we employ a comprehensive fixed effects model in Equation (1), which makes omitted variable bias unlikely in our regression analysis (see Brueckner et al., 2023 for further discussion). Our focal variables are interaction terms between train stops and COVID-19 dummies; this further reduces the likelihood of correlation with the regression error term (Brueckner et al., 2023). Unfortunately, the availability of valid instruments at the suburb level is limited in our current dataset.

5. Data

5.1. Train Stops, Selected sample Period, and the Sydney metropolitan area

Train stop (x, y) coordinates and monthly aggregated data on train-stop entries and exits are sourced from the Transport Open Data Hub (Transport for NSW, n.d.), established by the NSW Government. This dataset covers the area serviced by the Sydney Train Network in NSW.

Our sample period covers January 2016 to March 2024 and consists of monthly train usage. January 2016 represents the earliest available data on train usage, while March 2024 indicates the most recent data at the time of analysis. The COVID-19 pandemic first emerged in China in December 2019, and Australia introduced nationwide travel restrictions and WFH policies starting in March 2020. In NSW, the first public health order was issued on 24 March 2020, with the final order remaining in effect until 30 November 2022 (NSW Government, 2022). Based on this timeline, we categorise the pre-COVID period as January 2016 to February 2020, the COVID period as March 2020 to November 2022, and the post-COVID period as December 2022 to March 2024.

We focus on the Sydney metropolitan area, which comprises approximately 647 suburbs and a population of around 5.12 million. In this study, suburbs represent the most detailed geographic units available for analysis, with clearly defined boundaries that reflect neighbourhoods or localities within the urban landscape. On average, each suburb spans 5.6 square kilometres and has a population of approximately 7,200.

Fig. 1(a) shows the geographical locations of 647 suburbs and the distribution of 174 train stops within the Sydney Train network across the Sydney metropolitan area. Fig. 1(b) presents average monthly train usage over the study period, highlighting trends before, during, and after COVID-19. The figure demonstrates a significant decline in train usage during the COVID-19, driven by travel restrictions, public resistance to close contact, and increased WFH arrangements. Although monthly train usage recovered, it has not fully returned to pre-COVID levels, with our preferred interpretation being due to the continuation of WFH arrangements. Table 1 presents the percentage drop in average monthly train usage during and after the COVID period, compared to the average pre-COVID level.

5.2. Home sale prices and rents

Data on suburb home sale prices and rents are sourced from the Securities Industry Research Centre of Asia-Pacific (SIRCA) on behalf of CoreLogic. The dataset provides monthly median sale prices and rents for houses and units, covering all suburbs in NSW. We filter the data by suburbs and postcodes within the Sydney metropolitan area, spanning from January 2016 to March 2024. Among the

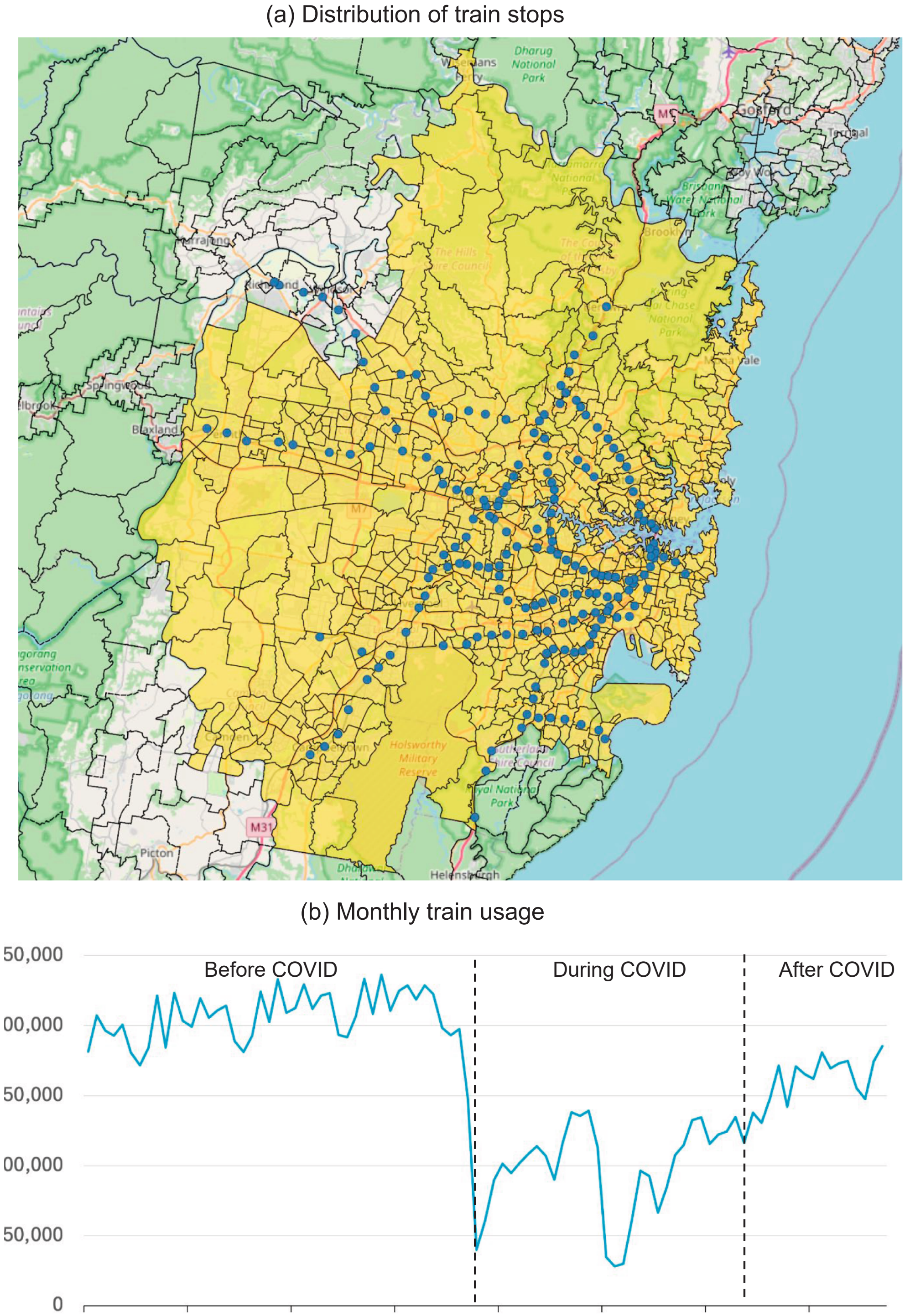

Fig. 1. Suburbs, Train Stops, and Monthly Train Usage This figure displays the distribution of train stops in the Sydney metropolitan area and the average monthly train usage before, during and after Covid. Suburbs are indicated in yellow, and train stops are shown as bule dots. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Percentages of Average Monthly Train Usage Drop.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
During-Covid (%)	57.6	48.5	42.2	51.3	52.1	45.8	69.2	72.3	69.2	64.4	62.1	60.7
Post-Covid (%)	24.6	17.4	21.2	22.8	23.2	20.4	40.6	38.7	38.9	39.2	39.1	42.2

This table shows the percentage drop in average monthly train usage during and after the COVID-19 pandemic, compared to pre-Covid levels. For example, train usage in January decreased by 57.6% during the pandemic, and by 24.6% in the post-pandemic period, compared to the pre-pandemic average.

647 suburbs, we further divide them into train-stop suburbs and non-stop suburbs based on the presence of a train stop, which is determined using the point-in-polygon algorithm in computational geometry.[2]

Fig. 2 illustrates the trends in sale prices and rents for houses and units in train-stop and non-stop suburbs over the sample period. Overall, houses demonstrated greater resilience to the COVID-19 shock, with both prices and rents exhibiting strong growth during and after the pandemic. Notably, unit prices in train-stop suburbs showed almost no growth during and after COVID-19, while unit rents experienced a significant decline during the pandemic but quickly rebounded in the post-pandemic period.

5.3. Suburb characteristics and housing affordability

The time-invariant variables such as distance to CBD and suburb area are from Google Maps. Suburb demographics (including population, age, education, and household income, etc.) are from the 2016 and 2021 Census. These Census data are then extrapolated at monthly intervals and matched with the home sales, rents, and train-stop usage datasets by suburb.

Fig. 3 presents heatmaps of property prices, rents, and household incomes across three periods: before, during, and after COVID. For houses, prices and rents increased primarily in the eastern and northern suburbs during and after COVID-19. For units, prices barely increased, while rents rose significantly and broadly across most suburbs during and after COVID-19. Household income growth appears fairly distributed across suburbs in the metropolitan area during the sample period.

Fig. 4 presents housing affordability trends across the Sydney metropolitan area. Fig. 4(a) shows that for houses, purchase affordability for homeowners and investors in train-stop and non-stop suburbs followed similar trends over the sample period, though this descriptive pattern does not control for other factors. However, rental affordability for houses improved remarkedly during COVID-19, particularly in train-stop suburbs, before declining in the post-pandemic period, with rental costs surpassing non-stop suburbs. Fig. 4(b) shows that for units, purchase affordability for homeowners remained similar between train-stop and non-stop suburbs throughout the period. However, purchase affordability for investors diverged between train-stop and non-stop suburbs during and after the pandemic, with train-stop suburbs becoming more affordable. In terms of rental affordability for units, the gap between train-stop and non-stop suburbs narrowed during the pandemic, then widened again, with rental affordability worsening more in train-stop suburbs in the post-pandemic period.

5.4. Summary statistics

Table 2 presents the key variables used in this research. To limit the impact of extreme values, the data are winsorised at the 1 % level in each tail. Panel A outlines the statistics for houses, Panel B provides the statistics for units, and Panel C presents the statistics for train stops and COVID periods. For houses, the average sale price is AUD 1.58 million, with an average weekly rent of AUD 719 over the study period. The price-to-rent ratio is approximately 40, the price-to-income ratio is 14, and the rent-to-income ratio is 0.33. In other words, for investors, this corresponds to an approximate yield of 2.5 %; for homeowners, it equates to about 14 years of income to purchase a house; and for renters, it reflects that approximately one-third of household income is spent on rent. For units, the average sale price is AUD 862,000, with a weekly rent of AUD 535. The price-to-rent ratio is 30, the price-to-income ratio is 7.69, and the rent-to-income ratio is about 0.26, indicating that units are significantly more affordable than houses. Over the study period, the pre-COVID period accounts for approximately 51 %, the COVID period for 33 %, and the post-COVID period for around 16 %. Among all suburbs, approximately 25 % have at least one train stop, indicating that one-quarter of suburbs in the Sydney metropolitan area have direct access to train services.

6. Results

6.1. Housing affordability and train stops

Table 3 presents the basic OLS panel regression results based on Equation (1), comparing housing affordability between train-stop and non-stop suburbs over the sample period. Panel A reports results for houses, while Panel B covers units. In Column (1), the price-to-rent ratio for houses was approximately 6.72 % higher in train-stop suburbs compared to non-stop suburbs before COVID. The pandemic increased the ratio by 4.72 % across all suburbs, but there was no statistically significant difference between train-stop and

[2] Refer to https://en.wikipedia.org/wiki/Point_in_polygon

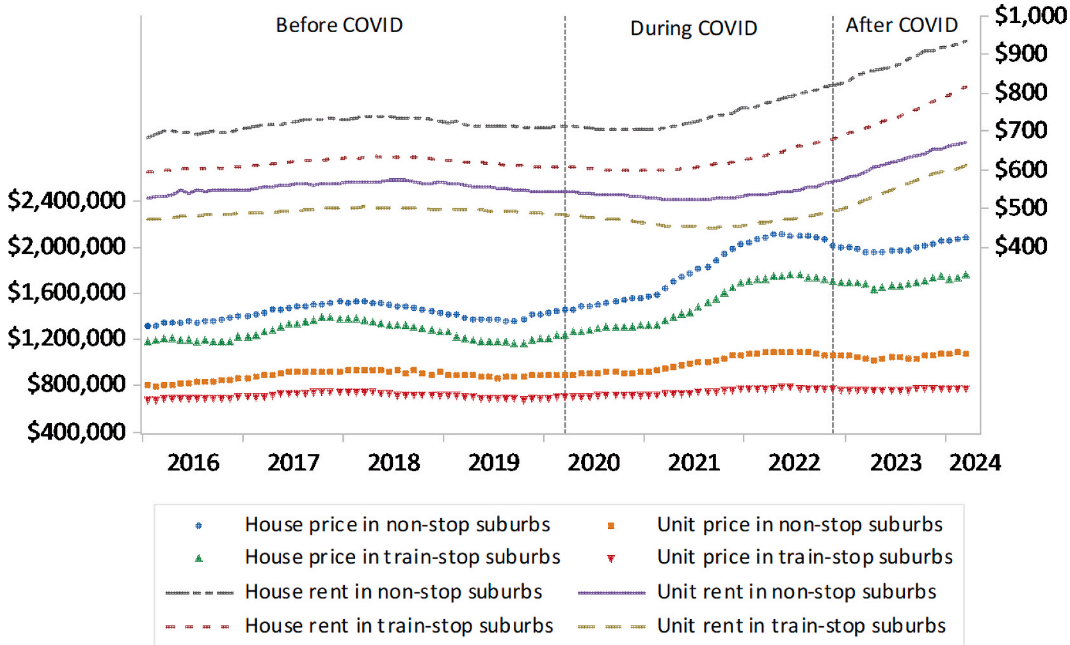

Fig. 2. Property Sale Prices and Rents This figure displays the trends in prices and rents for houses and units in train-stop and non-stop suburbs before, during, and after COVID-19. Monthly prices and rents are computed as the average of suburb-level median values within the Sydney metropolitan area over the sample period.

non-stop suburbs during or after COVID. Column (2) shows that the price-to-income ratio was 15.47 % higher in train-stop suburbs before COVID. The pandemic further raised this ratio by 3.12 % across all suburbs. However, compared to non-stop suburbs, affordability for homeowners in train-stop suburbs improved significantly by 3.00 % during COVID and 3.36 % post-COVID. Column (3) reports that the rent-to-income ratio was 8.03 % higher in train-stop suburbs before COVID. The pandemic led to a 1.45 % reduction across all suburbs. Relative to non-stop suburbs, rental affordability in train-stop suburbs improved by 2.63 % during COVID and by 2.17 % post-COVID. Overall, Panel A suggests that while housing affordability for houses was initially worse in train-stop suburbs, COVID-19 led to significant improvements in purchase affordability for homeowners and rental affordability for renters relative to non-stop suburbs, with affordability for investors largely unchanged.

Panel B presents the housing affordability results for units. Columns (4)–(6) show that before COVID, affordability for homeowners and investors in train-stop suburbs was not significantly different from non-stop suburbs, although rental affordability was approximately 5.30 % worse. COVID significantly worsened affordability for units across all suburbs, increasing the price-to-rent ratio by 6.92 % (Column 4) and the price-to-income ratio by 4.16 % (Column 5), while improving rental affordability through a 2.85 % decline in the rent-to-income ratio (Column 6). Compared to non-stop suburbs, train-stop suburbs experienced significant improvements in affordability for investors and homeowners by 5.17 % and 6.08 % during COVID, and 7.58 % and 8.47 % post-COVID, respectively. In contrast, rental affordability between train-stop and non-stop suburbs was not statistically different during or after COVID.

Comparing Panels A and B, we find that COVID and the shift to remote work had significant market-wide impacts on housing affordability, with effects varying across locations and property types, consistent with existing literature (e.g., D'Lima, 2022; Wang, 2022). Before COVID-19, housing affordability was worse in train-stop suburbs compared to non-stop suburbs, particularly for houses, while no significant difference was observed for units, supporting Hypothesis 1. During and after COVID-19, investment demand for houses remained largely unchanged, while for units it deteriorated significantly in train-stop suburbs, suggesting that house investors largely held on, whereas unit investors increasingly withdrew from these areas. Meanwhile, affordability for homeowners improved for both houses and units in train-stop suburbs, reflecting reduced demand for dense living near train stations. These findings align with Hypotheses 2 and 3, as the rise of WFH reduced the premium once attached to proximity to public transport, diminishing the attractiveness of investing and owning in train-stop suburbs. Units were particularly vulnerable to this shift due to their high supply elasticity. Houses, however, showed greater resilience, which may reflect the ongoing redevelopment potential in train-stop suburbs under TOD polices. On the other hand, rental affordability showed notable improvement for house renters but no significant change for unit renters, indicating that rental demand among households in the lower-priced unit segment—who may face spatial or financial constraints—remained strong, consistent with Hypothesis 3.

6.2. PSM results

Since train-stop suburbs are likely not directly comparable to non-stop suburbs, we employ a PSM method to minimise potential sample selection bias. Due to missing demographic data for some suburbs, 628 out of 647 suburbs were included in the matching

Fig. 3. Heatmaps for Property Prices, Rents, and Household Incomes Before, During, and After COVID-19 This figure presents heatmaps of property prices, rents, and household incomes before, during, and after COVID-19. Values are calculated as suburb-level averages for each period.

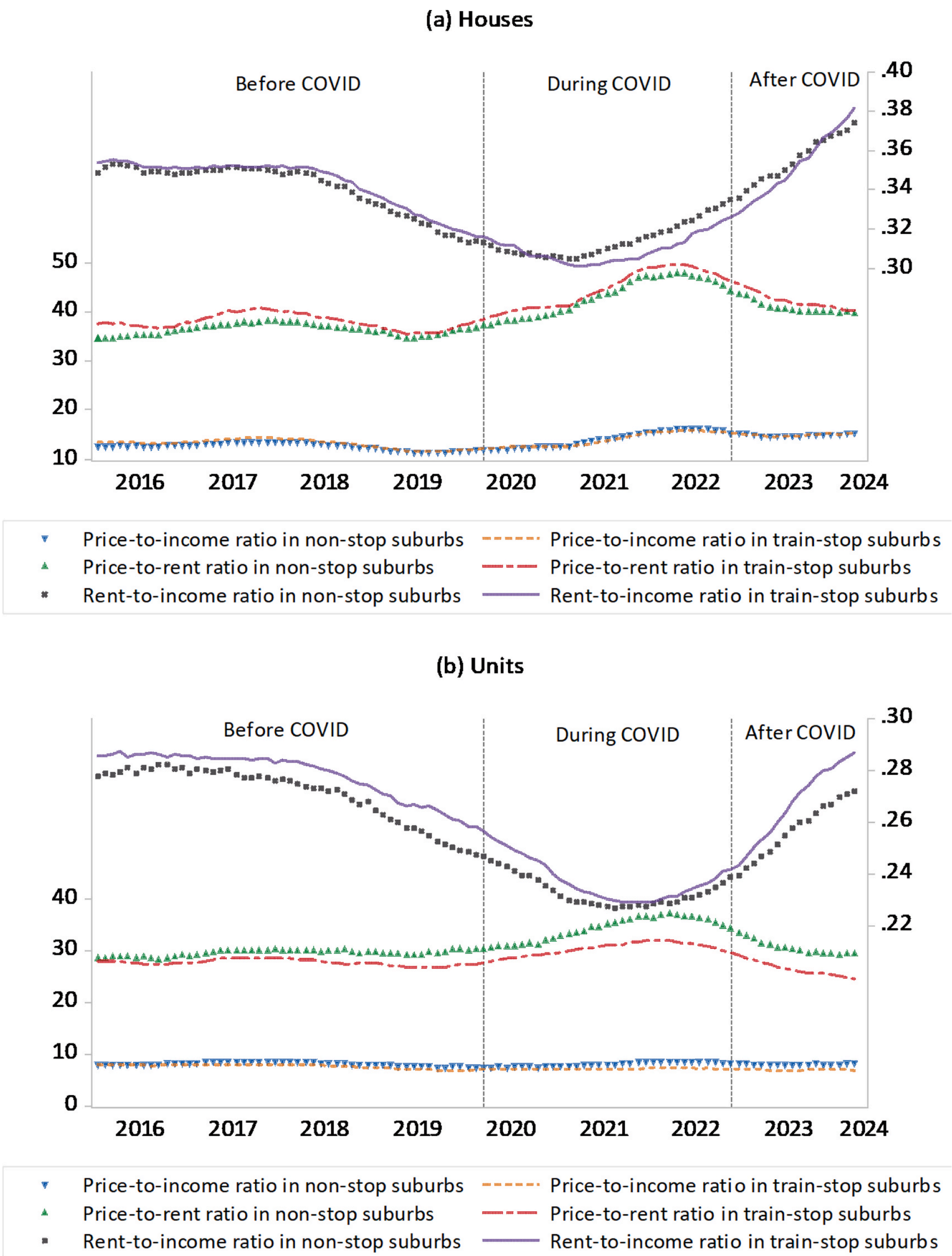

Fig. 4. Housing Affordability This figure displays housing affordability trends in train-stop and non-stop suburbs over the sample period. Figure (a) is for houses and Figure (b) is for units.

process. Among these, 27 suburbs could not be matched, resulting in a matched sample of 601 suburbs. Details on bias reduction and matching outcomes are provided in Appendix A.

Table 4 presents the outcomes of our analysis based on the restricted PSM samples. Panel A reports the results for houses, while Panel B provides the findings for units. Comparing these results with those from the full sample in Table 3, we find that the restricted PSM sample results are similar to that of the full sample. Therefore, the interpretation of our main results in Section 5.1 remains robust

Table 2
Summary Statistics.

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
	Panel A: House					
Median Price (AUD)	1,581,693	1,350,000	4,775,000	417,000	922,607	52,587
Median Rent (AUD/per week)	719	650	1,600	330	280	53,445
Price-to-rent Ratio	39.65	37.22	76.92	19.91	10.94	50,160
Price-to-income Ratio	13.56	12.65	32.52	4.56	5.76	51,822
Rent-to-income Ratio	0.33	0.32	0.60	0.16	0.09	52,701
	Panel B: Unit					
Median Price (AUD)	862,829	770,000	4,775,000	417,000	404,558	35,072
Median Rent (AUD/per week)	535	510	1,600	330	136	39,552
Price-to-rent Ratio	29.98	28.29	76.92	19.91	7.43	33,678
Price-to-income Ratio	7.69	7.34	32.52	4.56	2.21	34,449
Rent-to-income Ratio	0.26	0.25	0.60	0.16	0.06	38,883
	Panel C: Train Stops and Covid Periods					
Before Covid (yes = 1, no = 0)	0.51	1.00	1.00	0.00	0.50	64,053
During Covid (yes = 1, no = 0)	0.33	0.00	1.00	0.00	0.47	64,053
Post Covid (yes = 1, no = 0)	0.16	0.00	1.00	0.00	0.37	64,053
Train Stop (yes = 1, no = 0)	0.25	0.00	1.00	0.00	0.43	64,053

This table presents summary statistics of key variables for the analysis in this study. The panel contains 647 suburbs and 99 months over the sample period from January 2016 to March 2024. Note that not all suburbs have reported median prices and rents in the database, particularly for units.

Table 3
Basic OLS Panel Regression Results**.**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log *of affordability ratios*	Price-to-Rent	Price-to-Income	Rent-to-Income	Price-to-Rent	Price-to-Income	Rent-to-Income
	Panel A: Houses			**Panel B: Units**		
Train stop	0.0672 ***	0.1547 ***	0.0803 ***	−0.0155	0.0180	0.0530 **
	(0.0158)	(0.0216)	(0.0180)	(0.0260)	(0.0350)	(0.0216)
During Covid	0.0472 ***	0.0312 **	−0.0145 **	0.0692 ***	0.0416 ***	−0.0285 ***
	(0.0121)	(0.0124)	(0.0065)	(0.0123)	(0.0085)	(0.0090)
Post Covid	−0.0302	−0.0185	0.0198	0.0026	0.0194	0.0003
	(0.0218)	(0.0242)	(0.0125)	(0.0189)	(0.0125)	(0.0143)
Train stop x During Covid	−0.0052	−0.0300 ***	−0.0263 ***	−0.0517 ***	−0.0608 ***	−0.0136
	(0.0076)	(0.0090)	(0.0063)	(0.0114)	(0.0138)	(0.0083)
Train stop x Post Covid	−0.0120	−0.0336 ***	−0.0217 ***	−0.0758 ***	−0.0847 ***	0.0083
	(0.0075)	(0.0097)	(0.0084)	(0.0144)	(0.0173)	(0.0098)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.7797	0.8307	0.7572	0.6492	0.6438	0.6786
Panel observations	50,160	51,822	52,701	33,678	34,448	38,883
LGA x Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Monthly seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the basic OLS panel data fixed-effects regression results assessing the impact of train accessibility on housing affordability level in the Sydney Metropolitan Area before, during, and after COVID-19. Panel A reports results for houses, while Panel B focuses on units. Specially, we have estimated: $\ln(Affordability_{it}) = \beta_0 + \beta_1 TrainStop_{it} + \beta_2 Covid_t + \beta_3 PostCovid_t + \beta_4 TrainStop_{it} \bullet Covid_t + \beta_5 TrainStop_{it} \bullet PostCovid_t + y_t + m_t + \alpha_i + \mu_{it}$., where $Affordability_{it}$ denotes housing affordability for suburb i at month t, measured by the price-to-rent, price-to-income, and rent-to-income ratios, respectively. $TrainStop_{it}$ is a dummy variable equal to one if the suburb has at least one train stop, and zero otherwise. $Covid_t$ is a dummy variable indicating the COVID-19 pandemic period, equal to one for months between March 2020 and November 2022, and zero otherwise. $PostCovid_t$ is a dummy variable representing the post-COVID period, equal to one from December 2022 onwards, and zero otherwise. y_t captures year fixed effects, and m_t represents monthly seasonal fixed effects; α_i captures the location fixed effect within a postcode and Local Government Area (LGA) (postcode × LGA) and μ_{it} is the error term. The sample period is from January 2016 to March 2024. The standard errors are shown in parentheses and are clustered by postcodes and time (year x month). Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 4
The PSM Results.

	(1)		(2)		(3)		(4)		(5)		(6)	
Dependent variable: log of *affordability ratios*	Price-to-Rent		Price-to-Income		Rent-to-Income		Price-to-Rent		Price-to-Income		Rent-to-Income	
	Panel A: Houses						**Panel B: Units**					
Train stop	0.0693	***	0.1599	***	0.0824	***	0.0109		0.0325		0.0476	**
	(0.0158)		(0.0207)		(0.0180)		(0.0209)		(0.0355)		(0.0221)	
During Covid	0.0499	***	0.0324	***	−0.0165	**	0.0675	***	0.0417	***	−0.0279	***
	(0.0122)		(0.0122)		(0.0065)		(0.0118)		(0.0078)		(0.0088)	
Post Covid	−0.0277		−0.0171		0.0180		−0.0006		0.0162		0.0001	
	(0.0218)		(0.0240)		(0.0126)		(0.0187)		(0.0123)		(0.0142)	
Train stop x During Covid	−0.0059		−0.0271	***	−0.0239	***	−0.0458	***	−0.0571	***	−0.0132	
	(0.0076)		(0.0089)		(0.0062)		(0.0105)		(0.0120)		(0.0087)	
Train stop x Post Covid	−0.0127	*	−0.0316	***	−0.0204	**	−0.0682	***	−0.0793	***	0.0090	
	(0.0075)		(0.0099)		(0.0084)		(0.0139)		(0.0152)		(0.0100)	
Constant	Yes		Yes		Yes		Yes		Yes		Yes	
Adjusted R-squared	0.7790		0.8332		0.7589		0.6537		0.6468		0.6774	
Panel observations	48,973		50,650		51,622		32,536		33,415		37,891	
LGA x Postcode FE	Yes		Yes		Yes		Yes		Yes		Yes	
Monthly seasonal FE	Yes		Yes		Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes		Yes		Yes	

This table presents the results based on the restricted sample of 601 matched suburbs from the PSM analysis. See Appendix A for details on the PSM procedure and matching results. Specially, we have estimated: $\ln(Affordability_{it}) = \beta_0 + \beta_1 TrainStop_{it} + \beta_2 Covid_t + \beta_3 PostCovid_t + \beta_4 TrainStop_{it} \bullet Covid_t + \beta_5 TrainStop_{it} \bullet PostCovid_t + y_t + m_t + \alpha_i + \mu_{it}$., where $Affordability_{it}$ denotes housing affordability for suburb i at month t, measured by the price-to-rent, price-to-income, and rent-to-income ratios, respectively. $TrainStop_{it}$ is a dummy variable equal to one if the suburb has at least one train stop, and zero otherwise. $Covid_t$ is a dummy variable indicating the COVID-19 pandemic period, equal to one for months between March 2020 and November 2022, and zero otherwise. $PostCovid_t$ is a dummy variable representing the post-COVID period, equal to one from December 2022 onwards, and zero otherwise. y_t captures year fixed effects, and m_t represents monthly seasonal fixed effects; α_i captures the location fixed effect within a postcode and Local Government Area (LGA) (postcode × LGA) and μ_{it} is the error term. The sample period is from January 2016 to March 2024. The standard errors are shown in parentheses and are clustered by postcodes and time (year x month). Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.

and unchanged.

6.3. Omitted variables

To address the potential impact of omitted variables on our analysis, we incorporate additional locational and demographic variables into the basic OLS model. These include suburb distance to the CBD, suburb area, population, age distribution, percentage of Australian citizens, education levels, and the Reserve Bank of Australia (RBA) cash rate.[3] Table 5 displays the results of this extended analysis.

Panel A presents results for houses, and Panel B shows results for units. For houses, coefficients for train stops, COVID, and their interactions are generally consistent with those from the full sample, although the effect-sizes are reduced and less statistically significant. Similar findings are observed for units. Regarding the added suburb variables, demographic factors such as suburb age, percentage of Australian citizens, and higher education levels are statistically significant, while suburb population, distance to the CBD, and suburb area are not. Notably, the RBA cash rate is statistically significant, with a negative impact on the price-to-rent ratio and a positive effect on the rent-to-income ratio. For houses, a 10 % increase in the RBA cash rate decreases the price-to-rent ratio by 0.156 % and increases the rent-to-income ratio by 0.162 %. For units, the same 10 % increase leads to a 0.171 % decline in the price-to-rent ratio and a 0.152 % increase in the rent-to-income ratio. The RBA cash rate has no statistically significant effect on the price-to-income ratio. Although not causal, these results provide empirical evidence that the RBA cash rate influences housing affordability. Specifically, an increase in the cash rate dampens investment demand and worsens rental affordability, while having no measurable impact on purchase affordability for homeowners.

6.4. Additional checks

In the previous section, we demonstrated that housing affordability was affected differently in train-stop suburbs compared to non-stop suburbs due to COVID-19 and the shift towards remote work. However, each train stop may experience significantly different

[3] Although the RBA cash rate is nationwide, it is measured monthly and highly correlated with retail mortgage lending rates. Including it allows us to control for variation in interest rates beyond what month and year fixed effects capture, specifically accounting for monetary policy shocks that directly influence borrowing costs and housing demand.

Table 5
Additional Check of Suburb Characteristics and Interest Rates on Housing Affordability.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: log *of affordability ratios*	Price-to-Rent	Price-to-Income	Rent-to-Income	Price-to-Rent	Price-to-Income	Rent-to-Income
	Panel A: Houses			**Panel B: Units**		
Train stop	0.0513 ***	0.1009 ***	0.0371 **	0.0460	0.0442	0.0022
	(0.0172)	(0.0220)	(0.0170)	(0.0290)	(0.0303)	(0.0242)
During Covid	0.0286 **	0.0352 **	0.0111 ***	0.0426 ***	0.0428 ***	−0.0022
	(0.0136)	(0.0154)	(0.0040)	(0.0122)	(0.0098)	(0.0050)
Post Covid	−0.0213	−0.0126	0.0163 ***	0.0078	0.0263 **	0.0010
	(0.0204)	(0.0239)	(0.0050)	(0.0168)	(0.0122)	(0.0060)
Train stop x During Covid	−0.0078	−0.0406 ***	−0.0344 ***	−0.0414 ***	−0.0582 ***	−0.0229 **
	(0.0079)	(0.0098)	(0.0079)	(0.0110)	(0.0135)	(0.0094)
Train stop x Post Covid	−0.0107	−0.0496 ***	−0.0371 ***	−0.0594 ***	−0.0831 ***	−0.0088
	(0.0077)	(0.0115)	(0.0109)	(0.0139)	(0.0170)	(0.0107)
Log suburb distance to CBD	−0.1229 *	−0.2227 *	−0.1368 *	0.0146	0.0604	−0.0273
	(0.0631)	(0.1134)	(0.0760)	(0.0946)	(0.1058)	(0.1041)
Log suburb area	0.0050	0.0347 *	0.0135	−0.0027	0.0055	−0.0042
	(0.0148)	(0.0204)	(0.0107)	(0.0261)	(0.0349)	(0.0234)
Log suburb population	−0.0024	−0.0232	0.0065	0.0066	−0.0047	0.0075
	(0.0160)	(0.0247)	(0.0157)	(0.0256)	(0.0396)	(0.0315)
Log suburb median age	0.2942 ***	0.7684 ***	0.4379 ***	0.6236 ***	1.2635 ***	0.4362 **
	(0.1030)	(0.1857)	(0.1587)	(0.1683)	(0.1779)	(0.1936)
Percentage of Australian citizen	−0.2925 **	−1.3574 ***	−0.9281 ***	0.4176 **	−0.6306 ***	−1.0134 ***
	(0.1198)	(0.2239)	(0.1648)	(0.1720)	(0.1786)	(0.1767)
Percentage of higher education	0.9217 ***	−1.0402	−2.0367 ***	1.5501 ***	1.2935 **	−0.6805
	(0.3296)	(0.8917)	(0.7713)	(0.3518)	(0.5636)	(0.4975)
Log RBA cash rate	−0.0156 ***	0.0008	0.0162 ***	−0.0171 ***	−0.0012	0.0152 ***
	(0.0037)	(0.0040)	(0.0009)	(0.0031)	(0.0024)	(0.0009)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.8000	0.8733	0.7979	0.7027	0.6930	0.7219
Panel observations	47,071	49,205	50,064	31,815	33,068	37,268
LGA x Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Monthly seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results from additional controls for suburb characteristics and interest rates in the analysis of housing affordability. Specially, we have estimated: $\ln(Affordability_{it}) = \beta_0 + \beta_1 TrainStop_{it} + \beta_2 Covid_t + \beta_3 PostCovid_t + \beta_4 TrainStop_{it} \bullet Covid_t + \beta_5 TrainStop_{it} \bullet PostCovid_t + x_t + y_t + m_t + \alpha_i + \mu_{it}$., where $Affordability_{it}$ denotes housing affordability for suburb i at month t, measured by the price-to-rent, price-to-income, and rent-to-income ratios, respectively. $TrainStop_{it}$ is a dummy variable equal to one if the suburb has at least one train stop, and zero otherwise. $Covid_t$ is a dummy variable indicating the COVID-19 pandemic period, equal to one for months between March 2020 and November 2022, and zero otherwise. $PostCovid_t$ is a dummy variable representing the post-COVID period, equal to one from December 2022 onwards, and zero otherwise. x_t represents additional control variables including suburb distance to the CBD, suburb area, population, age, percentage of Australian citizens, percentage of higher education, and the RBA cash rate. y_t captures year fixed effects, and m_t represents monthly seasonal fixed effects; α_i captures the location fixed effect within a postcode and Local Government Area (LGA) (postcode × LGA) and μ_{it} is the error term. The sample period is from January 2016 to March 2024. The standard errors are shown in parentheses and are clustered by postcodes and time (year x month). Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.

usage, making direct comparisons challenging within our analysis (see Dai et al., 2016). To address these spatial and scale-related concerns, we construct a distance-weighted matrix of train usage for each suburb as follows:

$$TU_i = \sum_{j \in J(i)} \frac{U_j}{D_{ij}} \tag{2}$$

where TU_i represents the monthly train usage in suburb i, $J(i)$ denotes the set of all train stops j within a 2,000 m radius of suburb i, U_j is the monthly train usage at stop j, and D_{ij} is the direct distance between suburb i and train stop j. Monthly train-stop usage is measured as the total number of train entries and exits. We adopt a 2,000-metre radius as the cut-off for train accessibility, based on the assumption that this represents the upper limit of walking distance for urban commuters (approximately a 30-minute walk), beyond which the influence of train stations diminishes (Tennøy et al., 2022). This equation assigns greater weight to closer train stops by inversely weighting usage by distance.

Table 6 presents the results. Panel A displays the findings for houses, showing a strong correlation between housing affordability and train accessibility. Before COVID-19, affordability was worse in suburbs with higher train usage. During the pandemic, investment and homeownership demand increased across all suburbs, making both less affordable, while rental affordability remained largely unaffected. In the post-COVID period, rental affordability deteriorated significantly in all suburbs, but there was no notable impact on purchase affordability for homeowners and investors. Interestingly, in suburbs with high train usage, affordability for homeowners and renters improved after COVID-19, while affordability for investors remained unchanged. For example, a 10 % increase in monthly train

Table 6
Train Usage and Housing Affordability.

	(1)		(2)		(3)		(4)		(5)		(6)	
Dependent variable: log *of affordability ratios*	Price-to-Rent		Price-to-Income		Rent-to-Income		Price-to-Rent		Price-to-Income		Rent-to-Income	
	Panel A: Houses						**Panel B: Units**					
Log monthly train usage	0.0051	***	0.0125	***	0.0072	***	−0.0028	*	0.0003		0.0048	**
	(0.0014)		(0.0020)		(0.0015)		(0.0017)		(0.0027)		(0.0020)	
During Covid	0.0463	***	0.0421	***	−0.0017		0.0655	***	0.0480	***	−0.0171	*
	(0.0129)		(0.0139)		(0.0072)		(0.0129)		(0.0105)		(0.0095)	
Post Covid	−0.0234		0.0024		0.0331	**	0.0189		0.0365	**	0.0024	
	(0.0222)		(0.0255)		(0.0138)		(0.0204)		(0.0148)		(0.0155)	
Log monthly train usage x During Covid	0.0009		−0.0021	**	−0.0033	***	−0.0035	***	−0.0052	***	−0.0021	*
	(0.0008)		(0.0010)		(0.0007)		(0.0010)		(0.0013)		(0.0009)	
Log monthly train usage x Post Covid	−0.0010		−0.0039	***	−0.0026	***	−0.0084	***	−0.0084	***	0.0012	
	(0.0007)		(0.0009)		(0.0008)		(0.0012)		(0.0016)		(0.0010)	
Constant	Yes		Yes		Yes		Yes		Yes		Yes	
Adjusted R-squared	0.7784		0.8280		0.7561		0.6516		0.6443		0.6784	
Panel observations	50,160		51,822		52,701		33,678		34,448		38,883	
LGA x Postcode FE	Yes		Yes		Yes		Yes		Yes		Yes	
Monthly seasonal FE	Yes		Yes		Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes		Yes		Yes	

This table presents the additional analysis of train usage and housing affordability. Monthly train usage is measured using a distance-weighted approach, incorporating the total number of entries and exits at all train stops within a 2000 m radius from the centre of each suburb. Specially, we have estimated: $\ln(Affordability_{it}) = \beta_0 + \beta_1 TrainUsage_{it} + \beta_2 Covid_t + \beta_3 PostCovid_t + \beta_4 TrainUsage_{it} \bullet Covid_t + \beta_5 TrainUsage_{it} \bullet PostCovid_t + y_t + m_t + \alpha_i + \mu_{it}$., where $Affordability_{it}$ denotes housing affordability for suburb i at month t, measured by the price-to-rent, price-to-income, and rent-to-income ratios, respectively. $TrainUsage_{it}$ is a monthly train usage for suburb i at month t. $Covid_t$ is a dummy variable indicating the COVID-19 pandemic period, equal to one for months between March 2020 and November 2022, and zero otherwise. $PostCovid_t$ is a dummy variable representing the post-COVID period, equal to one from December 2022 onwards, and zero otherwise. y_t captures year fixed effects, and m_t represents monthly seasonal fixed effects; α_i captures the location fixed effect within a postcode and Local Government Area (LGA) (postcode × LGA) and μ_{it} is the error term. The sample period is from January 2016 to March 2024. The standard errors are shown in parentheses and are clustered by postcodes and time (year x month). Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1The standard errors are shown in parentheses and are clustered by postcodes and time (year x month). Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.

usage is associated with a 0.021 % decline in the price-to-income ratio during COVID-19 and a 0.039 % decline post-COVID, as well as a 0.033 % decrease in the rent-to-income ratio during COVID-19 and 0.026 % post-COVID.

Compared to Panel A, Panel B shows distinct differences in the unit market. Before COVID-19, train usage had little statistical impact on unit affordability, indicating that unit affordability in train-stop suburbs was comparable to that in non-stop suburbs. However, during and after COVID-19, purchase affordability for homeowners and investors improved significantly in high train-usage suburbs, while rental affordability for renters remained unaffected. The magnitude of improvement was much greater than that observed for houses in Panel A, suggesting that the unit market in suburbs with high train usage was most affected. Although purchase affordability for investors and homeowners improved for units, this did not translate into better rental affordability for renters. Instead, rental affordability for unit renters rebounded to pre-COVID levels.

The observed shifts in affordability in suburbs with higher train usage suggest that areas, often transit hubs or key commuting nodes, were more sensitive to changes in commuting patterns. As WFH reduced the need for daily commuting, the location premium due to transport accessibility in these areas declined more sharply than in lower-usage suburbs. Survey data from Roy Morgan (2025) shows that nearly 70 % of Sydney CBD workers worked from home at least some of the time between July 2024 and June 2025. Similarly, Currie et al. (2021) estimate that long-term post-COVID commuter volumes in Melbourne are expected to decline by around 6 % overall but by as much as 20 % in the CBD due to continuous WFH arrangements. Our results highlight this heterogeneous impact, with high-usage train suburbs experiencing the greatest improvement in housing affordability compared with both lower-usage or non-stop suburbs during and after the pandemic. Despite the decline in ownership and investment demand, rental affordability in high train-usage suburbs remained relatively stable or rebounded. This suggests that while remote work reduced some demand, a core group of workers may still rely on public transport, reinforcing the resilience of rental demand near major train stops (Bohman, 2021).

7. Conclusion and policy implications

This study has explored how train accessibility interacts with housing affordability in Sydney within the unique context of COVID-19 and the rise of WFH. By combining panel regression with propensity score matching, we provide robust evidence on affordability dynamics shifted across both houses and unit markets, and between suburbs with and without train stations. Our findings show that housing affordability around train stations is sensitive to external shocks and behavioural change, with the pandemic and WFH reshaping commuting patterns and housing demand. In particular, the accessibility premium in train-stop suburbs has weakened during and after the pandemic. For houses, affordability has improved for homeowners and renters but not for investors; For units, affordability has improved for homeowners and investors but not renters. The study offers new insights into the evolving relationship between transport accessibility, housing markets, and the challenges of affordability in a post-pandemic urban environment.

Our findings offer valuable policy implications, particularly for the NSW Government's TOD initiatives. First, while TOD policies aim to increase housing supply and accessibility, declining investment and ownership demand for units near train stations, driven by WFH, raises concerns about the viability of high-density residential development in these areas. Housing affordability initiatives may consider extending beyond strict proximity to train stations and instead incorporate a balanced mix of house and unit development, distributed across the city with broader lifestyle and amenity considerations. Although this study does not provide an optimal supply ratio between houses and units, the empirical findings suggest the need for adaptive strategies that respond to shifting homeownership preferences. These could include increasing the supply of low-rise housing types such as terraces, duplexes, and semi-detached homes more widely across urban areas.

Second, the greater affordability shifts observed in high train-usage suburbs highlight the long-term impact of evolving commuting behaviours and remote work trends on location premiums. Transit hubs and inner-city areas, once valued for accessibility, may face neighbourhood declining if high-density supply continues to outpace preferences, resulting in long-term social and economic challenges. With these considerations in mind, future TOD planning should incorporate flexible zoning, promote mixed-use developments, invest in neighbourhood amenities, and improve last-mile transport options. These measures aim to enhance the living experience of unit owners and attract residents to high-density environments, contributing to the long-term success of TOD initiatives.

Third, despite weaker investment and ownership demand, rental demand near train stations has remained strong, particularly for units. At the same time, WFH raises equity concerns, as it is disproportionately concentrated among higher-income groups (Roy Morgan, 2025), leaving lower-income households more reliant on public transport and more exposed to housing cost pressures. Addressing these disparities may require complementary measures such as transport subsidies (for example, reduced or free public transport) and rental-focused initiatives like build-to-rent schemes or protections against excessive rent increases.

For future research, more granular micro-level housing transaction and rental data would provide deeper insights into affordability trends. Incorporating individual household income, employment, and migration data could also enhance understanding of affordability shifts and residential decisions. One limitation of this study is that while affordability changes are attributed to WFH, the adoption of remote work across suburbs or industries is not directly measured. Future research could integrate employment and commuting data to strengthen the analysis. Additionally, the long-term impact of WFH on housing demand is still evolving. Although post-COVID trends suggest a shift in preferences, further research is needed to assess whether these changes are permanent or subject to future reversals.

CRediT authorship contribution statement

Song Shi: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yuming Ou:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Tuo Mao:** Writing-original draft, Formal analysis.

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.

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Appendix

Appendix A: PSM procedure and matching results

To perform the PSM analysis, we first classify all suburbs into two groups: train-stop suburbs (TS = 1) and non-stop suburbs (TS = 0), based on whether a suburb has at least one train stop. Next, we use a logistic regression model to examine the characteristics of train-stop suburbs, incorporating demographic data from the 2021 Census. The logit model results indicate that most coefficients are statistically significant, suggesting that these covariates influence the likelihood of a suburb having a train stop.

We then calculate each suburb's propensity score, defined as $\log(p/1-p)$, where p is the predicted probability of being a train-stop suburb. Using these scores, we perform nearest neighbour matching, selecting for each train-stop suburb a corresponding non-stop suburb with the closest propensity score. To ensure the validity of the matching process, we conduct a balance test following Garnefeld et al. (2019). This includes (1) testing whether the differences in matching covariates between train-stop and non-stop suburbs remain statistically significant after matching and (2) computing the percentage reduction in bias for each matching variable, following Rosenbaum and Rubin (1983).

The PSM matching results are presented in Table A1. which demonstrates that PSM significantly reduces differences in suburb characteristics between train-stop and non-stop suburbs post-matching. The results confirm that the PSM method effectively minimises selection bias, ensuring a more robust comparison between train-stop and non-stop suburbs in our analysis.

Table A1
Propensity Score Matching Outcomes.

Variable	Sample	Treated mean	Control mean	Bias (%)	Bias reduction (%)	*t*-test	*t*-test p value	Variance (treated) / Variance (control)
Median age	Unmatched	36.734	40.096	−63.0		−6.09	0.000	0.30*
	Matched	36.914	37.026	−2.1	96.7	−0.24	0.811	0.63*
Australian citizen (%)	Unmatched	0.759	0.853	−88.7		−10.67	0.000	2.15*
	Matched	0.766	0.774	−7.2	91.8	−0.63	0.530	1.78*
Average household size	Unmatched	2.665	2.837	−41.0		−4.22	0.000	0.62*
	Matched	2.659	2.677	−4.2	89.7	−0.38	0.705	0.69*
Flat and apartment (%)	Unmatched	0.387	0.18	75.1		8.38	0.000	1.22
	Matched	0.379	0.418	−14.1	81.3	−1.09	0.279	0.78
House and semi-terrace (%)	Unmatched	0.604	0.813	−74.6		−8.26	0.000	1.15
	Matched	0.612	0.576	12.9	82.8	1.00	0.317	0.77
Dwelling vacancy (%)	Unmatched	0.086	0.078	12.5		1.18	0.237	0.21*
	Matched	0.085	0.08	8.2	34.5	0.89	0.374	0.38*
Unemployment rate (%)	Unmatched	0.06	0.044	62.7		6.82	0.000	1
	Matched	0.059	0.056	12.3	80.4	1.06	0.288	0.94
Use other language and English (%)	Unmatched	0.275	0.164	97.7		11.26	0.000	1.57*
	Matched	0.269	0.275	−5.3	94.6	−0.44	0.659	1.17
Children under 15 years (%)	Unmatched	0.315	0.312	3.4		0.34	0.735	0.51*
	Matched	0.317	0.319	−2.7	19.2	−0.23	0.815	0.50*
Tertiary education (%)	Unmatched	0.061	0.05	47.3		4.83	0.000	0.57*
	Matched	0.06	0.061	−3.9	91.8	−0.34	0.736	0.49*
Median weekly household income	Unmatched	2044.7	2408.3	−55.0		−5.54	0.000	0.50*
	Matched	2054.5	2048.8	0.9	98.4	0.10	0.921	1.45*
Speaks English only (%)	Unmatched	0.482	0.651	−83.9		−9.36	0.000	1.23
	Matched	0.493	0.484	4.4	94.7	0.39	0.698	1.19
Median monthly mortgage payment	Unmatched	2440.3	2824.9	−57.7		−5.59	0.000	0.32*
	Matched	2448.3	2474.4	−3.9	93.2	−0.53	0.598	1.42*
Married de facto (%)	Unmatched	0.351	0.38	−36.0		−3.72	0.000	0.65*
	Matched	0.352	0.361	−11.9	66.9	−1.06	0.289	0.74
Public transport to work (%)	Unmatched	0.071	0.025	139.2		18.15	0.000	4.14*
	Matched	0.066	0.072	−18.0	87.0	−1.28	0.200	0.56*
Professional occupation (%)	Unmatched	0.303	0.274	28.5		3.02	0.003	0.82
	Matched	0.306	0.293	12.1	57.4	1.17	0.243	1.25
Same address for five years (%)	Unmatched	0.5	0.588	−63.0		−6.79	0.000	0.94
	Matched	0.503	0.509	−4.1	93.5	−0.36	0.717	1.05
Christianity (%)	Unmatched	0.402	0.514	−94.3		−9.82	0.000	0.69*
	Matched	0.407	0.416	−7.2	92.3	−0.76	0.446	1.37
Median weekly rent	Unmatched	471.38	550.67	−52.4		−5.01	0.000	0.26*
	Matched	472.09	482.24	−6.7	87.2	−0.88	0.380	0.91
Population	Unmatched	12,253	5772.4	90.0		11.02	0.000	2.48*
	Matched	11,771	12,358	−8.2	90.9	−0.54	0.592	0.59*
Renting (%)	Unmatched	0.417	0.278	84.2		8.76	0.000	0.69*
	Matched	0.413	0.387	16.0	81.0	1.55	0.123	1.04
No motor vehicles %)	Unmatched	0.137	0.075	70.9		7.91	0.000	1.22
	Matched	0.134	0.12	15.8	77.7	1.33	0.185	1.05

In this table, we present the PSM outcomes. * if variance ratio outside [0.73, 1.37] for unmatched sample and [0.73, 1.38] for matched sample. The percentage reduction in bias for each matching variable is calculated according to Rosenbaum and Rubin (1983). See Appendix A for detailed descriptions of the PSM procedures.

Data availability

The authors do not have permission to share data.

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