The effect of housing costs on household transportation: Evidence from longitudinal data in Australia

Faye Khammo [a]

Jun Sung Kim [b]

Liang Choon Wang [c]

Abstract

We use longitudinal data from Australia and a novel fixed-effect instrumental variable approach to estimate the causal effect of housing costs on five measures of household transportation: work commute time, relocation, and the respective expenditure shares on motor vehicle fuel, public transport and taxi, and total transportation. We utilize a composite housing cost measure that combines the average rental and mortgage payments faced by the representative household in an area to capture their opportunity costs for residing in the area. The instrumental variable exploits arguably exogenous variation in housing costs induced by foreign investments that flow differentially into regions in Australia according to the past settlement patterns of immigrants. We find that higher housing costs increase an individual's work commute time and the probability of relocation, and lead to a shift in the household's expenditure away from fuel towards public transportation.

Keywords: Housing cost; transportation cost; commute time; household relocation; transportation expenditure; transportation mode

JEL classifications: R20; R21; R40; F21

[a] Affiliation: The Reserve Bank of Australia, Australia. Email: fayekhammo@outlook.com.
[b] Corresponding author. Affiliation: Department of Economics, Sungkyunkwan University, Republic of Korea. Email: jskim1221@g.skku.edu.
[c] Affiliation: Department of Economics, Monash University, Australia. Email: liang.c.wang@monash.edu.
Acknowledgments: We thank seminar participants at Monash University for their feedback and helpful suggestions. This paper uses unit record data from Household, Income and Labour Dynamics in Australia Survey [HILDA] conducted by the Australian Government Department of Social Services (DSS). The findings and views reported in this paper, however, are those of the author and should not be attributed to the Reserve Bank of Australia, the Australian Government, DSS, or any of DSS' contractors or partners. This paper also uses data supplied by Securities Industry Research Centre of Asia-Pacific (SIRCA) on behalf of RP Data.
Declarations of interest: none to declare.

1. Introduction

The housing-transport affordability crisis is a major global economic issue. Growth in household expenditure share on housing and transportation has persisted over the past decade – on average, reaching over one-third of total household expenditure in the European Union and Organisation for Economic Co-operation and Development (OECD) countries (OECD, 2021). The housing crisis may generate spillover effects and adversely influence other housing-associated costs, including commuting time, transportation expenditure, and household relocation. These negative spillover effects can disproportionately affect vulnerable groups with low socio-economic backgrounds (Li, Dodson & Sipe, 2018; Mitra & Saphores, 2019; Winke, 2021). If rising housing costs exacerbate transportation costs, there are important policy implications regarding the distribution of low-cost transportation access for the affected households, to more effectively reduce the stress and financial burden they face (Jin, Kim, & Jin, 2022; Vidyattama, Tanton, & Nepal, 2013). However, given that housing and transportation costs influence each other, empirically identifying the effect of housing costs on transportation is particularly challenging.

This paper investigates the causal effect of housing costs on various measures of household transportation: work commute time, relocation, and the respective expenditure shares on fuel, public transport and taxi, and total transportation. We contribute to the literature by introducing a novel fixed-effect instrumental variable (FE-IV) approach to address potential reverse causality and identify this causal relationship. Using longitudinal data from Australia and focusing primarily on outcomes of native-born individuals, we exploit arguably exogenous variation in housing costs, which is driven by foreign investments from various countries that flow differentially into local government areas (LGA) according to the past settlement patterns of immigrants from these countries. The instrument variable relies on the tendency for foreign investors to invest in LGAs with a greater share of immigrants from their home country. In particular, non-resident foreign investors exhibit country-of-origin bias in their locations of real estate investment (Badarinza & Ramadorai, 2018), while real estate agents in areas with large enclaves of immigrants tend to tailor their services to these foreign investors (Rogers, Lee, & Yan, 2015). We further strengthen the claim of exogeneity of the instrument by focusing on the outcomes of Australian-born individuals who are less likely to directly affect or be directly affected by national-level foreign investments into Australia.

Australia presents a suitable setting for comprehensively examining the causal relationship between housing costs and various measures of household transportation for the following reasons. First, the availability of Household Income and Labour Dynamics in Australia (HILDA) survey data that span 18 years accounts for the periods of housing boom and bust in Australia. This longitudinal data set provides several comprehensive measures of transportation at the individual and household levels; work commute time, relocation behaviour, and household expenditure on different modes of transportation.

Second, the changes in Australia's migration program in the mid-1990s and Australia's relatively open foreign investment policy provide an ideal setting for our instrumental variable approach that exploits foreign investment fluctuations. In the mid-1990s, Australia shifted its migration focus from being family-based to being skill-based following the victory of the conservative Liberal-National coalition in the federal election (Larsen, 2013). This change in immigration policy had a significant impact on Australian immigrant population, resulting in a large increase in the number of high-skilled immigrants. These immigrants who can afford to own homes tend to settle in areas where fellow immigrants from the same country of origin have already established themselves (Kim & Wang, 2023). Consequently, there is a strong demand for residential properties among these high-skilled immigrants, leading to the emergence of real estate agents specializing in providing services tailored to immigrants and foreign investors from specific countries (Rogers et al., 2015). Additionally, the Foreign Investment Review Board (FIRB) grants permission to foreign investors to purchase land for various purposes, such as constructing a new dwelling, redeveloping an existing dwelling, or acquiring newly built properties. FIRB's residential approvals doubled within a few years upon the migration program changes (Gauder, Houssard, & Orsmond, 2014). Thus, foreign investments originating from a large number of countries fluctuate differentially across LGAs in Australia. Along with individual fixed effects in our empirical model, these features ensure that there is sufficient variation for the instrumental variable to provide plausibly exogenous variation in housing costs.

An important contribution of this paper is that it investigates the effects of rising housing costs by using a composite housing cost measure as the key explanatory variable. The composite housing cost is constructed by considering the average market prices for rent and mortgage repayment costs and weighting them based on the proportion of renters and homeowners in each LGA, respectively. While a branch of prior literature uses average property prices as a measure of housing costs, it ignores the costs faced by renters (e.g., Atalay, Edwards, & Liu, 2017; Mitra & Saphores, 2019; Tsai, 2018). Similarly, papers using rental prices ignore the costs for mortgagors and owners (e.g., Mattingly & Morrissey, 2014; Winke, 2021). More importantly, the rental price is a flow measure capturing the ongoing cost of housing for renters, while the property price itself is not a flow measure capturing the ongoing cost of housing for owners. Thus, the composite housing cost allows us to measure the ongoing opportunity cost of housing that a representative household faces for living in a particular housing market.

Our main findings reveal significant effects on commute time, relocation, and expenditure share on specific transportation modes, in response to a rise in housing costs in a given LGA. Specifically, we find that work commute time and the probability of an individual relocating both increase in response to housing cost increases. When we separately examine households that relocated since the previous year and those who have not relocated, we find that in response to rising housing costs, relocators experience a greater increase in work commute time compared to non-relocators. The analyses of transportation expenditure show that individuals are shifting away from motor-vehicle transportation towards public transport and taxi as housing costs rise. The heterogeneity analysis highlights that individuals with a lower level of education face larger effects of housing costs on transportation costs compared to highly educated individuals. We show that our main results and analysis of heterogeneous effects are robust to the inclusion of immigrants in our sample and additional controls, such as age, income, and population size. Our findings are also robust when we instrument the total population with an immigrant instrument to account for potential changes in population size that may be correlated with the foreign investment instrument and unobserved influences of transportation costs.

2. Related literature

Existing literature tends to examine the trade-off between housing and transportation costs incurred by households – greater affordability for one is strongly associated with weaker affordability for the other. Specifically, regions with more developed transportation infrastructure are associated with higher housing costs due to the attractiveness of transport accessibility. In comparison, areas with a worse transportation infrastructure that are further away from the employment centres tend to have lower housing costs (Renne, Tolford, Hamidi, & Ewing, 2016; Saberi, Wu, Amoh-Gyimah, Smith, & Arunachalam, 2017; Schouten, 2021). Although previous papers highlight the negative correlation between housing and transport affordability, the channels through which the relationship transpires are ambiguous. By employing the FE-IV approach, we contribute to the literature by identifying a unidirectional causal impact of housing costs on household transportation costs.

Another branch of literature provides evidence of the potential for reverse causality: the effect of transportation infrastructure improvements on real estate prices, showing that premiums on property values increase in response to transportation infrastructure developments (Agostini & Palmucci, 2008; Bao, Larsson, & Wong, 2021; Liang, Koo & Lee, 2021). Indeed, we find in our setting that the pooled ordinary least squares (POLS) and fixed effects (FE) estimations substantially underestimate the effects of housing costs on transportation costs compared to the FE-IV estimation. Thus, the effect of transportation infrastructure on housing prices may dampen the effect of the relationship under investigation - highlighting the importance of our FE-IV empirical strategy.

A strand of housing-transport literature also investigates the causal effect of rising housing costs on specific transportation measures. For example, Mitra and Saphores (2019) use structural equation modelling to study the causal relationship between median home values and the likelihood of long commuting time using one year of data. Similarly, using a difference-in-differences approach, Winke (2021) examines the causal effect of local rental prices on household relocation behaviour. Winke (2021) finds that more expensive housing may lead households to relocate to lower-cost housing regions further away from the city and with poorer transportation infrastructure – while Mitra and Saphores (2019) suggest households living in lower housing cost regions are more likely to commute long distances. We advance this strand of literature by examining several measures of transportation, including work commute time, relocation, and household expenditure shares on different modes of transportation with the help of a novel FE-IV approach and the composite housing cost measure.

This paper also contributes to the important urban economics literature on housing and residential location choice that are related to urban workers' commuting journey. White (1988) develops a theoretical urban model that provides decentralizing workers' employment in either central business districts or suburbs. Using the American Housing Survey spanning the years 1985 to 2007, Ferreira, Gyourko, and Tracy (2010) demonstrate that negative equity and rising interest rates hinder the relocation of homeowners. Donovan and Schnure (2011) find a negative relation between housing prices and residential mobility with a stronger impact observed for intra-county move than for inter-county move in the United States. Recently, Gaigné, Koster, Moizeau, and Thisse (2022) conduct research using Dutch data and find that individuals make residential choices based on both local amenities and commuting costs, with this pattern varying by income. Delventhal, Kwon, and Parkhomenko (2022) delve into the effects of remote work on job and residential locations, as well as housing prices, using a quantitative model of city structure and focusing on Los Angeles. Our paper expands on the existing literature by examining the effects of rising housing costs on relocation decisions and transportation means and expenses.

3. Data

To estimate the effect of housing costs on transportation, we utilize data from several sources. We use the Household Income and Labour Dynamics in Australia (HILDA) longitudinal dataset (Watson & Wooden, 2012) for five individual-level measures of transportation outcomes – average weekly work commute hours, household relocation since the previous year, expenditure share on motor vehicle fuel, expenditure share on public transport and taxi, and total transport expenditure share. The main period of interest in this study begins from 2002, when HILDA started collecting transport variables. Commute time and relocation variables are available from 2002 onwards, while expenditure variables are available from 2005 onwards. To calculate household expenditure share on transportation, we first sum the total annual household-level non-housing expenditure in several categories, including motor vehicle fuel, public transport and taxi, groceries, alcohol, tobacco, clothing, education, utilities, insurance, and healthcare. We then take each individual's household expenditure on motor vehicle fuel, public transport and taxi, and total transport expenditure, to create three different variables for their respective shares of total expenditure.[1]

We use the composite housing costs, first introduced by Saberi et al. (2017) as the explanatory variable of interest. The composite housing costs are composed of two elements: the rental component and the mortgage component, which together represent the average housing cost for a household living in a given LGA and year. The rental component is calculated by weighing

[1] As Surprenant-Legault, Patterson, and El-Geneidy (2013) suggest that two-worker households minimize their total commuting distance, we also construct a household-level commute time variable in a few different ways, such as the sum of the total commute time over all household members and average commute time of household members. Whilst we do not report the results, our estimates are robust to the different ways of constructing household-level commute time.

the average market rent faced by households in an LGA according to the proportion of renters in the LGA and year. The average market rent is the mean annual cost of renting a residential property. The mortgage component is determined by weighing the average market mortgage cost based on the proportion of homeownership in the LGA. The average market mortgage cost is computed as the product of the mean mortgage rates and the mean price of residential properties. It is worth noting that the ownership proportion includes households that fall into the categories of mortgagors or outright homeowners. Outright homeowners do not pay any explicit rent or mortgage payments; however, the market interest cost associated with the average property price serves as a measure of the opportunity cost of complete homeownership within the LGA in a particular year. Likewise, mortgagors face an opportunity cost while residing in the LGA during a particular year.

To construct the composite housing costs – we utilize data from multiple sources. First, we incorporate property transaction data from CoreLogic, sourced from the Securities Industries Research Centre of Asia-Pacific (SIRCA). These data provide mean property and rental prices for each LGA and year from 2002 to 2019.[2] These mean prices serve as representative figures for the average market rent and purchase price faced by households within a specific LGA and year.

Second, we rely on census community profiles from the Australian Bureau of Statistics (ABS). The census community profiles furnish us with LGA-level tenure information data, such as the numbers of property renters and owners for every LGA in Australia. We use the tenure information data to calculate the respective proportions of renters and owners in each LGA and year. These proportions serve as weights in the composite housing costs. Since our study is based on annual data and the census community profiles are available every five years, we obtain the proportions for the missing inter-census years by interpolation and extrapolation.

Third, we incorporate indicator lending rates obtained from the Reserve Bank of Australia (RBA) to capture the monthly average mortgage rate from 2002 to 2019. Specifically, we use the standard variable owner-occupier rate offered by banks to determine an average annual national mortgage rate, which forms a component of the composite housing costs. We use the variable rate as it is representative of the prevailing market interest rate. Additionally, the owner-occupier rate is used to accurately capture the cost of housing rather than the cost of investment in the housing

[2] We supplement the SIRCA rental data with Census and HILDA rental data for when SIRCA data are missing for certain LGAs in some years.

market. To convert the monthly mortgage rate data into annual data, we calculate the average mortgage rate over the corresponding twelve-month period.

Lastly, in cases where individuals have relocated to a different LGA since the previous HILDA wave (approximately 14.5 percent of the sample), we consider the current housing costs of their previous LGA from which they departed instead of the current housing costs of their present LGA. This approach ensures that the housing costs they currently face are not driven by their decision to relocate. Henceforth, we use the term, housing costs, to refer to the composite housing costs.

To construct our instrumental variable, we gather data from two primary sources. First, we utilize the census community profiles to obtain information regarding the number of individuals born in foreign countries listed in the census, as well as the number of individuals born in Australia, for 672 LGAs.[3] We specifically focus on the country of birth data from year 1991, which allows us to calculate the historical distribution of immigrant settlements across LGAs. This procedure involves determining the share of total immigrants from a particular country who are living in the given LGA in 1991. Second, we acquire foreign investment data from the international investment position time series data provided by the ABS. This dataset covers the period from 2002 to 2019 and the total foreign investment includes various types of foreign investment, such as foreign direct investment, portfolio investment, financial derivatives, and other investments.

Table 1 shows the descriptive statistics of our final dataset. The average weekly work commute time is 2.6 hours, and the average frequency of relocation is 16.7% during the sample period. The average expenditure share of total transportation is about 6.8%, and most of the transportation expenditure comes from motor vehicle fuel (5.8% out of 6.8%). The average housing costs are 26,021 Australian dollars (AUD), ranging from 1,863 AUD to 222,457 AUD. Approximately 40% of the individuals are with a high education, and 68% of the individuals live in metropolitan LGAs. Note that we define a highly educated individual as one who, as reported in their initial wave of joining the HILDA survey, has completed any level of education above high school: certificate III or IV, diploma, bachelor, or a postgraduate degree.

[Table 1 here]

[3] Given that some LGA borders are inconsistent across census years, we merged some LGAs to produce LGAs with consistent borders for census years 1991 to 2016.

4. Methodology

4.1 Empirical strategy

We are interested in estimating the following fixed-effect specification:

$$T_{ijt} = \beta \; log \;\; H_{jt} \; + \pi_i + \gamma_t + \varepsilon_{ijt} \qquad (1)$$

The dependent variable, T_{ijt}, is the transportation cost faced by an individual i, in LGA j, in year t. We use five different outcome measures of transportation cost: average weekly work commute hours, household relocation since the previous year, expenditure share on motor vehicle fuel, expenditure share on public transport and taxi, and total transport expenditure share. The key explanatory variable, $log\ H_{jt}$, is the logarithm of average household's housing costs in a given LGA and year. The HILDA data enable us to control for any time-invariant characteristics or preferences across individuals by incorporating individual fixed effects (π_i). Time fixed effects (γ_t) are incorporated to control for changes in the outcome variables occurring in the year t that have a uniform effect on all households in Australia, such as national-level price shocks. The time fixed effects address the issue of the estimated effects being driven by national-level policy shocks or general price-level fluctuations (e.g., food and petrol price shocks). The error term ε_{ijt} captures any other individual and LGA-specific time-varying unobserved influences. We also use standard errors clustered at the LGA level.

We are interested in β , which measures the change in transportation costs in response to a 100 percent change in housing costs. Given that our model is a level-log specification, for ease of interpretation, we focus on ($\beta \cdot 0.1$) to measure the change in transportation costs in response to a 10 percent change in housing costs. For the causal interpretation of β, the housing costs must be exogenous to other unobserved influences of transportation costs in the error term. However, this assumption may not hold due to reverse causality. For example, transportation infrastructure improvements within an LGA over time can influence both transportation and housing costs. Infrastructure improvements may likely impact transportation costs through reducing expenditure or commute time. The favourable infrastructure changes are likely to increase housing costs within the region due to increased transport accessibility and, therefore, higher demand for housing in these regions. Therefore, lower transportation costs may lead to higher housing costs. From this example, we conjecture that the FE estimates are likely to underestimate the effects of housing costs on transportation costs. In sum, transportation and housing costs are likely to be jointly determined, which may introduce endogeneity bias if Equation (1) is estimated via a FE estimator.

4.2 Identification strategy

To address the potential issue of endogeneity bias in the fixed effects model, we propose the following instrument for housing costs and employ a FE-IV approach.

$$z_{jt} = log \left[\sum_{c=1}^{n} \frac{F_{jc1991}}{F_{c1991}} FI_{ct}\right] \tag{2}$$

There are two key components to this instrument. First, FI_{ct} is the total national-level foreign investment in Australia from foreign country *c* in year *t*. Recall that foreign investment includes direct investment, portfolio investment, financial derivatives, and other investments. Therefore, the foreign purchase of property and the establishment of a new business in Australia are captured by this measure. As reported by the Department of Foreign Affairs and Trade (2022), real estate activities are the second largest Australian industry attracting foreign investment. Thus, we expect foreign investment to strongly influence housing market prices. Secondly, we compute the share of total immigrants born in country *c* living in LGA *j* year 1991, $\frac{F_{jc1991}}{F_{c1991}}$. To avoid reverse causality, we employ the past distribution of immigrant settlements rather than the current distribution, which is a commonly employed strategy in papers that use shift-share instruments (e.g., Card, 2009).

The instrument essentially allocates the foreign investment from a given country *c* in year *t* into different LGAs based on the settlement patterns of immigrants from country *c* across LGAs back in 1991. According to this fixed allocation mechanism, the total foreign investment flow into a particular LGA *j* is the sum of the allocated foreign investment flows from a range of countries of origin. The instrument is based on the observation that foreigners invest in LGAs with a higher proportion of immigrants from their own country. This country-of-origin bias influences their investment decisions and leads to a concentration of foreign investment in regions with a significant share of immigrants from their background. Badarinza and Ramadorai (2018) support this mechanism – foreign risk significantly affects housing prices in regions with a larger share of immigrants from the same country as the investor. Similarly, Moallemi, Melser, Chen, and De

Silva (2022) find that the Australian local housing markets respond to the weighted index of economic activities in the origin countries of immigrants. If this mechanism holds true within the context of our study, it implies that foreign investment increases housing costs differentially across LGAs. Furthermore, local real estate agencies in ethnic enclaves target foreign investors from countries with large local immigrant communities – mainly through cross-border internet communications, the employment of agents from the target immigrant background, and overseas travel, to directly reach the foreign investor market (Kim & Wang, 2023; Rogers et al., 2015). With specialized real estate services tailored to foreign investors, we anticipate that housing costs are particularly responsive to changes in foreign investment flows.

For z_{jt} to serve as a valid instrument for housing costs, it is necessary that z_{jt} is conditionally exogenous. To satisfy the exogeneity condition, the instrument must only affect household transportation costs indirectly through housing costs. To see this, first, it is reasonable to assume that at the individual level, people do not have influence over the level or distribution of national-level foreign investment in Australia. Second, we employ the historical immigrant settlement as a fixed allocation mechanism to distribute national-level foreign investment across LGAs. This approach helps prevent reverse causality issues due to simultaneous determination. Additionally, by including individual fixed effects, we control for time invariant characteristics of individuals and any influences of settlement decision of immigrants that may be potentially correlated with the unobserved influences of natives' transportation costs. Importantly, because we focus on the effects of housing costs on the transportation costs of Australian-born individuals, they are less likely to be directly affected by shocks to the foreign economies that influence foreign investment. Third, foreign investment flows may also differentially affect transportation infrastructure across LGAs, such that areas attracting more investment may have greater improvements to their infrastructure. However, even if this holds, it is unlikely that the level of transportation infrastructure would change within a year – as we particularly look at annual fluctuations in foreign investment, housing costs, and transportation costs. Finally, we also examine potential threats to identification by adding additional controls for age, income, and LGA population in a robustness section (see section 5). The robustness of our estimates to the inclusion of these additional controls would imply the absence of these threats in our study.

5. Results

5.1 Main results

Table 2 shows the estimates from the POLS and FE estimations for the effect of housing costs on work commute time, relocation, and expenditure share on motor vehicle fuel, public transportation and taxi, and total transportation, respectively. Note that the number of observations for the expenditure variables is different from the number of observations for work commute time and relocation due to the expenditure variables only being available from 2005 onwards.[4] Panel A reports the POLS estimation, including year fixed effects. We estimate a 7.4 minutes increase in weekly work commute time when an LGA's average housing cost rises by 10 percent. However, we do not find a statistically significant relationship between housing costs and relocation. Panel A shows a statistically significant relationship between housing cost and transportation expenditure shares. We interpret the results as a 0.2 percentage point decrease in motor vehicle fuel expenditure share and a 0.1 percentage point increase in public transport and taxi expenditure share when housing costs increase by 10 percent. We estimate that a 0.08 percentage point decrease in transport expenditure is associated with a 10 percent increase in housing costs.

Panel B of Table 2 reports the FE estimation that includes individual fixed effects in addition to year fixed effects. There is a statistically significant and positive relationship between housing costs and work commute time (p-value < 0.01). The estimate can be interpreted as an average 3.5 minutes increase in weekly work commute time when average housing costs increase by 10 percent in an LGA. Secondly, we estimate a statistically significant and positive relationship between housing costs and relocation, whereby a 10 percent increase in housing costs is associated with a 0.55 percentage point increase in the probability that an individual will relocate. Third, we find that as housing costs increase, the expenditure share on fuel decreases, while the expenditure share on public transport and taxi increases. These outcomes show that individuals shift their expenditure away from fuel and towards public transport. Furthermore, the results suggest that individuals are changing the mode of transportation from motor vehicles to public transport when housing costs increase. In particular, a 10 percent increase in housing costs is associated with a 0.1 percentage point decrease in expenditure share on fuel and a 0.1 percentage point increase for public transport and taxi. Overall, transportation expenditure decreases by 0.03 percentage points when housing costs increase by 10 percent.

[4] Table A1 in the Appendix reports robustness checks for the fixed-effect instrumental variable estimation, restricting to years 2005-2019 when all variables of interest are available.

[Table 2 here]

When we use the FE-IV estimation, we obtain the results reported in Table 3. Panel B of Table 3 reports the first stage estimates as well as the Cragg-Donald F-statistics and corresponding Stock and Yogo 10 percent critical value. The results show that the instrumental variable is a strong predictor of housing costs. The second stage results reported in Panel A of Table 3 show that when we use an instrumental variable to deal with potential endogeneity, we find that the POLS and FE estimates substantially underestimate the effect of housing costs on transportation costs. We find a statistically significant effect of housing costs on four measures of transportation costs. We estimate that a 10 percent increase in housing costs increases weekly work commute time by 13.6 minutes. The FE-IV estimate is approximately four times greater than the FE estimate. Secondly, we find that the probability of an individual relocating increases by 1.44 percentage points in response to a 10 percent increase in housing costs. These findings may suggest that individuals experience a longer work commute time due to relocating in response to higher housing costs, possibly to a location further away with lower housing costs, as past studies such as Winke (2021) and Mitra and Saphores (2019) suggest.

Statistically significant effects are also found for the effect of rising housing costs on household expenditure share on different modes of transportation. In particular, we observe a 0.22 percentage point decrease in expenditure share on motor vehicle fuel, and a 0.16 percentage point increase in expenditure share on public transport and taxi. Our findings suggest that individuals are shifting their expenditure away from motor vehicles and towards public transport, which may be an alternative explanation for the longer work commute time given that public transport is the more time-consuming transportation mode. Lastly, Table 3 reports insignificant results for the effect of housing costs on total transportation expenditure share. A possible explanation is that the decrease in motor vehicle fuel expenditure share is offset by the increase in public transport expenditure share, leading to no significant change in total transportation.

[Table 3 here]

5.2 Heterogeneity: Relocation

We extend our analysis further to investigate the heterogeneity in the effect of housing costs on transportation costs, and to understand which groups are most impacted by rising housing costs. Our estimates for the effect of housing costs on work commute time and relocation suggest that relocation may be at least partially driving the increase in commuting time. Therefore, in Table 4, we extend the analysis to investigate the effect of housing cost on commute time for two restricted samples: (A) individuals who have relocated since the previous year; and (B) individuals who have the same address as the previous year.

On average, we find that individuals who have relocated since the previous year experience a 38.6-minute increase in their weekly work commute time in response to a 10 percent increase in housing costs in their LGA, compared to a 10-minute increase for individuals who have not relocated. Therefore, relocators experience a greater increase in work commute time. The second stage estimates indicate that, in response to rising housing costs, only non-relocators decrease their expenditure share on motor vehicle fuel and increase their expenditure share on public transport and taxi on average, while relocators do not experience a significant change in expenditure share for any specific mode of transport. These results suggest that individuals who do not relocate continue to bear the higher housing costs and may consequently switch to lower-cost transportation modes to relieve the financial burden. Table 4 reports the opposite effects of housing costs on total transportation expenditure share for relocators compared to non-relocators. On average, relocators experience an increase in total transport expenditure share of 0.4 percentage points, while non-relocators experience a decrease of 0.1 percentage points. Our findings may suggest that relocators are moving to areas further from work that have lower housing costs, leading to an overall increase in transportation expenditure share as they need to commute longer distances to get to work, for example. In contrast, non-relocators experience a decrease in transport expenditure share as they do not change location and shift their mode of transport away from cars towards a cheaper mode of transport, public transport, to help endure the burden of higher housing costs.

[Table 4 here]

5.3 Heterogeneity: Education level

Next, we extend our analysis of heterogeneous effects to differentiate between individuals with a high education and low education level, as reported in Table 5. We use the individual’s education level in their initial year of joining the sample and hold that level constant for all years in the analysis. Initial education level is used as a proxy for income and skill level, as it is less endogenous in the context of our model.

Panel A of Table 5 reports the FE-IV estimates for individuals with a high level of education. Recall that we define a highly educated individual as one who, as reported in their initial wave of joining the HILDA survey, has completed any level of education above high school. We report the FE-IV estimates for individuals with a low level of education in Panel B of Table 5. We define a lowly educated individual as one who reports high school or below as their highest level of education. Table 4 reports that the effect of housing costs on work commute time is greater for lowly educated individuals, who experience almost double the magnitude of the effect for highly educated individuals. We find that the effect of housing costs on relocation likelihood is insignificant for both high and low education levels. This result may be due to the limitation of a smaller sample size when restricting the sample by relocation behaviour and education level.

In our analysis of heterogeneity across education levels for expenditure share on transportation, we find that the effect of housing price growth is greater in magnitude for lowly educated individuals for both expenditure shares on fuel and public transport and taxi. In particular, motor vehicle expenditure share decreases by 0.19 percentage points for highly educated individuals, compared to 0.2 percentage points for lowly educated individuals, in response to a 10 percent increase in housing prices. The expenditure share on public transport and taxi increases by 0.06 percentage points for highly educated individuals, compared to almost triple the effect for lowly educated individuals who, on average, experience a 0.17 percentage point increase in response to a 10 percent increase in housing costs. Therefore, we find that the effect of housing costs rising on the shift from motor vehicle expenditure to public transport expenditure is greater for lower-educated individuals. This shift towards public transport may also explain the greater increase in commute time for lower-educated individuals compared to higher-educated individuals. We observe a smaller decrease in overall expenditure share on transportation for individuals with a low education level, which may be partially attributed to the greater relative increase in their expenditure on public transport and taxi. Overall, Table 5 reports that lowly educated individuals face a greater transportation cost burden in response to housing cost increases than highly educated individuals.

[Table 5 here]

5.4 Heterogeneity: Metropolitan and non-metropolitan areas

We also examine whether there are heterogeneous effects of housing costs on transportation for individuals who live mostly in metropolitan compared to non-metropolitan areas. Panel A of Table 6 reports the FE-IV estimates for individuals who lived in metropolitan areas for the majority of the 18 years. Panel B reports the estimates for those living in non-metropolitan areas. The results demonstrate no substantial heterogeneity in the effects of housing costs on work commute time across metropolitan and non-metropolitan regions. Both groups experience increases in their work commute time. However, the estimates show that in response to rising housing costs, the probability of relocating decreases for individuals living in metropolitan areas. In contrast, this probability increases for individuals located in non-metropolitan regions. We also find that the shift away from motor vehicle transportation towards public transportation is greater for individuals living in metropolitan areas. The findings suggest that individuals living in non-metropolitan areas respond to rising housing costs by relocating, which may be driving their commute time increase. In contrast, individuals living in metropolitan areas tend to switch transportation modes to help bear the higher housing cost burden, also contributing to longer commute times.

[Table 6 here]

6. Robustness checks

The FE-IV estimates reported above are based on our preferred specifications that exclude immigrants from the sample to minimize potential concerns of endogeneity biases, given that immigrants living in Australia are more likely to be directly influenced by shocks affecting foreign investment from their home country than Australian-born individuals. Panel A of Table 7 shows the results for the FE-IV estimation for the sample including immigrants. As reported in Table 7, the estimated effects of housing costs on work commute time, relocation, and respective expenditure shares on fuel and public transport are robust to the inclusion of immigrants in the sample.

The validity of our IV hinges on whether the exogeneity condition is satisfied. A potential threat to identification is the omitted variables that are potentially correlated with the IV. Consider, for example, that the weighted distribution of foreign investment does not only differentially affect housing costs across LGAs, but also the level of business activity. This may lead to higher incomes within the LGA, therefore posing a threat to our identification. Furthermore, this may also affect the age of individuals who end up settling in certain LGAs with improving employment prospects for working-age individuals. We therefore analyze the sensitivity of our estimates to the inclusion of time-varying characteristics, such as age and disposable income, as additional controls.[5] Similarly, a relatively higher level of foreign investment into a given LGA may lead to more economic activity and employment, and potentially attract a larger population to this area. Population size is also correlated with the level of price competition (Campbell & Hopenhayn, 2005). For example, retail market structures and the level of competition may differ across LGAs, which may consequently lead to retailers differentially passing on cost changes to consumers depending on the level of competition in the given LGA. Therefore, the robustness of our estimates to controlling for the size of LGA population would suggest the absence of these threats to identification. Since the size of LGA population may be endogenous in our model, we instrument for the size of LGA population using an immigrant IV, consistent with the approach used in prior immigration literature (Saiz, 2007; Moallemi et al., 2022; Kim & Wang, 2023). Our instrument is constructed such that the national-level immigrant stock from a given country of birth is allocated across LGAs based on the historical immigrant distribution in 1991.[6] Panel B of Table 7 reports the results of the FE-IV estimation, including the additional controls while instrumenting for LGA-level population – our findings are robust to this specification.[7]

[Table 7 here]

7. Conclusion

[5] Note that we use the lag of disposable income as a control variable to minimize endogeneity, although the results are similar when we use the current disposable income as a control variable.
[6] We use country of birth and LGA-level population data from the censuses and also interpolate or extrapolate inter-census-year data to construct the immigrant IV.
[7] Our results in the heterogeneous analyses from Section 4 are also robust to the inclusion of additional controls. The results are available upon request.

In this paper, we implement a novel FE-IV approach to identify the causal effects of housing costs on five measures of transportation costs – work commute time, relocation, and expenditure share on motor vehicle fuel, public transport including taxi, and total transport. Our identification strategy relies on the differential effects of foreign investment inflows on housing costs across LGAs that are channelled through the past settlement patterns of immigrants across LGAs. Our FE-IV results indicate that rises in housing costs lead to an increase in transportation costs in the form of longer work commute times and an increase in the likelihood for individuals to relocate. Furthermore, our results show that in response to higher housing costs, households reallocate their budget away from motor vehicle fuel expenditure and towards public transport and taxi expenditure. These FE-IV estimates are much larger than those based on POLS and FE estimators, suggesting that reverse causality is likely to be present in the POLS and FE estimators.

When examining heterogeneity in the causal effects, our findings highlight that households that relocate experience a greater increase in commuting time in response to higher housing costs. Our results also indicate that households who relocated experience an increase in their overall transportation expenditure share, potentially attributable to the longer commute distances after moving to lower cost housing. Non-relocators, on the other hand, experience a decrease in overall expenditure share on transport, which may be due to the reallocation of budget away from motor vehicle fuel to public transport, a lower-cost transportation mode. Furthermore, our results indicate that lowly educated individuals are more impacted by rising housing costs in the forms of bearing the cost of longer commute times and shifting away from motor vehicle transportation to public transportation. We find no heterogeneity in the effects of housing cost increases on the work commute time between individuals predominantly living in metropolitan and non-metropolitan areas – however the results demonstrate that non-metropolitan individuals are more likely to relocate in response to higher housing costs, whereas the probability of relocation decreases for metropolitan individuals.

One potential limitation of our study is the exogeneity of our instrumental variable, as there is no formal test to prove that the exclusion restriction is satisfied. One potential mechanism to consider is that foreign investment that differentially flows into LGAs across Australia may affect factors other than housing costs, such as economic activity, which may impact on households' incomes and therefore expenditures. There may also be a concern that as foreign investment differentially flows into LGAs, the population size may also fluctuate differentially, leading to congestion in increasingly populated LGAs. Similarly, there may also be other time varying unobserved influences that are correlated with population size, such as time-varying local price response driven by the market structure of an area. However, when we add additional controls for age, income and the size of LGA population, our findings are robust.

Another potential limitation of this paper is that composite housing costs are measured with errors. For example, we use the market mortgage interest rate to capture the opportunity cost faced by outright homeowners, but in reality, the opportunity cost could be the market saving interest rate. We also ignore other potential costs incurred by homeowners, such as costs on renovations, repairs, and other maintenance. Nevertheless, as long as our instrument satisfies the exogeneity condition, our FE-IV approach addresses the potential estimation bias due to this measurement error problem in the explanatory variable.

There are policy implications from our findings of heterogeneity in the effects of rising housing costs on transportation costs – in particular, lower-educated individuals face higher transportation costs in the form of longer commute times and a greater shift in mode of transportation toward public transport. Therefore, transportation cost assistance in the form of public transport concessions directed towards lower-income individuals may assist with the management of an increase in public transport expenditure in response to higher housing cost burden. Furthermore, from the shift in expenditure share away from motor vehicle fuel, towards public transport, we gather a shift in mode of transportation. Therefore, if we consider that individuals are using more public transport in response to housing cost increases, the implementation of more frequent services, as well as the expansion of routes and transport infrastructure, would assist in decreasing transportation costs in the form of commute time and expenditure. Moreover, tax revenue collected from foreign investors, including stamp duty and foreign purchaser additional duty can be redistributed to partially fund the transport financial assistance to lower-income individuals and transport network improvements.

References

Agostini, C. A., & Palmucci, G. A. (2008). The anticipated capitalisation effect of a new metro line on housing prices. *Fiscal Studies*, *29*(2), 233–256. https://doi.org/10.1111/j.1475-5890.2008.00074.x

Atalay, K., Edwards, R., & Liu, B. Y. J. (2017). Effects of house prices on health: New evidence from Australia. *Social Science & Medicine*, *192*, 36–48. https://doi.org/10.1016/j.socscimed.2017.09.008

Badarinza, C., & Ramadorai, T. (2018). Home away from home? Foreign demand and London house prices. *Journal of Financial Economics*, *130*(3), 532–555. https://doi.org/10.1016/j.jfineco.2018.07.010

Bao, H. X., Larsson, J. P., & Wong, V. (2021). Light at the end of the tunnel: The impacts of expected major transport improvements on residential property prices. *Urban Studies*, *58*(14), 2971–2990. https://doi.org/10.1177/0042098020967308

Card, D. (2009). Immigration and inequality. *American Economic Review*, 99(2), 1-21.

Campbell, J. R., & Hopenhayn, H. A. (2005). Market size matters. *Journal of Industrial Economics*, *53*(1), 1–25. https://doi.org/10.1111/j.0022-1821.2005.00243.x

Delventhal, M. J., Kwon, E., & Parkhomenko, A. (2022). JUE Insight: How do cities change when we work from home?. *Journal of Urban Economics*, 127, 103331.

Department of Foreign Affairs and Trade. (2022, May). *Australian industries and foreign direct investment*. DFAT. https://www.dfat.gov.au/trade/resources/investment-statistics/australian-industries-and-foreign-investment

Donovan, C., & Schnure, C. (2011). Locked in the house: Do underwater mortgages reduce labor market mobility?. Available at SSRN 1856073.

Ferreira, F., Gyourko, J., & Tracy, J. (2010). Housing busts and household mobility. *Journal of Urban Economics*, 68(1), 34-45.

Gaigné, C., Koster, H. R., Moizeau, F., & Thisse, J. F. (2022). Who lives where in the city? Amenities, commuting and income sorting. *Journal of Urban Economics*, 128, 103394.

Gauder, M., Houssard, C., & Orsmond, D. (2014). *Foreign Investment in Residential Real Estate*. Reserve Bank of Australia. https://www.rba.gov.au/publications/bulletin/2014/jun/pdf/bu-0614-2.pdf

Jin, E., Kim, D., & Jin, J. (2022). Commuting time and perceived stress: Evidence from the intra- and inter-city commuting of young workers in Korea. *Journal of Transport Geography*, *104*, 103436. https://doi.org/10.1016/j.jtrangeo.2022.103436

Kim, J. S., Wang, L. C. (2023). The differential effects of exchange rate fluctuations on local housing price growth: evidence from Australia. *Regional Studies*, forthcoming. https://doi.org/10.1080/00343404.2023.2187044

Larsen, G. (2013). *Family Migration to Australia* (Vol. 23). Parliamentary Library.

Liang, J., Koo, K. M., & Lee, C. L. (2021). Transportation infrastructure improvement and real estate value: impact of level crossing removal project on housing prices. *Transportation*, *48*(6), 2969–3011. https://doi.org/10.1007/s11116-020-10157-1

Li, T., Dodson, J., & Sipe, N. (2018). Examining household relocation pressures from rising transport and housing costs – An Australian case study. *Transport Policy*, *65*, 106–113. https://doi.org/10.1016/j.tranpol.2017.03.016

Mattingly, K., & Morrissey, J. (2014). Housing and transport expenditure: Socio-spatial indicators of affordability in Auckland. *Cities*, *38*, 69–83. https://doi.org/10.1016/j.cities.2014.01.004

Mitra, S. K., & Saphores, J. M. (2019). Why do they live so far from work? Determinants of long-distance commuting in California. *Journal of Transport Geography*, *80*, 102489. https://doi.org/10.1016/J.JTRANGEO.2019.102489

Moallemi, M., Melser, D., Chen, X., & De Silva, A. (2022). The globalization of local housing markets: Immigrants, the motherland and housing prices in Australia. *The Journal of Real Estate Finance and Economics*, 65(1), 103-126.

The Organization for Economic Cooperation and Development. (2021). *Hc1.1 Housing-Related Expenditure of Households*. https://www.oecd.org/els/family/HC1-1-Housing-related-expenditure-of-households.pdf.

Renne, J. L., Tolford, T., Hamidi, S., & Ewing, R. (2016). The cost and affordability paradox of transit-oriented development: A comparison of housing and transportation costs across transit-oriented development, hybrid and transit-adjacent development station typologies. *Housing Policy Debate*, *26*(4–5), 819–834. https://doi.org/10.1080/10511482.2016.1193038

Rogers, D., Lee, C. L., & Yan, D. (2015). The politics of foreign investment in Australian housing: Chinese investors, translocal sales agents and local resistance. *Housing Studies*, *30*(5), 730–748. https://doi.org/10.1080/02673037.2015.1006185

Saberi, M., Wu, H., Amoh-Gyimah, R., Smith, J., & Arunachalam, D. (2017). Measuring housing and transportation affordability: A case study of Melbourne, Australia. *Journal of Transport Geography*, *65*, 134–146. https://doi.org/10.1016/j.jtrangeo.2017.10.007

Saiz, A. (2007). Immigration and housing rents in American cities. *Journal of Urban Economics*, *61*(2), 345–371. https://doi.org/10.1016/j.jue.2006.07.004

Schouten, A. (2021). Residential location and household spending: Exploring the relationship between neighborhood characteristics and transportation and housing costs. *Urban Affairs Review*, 107808742110288. https://doi.org/10.1177/10780874211028814

Surprenant-Legault, J., Patterson, Z., & El-Geneidy, A. M. (2013). Commuting trade-offs and distance reduction in two-worker households. Transportation Research Part A: Policy and Practice, 51, 12-28. https://doi.org/10.1016/j.tra.2013.03.003

Tsai, I. C. (2018). Housing price convergence, transportation infrastructure and dynamic regional population relocation. *Habitat International*, *79*, 61–73. https://doi.org/10.1016/J.HABITATINT.2018.07.004

Vidyattama, Y., Tanton, R., & Nepal, B. (2013). The effect of transport costs on housing-related financial stress in Australia. *Urban Studies*, *50*(9), 1779–1795. https://doi.org/10.1177/0042098012468342

Watson, N., &Wooden, M. P. (2012). The HILDA survey: a case study in the design and development of a successful household panel survey. *Longitudinal and Life Course Studies*. https://doi.org/10.14301/llcs.v3i3.208

White, M. J. (1988). Location choice and commuting behavior in cities with decentralized employment. *Journal of Urban Economics*, 24(2), 129-152.

Winke, T. (2021). Housing affordability sets us apart: The effect of rising housing prices on relocation behaviour. *Urban Studies*, *58*(12), 2389–2404. https://doi.org/10.1177/0042098020943482

Table 1: Descriptive statistics of the final dataset

	Mean	SD	Min.	Max.
Work commute time	2.602	3.692	0	50
Relocation	0.167	0.167	0	1
Expenditure share of motor vehicle fuel	0.058	0.051	0	1
Expenditure share of public transport and taxi	0.010	0.025	0	0.852
Expenditure share of total transport	0.068	0.053	0	1
Housing cost	26,021	12,236	1,863.4	222,457
ln(housing cost)	10.070	0.441	7.530	12.312
IV- foreign investment	0.014	0.021	0.000	0.144
High-education indicator	0.403	0.490	-12.251	-1.941
Indicator for living in metropolitan LGAs	0.681	0.466	0	1
Age	43.352	18.488	14	101
Income in the previous year	36,328	35,747	-495,686	928,682
Total population in an LGA	182,400	228,766	489	1184,753
IV - immigration	33,081	43,104	-0.286	221,047

Notes: The descriptive statistics are averaged over 178,211 observations except the income in the previous year, which is averaged over 173,940 observations. SD refers to the standard deviation. Lagged population in the LGA refers to population in the previous census year.

Table 2: The effects of housing cost on household transportation - POLS and FE estimations

	(1) Work commute time	(2) Relocation	*Expenditure share* (3) Motor vehicle fuel	(4) Public transport and taxi	(5) Total transport
A. POLS estimation					
ln(housing cost)	1.236***	-0.001	-0.020***	0.012***	-0.008***
	(0.084)	(0.010)	(0.002)	(0.001)	(0.001)
Individual fixed effects	No	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	178,211	178,211	152,558	152,558	152,558
R-squared	0.020	0.000	0.042	0.031	0.019
B. FE estimation					
ln(housing cost)	0.577***	0.054***	-0.010***	0.008***	-0.003**
	(0.080)	(0.016)	(0.001)	(0.001)	(0.001)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	178,211	178,211	152,558	152,558	152,558
R-squared	0.004	0.005	0.027	0.004	0.020
Number of persons	19,152	19,152	17,906	17,906	17,906

Notes: Robust standard errors clustered at the LGA-level are reported in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

.

Table 3: The effects of housing cost on household transportation - FE-IV estimation

			Expenditure share		
	(1) Work commute time	(2) Relocation	(3) Motor vehicle fuel	(4) Public transport and taxi	(5) Total transport
Second stage:					
ln(housing cost)	2.276***	0.144**	-0.022***	0.016***	-0.006
	(0.267)	(0.068)	(0.004)	(0.003)	(0.005)
First stage:					
IV- foreign investment	0.092***	0.092***	0.085***	0.085***	0.085***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	15,349.9	15,349.9	11,828.7	11,828.7	11,828.7
Stock-Yogo 10% critical value	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F statistics	84.55	4.10	24.59	39.20	1.40
Anderson-Rubin p-value	[0.00]	[0.04]	[0.00]	[0.00]	[0.24]
Observations	178,211	178,211	152,558	152,558	152,558
Number of persons	19,152	19,152	17,906	17,906	17,906

Notes: See Section 3 for a detailed description of how the foreign investment IV is constructed. Robust standard errors clustered at the LGA-level are reported in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 4: Heterogeneity – Relocators and non-relocators

		Expenditure share		
	(1)	(2)	(3)	(4)
	Work commute time	Motor vehicle fuel	Public transport and taxi	Total transport
A. Relocators				
Second stage:				
ln(housing cost)	6.459***	0.019	0.023	0.042*
	(1.225)	(0.021)	(0.014)	(0.025)
First stage:				
IV-foreign investment	0.025***	0.020***	0.020***	0.020***
	(0.003)	(0.003)	(0.003)	(0.003)
Individual fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	157.8	88.27	88.27	88.27
Stock-Yogo 10% critical value	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F statistics	27.67	0.871	2.832	3.155
Anderson-Rubin p-value	[0.00]	[0.35]	[0.09]	[0.08]
Observations	25,077	20,781	20,781	20,781
Number of persons	7,182	6,269	6,269	6,269
B. Non-relocators				
Second stage:				
ln(housing cost)	1.675***	-0.026***	0.015***	-0.011**
	(0.246)	(0.004)	(0.002)	(0.005)
First stage:				
IV-foreign investment	0.134***	0.131***	0.131***	0.131***
	(0.008)	(0.008)	(0.008)	(0.008)
Individual fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	24,696.0	20,946.9	20,946.9	20,946.9
Stock-Yogo 10% critical value	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F statistics	53.81	34.85	39.81	6.05
Anderson-Rubin p-value	[0.00]	[0.00]	[0.00]	[0.01]
Observations	147,266	126,237	126,237	126,237
Number of persons	17,697	16,563	16,563	16,563

Notes: Panel A reports FE-IV estimates when restricting the sample to individuals who have relocated since the previous year. Panel B reports the same for individuals who have the same address as the previous year. Robust standard errors clustered at the LGA-level are reported in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 5: Heterogeneity – High and low education levels

	(1) Work commute time	(2) Relocation	*Expenditure share* (3) Motor vehicle fuel	(4) Public transport and taxi	(5) Total transport
A. High education level					
Second stage:					
ln(housing cost)	1.330***	0.117	-0.019***	0.006*	-0.013*
	(0.422)	(0.103)	(0.006)	(0.003)	(0.007)
First stage:					
IV- foreign investment	0.090***	0.090***	0.087***	0.087***	0.087***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	5,820.5	5,820.5	4,707.1	4,707.1	4,707.1
Stock-Yogo 10% critical value	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F statistics	11.04	1.212	10.71	3.439	3.720
Anderson-Rubin p-value	[0.00]	[0.27]	[0.00]	[0.07]	[0.06]
Observations	71,771	71,771	61,108	61,108	61,108
Number of persons	7,163	7,163	6,739	6,739	6,739
B. Low education level					
Second stage:					
ln(housing cost)	2.205***	0.032	-0.022***	0.017***	-0.005
	(0.423)	(0.064)	(0.006)	(0.003)	(0.007)
First stage:					
IV-foreign investment	0.094***	0.094***	0.086***	0.086***	0.086***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	6,707.9	6,707.9	4,692.3	4,692.3	4,692.3
Stock-Yogo 10% critical value	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F statistics	31.30	0.247	12.29	38.39	0.422
Anderson-Rubin p-value	[0.00]	[0.62]	[0.00]	[0.00]	[0.52]
Observations	74,930	74,930	61,464	61,464	61,464
Number of persons	7,653	7,653	6,909	6,909	6,909

Notes: Panel A reports FE-IV estimates when restricting the sample to individuals with a high level of education. Panel B reports the same for individuals who have a low education level. Robust standard errors clustered at the LGA-level are reported in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 6: Heterogeneity - Metropolitan and non-metropolitan areas

			Expenditure share		
	(1) Work commute time	(2) Relocation	(3) Motor vehicle fuel	(4) Public transport and taxi	(5) Total transport
A. Metropolitan areas					
Second stage:					
ln(housing cost)	2.073***	-0.152*	-0.026***	0.015***	-0.011
	(0.411)	(0.090)	(0.006)	(0.004)	(0.008)
First stage:					
IV- foreign investment	0.083***	0.083***	0.076***	0.076***	0.076***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	7,840.2	7,840.2	5,917.0	5,917.0	5,917.0
Stock-Yogo 10% critical value	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F statistics	30.59	3.196	14.67	12.58	1.818
Anderson-Rubin p-value	[0.00]	[0.08]	[0.00]	[0.00]	[0.18]
Observations	121,330	121,330	104,349	104,349	104,349
Number of persons	13,018	13,018	12,202	12,202	12,202
B. Non-metropolitan areas					
Second stage:					
ln(housing cost)	2.342***	0.458***	-0.018***	0.017***	-0.000
	(0.298)	(0.054)	(0.006)	(0.002)	(0.006)
First stage:					
IV-foreign investment	0.106***	0.106***	0.101***	0.101***	0.101***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	7,818.7	7,818.7	6,165.0	6,165.0	6,165.0
Stock-Yogo 10% critical value	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F statistics	76.51	104.61	10.02	51.71	0.000
Anderson-Rubin p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.98]
Observations	56,881	56,881	48,209	48,209	48,209
Number of persons	6,134	6,134	5,704	5,704	5,704

Notes: Panel A reports FE-IV estimates when restricting the sample to individuals who live in metropolitan areas for the majority of the sample period. Panel B reports the same for individuals who live in non-metropolitan areas for the majority of the sample period. Robust standard errors clustered at the LGA-level are reported in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 7: Robustness - Main results

	(1) Work commute time	(2) Relocation	*Expenditure share* (3) Motor vehicle fuel	(4) Public transport and taxi	(5) Total transport
A. Full sample, including immigrants					
Second stage:					
ln(housing cost)	2.154***	0.160**	-0.023***	0.017***	-0.006
	(0.241)	(0.066)	(0.004)	(0.002)	(0.005)
First stage:					
IV- foreign investment	0.091***	0.088***	0.082***	0.082***	0.082***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	18,081.0	27,351.9	21,214.7	21,214.7	21,214.7
Stock-Yogo 10% critical value	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F statistics	83.96	5.210	31.23	63.77	1.569
Anderson-Rubin p-value	[0.00]	[0.02]	[0.00]	[0.00]	[0.21]
Observations	227,932	360,593	308,725	308,725	308,725
Number of persons	24,408	34,690	32,358	32,358	32,358
B. Controlling for age, income, and population, instrumenting for population					
Second stage:					
ln(housing cost)	2.200***	0.111	-0.021***	0.009***	-0.013*
	(0.395)	(0.076)	(0.005)	(0.003)	(0.006)
First stage: housing cost					
IV-foreign investment	0.078***	0.078***	0.070***	0.070***	0.070***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
IV-immigration	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
First stage: population					
IV-foreign investment	7995.0***	7995.0***	7513.74***	7513.74***	7513.74***
	(1,129.4)	(1,129.4)	(1,105.6)	(1,105.6)	(1,105.6)
IV-immigration	4.466***	4.466***	4.412***	4.412***	4.412***
	(0.157)	(0.157)	(0.154)	(0.154)	(0.154)
LGA fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	3,939.5	3,939.5	2,884.2	2,884.2	2,884.2
Stock-Yogo 10% critical value	[7.03]	[7.03]	[7.03]	[7.03]	[7.03]
Anderson-Rubin F statistics	34.83	1.890	10.54	30.47	3.956
Anderson-Rubin p-value	[0.00]	[0.15]	[0.00]	[0.00]	[0.02]
Observations	173,940	173,940	149,032	149,032	149,032
Number of persons	18,293	18,293	17,191	17,191	17,191

Notes: Panel A reports FE-IV estimates including immigrants in the sample. Panel B reports FE-IV estimates with additional controls; age, income, LGA-level population, and instrumenting for population using an immigrant IV. See Section 5 for a description of the immigrant IV. Robust standard errors clustered at the LGA-level are reported in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Appendix

Table A1: Robustness – Restricting sample to years 2005-2019

	(1) Work commute time	(2) Relocation	(3) Motor vehicle fuel	(4) Public transport and taxi	(5) Total transport
			Expenditure share		
Second stage:					
ln(housing cost)	2.070***	0.130*	-0.022***	0.016***	-0.006
	(0.294)	(0.077)	(0.004)	(0.003)	(0.005)
First stage:					
IV-foreign investment	0.085***	0.085***	0.085***	0.085***	0.085***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F statistic	11,828.7	11,828.7	11,828.7	11,828.7	11,828.7
Stock-Yogo 10% critical value	[16.38]	[16.38]	[16.38]	[16.38]	[16.38]
Anderson-Rubin F statistics	54.63	2.634	24.59	39.20	1.400
Anderson-Rubin p-value	[0.00]	[0.11]	[0.00]	[0.00]	[0.24]
Observations	152,558	152,558	152,558	152,558	152,558
Number of persons	17,906	17,906	17,906	17,906	17,906

Notes: FE-IV estimates are reported, only including years 2005-2019; when all transport variables of interest are available. Robust standard errors clustered at the LGA-level are reported in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.