Transit Infrastructure, Couples' Commuting Choices, and Household Wage Structure

Daniel Velásquez*
University of Michigan

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Abstract: I study how urban transit infrastructure affects labor supply and gender inequality in the presence of married households. In such households, labor and commuting decisions are made jointly. When one spouse earns a higher wage, the household may sacrifice a portion of the other spouse's earnings to reduce commuting costs. Therefore, improving commute times can affect one partner's commuting by impacting their prospects (direct channel) and their spouse's (indirect channel). I set up a general equilibrium model featuring single and married households and use it to study new transit infrastructure in Lima, Peru. In the counterfactual analysis, areas that experienced the largest reductions in commuting times, the gender gap in real earnings among married households decreased by 12%. However, the gap remained unchanged among single households. The gap decreased through the direct channel but increased through the indirect channel.

Keywords: Mass Transit, Gender Gap, Family, Dual-Earners, Quantitative Spatial Models, Cities in Latin America.

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1 Introduction

Urbanization brings forth advantages and challenges, some of which are specific to women. For example, some cities have a higher concentration of service industries, creating more employment opportunities for women. However, longer commutes disproportionately burden women as they try to balance their work and family responsibilities, limiting their economic gains in urban areas.[1] With the global urban population expected to increase by more than 2.5 billion by 2050, primarily in middle- and low-income countries, the challenges faced by women due to urbanization are likely to become even more pronounced.

In the face of growing urbanization, governments worldwide have invested heavily in infrastructure projects to enhance commuting in urban areas. To understand how these investments impact households, and women in particular, it is essential to consider married households which typically constitute more than 50% of all households (OECD, 2023). In such households, labor supply and commuting decisions are made jointly, which means that when one spouse earns a higher wage, the household may be willing to sacrifice a portion of the other spouse's earnings to reduce overall commuting costs. Thus, in this paper I ask: How does urban transit infrastructure affect labor supply and gender inequality in the presence of married households?

I provide new theory and evidence about the interaction of transit infrastructure and the presence of married households by studying the response to the Bus Rapid Transit system (BRT) and Line 1 subway construction in Lima, Peru. I assemble a variety of georeferenced data sets at the neighborhood level including commuting and household surveys, census, firm surveys, and infrastructure data. I start by documenting two facts. First, commuting elasticities are heterogeneous across household groups. Specifically, women's commuting flows are more sensitive to improvements in commuting times than men's, especially when women cohabit with a partner. Second, the choice of where to work depends on the spouse's commuting choice, implying that choices are interdependent within dual-earner households. These facts suggest that transit infrastructure may have gendered impacts due to the heterogeneity in commuting elasticities (Fact 1) and the interdependence in commuting choices (Fact 2). Therefore, these are two key dimensions that the model should consider.

To gain a better understanding of the interaction between commute times and within household choices, I develop a partial equilibrium model of commuting for married household. I microfound the partial equilibrium model by utilizing a standard framework in family eco-

[1] Ngai and Petrongolo (2017) show that the rise of services raises women's relative wages and market hours in the U.S. Moreover, Black, Kolesnikova, and Taylor (2014) show that labor force participation rates of married women are negatively correlated with the metropolitan area commuting time in the U.S. Barbachon, Rathelot, and Roulet (2021) show that gender differences in commute valuation can account for 14% of the residualized gender wage gap in France. Liu and Su (2022) find that gender differences in commuting preferences lead to a gender wage gap only if there is a wage penalty for shortening commutes in the U.S.

nomics, that is, by assuming that married households achieve Pareto efficiency. This approach explicitly takes account of the fact that married households consist of several members sharing the same budget constraint. The main implication is that commuting choices are interdependent across spouses as suggested by Fact 2. Hence, there are two channels through which improved commute times can affect households. On the one hand, the *direct use channel* is the mechanism present in the standard class of spatial models. It says that when times between origins and destinations improve, income at origins increases only if the new destinations are high-wage locations. Otherwise, if the new destinations are low-wage locations, improvements in commuting times may induce some workers to give up some of their earnings to have a shorter commute. On the other hand, the *indirect use channel* (or within-household spillovers) says that, when commute costs for one of the spouses decreases leading to higher household earnings, the household becomes more willing to sacrifice the other spouse's earnings in order to decrease her commute costs. Thus, the final impact on the gender gap through these two channels depends on the geography of commute times improvements and the distribution of male and female wages across locations.

Next, I embed the partial equilibrium model of commuting choices for married households into a general equilibrium model of city structure in the spirit of Ahlfeldt et al. (2015) and Tsivanidis (2021). In order to bring the model to the data, I consider both single and married households. I allow for commuting elasticities to be heterogeneous across genders and civil status, which is consistent with Fact 1. Moreover, the model includes a residential location choice with location elasticities that differ between single and married households. In addition, married households can choose to be either dual-earner or male-breadwinner households, meaning that they can evaluate whether to send both spouses to the labor market or to have one spouse specialize in household production. Thus, this is a labor participation choice for married women.[2] From the production side, the model includes multiple sectors that employ workers of each gender with a certain degree of substitution, allowing for the presence of gender gaps in the workplace (Acemoglu et al., 2004). Finally, the model allows for endogenous sectoral TFP to account for density effects (Rosenthal and Strange, 2012; Ahlfeldt, et al., 2015; Tsivanidis, 2021).

I calibrate and estimate the model using Peruvian data. To estimate commuting elasticities, I exploit data on bilateral flows and times, in addition to the gravity structure of the model for commuting probabilities. Moreover, to estimate scale elasticities, I leverage the introduction of the new transit infrastructure to construct instruments. Once parameters are estimated I show that the model with interdependent commuting choices within couples fits

[2] I assume that married households are comprised of a male individual, i.e. the husband, and a female individual, i.e. the wife. A simplifying assumption usually done in the literature on family economics is that the husband always works. Moreover, in the data female breadwinner households constitute just 1.3% of all households. This is why I turn off this margin: it does not seem to be quantitatively important but would add greater complexity to the model.

better the data on bilateral commuting flows of dual-earner households than a model with independent commuting choices.

To understand the impact of improving commute times on gender inequality, I study a counterfactual where commute times are set to pre-Metro and BRT implementation levels. This exercise allows me to understand how improving commute times affects income by gender, the quantitative importance of the direct and indirect margins, and the relevance of general equilibrium effects.

First, I find that improving commute times decreased the gender gap in aggregate earnings among couples by more than 12% in the fringe of the city, that is, in the set of locations that gained access the most.[3] However, the gap remained constant among singles. Second, on average, income increased for males and females. Third, a decomposition analysis indicates that commuting times decreased more significantly along the routes used by married women than those used by married men. This, coupled with the higher elasticity of commuting with respect to commute time for women (Fact 1), contributed to a decrease in the gender gap through the direct use channel. Fourth, the interdependence in commute choices within married households (Fact 2) worsened gender inequality through the indirect use channel. Absent the indirect use channel and considering all locations in the city, the gender gap in dual earner households would have decreased 25% more. This is due to some households willing to give up a portion of the wife's earnings to reduce the household's overall commuting costs. Finally, general equilibrium effects marginally widened the gap due to women's increased labor supply interacting with a downward sloping labor demand.

Last, I perform a policy counterfactual exercise and predict what would happen if the planned network of Metro lines is constructed. The purpose of this counterfactual exercise is to quantify the importance of the Metro network in affecting the gender inequality when a different set of locations experience an improvement in commute times. My results show that the gap in aggregate earnings among married in remote locations would decrease by 16%. My analysis demonstrates that, once again, the direct use channel explains most of the reduction and the indirect use margin tends to widen the gap.

Literature

First, this paper contributes to the literature of economic geography and of urban structure. By relying on models with a single income earner per household, this literature shows that improving commute times through a BRT (Tsivanidis, 2021), a Metro system (Severen, 2021; Zarate, 2021), steam railways (Heblich et al., 2020) or cable cars (Khanna et al., 2022) can

[3] The gap is defined as $\frac{\text{Male income}}{\text{Female income}}$ where in this example, males and females belong to married households. So, an effect of 12% means that female income grew 12 percentage points faster than male income: $\Delta \log(\text{Male income}) - \Delta \log(\text{Female income}) = -12\%$.

have major impacts on many margins such as housing, employment, crime, informality, and welfare.[4] However, real households typically have multiple members, and this aspect is likely to be relevant when assessing the effects of new transit infrastructure. For example, Blundell et al., (2007) document that labor supply responses of couples depend on how they share resources within the household. This way, my paper bridges the field of family and household economics to the field of economic geography. I highlight that incorporating other members to households changes the way households are affected by reductions in commute costs. Specifically, since each member contributes to the household's total income, exposure to various shocks such as commute cost reductions depends on the degree of exposure and relative importance of each income source. Hence, reduced commute times can impact commuting choices through two channels: by affecting an individual's prospects and by affecting those of their spouse.[5] I also contribute to the literature on economic geography by providing new estimates of agglomeration forces. Most estimates of agglomeration forces exploit variation of *overall* employment *across regions* for identification (e.g. Rosenthal and Strange, 2004; Combes et al., 2008; De la Roca and Puga, 2017). Rather I estimate *sectoral* agglomeration forces *within a city*.[6]

Second, this paper contributes to the literature on family and household economics, which encompasses two main areas: the dynamics within existing unions and mate selection (Browning et al., 2011). My work mainly contributes to the first strand by showcasing how relaxing time constraints can impact earnings inequality within households through spouses' choices (see Chiappori, et al. (2022) for a review). This paper also illustrates how the family dynamic can influence decisions related to the spatial aspect of the data, such as choices about where to live and where to commute.

Third, this paper relates to the literature that examines the trade-off between wages and non-wage job characteristics across genders. Le Barbanchon et al. (2021) use French administrative data on job search criteria and document that unemployment women have a shorter maximum acceptable commute than unemployed men. Using a job search model, they estimate that gender differences in commute valuation account for 14% of the residualized gender wage gap. Field and Vyborny (2022) through means of an experiment in Pakistan show that

[4] See as well: Ahlfeldt et al. (2015), Allen et al. (2015), Monte et al. (2018), Owens III et al. (2020), and Brinkman and Lin (2022).

[5] A similar logic could be applied to reductions in trade costs and productivity shocks. When a household's income relies on multiple sources, the impact of a shock to any given source will be greater if that source contributes a larger portion of the household's total income. In other words, the more important a source of income is to the household, the more vulnerable they are to any disruptions or changes to that source. Thus, the conclusions I extract from this analysis can be extended to trade and economic geography models. See Redding and Rossi-Hansberg (2017) for a review of spatial quantiative models.

[6] There are only a few papers estimating sectoral agglomeration forces within a city (e.g. Zarate, 2021). Examples of within-city estimates for a single sector are Ahlfeldt et al. (2015), Tsivanidis, (2021), and Heblich et al. (2020).

reducing mobility constraints has a large impact on job searching for women. Liu and Su (2022) utilizing U.S. data show that the commuting and wage gaps are considerably smaller among workers living near city centers, especially for occupations with a high geographic concentration of high-wage jobs. They highlight that the geography of jobs amplifies the impact of commuting preferences on the gender wage gap. A related literature also indicates that gender differences in the relationship between commuting and employment tend to be magnified among married individuals. Black et al. (2014) document a very large variation in the labor supply of married women across U.S. cities due to differences in commuting times. Kawabata and Abe (2018) examine the relationship between commute times and female labor force participation within Tokyo, showing that it differs markedly across households of different civil status. Alam et al. (2021) document a similar finding for Mumbai. Carta and De Philippis (2018) explore the relationship between husbands' commuting times and wives' employment and family time allocation in Germany, revealing that a 1% increase in the husband's commuting distance reduces his wife's employment probability by 0.016 percentage points. Gu et al. (2021) use administrative records of home mortgages in Beijing and show that dual-income households systematically buy homes that are closer to the wife's workplace. My contribution to this literature is to incorporate the family and spatial dimension together into a single tractable general equilibrium model, allowing me to quantify the aggregate impact of new transit infrastructure in the presence of married households. As a by-product, this framework also provides me with the means to quantify the importance of female labor force participation and the location choice in shaping the aggregate impact of transit infrastructure.

Fourth, my paper contributes to recent work in macroeconomics studying how family and gender have repercussions on the aggregate. Doepke and Tertlit (2016) argue that family economics should be an integral part of macroeconomics, since accounting for family have important consequences on short-term fluctuations and long-term development though savings and labor supply choices. Mankart and Oikonomou (2017) set up a model with labor market frictions and multiple-member households. They use the model to explain cyclical properties of aggregate employment. Bardóczy (2022) develops a Heterogeneous Agent New Keynesian model with dual-earner households providing insights regarding the role of spousal labor supply as insurance to busts along the business cycle. My work contributes to this research by showcasing that, even in a static model, the family structure may have important implications on the determination of aggregates once that we account for the spatial distribution of economic activity.

2 Lima's Metro and Bus Rapid Transit System

Lima is an ideal setting to perform this study for several reasons. First, as the political and economic hub of Peru, it comprises 30% of the population and 40% of the country's GDP, leading to a diverse range of economic activities across the region. Manufacturing, commerce, construction, and services are among the primary sectors, with the region of Lima contributing over 50% of their respective GDPs. These industries often exhibit gender-based disparities in employment opportunities, further accentuating the variation in labor prospects across different locations within the city. Second, Lima's significant traffic congestion is worth noting, with buses serving as the primary mode of transportation for 69% of work trips in 2010 (before the new transit infrastructure were introduced), followed by taxis, 'colectivos', or motorbike taxis (11%), and personal cars (9%). Third, there exist differences in commuting patterns based on gender and civil status. According to time use surveys, men make up over 60% of total commute time. Furthermore, married men account for more than 70% of total commute time among married workers, indicating the possibility of specialization in commuting roles within households. This pattern is consistent with findings from other countries. Fourth, and mainly, two transportation infrastructures were implemented in recent years, generating variation in transportation access across different locations within the city. These were the Line 1 of the Metro and the Bus Rapid Transit System (BRT).

The Line 1 of the Metro is a 34.4 km long transportation system that serves over 500,000 daily passengers. The first 22 km were completed in 2011, with the remaining 12.4 km completed in 2014. Although the Metro does not directly cross through the central business district, it runs through high-demand areas, including one of the most significant commercial centers in the city, the "Gamarra" market (see Figure B.1). The Metro has significantly improved commuting times, with travel times reduced from 2 hours and 45 minutes to just one hour for end-to-end trips. On average, work trips on the Metro take around 24 minutes (JICA, 2013).

The introduction of the BRT system in Lima occurred around 2010. Typically, a BRT system consists of a dedicated system of roadways for buses and has been successfully implemented in cities such as Bogota and Buenos Aires. The goal of the BRT system is to provide faster speeds while maintaining the simplicity of a bus system. As shown in Figure B.2, Lima's BRT system connects the fringe to the modern districts, as well as the central business district (CBD). The system spans 26 km and serves approximately 700,000 passengers daily. A World Bank study found that commuting times were reduced by approximately 25-45% as a result (Oviedo et al., 2019).

3 Data Sources and Stylized Facts

I start by briefly summarizing the data sources. Then, I explain two stylized facts highlighting how commuting might be different for couples compared to singles. Finally, in Appendix A2, I present a set of reduced-form impacts of the new transit infrastructure..

3.1 Data sources

For this paper's analysis, I require several sources of data geographically identified at a fine scale. A zone is a set of 25 blocks approximately. A block is the finest available disaggregation used by the National Institute of Statistics and Informatics. Lima in 2017 was partitioned into more than 30,000 blocks and more than 1500 zones. My analysis is performed always at the zone level. Hence, throughout the paper, I refer to zones and blocks interchangeably.[7]

In particular, (i) I use the Population Census from 1993, 2007 and 2017 to get residence counts at the zone level for single men and women, and cohabiting couples. (ii) I also use the Economic Census of 2008 and an open administrative data for firms' location and employment figures in 2015 to calculate employment levels at the block-by-industry level (available here). To compute commuting flows, I rely on several sources of data. (iii) I use the Population Census from 2017, which has data on commuting flows at the municipality level. (iv) I complement this with several commuting surveys collected during 2010-2018 for the city of Lima. Then, (v) I use data on the road network from Open Street Maps and Google Maps API. Furthermore, (vi) I use the National Household Survey (ENAHO) from 2007-2017 waves, which is precisely georeferenced, to analyze rents at the zone level. (vii) Data on land use come from the Metropolitan Institute of Planning of Lima. Finally, (viii) I use the 2010 National Time Use survey to complement the data on commute times. Using my data set, I document two stylized facts that motivate my empirical design and modeling approach.

More information about the data is available in the Data Appendix, which can be found in Section A1.

3.2 Stylized facts

The following stylized facts motivate the idea of incorporating married households into standard spatial models.

Fact 1: Commuting elasticity differs by civil status and gender. Using the Population Census, I classify households into five different groups. The first two consist of (i) *single females* and (ii) *single males*, which comprises 31.9% and 35.9% of households in 2017. Then I consider

[7] I also use the word "location" to refer to zones. When talking about commuting, I use the word "origin" to refer to the zones where households live, and "destination" to refer to the zones where households work.

(iii) *male breadwinner* households, that is, households where the wife stays at home while the husband goes to work (13.3% of households). For the sake of completeness, I also consider (iv) *female breadwinner* households, although they just constitute 1.3% of households. Finally, I consider (v) *dual-earner* households, which represent 17.6% of households. For each of these groups, I run the following reduced form regression:

$$\log \pi_{j|i,k} = \beta_k time_{ij} + FE_{i,k} + FE_{j,k} + \varepsilon_{ij} \tag{1}$$

where $\pi_{j|i,k}$ is the share of members of civil status-by-gender k that live in origin location i that commute to location j.[8] $time_{ij}$ is the time that takes to commute from i to j. Moreover, $FE_{i,k}$ and $FE_{j,k}$ are fixed effects by origin i and destination j. Finally, β_k is the *commuting elasticity*, that is, it measures how the probability of commuting to j would change in relative terms after increasing the commuting time by one minute.

To compute commuting probabilities $\pi_{j|i,k}$ I rely on the 2017 population Census, and aggregate the data at the district level.[9] I measure commuting times by zones using two data sources: Open Street Maps (OSM) and the 2010-2018 waves of Lima's Commuting Survey. I assign speeds to match documented speed times in Lima. I then aggregate these times to the district level by taking the median value across zones within districts. I show that these times are well correlated with times reported in commuting surveys (see Figure B.3).

Table 1 shows the result of estimating this equation by PPML. Columns (1) and (2) show commuting elasticities for single males and females, respectively. These estimates suggest that single females are 20% more sensitive to changes in commuting times than single males. This difference is statistically significant at the 1% level. Columns (3) and (4) exhibit these estimates for breadwinner households. Comparing males and females in breadwinner households leads to a similar conclusion. Females are more sensitive than males in breadwinner households and the gap widens to 36%. This difference is statistically significant at the 1% level. Finally, columns (5) and (6) deliver the estimates for males and females in dual-earner households, showing that females are 40% more sensitive than males. This difference is statistically significant at the 1% level.

Figure 1 depicts the bin scatter between the residual of log commuting probabilities, net of origin and destination fixed effects, and the residual of commuting times. Panel A does it for singles, while Panel B for married in male and female breadwinner households. The graph confirms the log-linear relationship between commuting probabilities and commuting times, and the fact that the gap in elasticities is wider among the married.

All in all, these results show that women are more sensitive to improvements in commuting

[8] I use the word 'Married' to refer to couples in a general sense. See Section A1 for more information.

[9] While I can locate the origin of households at the block level, the data only records the destination district, and so I perform this analysis at the district level.

times than men especially when cohabiting with a partner, which is in line with previous findings in the literature about the trade-off between wages and non-wage job attributes. Hence, the model should allow for heterogeneity in commuting elasticities.

Fact 2: Choice of where to work depends on spouse's choice. In dual-earner households, the choice of where to work depends on the spouse's destination choice. To see this, first, note that if the household cares about some weighted average of the members' utility, then the household will dislike members commuting to locations farther away. Second, conditioning on the first spouse's destination, the utility that the household derives from sending the other spouse to some destination may depend on the income the first spouse is already bringing to the household. For example, if one of the spouses is already commuting to a high wage location, thus increasing household income, then the other spouse's supply may be less sensitive to further increases in her own wage. This is akin to a classic result in labor economics where an income effect may reduce the labor supply elasticity (Blundell et al., 2007).

I can test whether commuting probabilities of one spouse depend on those of the other spouse by leveraging the fact that I observe each member's commuting choice in dual-earner households. This allows me to compute *conditional* commuting probabilities. In turn, I can test whether the interaction of destinations is predictive of conditional commuting probabilities once that I partial out each member's independent reasons to work in such locations, such as expected earnings. In a world with interdependence, the interaction of destinations should be highly predictive of conditional commuting probabilities once that I control for each members' independent reasons to work in a particular destination pair.

I denote the conditional probability of member g of working in location j given that the spouse commutes to j' and lives in i as $\pi_{j|ij',g}$. I compute commuting probabilities at the district level. Given the city has say 50 locations, this object has $50 \times 50 \times 50$ cells as spouse g living in i can commute to j, while the other commute to j'. I estimate the following regression for each member in dual-earner households:

$$\log \pi_{j|ij',g} = \beta time_{ij} + FE_{i,j',g} + FE_{j,j',g} + \varepsilon_{ijj',g} \tag{2}$$

where $FE_{i,j',g}$ are a set of origin-spouse's destination fixed effects, which control for the fact that certain origin-spouse's destination pairs may provide greater access to labor markets to member g. Special focus should be given to $FE_{j,j',g}$, which are a set of destination pairs fixed effects controlling for the fact that certain destination pairs might be more desirable than others.

My procedure goes as follows. First, I estimate the previous equation. Then, I recover the estimates of $FE_{j,j',g}$. If one's choice depends on the other spouse's choice, then the residual of $FE_{j,j',g}$—after controlling for fixed effects at one's own location j and the spouse's location j'—should be predictive of commuting probabilities as noted above.[10] That is, the coefficient ψ from $\log \pi_{j|j',g} = \psi_g \hat{FE}_{j,j'} + FE_j + FE_{j'}$ should be different than zero. The greater the value of ψ, the lesser that choices are independent.[11]

I show that this is in fact true. Figure 2 depicts a scatter plot between residualized commuting probabilities and the residuals of $FE_{j,j'}$. Panel A depicts this plot for husbands while Panel B, for wives. We can see that residualized $FE_{j,j'}$ are highly predictive of residualized commuting probabilities for both spouses. In fact, $\hat{\psi} = 0.87$ for males, while $\hat{\psi} = 0.54$ for females.

One could still argue that this procedure is capturing anything that varies at the destination-pair level, but that is unrelated to the joint decision that partners make regarding their commuting. I now provide suggestive evidence of the income effect explained above. Using firm-survey data, I compute average wages by gender across locations. I drop the destination-pair fixed effect in equation 2 and instead add the average wage at destination j (where g commutes to) and the average wage at destination j' (where the spouse commutes to). Moreover, I interact wages at one's destination with the total income the couple would obtain at a destination pair j, j'. I show the results of this specification in Table B.1. These results show that the greater the household income, the lesser the sensitivity to further increases in one's own wage. Moreover, there is some heterogeneity around the average own-gender wage elasticity.[12] In the case of husbands in dual-earner households, this elasticity goes between 1.856% and 3.054% (column 1), whereas for wives this elasticity goes between 1.178% and 1.914% (Column 2).

To sum up, the evidence I provide suggests that women are more sensitive to improvements in commute times, and that commuting choices are interlinked in dual-earner households. In the theoretical and quantitative section of the paper I quantify how important is this interdependence when evaluating the impact of new transit infrastructure.

Reduced-form evidence. The new transit infrastructure can impact households through improved commuting times and changes in local amenities and land prices (Brinkman and Lin, 2022). Using census data and household surveys, I explore these issues with reduced-form specifications, which capture the overall impact, in Appendix A2.

[10] I also control for the time it takes to go from workplace in j to workplace in j' to take into account that couples may decide destinations partially based on the distance between jobs.

[11] For simplicity note that I have averaged $\pi_{ij|j',g,k}$ over origins, and so $\pi_{j|j',g}$ is the average probability than one commutes to j given that his or her spouse commutes to j'.

[12] I obtain average wages for each gender from the 2015-2017 waves of the national firm-level survey data. I have demeaned the variable for log total income, hence the coefficient associated to one's own gender's wages yields the average elasticity.

4 Theory

To build intuition, I set up a simple model of commuting only with married households. Then, I study the model's implications. In Section 5, I embed this choice structure into a spatial model of city structure.

4.1 Microfoundation of a household utility for married households

Environment. City consists of N married households distributed in J locations. Locations are indexed by i, j or j'. Spouses are indexed by k or k' (or h and w when indicated).

Preferences for each spouse are defined by V_{ij}^k, which is the utility of spouse k living in i and working in j, such that:

$$V_{ij}^k \quad = \quad \log \frac{C_{k,i}^{\beta^k} H_{R_i}^{1-\beta^k}}{d_{ij}^k} \tag{3}$$

where $C_{k,i}$ is the consumption of family member k of the final good, H_{R_i} is the household consumption of residential floorspace. Note that residential floorspace is a public good within the couple, which explains why I drop the k subscript. d_{ij}^k is an iceberg commuting cost $d_{ij}^k = \exp(\kappa_k t_{ij})$. t_{ij} is the time it takes to commute to j from i, and κ_k is the rate at which commute times are transformed into commute costs.

The household budget constraint is:

$$PC_{k,i} + PC_{k',i} + r_{R_i} H_{R_i} = w_{k,j} + w_{k',j'}$$

where P is the price of the final good, which does not depend on the origin location, because in the quantitative exercise I assume that the final good is freely traded within the city. r_{R_i} is the rental value of the residential floorspace. Finally, $w_{k,j}$ is the wage received by member k when working at j, whereas $w_{k',j'}$ is the wage received by the other member at j'.

Optimal consumption of the final good and floorspace. Following the literature on family economics, I assume households only choose efficient outcomes (Browning et al., 2011). That is, conditional on residential and workplace locations, for any given vector of prices and wages $(P, r_{R_i}, w_{k,j}, w_{k',j'})$ and location characteristics $(d_{ij}^k, d_{ij'}^{k'})$, an allocation $(C_{k,i}, H_{R_i})$ is efficient if there exists a feasible $\bar{V_{ij}}^{k'}(P, r_{R_i}, w_{k,j}, w_{k',j'})$ such that $(C_{k,i}, H_{R_i})$ solves the problem:

$$\begin{aligned}
\max_{C_{k,i}, H_{R_i}} \quad & V_{ij'}^k \\
\text{s.t.} \quad & PC_{k,i} + PC_{k',i} + r_{R_i} H_{R_i} = w_{k,j} + w_{k',j'} \\
\text{and} \quad & V_{ij}^{k'} \geq \bar{V_{ij}}^{k'}(P_i, r_{R_i}, w_{k,j}, w_{k',j'})
\end{aligned}$$

This maximization problem can be broken into two stages. In the first stage, households choose the optimal level of residential floorspace H_{R_i} and the disposable income allocated to each spouse, $x_{k,i}, x_{k',i}$. In the second, each spouse allocates their income into the consumption of the final good. Then, the first stage becomes:

$$\begin{aligned} \max_{x_{k,i}, H_{R_i}} \quad & W_{ijj'} \equiv \lambda V_{ij'}^{k'} + V_{ij}^{k} \\ \text{s.t.} \quad & x_{k,i} + x_{k',i} + r_{R_i} H_{R_i} = w_{k,j} + w_{k',j'} \equiv y_{ijj'} \end{aligned}$$

The first order conditions yield two sets of equations. The first set equalizes the marginal utility derived from the consumption of one spouse to that of the other spouse: $\lambda \frac{\partial V_{ij}^{k'}}{\partial x_{k',i}} = \frac{\partial V_{ij'}^{w}}{\partial x_{k,i}}$. The second set, also known as the Bowe-Lindahl-Samuelson conditions, says that members' marginal willingness to pay should be equalized to the marginal price of residential floorspace: $\frac{\partial V_{ij}^{k}/\partial H_{R_i}}{\partial V_{ij}^{k}/\partial x_{k,i}} + \frac{\partial V_{ij'}^{k'}/\partial H_{R_i}}{\partial V_{ij'}^{k'}/\partial x_{k',i}} = r_{R_i}$.

In the quantitative exercise, I abstract away from bargaining considerations within households and only consider the feature that spouses share the same budget. For that reason, I assume that λ, typically thought as a measure of bargaining power, is exogenous and equal to one so that the household weights spouses' utility equally. Under this assumption, households behave as a single entity that makes all choices, i.e. households behave as unitary households. Moreover, I assume that spouses have the same preferences over consumption and housing and so $\beta^k = \beta^{k'} = \beta$. These assumptions and the first order conditions yield the following solutions to the maximization problem: $x_{ijj'}^{k} = x_{ijj'}^{k'} = \frac{\beta}{2} y_{ijj'}$ and $r_{R_i} H_{R_i} = (1-\beta) y_{ijj'}$.

Household's indirect utility. Plugging solutions back into the household utility function, I get that:[13]

$$\tilde{W}_{ijj'} \propto \left(d_{ij}^{k} d_{ij'}^{k'}\right)^{-1} \left(\frac{w_{k,j} + w_{k',j'}}{P^{\beta} r_{R_i}^{(1-\beta)}}\right) \tag{4}$$

This household utility postulates that the household dislikes the commuting performed by both members, which is a natural outcome from the fact that the household cares about the average utility of members. Moreover, greater income net of prices provide greater household utility.

4.2 Implications

Marginal rates of substitution. In this section, I explain what are the implications of this choice structure. Specifically, I ask two questions. First, say that the times from origin i to

[13] I have taken the exponential function to both sides, taken the root square and redefined the meaning of κ^k. These preferences should represent the same preferences ordering since all operations were monotonic transformations.

destination j' improve for the wife by one minute. How much can the husband's commuting times increase while keeping household utility $\tilde{W}_{ijj'}$ constant? Second, keeping husband's commuting times constant, what is the wage of the wife that the household would be willing to give up in order to improve her commute time by one minute?

To answer the first question, we can take a total derivative of the utility function with respect to commute times of spouses and equalize it to zero. This yields $dt^h_{ij} = -\frac{\kappa_h}{\kappa_w} dt^w_{ij}$ where h and w index the husband and the wife. This result means that the household can substitute the time freed up from the wife's commuting with $\frac{\kappa_h}{\kappa_w} dt^w_{ij'}$ minutes in husband's commuting. $\frac{\kappa_h}{\kappa_w}$ acts as an exchange rate at which the time of the wife can be substituted with the time of the husband.

To answer the second question, I follow a similar strategy. To decrease the commute times of the wife by one minute, the household would be willing to give up income $w_{h,j} + w_{w,j'}$ by κ_w log points: $d\log(w_{h,j} + w_{w,j'}) = -\kappa_w dt^w_{ij'}$. This is a feature also present in the class of spatial models with iceberg costs and constant returns to scale utility functions. The difference in this setting is that I generalize it: income depends on the wage of the two spouses, and so each spouse's commuting is responsible of sourcing a share of the household's income. Noting that $d\log(w_{h,j} + w_{w,j'}) = \frac{1}{w_{h,j}+w_{w,j'}} dw_{w,j'}$, then $\frac{dw_{w',j}}{w_{w,j'}} = \kappa_w \frac{w_{h,j}+w_{w,j'}}{w_{w,j'}} dt^w_{ij'}$. Thus, as $w_{h,j}$ increases, households' willingness to give up the wife's wage in exchange of reduced commute times rises.

Gravity equations. I now assume that there is a continuum of households indexed by ω. Moreover, I assume that individuals' utility function (equation 3) is heterogeneous over their commute destinations, $\epsilon_{k,j}(\omega)$, and $\epsilon_{k',j'}(\omega)$. Solving the maximization problem yields:

$$W_{ijj'}(\omega) \propto \frac{\epsilon_{k,j}(\omega)\epsilon_{k',j'}(\omega)}{d^k_{ij} d^{k'}_{ij'}} \left(\frac{w_{k,j} + w_{k',j'}}{P^\beta r_{R_i}^{(1-\beta)}} \right) \tag{5}$$

I assume preference shocks are Frechet distributed with shape parameters θ_k and $\theta_{k'}$. Thus, conditional on spouse k''s destination j', the household evaluates the utility it would get from sending k to each possible destination and chooses the one that maximizes it. Similarly, conditional on spouse k's destination j, the household evaluates all possible destinations of member k'. Then, I get that:

$$\pi^k_{j|ij'} = \frac{W^{\theta_k}_{ijj'}}{\sum_l W^{\theta_k}_{ilj'}} \quad \text{and} \quad \pi^{k'}_{j'|ij} = \frac{W^{\theta_{k'}}_{ijj'}}{\sum_l W^{\theta_{k'}}_{ijl}}$$

The first expression says that the share of spouses k commuting to location j conditional on their residence i and their spouses commuting to j' depends on total income $w_{h,j} + w_{w,j'}$ net of commute costs $d^k_{ij} d^{k'}_{ij'}$, relative to available options $\sum_l W^{\theta_k}_{ilj'}$. For simplicity in this exposition, I assume that $\theta_k = \theta_{k'} = \theta$. In the quantitative exercise, I allow for the shape parameters to vary across household members which is consistent with Fact 1. Note that both sets of commuting probabilities have a gravity structure: there is a linear relationship between the log of commuting probabilities of member k and his or her commuting times. The product $\theta\kappa_k$ becomes the commuting elasticity. Finally, unconditional commuting probabilities are:

$$\pi^k_{j|i} = \frac{\sum_l W^\theta_{ijl}}{\sum_{l'}\sum_l W^\theta_{ill'}} \quad \text{and} \quad \pi^{k'}_{j'|i} = \frac{\sum_l W^\theta_{ilj}}{\sum_{l'}\sum_l W^\theta_{ill'}}$$

Comparative statics. I compute the impact of improving the commuting times of spouse k' on the commuting probabilities of spouse k. First, note that improving k''s commuting times does not affect k's conditional commuting probabilities. This is because when k''s commuting times to j' improve, the utility received in every destination of k changes proportionally to the initial utility: $\frac{dW_{ijj'}}{dt^{k'}_{ij'}} = -\kappa_{k'}W_{ijj'}, \forall j$.

However, k's unconditional probabilities are affected as the relative ranking of utility $W_{ijj'}$ across destinations j and j' is reordered thanks to the improvement in commuting times: $\pi^k_{j|i} = \frac{\sum_l (W_{ijl}+1[l=j']\kappa_{k'}W_{ijj'})^\theta}{\sum_{l'}\sum_l (W_{ill'}+1[l'=j']\kappa_{k'}W_{ilj'})^\theta}$. This is as if households, by having more time at their disposal, reallocate spouses across destinations such that utility is maximized. Commuting to location j will increase if the resulting numerator $\sum_l (W_{ijl} + 1[l = j']\kappa_{k'}W_{ijj'})^\theta$ is greater than the numerator of the remaining options. Intuitively, this will happen when the location j features high wages or low commute costs, as the impact on $W_{ijj'}$ is proportional. If wages in j are too low or commute costs to j too high, utility maximization leads households to decrease the probability at which they send spouses k to such destination.

Mathematically, how do k's unconditional probabilities change when k''s times improve? Taking a derivative with respect to $t^{k'}_{ij'}$, I get:

$$\frac{\partial \pi^k_{j|i}}{\partial t^{k'}_{ij'}} = -\theta\kappa_{k'}\pi^{k'}_{j'|i}\left(\pi^k_{j|ij'} - \pi^k_{j|i}\right) = -\theta\kappa_{k'}\pi^k_{j|i}\left(\pi^{k'}_{j'|ij} - \pi^{k'}_{j'|i}\right) \tag{6}$$

Spouses k will increase their probability of commuting to location j if the probability that spouses k use the route j given that their spouses k' use the improved route j' is higher than the unconditional probability that spouses k use the route j. In other words, the probability that k commutes to j will increase when initial conditional commuting probabilities $\pi^k_{j|ij'} = (\frac{w_{k,j}+w_{k',j'}}{d^k_{ij}})^\theta / \sum_l (\frac{w_{k,l}+w_{k',j'}}{d^k_{il}})^\theta$ are high enough.

How improvements in commuting time affect income? Defining spouses k's income at origin i as the sum of wages across destinations $y^k_i = \sum_l w_{k,l}\pi_{k,l|i}N^k_i$, where N^k_i is the number of spouses k living in origin i. Differentiating it with respect to commute times between origin i and a destination j' of both spouses k and k', I get:

$$-\frac{\partial}{\partial t_{ij'}}\log y^k_i = \underbrace{\theta\kappa_k \frac{w_{k,j'}\pi^k_{j'|i}}{\sum_l w_{k,l}\pi^k_{l|i}}\left(1 - \frac{\bar{y}^k_i}{w_{k,j'}}\right)}_{\text{direct use}} + \underbrace{\theta\kappa_{k'}\sum_l \frac{w_{k,l}\pi^k_{l|i}}{\sum_l w_{k,l}\pi^k_{l|i}}\left(\pi^{k'}_{j'|il} - \pi^{k'}_{j'|i}\right)}_{\text{indirect use}} \tag{7}$$

The effect on total income in origin i for spouse k depends on two terms: the direct use channel, and the indirect use channel (or within household spillovers). The direct use channel will be positive if $w_{k,j'} > \bar{y}_i^k$, where $\bar{y}_i^k = \sum_j \left(w_{k,j}\pi_{j|i}^k\right)$. In other words, when times between origin i and destination j' improve, aggregate income in origin i increases if wages at the destination that is now more accessible are higher than the average income in origin i. The intuition is that income should increase only if the new destination j' is a high-wage location. Otherwise, if the new destination is a low-wage location, improvements in commuting times may induce some workers to give up some of their earnings to have a shorter commute.[14] How much would it increase depends on three terms. First, it depends on the share of income that destination j' accounts for, $\frac{w_{k,j'}\pi_{j'|i}^k}{\sum_j \left(w_{k,j}\pi_{j|i}^k\right)}$. Second, it depends on the difference between wages $w_{k,j'}$ and average income $\bar{y}_i^k$. Finally, it depends on the commuting elasticity $\theta\kappa^k$.

The indirect use channel indicates that when commute costs for spouses k' decrease, then this affects the households' allocation of spouses k across destinations as explained above. When this happens, the origin i stops receiving the income from locations where the spouse k is no longer working (i.e. when $\pi_{j'|il}^{k'} < \pi_{j'|i}^{k'}$), but starts receiving the income from locations where spouses k are commuting to (when $\pi_{j'|il}^{k'} > \pi_{j'|i}^{k'}$). We need to sum across all locations l to account for all spillovers generated by spouses k' to spouses k working in locations l. Finally, note that if choices are independent, as in the case of standard spatial models, then conditional commuting probabilities become equal to unconditional probabilities, collapsing the indirect channel to zero.

In sum, in this section I have shown the microfoundation of a utility function tailored for married households. Then, I have explained the major implications of this choice structure in terms of commuting and have shown how improvements in commute times may impact income across origins. The main idea is that there are two channels through which improved commute times can affect households. One is the direct use channel, and the other one is the indirect use channel (or within household spillovers). In the next section, I bring this model to the data.

5 Bridging Theory and Data

This section starts by summarizing the main components of the quantitative model. Afterwards, it describes the calibration and estimation procedures. Finally, it shows evidence about the model's performance when matching untargeted moments.

[14] Note, however, that new metro lines improve commuting times between a set of origin and destination locations. The derivative I have taken only considers an improvement between a particular origin and a particular destination, assuming all other times remain the same which is physically impossible. If if its quicker to reach j' from i, it will also be quicker to reach a neighboring location j''.

5.1 Quantitative Model of City Structure and Couples

5.1.1 Environment

This is a model in which the internal structure of the city is driven by a tension between agglomeration forces (production and positive residential externalities) and dispersion forces (commuting costs and an inelastic supply of land).

The city consists of a set of discrete locations indexed by $i = 1, ..., S$. These locations differ in their commute times to other locations, their housing floorspace, households' productivity (in household production), amenities, and industries' productivity as I explain later.

Moreover, the city is populated by a fixed measure of households N_k, where $k \in \{m, f, mf\}$. If $k = m$ or $k = f$ the household is composed of a single male worker or a single female worker, respectively. If $k = mf$ the household is a couple. For simplicity, singles and husbands always work in this model.[15] Thus, there are five groups of workers: single males, single females, married males in male-breadwinner households, and males and females in dual-earner households.

Furthermore, each location houses multiple industries which produce a consumption good using labor and commercial floorspace. Each location-by-industry's consumption good is aggregated into a final good with CES preferences. Males and females are imperfect substitutes in the production function. Finally, landowners choose how to allocate a fixed amount of floorspace across residential and commercial use.

5.1.2 Households

Single households

A. Preferences in single households. Singles derive Cobb-Douglas utility from the consumption of a freely traded numeraire good $(C^g(\omega))$ with parameter β^g, from the consumption of residential floorspace $H_{R^g}(\omega)$ with parameter $1 - \beta^g$, and from an amenity accounting for the average preference of each group to live in location i (u_i^g). Moreover, individuals experience disutility from commuting in an iceberg fashion, $d_{ij}^g \geq 1$, where $d_{ij}^g = \exp(\kappa^g t_{ij})$, and t_{ij} is the time it takes to commute between locations i and j. The parameter κ^g governs the size of these commuting costs for each gender. Finally, workers are heterogeneous in their preferences for working in location j, $\epsilon_j^g(\omega)$, and for living in residence i, $\nu_i^g(\omega)$. Hence, singles need to decide where to work based on the trade-off between the possibility of higher wages but longer commutes. Similarly, they need to decide where to live by balancing out the expected

[15] To simplify, in this paper couples are comprised of a male and a female. Another simplifying assumption usually done in the literature on family economics is that the husband always works. Moreover, in the data female breadwinner households constitute just 1.3% of all households. This is why I turn off this margin: it does not seem to be quantitatively important but would add greater complexity to the model.

income against housing costs and amenities. Concretely, indirect utility is given by:

$$V_{ij}^{g}(\omega) \quad \propto \quad u_i^g \nu_i^g(\omega) P^{-\beta^g} r_{R_i}^{\beta^g - 1} \left[\frac{w_{jg} \epsilon_j^g(\omega)}{d_{ij}^g} \right] \tag{8}$$

where P is the price of the freely traded final good, and r_{R_i} is the rental value of residential floorspace. Panel A of Figure B.9 depicts the timing assumptions.

<u>*B. Commuting.*</u> Conditional on where to live, singles (indexed by ω) draw a vector of location-specific preferences for work across the city, $\epsilon_j^g(\omega)$, iid from a Frechet distribution $F(\epsilon_j) = \exp\left(-T^g \epsilon_j^{-\theta^g}\right)$. From standard Frechet operations, we know that:

$$\pi_{j|i}^{g} \quad = \quad \frac{\left(\frac{w_{jg}}{d_{ij}^g}\right)^{\theta^g}}{\Psi_{R_i^g}} \tag{9}$$

where the probability singles g choose destination j given origin i is: $\pi_{j|i}^g$. Moreover, $\Psi_{R_i^g} = \sum_{l=1}^{S} \left(\frac{w_{lg}}{d_{ij}^g}\right)^{\theta^g}$ is a market access term indicating how close are jobs to people. Thus, one key trade-off is that individuals are attracted to locations paying a high wage but dislike commuting long distances. That is, they compare the net wage they would get from commuting to particular destination with other available options embodied in $\Psi_{R_i^g}$. The dispersion of preferences is specific for each gender, and it determines how sensitive singles are to changes in commute costs. For example, when the dispersion of preferences shocks is low (i.e. high θ^g), choices are more sensitive to commute costs.

<u>*C. Residence Location.*</u> Before singles draw a vector of location-specific preferences, they draw a value for residence preferences, $\nu_i^g(\omega)$, and decide where to live. $\nu_i^g(\omega)$ is distributed Frechet with shape parameter $\eta^g > 1$ and average E^g. So, singles choose to live in i only if they attain a higher expected utility than in all other locations. Then, the probability that single ω lives in location i is:

$$\pi_i^g = \frac{\left(\frac{r_{R_i}^{1-\beta^g}}{u_i^g \Psi_{R_i^g}^{1/\theta^g}}\right)^{-\eta^g}}{\sum_l \left(\frac{r_{R_l}^{1-\beta^g}}{u_l^g \Psi_{R_l^g}^{1/\theta^g}}\right)^{-\eta^g}} \tag{10}$$

This expression says that, when deciding where to live, singles will balance out locations with better amenities and greater access to jobs against the cost of housing.

Married households

A. Preferences in married households. Individuals in married households derive utility from the same components as singles. Thus, preferences for married households can be micro-founded following a similar procedure as in Section 4.1. Note that I denote husbands and wives using the subscripts h and w, respectively.

I additionally incorporate the labor participation choice of women, which might be a relevant margin in this context. To do so, I assume that households can engage in household production with location-specific productivity $\xi_{i\ell}^{mf}$, which depends on whether both spouses work ($\ell = 1$) or just one ($\ell = 0$). There could also be ideosyncratic reasons why a household prefers to have both spouses working in the labor market, which are embodied in α_{ℓ}^{mf}. I further assume that males and females have the same preference over residential location ν_i^{mf} and derive the same utility from local amenities u_i^{mf}. They only differ on their preferences over destinations for work, ϵ_j^k, and commuting time d_{ij}^k. Thus, indirect utility of a couple ω living in i, with the husband working at j and the wife in j' (if she works) is given by:

$$W_{i\ell jj'}^{mf}(\omega) \quad \propto \quad u_i^{mf} \nu_i^{mf}(\omega) \xi_{i\ell}^{mf} \alpha_{\ell}^{mf}(\omega) \frac{\epsilon_j^h(\omega)}{d_{ij}^h} \left(\frac{\epsilon_{j'}^w(\omega)}{d_{ij'}^w} \right)^{\ell} P^{-\beta^{mf}} r_{R_i}^{\beta^{mf}-1} y_{\ell jj'}^{mf}(\omega)$$

where household ω's income is $y_{\ell jj'}^{mf}(\omega) = w_{jh} + w_{j'w}\ell(\omega)$. Notice that a couple ω performs the same choices as singles. Additionally, they have to choose whether the wife is going to work ($\ell = 1$ if she works, $\ell = 0$ if she stays at home), and the location where she is going to work (indexed by j'). Thus, married couples face additional trade-offs. First, if the wife decides to work, households will dispose of more income to spend in housing and the final good. However, if the wife stays, households will use her unit of labor to produce a household good with location-specific productivity $\xi_{i\ell=0}^{mf}$. Second, there is a potential trade-off between commute time and income, as explained in the previous section. Panel B of Figure B.9 depicts the timing assumptions.

I start with the case where the wife participates in the labor market. Afterwards, I solve for the case where the wife stays at home performing household production. Then, I determine labor participation and residence choices.

B. Husbands' Commuting Choice in Dual-Earner Households. I assume for simplicity that households choose the husband's workplace after knowing the workplace of the wife. Households compare the utility they would receive if the husband works in a particular location, against the utility they would derive if he works in some other location, all conditional on where the wife works. Hence, we are interested in computing the *conditional* probability that married men living i commute to j given that their wives work and commute to j', i.e. $\pi_{j|i,\ell=1,j'}^h = P\left[W_{i,\ell=1,j,j'}(\omega) \geq \max_{l \neq j} W_{i,\ell=1,l,j'}(\omega)\right]$, where $\ell = 1$ indicates that the wife participates in the labor market. Simple manipulations result in the following expression:

$$\pi^h_{j|i,\ell=1,j'} = \frac{\left(\frac{w_{jh}+w_{j'w}}{d^h_{ij}}\right)^{\theta^h}}{\Phi^h_{R_{i,\ell=1,j'}}} \tag{11}$$

where $\Phi^h_{R_{i,\ell=1,j'}} = \sum_l \left(\frac{w_{lh}+w_{j'w}}{d^h_{il}}\right)^{\theta^h}$ is a market access term for husbands. It indicates how close are jobs to husbands but conditional on the wife's wage. It can also be thought as the expected utility of households when the wife works at j', but before households have decided where to send the husband. As in single households, married men are more likely to commute to a location when it pays a high income net of commute cost. However, now income includes the wage earned by the wife when she works at j'.

C. Wives' Commuting Choice in Dual-Earner Households. To decide where the wife should work, the household compares the expected utility it would receive across all possible options. In particular,

$$\pi^w_{j'|i,\ell=1} = \frac{\left(\frac{\left(\Phi^h_{R_{i,\ell=1,j'}}\right)^{1/\theta^h}}{d^w_{ij'}}\right)^{\theta^w}}{\Phi^w_{R_{i,\ell=1}}} \tag{12}$$

where $\Phi^w_{R_{i,\ell=1}} = \sum_l \left(\frac{\left(\Phi^h_{R_{i,\ell=1,l}}\right)^{1/\theta^h}}{d^w_{il}}\right)^{\theta^w}$ is a market access term for dual-earner households. These households can have greater access to jobs either through the husband or the wife, and so $\Phi^w_{R_{i,\ell=1}}$ acts as an average of the two. This equation says that wives will commute to locations where they expect a higher household income, $\Phi_{R^h_{i,\ell=1,j'}}$, net of their own disutility of commuting, $d^w_{ij'}$.

D. Husbands' Commuting Choice in Male Breadwinner Households. In the case of male breadwinner households, a similar logic as in the case of single households delivers the following expression for commuting probabilities:

$$\pi^h_{j|i,\ell=0} = \frac{\left(\frac{w_{jh}}{d^h_{ij}}\right)^{\theta^h}}{\Phi^h_{R_{i,\ell=0}}} \tag{13}$$

So, in terms of commuting, married males in breadwinner households and single males behave quite similarly, although with potentially different commuting elasticities.

E. Labor Force Participation. Conditional on their residence, households compare the expected utility they would obtain if the wife works or if she stays at home performing household production. Since households are heterogeneous in their preference for a stay-at-home wife, and assuming this heterogeneity is distributed Frechet with shape parameter ν, the probability that a couple decides to be a dual-earner household is:

$$\mu_i = \frac{\left[\left(\Phi^w_{R_{i,\ell=1}}\right)^{1/\theta^w}\right]^\nu}{\Psi^{mf}_{R_i}} \tag{14}$$

where $\Psi^{mf}_{R_i} = \left[\left(\Phi^w_{R_{i,\ell=1}}\right)^{1/\theta^w}\right]^\nu + \left[\xi_{i\ell=0}\left(\Phi^h_{R_{i,\ell=0}}\right)^{1/\theta^h}\right]^\nu$. Household productivity in domestic goods $\xi_{i\ell=1}$ is normalized to one, and hence $\xi^{mf}_{i\ell=0}$ indicates how much more productive are households on domestic production in location i when the wife stays at home relative to the situation in which she participates in the labor market.[16] This expression says that if both spouses have opportunities to work by having access to nearby jobs, then the likelihood of both working increases relative to the situation where only males have greater access to jobs.

F. Residence Location. Couples choose to live in i only if they attain a higher expected utility than in all other locations. Then the probability household ω in location i is:

$$\pi^{mf}_i = \frac{\left(\frac{r^{1-\beta^{mf}}_{R_i}}{u^{mf}_i \Psi^{1/\nu}_{R^{mf}_i}}\right)^{-\eta^{mf}}}{\sum_l \left(\frac{r^{1-\beta^{mf}}_{R_i}}{u^{mf}_l \Psi^{1/\nu}_{R^{mf}_l}}\right)^{-\eta^{mf}}} \tag{15}$$

Hence, not only the location elasticity η is different in single households than in married couples, but also the married have other considerations when deciding where to live. That is, they consider locations where on average both spouses have better labor opportunities. If only males have good opportunities then they look for locations with greater household productivity. Thereby, this directly links females and males market conditions.

Aggregation

I aggregate the supply of residents and of workers to jobs. Once commuting probabilities are known, one can compute aggregate income by origin by weighing wages in each destination with the corresponding commuting probability.

Supply of residents. Equation 10 characterizes the location choice of singles, whereas equation 15 does it for married couples. Given the aggregate number of households-by-group we can

[16] Since $\left(T^h\right)^{1/\theta^h}\Gamma\left(\frac{\theta^h-1}{\theta^h}\right)$ only affects the scale of welfare I have normalized this constant to one hereafter.

compute the supply of households in each location i:

$$N_{R_i^g} = \pi_i^g N^g, g \in \{m, f\} \quad \text{and} \quad N_{R_i^{mf}} = \pi_i^{mf} N^{mf} = \underbrace{(1-\mu_i)\,\pi_i^{mf} N^{mf}}_{N_{R_{i,0}^{mf}}} + \underbrace{(\mu_i)\,\pi_i^{mf} N^{mf}}_{N_{R_{i,1}^{mf}}} \tag{16}$$

Note that given the number of married couples in location i, $N_{R_i^{mf}}$, I endogenously determine which are dual-earner $N_{R_{i,1}^{mf}}$ or male breadwinner $N_{R_{i,0}^{mf}}$ households.

Supply of workers to jobs. After computing how many households live in block i as given by equation 16, and the probability of commuting to any block as given by equations 9, 11, 12, and 13, we can calculate the supply of workers of gender g to any location:

$$\begin{aligned} L_{F_{jm}} &= \sum_i \left\{\pi_{j|i}^m N_{R_i^m}\right\} + \sum_i \left\{\pi_{j|i,\ell=0}^h N_{R_{i,0}^{mf}}\right\} + \sum_i \left\{\pi_{j|i,\ell=1}^h N_{R_{i,1}^{mf}}\right\} \\ L_{F_{jf}} &= \sum_i \left\{\pi_{j|i}^f N_{R_i^f}\right\} + \sum_i \left\{\pi_{j|i,\ell=1}^w N_{R_{i,1}^{mf}}\right\} \end{aligned} \tag{17}$$

where the commuting probability of males in dual-earner households $\pi_{j|i,\ell=1}^h$ is given by

$$\pi_{j|i,\ell=1}^h = \textstyle\sum_l \pi_{j|i,\ell=1,l}^h \cdot \pi_{l|i,\ell=1}^w \tag{18}$$

Finally, aggregate income in origin i of individuals belonging to group k becomes $y_i^k = \sum_l w_{k,l} \pi_{il}^k N_i^k$. Given Cobb-Douglas preferences, we know how much income is destined into the final good and into housing.[17]

5.1.3 Production

I model the production side using standard assumptions in the literature.

Technology

Following an Armington assumption, there are $s \in 1, ..., K$ industries which produce varieties differentiated by location under perfect competition. These goods are aggregated with CES preferences by consumers with an elasticity of substitution of $\sigma_D > 1$. Following Tsivanidis (2021), firms produce using a Cobb-Douglas technology over labor and commercial floorspace:

$$\begin{gathered} Y_{js} = A_{js} N_{js}^{\alpha_s} H_{F_{js}}^{1-\alpha_s} \\ \text{where} \quad N_{js} = \left(\textstyle\sum_g \alpha_{sg} \tilde{L}_{F_{jgs}}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \end{gathered}$$

[17]To avoid the inefficiency generated by absentee landlords, I am assuming that landlords spend all their income in consuming the final good.

Industries aggregate workers of different genders using a CES aggregator over each gender's labor with an elasticity of substitution of σ.[18] Note as well that the total labor share is the sum of each gender's labor share: $\alpha_s = \sum_g \alpha_{sg}$. Finally, A_{js} is the productivity of location j for firms in industry s. Importantly, industries differ in the intensity in which they use different type of workers α_{sg}.

5.1.4 Housing

I model the housing market in a straightforward way.

Market clearing

Each location is characterized by a fixed amount of floorspace H_i. A fraction ϑ_i is allocated to residential use and $1-\vartheta_i$ to commercial use. Market clearing requires the supply of residential floorspace, $\vartheta_i H_i r_{R_i}$, to equal demand, $H_{R_i} = \sum_k H_{R_i^k}$, where k indexes household groups. This is the same for commercial floorspace. The supply of commercial floorspace, $(1-\vartheta_j)H_j r_{F_j}$, must equal the demand from the production-side, $H_{F_j} = \sum_s H_{F_{js}}$.

Floorspace use allocation.

As in Ahlfeldt et al. (2015) landowners allocate floorspace to its most profitable use. When convenient they allocate ϑ_i to residential. They receive r_{R_i} per unit. For commercial use, land regulations limit the return to each unit, hence they receive $(1-\tau_i)r_{F_i}$. Then:

$$\begin{aligned} \vartheta_i = 1, &\quad \text{if } r_{R_i} > (1-\tau_i) r_{F_i} \\ (1-\tau_i) r_{F_i} = r_{R_i}, &\quad \forall \{i : \vartheta_i \in (0,1)\} \\ \vartheta_i = 0, &\quad \text{if } r_{R_i} < (1-\tau_i) r_{F_i} \end{aligned} \tag{19}$$

5.1.5 Agglomeration spillovers

Previous literature has found that agglomeration spillovers might shape the aggregate impact of new transit infrastructure (Tsivanidis, 2021). In particular, productivity per sector A_{js} can be decomposed into two components, one which is exogenous and captures fundamentals, and the other which is endogenous capturing externalities.

Productivity in each location depends on an exogenous component $\bar{A}_{js}$ that reflects the location's fundamentals (such as slope of the land, access to roads, etc.), and the endogenous

[18] Hence, in equilibrium, a gender gap between males and females wages may arise in each location. Also, I assume that single and married males are perfect substitutes. Single and married females are perfect substitutes too. Hence, conditional on a particular destination, married and single individuals of a particular gender will receive the same wage. However, income may vary across these groups depending on their preferred origins and destinations.

employment in industry s in that location. I model endogenous productivity using constant scale elasticity, but allowing it to vary across sectors. In other words:

$$A_{js} \quad = \bar{A}_{js} \left(\tilde{L}_{F_{js}} \right)^{\phi_{F_s}} \tag{20}$$

where ϕ_{F_s} measures the overall effect of agglomeration forces in sector s.

5.1.6 Definition of Equilibrium

I assume that $A_{js} > 0$, $u_{ig} > 0$ and $\xi_{i\ell} > 0$ for all locations, sectors, and household groups. Corner solutions are taken care off in Appendix A3.

Definition 1. Given the model's parameters $\{\beta^k, \kappa^k, \theta^k, T^k, E^g, \eta^k, \alpha_{sg}, \sigma, \sigma_D, \phi_{Fs}, , \nu\}$, city population by household-group $\{N^k\}$, and exogenous location-specific characteristics $\{H_i, \xi_{i\ell}, \bar{u}_i^k, \bar{A}_{js}, t_{ij}, \tau_i\}$, the general equilibrium of the model is given by the vector $\{N_{Ri}^k, \mu_{i\ell}, L_{F_{jg}}, w_{jg}, r_{R_i}, r_{F_j}, \vartheta_i, \}$ such that labor markets clear, floorspace markets clear, and the population adds up to the city total.

The solution algorithm is presented in Appendix A3.

5.2 Calibration and Estimation From Aggregate Data

I estimate from aggregate data the labor input share by industry-gender, and the household expenditures in housing (Panel A of Table 2). Finally, I calibrate the elasticity of substitution between male and female workers in the production function, the elasticity of substitution of demand, and the labor input share by industry (Panel B).

5.3 Estimation Outside the Model: Commuting Elasticities

By taking logs to commuting probabilities in single and breadwinner households I can estimate the parameters of interest by PPML. From equations 9 and 13 I get the following:

$$\log \frac{L_{R_{ij}^g}}{N_{R_i^g}} = -\theta^g \kappa^g \cdot t_{ij} + \underbrace{\theta^g \cdot \log\left(w_{jg}\right)}_{\text{FE}_j} - \underbrace{\log \Psi_{R_i^g}}_{\text{FE}_i} \quad \text{and} \quad \log \frac{L_{R_{ij,\ell=0}^h}}{N_{R_{i,0}^{mf}}} = -\theta^k \kappa^k \cdot t_{ij} + \underbrace{\theta^h \cdot \log\left(w_{jh}\right)}_{\text{FE}_j} - \underbrace{\log \Phi_{R_{i,\ell=0}}^h}_{\text{FE}_i}$$

which are exactly the same equations I estimate for Fact 1 reported in columns 1 to 4 of Table 1. I plug into the model the commuting elasticities I estimate for singles. For married households, I plug in the commuting elasticities of breadwinner households.[19] The underlying assumption is that among married of a given gender there is no heterogeneity in the shape

[19]While in the model I am not considering female breadwinner households as they make up less than 2% of households, I can still use data on them to estimate the commuting elasticity of married women.

parameter associated to their commuting preference shocks.[20] Finally, to get an estimate for the Frechet shape parameters in the commuting preferences, I follow the growing consensus in the literature (Ahlfeldt et al., 2015; Tsivanidis, 2021; Zarate, 2021) and set the iceberg disutility parameter κ^k to $\kappa^k = 0.01$, from which I get estimates of $\hat{\theta}^m = 5.14$, $\hat{\theta}^f = 6.17$, $\hat{\theta}^h = 4.66$, and $\hat{\theta}^w = 6.34$, as shown in Panel C of Table 2.

5.4 Estimation Within the Model

Model inversion. From observed data, I need to recover unobserved characteristics such as wages, productivities, amenities, household productivity, and land use wedges. We can recover values of location productivities, household productivities and amenities that rationalize the observed data as a model equilibrium. From the production-side we only need to observe workplace employment levels per industry rather than employment by gender. This is helpful since data on location-level employment by gender is unavailable in this setting. Intuitively, given male and female intensities per industry, a greater employment from a particular sector is informative of employment levels by gender. This is the same intuition as in Tsivanidis (2021). The propositions in Appendix A4.1, A4.2, and A4.3 formalize these ideas.

Agglomeration economies. I can recover productivity from $A_{js} = W_{js}^{\alpha_s} r_{F_j}^{1-\alpha_s} X_{js}^{1/(\sigma_D - 1)} X$. Hence, productivity is the residual that ensures the definition for firm sales X_{js} to hold. In this way, we know that locations characterized by high employment levels relative to the price of commercial floorspace and wages are also locations with high productivity, at least according to the model. I recover productivity in 2007, before transit improvements, and in 2017. Dividing by the geometric mean, taking logs, and then taking first differences, we can express agglomeration economies in equation 20 as:

$$\Delta \ln \frac{A_{js}}{\tilde{\bar{A}}_s} = \phi_{F_s} \Delta \ln \frac{\tilde{L}_{F_{js}}}{\tilde{\bar{L}}_F} + \Delta \ln \frac{\bar{A}_{js}}{\tilde{\bar{A}}_s}$$

Estimating the strength of agglomeration economies is a challenging endeavor as locations may be more productive because more people work there, or because locations with high productivity attract more workers. To identify this parameter, we need to use a shock to labor supply. Therefore, we can exploit the model and the introduction of new transit infrastructure to generate such an instrument. In particular, by taking a full differentiation to $\left\{\sum_k \sum_i \pi^k_{j|i,\ell} N_{R^k_i}\right\}$ with respect to commuting times from origin locations (while keeping market

[20]In part, I make this assumption because equations 12 and 18 state that conditioning on origin and destination fixed effects may not be enough to consistently estimate the commuting elasticities for dual-earner households. In any case, columns 5 to 6 show very similar elasticities as those shown in column 3 and 4.

access terms constant) we get the following Bartik-style instruments:

$$Z^m_{Fj} = -\theta^m \kappa^m \sum_{i'} \frac{\pi^m_{j|i'} N_{R^m_{i'}}}{\sum_i \pi^m_{j|i} N_{R^m_i}} \cdot dt_{i'j} \qquad Z^f_{Fj} = -\theta^f \kappa^f \sum_{i'} \frac{\pi^f_{j|i'} N_{R^f_{i'}}}{\sum_i \pi^f_{j|i} N_{R^f_i}} \cdot dt_{i'j}$$

$$Z^w_{Fj} = -\theta^w \kappa^w \sum_{i'} \frac{\pi^w_{j|i',\ell=1} N_{R^{mf}_{i',\ell=1}}}{\sum_i \pi^w_{j|i,\ell=1} N_{R^{mf}_{i,\ell=1}}} \cdot dt_{i'j} \qquad Z^h_{Fj\ell=0} = -\theta^h \kappa^h \sum_{i'} \frac{\pi^h_{j|i',\ell=0} N_{R^h_{i',\ell=0}}}{\sum_i \pi^h_{j|i,\ell=0} N_{R^h_{i,\ell=0}}} \cdot dt_{i'j}$$

$$Z^h_{Fj\ell=1} = -\theta^h \kappa^h \sum_{i'} \frac{\pi^h_{j|i',\ell=1} N_{R^{mf}_{i',\ell=1}}}{\sum_i \pi^h_{j|i,\ell=1} N_{R^{mf}_{i,\ell=1}}} \cdot dt_{i'j} \quad - \quad \theta^w \kappa^w \sum_{i'} \frac{\pi^h_{j|i',\ell=1,j} \pi^w_{j|i',\ell=1} N_{R^{mf}_{i',\ell=1}}}{\sum_i \pi^h_{j|i,\ell=1} N_{R^{mf}_{i,\ell=1}}} \cdot dt_{i'j}$$

For each destination j, the Bartik-instruments weight the change in commuting times with the share of workers from each origin. I use inferred shares $\pi_{j|i}$ from 2007 data. Since I have many groups of households this calculation has to be made for each, providing us with five possible instruments to exploit. The identifying assumption is that the growth of exogenous productivities is uncorrelated with the Bartik instruments: $\mathcal{E}\left[\Delta \log \bar{A}_{js} \cdot Z^k_{Fj\ell}\right] = 0$.

To construct sector-specific instruments, I use the model to compute the share of female and male workers in each location-by-industry in 2007, which then I use to average the five instruments presented above in the following way:

$$Z_{Fjs} = \frac{L_{F_{jfs}}}{L_{Fjs}}(0.5 \cdot Z^f_{Fj} + 0.5 \cdot Z^w_{Fj}) + \frac{L_{F_{jms}}}{L_{Fjs}}(0.33 \cdot Z^m_{Fj} + 0.33 \cdot Z^h_{Fj\ell=1} + 0.33 \cdot Z^h_{Fj\ell=0})$$

So, in location-by-sectors that employ a greater share of females, my sector-specific instrument gives more weight to female Bartik shocks such as Z^f_{Fj} and Z^w_{Fj}, and vice-versa.

Results are shown in Panel A of Table 3.[21] Two observations are in order. First there is some heterogeneity in the strength of agglomeration economies across industries (see column 2 of Panel A). We have sectors such as Services with a scale elasticity statistically indistinguishable from zero, and Retail Trade where the scale elasticity is 0.24. Second, this heterogeneity might affect the extent to which the new infrastructure affects the gender gap since industries are located in different places of the city and employ different shares of female and male workers. If the new transit infrastructure provides women with access to female-intensive industries that have high agglomeration economies (such as textiles), then the gender gap might close compared to a counterfactual city where the new transit infrastructure is placed somewhere else.

[21] I control for a set of block-level covariates to account for differential growth in locations of such characteristics. In particular, I include the euclidean distance to the closest BRT station, the euclidean distance to the closest Metro station, and the euclidean distance to the Central Business District and its square. This allows me to control for anything that might have changed in places near stations but that are not related to improvement in commuting times. I also control for the physical size of the block and its square, its size in terms of the number of households in 2007, its slope, its elevation, and the number of dual-earner households as a share of married couples in 2007. Moreover, I include the average market access across household-types as measured in 2007. Finally, I control for the dependent variable at its value in 2007.

Labor supply elasticity. I recover wages and compute market access measures $\Phi^w_{R_{i\ell=1}}$ and $\Phi^h_{R_{i\ell=0}}$. Then, by taking logs to the odds ratio of labor force participation in equation 14 and taking first differences I get:

$$\Delta \log \frac{\mu_i^{mf}}{1-\mu_i^{mf}} = \nu \left[\frac{\Delta \log \Phi_{R^w_{i,\ell=1}}}{\theta^w} - \frac{\Delta \log \Phi_{R^h_{i,\ell=0}}}{\theta^h} \right] + \nu \left(\Delta \log \xi_{i\ell=1} - \Delta \log \xi_{i\ell=0} \right)$$

where the term in bracket measures how the accessibility to jobs for dual-earner households improved relative to job accessibility for male breadwinner households. If changes in job access are correlated with changes in household productivity, then estimating this equation by OLS will lead to biased estimates of ν. To bypass this endogeneity concern I use the model to produce instruments. Since this is a supply-side parameter, we require variation from the demand. In particular, I use the TFP terms I recovered to define the following instruments exploiting destination-level changes in TFP:

$$Z_{R^{mf}_{is}} = \sum_j \left(d^w_{ij} \right)^{-\theta^w} d \ln A_{js}$$

The identifying assumption is that $\mathbb{E}_i \left[\left(\Delta \log \xi_{i\ell=1} - \Delta \log \xi_{i\ell=0} \right) \cdot Z_{R^{mf}_{is}} \right] = 0$. Results are show in Panel B of Table 3.[22] I estimate a labor supply elasticity ν of 1.28.

Location elasticity. I recover wages and household productivity and compute market access measures $\Psi_{R^g_i}$ and $\Psi_{R^{mf}_i}$. Manipulating the equations for location choices in 10 and 15, I get:[23]

$$\begin{aligned}
\Delta \log \frac{N_{R^g_i}}{N^g} &= \chi_g + \eta^g \left[(\beta^g - 1) \Delta \log r_{R_i} + \frac{1}{\theta^g} \Delta \log \Psi_{R^g_i} \right] + \eta^g \Delta \log u^g_i \\
\Delta \log \frac{N_{R^{mf}_i}}{N^{mf}} &= \chi_{mf} + \eta^{mf} \left[\left(\beta^{mf} - 1 \right) \Delta \log r_{R_i} + \frac{1}{\nu} \Delta \log \Psi_{R^{mf}_i} \right] + \eta^{mf} \Delta \log u^{mf}_i
\end{aligned}$$

If growth in exogenous amenities is correlated with the growth in market access measures $\Psi_{R^g_i}$ and $\Psi_{R^{mf}_i}$ then the estimation of the location elasticities η^g and η^{mf} would be biased. Once again, I exploit changes in TFP to construct instruments for the growth in market access measures. Results are shown in Panel B of Table 3.[24] My results indicate that singles

[22] Once again I control for the complete set of euclidean distances (to the BRT, to the Metro, to the CBD). Moreover, I control for the physical size of the block, for its size in terms of the number of households in 2007, total employment in 2007, the number of dual-earner households as a share of married couples in 2007, and the block's slope and its area.

[23] Constants are defined as $\chi_g = \log \Delta \sum_l \left(\left(u^g_l \Psi^{1/\theta^{g,g}}_{R^{g,g}_l} \right)^{-1} r^{1-\beta^g}_{R_l} \right)^{-\eta^{g,g}}$ and $\chi_{mf} = \log \Delta \sum_l \left(\left(u^{mf}_l \Psi^{1/\nu}_{R^{mf}_l} \right)^{-1} r^{1-\beta^{mf}}_{R_l} \right)^{-\eta^{mf}}$.

[24] I include controls such as the euclidean distance to the Metro, to the BRT and to the CBD. I also include

($\hat{\eta}^f \approx \hat{\eta}^m \approx 2$) are much more mobile than married couples ($\hat{\eta}^{mf} \approx 1$).

5.5 Over-identification and Commuting Probabilities

In this subsection, I examine the extent to which the model can account quantitatively for the observed variation in commuting probabilities. I use the Census data to compute the probability that a worker of a particular household type and gender commutes between any of the 49 districts of Lima in 2017, yielding 2401 pairs of bilateral commuting probabilities. I solve the model using 2017 exogenous characteristics and commuting times under two models, one in which commuting is independent and one where it depends on the other spouse's behavior.[25] Then, I compare the predicted commuting probabilities with those observed in the 2017 Census.

Figure B.10 plots a bin scatter of commuting probabilities in the model and in the data. Panel A focuses on females in dual-earner households. The left hand side of Panel shows that the model with independent commuting probabilities underestimate commuting flows. For every percentage point that the model predicts, the data display probabilities 13.45% lower since the slope is 0.8655. Moreover, the model is able to predict around 36% of the variation in the data. On the right hand side, Panel A of Figure B.10 reveals that on average the model with interdependent commuting probabilities correctly predicts commuting probabilities. In fact, the slope between predicted and observed commuting probabilities is 0.99. Moreover, the model is able to explain 52% of the variation in the data. Panel B exhibits the results for males in dual-earner households. The model with independence performs well since the slope between the commuting probabilities in the data and in the model is of 0.9779. However, the model with interdependent commuting probabilities is capable to improve performance, yielding a slope between probabilities in the data and in the model of 1.0142.

Therefore, despite the model being an abstraction, it is able to capture key features of couples' commuting patterns that the model with independent choices is unable to capture, especially in the case of females in dual-earner households.

6 The Impact of the Line 1 of the Metro and BRT

This section quantifies how the new transit infrastructure affected the gender earnings gap and aggregate real earnings through improved commute times. It also provides evidence of

the size of the block, its slope and its elevation, the 2007 rents, and dependent variable at its value in 2007.

[25] Maximizing utility function: $U^{mf}_{i\ell jj'}(\omega) = u^{mf}_i \nu^{mf}_i(\omega) \cdot \xi^{mf}_{i\ell} \alpha^{mf}_\ell(\omega) \cdot \frac{\epsilon^h_j(\omega)}{d^h_{ij}} C^h_{i\ell j}(\omega)^{\beta^{mf}} H_{R^h_{i\ell j}}(\omega)^{1-\beta^{mf}} \cdot \left[\frac{\epsilon^w_{j'}(\omega)}{d^w_{ij'}} C^w_{i\ell j'}(\omega)^{\beta^{mf}} H_{R^w_{i\ell j'}}(\omega)^{1-\beta^{mf}}\right]^\ell$ subject to budget constraints $PC^h_{i\ell j}(\omega) + r_{R_i} H_{R^h_{i\ell j}}(\omega) = w_{jm}$ and $PC^w_{i\ell j'}(\omega) + r_{R_i} H_{R^w_{i\ell j'}}(\omega) = w_{j'f}\ell_i$ delivers a model with independent commuting probabilities.

the mechanisms in the paper, and how my quantitative results would change if I use a model in which choices are independent rather than interdependent.

Counterfactual exercises. I conduct a counterfactual exercise where I remove the Metro and the BRT from the city, while keeping exogenous characteristics fixed at their 2017 values. This informs about the impact of changing commuting times. I perform this counterfactual exercise for two cases, one in which spouses perform their commuting choices independently from each other, and one in which one spouse's choice is dependent on the other spouse's choice. To perform these counterfactual exercises, I use observed data to recover unobservables under the two models. Then, I solve each model conditionally on the corresponding unobservables.

Outcomes of interest. For each gender in each type of household I construct a measure of real income across locations $RY_i^k = \frac{y_i^k}{P(\beta^k) r_R^{1-\beta^k}}$ where k indexes a gender-by-household group. Then, I compute aggregate real income RY^k simply by summing up RY^k over all locations. Since I am interested not only on aggregate income but on average earnings, I construct a measure of real income per worker $R\bar{Y}^k = RY^k / N_{R^k}$, where N_{R^k} is the number of workers that belong to gender-household type k. Using these measures of real income I compute the gender earnings gap by dividing male real income by female real income and subtracting one: $\text{Gap} = RY^{k,m}/RY^{k,f} - 1$ or $\bar{\text{Gap}} = R\bar{Y}^{k,m}/R\bar{Y}^{k,f} - 1$, where now k indexes single and married households. Finally, I also compute the number of dual-earner households as a share of married households.

6.1 Interdependent commute choices

6.1.1 Impact on the gender earnings gap across locations

Figure 3 maps the evolution of real income RY_i and gender gap $\text{Gap}_i^k = RY_i^{k,m}/RY_i^{k,f}$ across origins i caused by the improved times. Each color accounts for 20% of observations. The map in the left hand side of Panel A shows that real income increased mostly in the northern and southern fringe of the city, while it shrunk in central areas of the city and on the eastern fringe. This is the consequence of two features. (i) Households in the northern and southern fringe of the city were the main beneficiaries of the infrastructure, as it allowed them to commute faster to central areas. (ii) Increased labor supply coming from the northern and southern fringe pushed down wages, especially in destinations in central areas. In the right hand side of Panel A I exhibit the impact on the gender gap in aggregate real income. The most salient feature of this graph is that the gap decreased the least in central areas, and the most in the fringe. However, impacts vary by household-type and location. Panel B maps the impact on the gender gap in single households and in married households. Two differences between singles and married arise. First, gap reductions tend to be larger for married. Second, the decrease in the aggregate gender gap among married tend to be concentrated in the northern and southern fringe. This is also true for singles but to a lesser extent.

In Figure 4, I estimate average impacts in different parts of the city by comparing the gap when the Metro and BRT are available against the gap without them. I compute these impacts for locations within 0 to 5 km from the CBD, from 5 to 7.5 km, from 7.5 to 10 km, from 10 to 12.25 km, and from more than 12.5 km. In Panel A, I show the impact on the aggregate real earnings gap per location, whereas in Panel B, I show the impact on the average real earnings gap. I show that both gaps decreased mainly in the fringe. This effect is almost entirely driven by married households for which aggregate gaps decreased by more than 12% and per worker gaps by 6.9%. Furthermore, the aggregate earnings gap increased for singles in some locations, but the average gap remained the same.

In sum, the improvement in commute times reduced the gender gap among married households according to the model with interdependent choices. This effect was greater in the fringe of the city. Next, I summarize aggregate impacts.

6.1.2 Aggregate impact

Table 4 reports my aggregate findings. It reports the percentage growth in the outcomes described above. Panel A shows the results of using the full model. First, both single males and single females see their income grow modestly by 0.60% and 0.39%. Since males aggregate income grew faster than females', the gender gap in aggregate earnings increased by 0.48%. When looking at average earnings, the gender gap increased by 0.56%. Second, turning to married households, aggregate income from male breadwinner households decreased by 1.61%, but average income increased by 0.66%. This is because many breadwinner households endogenously became dual-earner households. In fact, the new transit infrastructure led to an increase in female labor force participation of 1.74%, representing 9.48% of the total growth in labor force participation in the data. Since the number of dual-earner households is increasing endogenously, it is helpful to look at the increase on average earnings. Males' average earnings in dual-earner households grew by 1.17%, whereas females' average earnings rose by 2.19%. These impacts led to a reduction of the gender gap in aggregate and average earnings, which decreased by 4.13% and 2.54%, respectively. Finally, regarding the overall impact of the new transit infrastructure, aggregate and real income per worker grew by 1.07% and 0.70%.

6.1.3 Decomposition

For a set of commute times changes $dt_{ij'}, \forall i, j'$, I can use equation 7 to decompose the aggregate impact into three pieces: the direct use channel, the indirect use channel, and the general equilibrium impact (which is the difference between the total impact and the sum of the direct and the indirect use channels). Figure 5 depicts how the impact on aggregate income can be decomposed into these three pieces for singles, dual-earner households, and women in dual-earner households against men in male-breadwinner households. Panel A does so when using the model with interdependent choices. It reveals that from a direct use perspective, the Metro and the BRT marginally reduced the gap among singles. In other words, single women tended to use the routes that were improved marginally more than single men. However, general equilibrium effects favored single men, increasing marginally the gap among singles. Why general equilibrium effects favored men relative to women? In part this is because the increased labor supply of women led to a decrease in average wages at workplaces. On average, wages decreased by 1.6% for males, they decreased by 2.3% for females.

Panel A also shows the impacts among spouses in dual-earner households. It reveals that the direct use channel contributed the most in reducing gaps. This means that married women were initially more exposed to the routes that were improved. However, the indirect use channel and the general equilibrium effects tended to widen the gaps. Recall that according to Equation 7, the probability that wives will commute to low-wage locations increases through the indirect use channel when the initial conditional commuting probabilities to these locations are high enough. Since women tended to commute to low-wage locations, the indirect channel led to a widening of the gap.

Finally, this figure also shows the comparison of women in dual-earner households against men in male breadwinner households. Here, the general equilibrium channel tended to decrease the gap in aggregate earnings. This is because the share of male breadwinner households decreased, and so the mass of income they generated also decreased relative to dual-earner households.

In sum, this exercise indicates that the gender gap decreased for married households because the new transit infrastructure improved the routes that married women were using the most. However, the indirect use channel reinforced existing gaps.

6.1.4 Mechanisms

In this section I turn off mechanisms from the full model in order to assess their quantitative relevance. Results are shown in Table 5. For comparison, the first column shows the aggregate impact on real income and the gender gap using the complete model.

The second column removes externalities, and assume that productivity and amenity terms observed in 2017 remain fixed. This column reveals that the impact on real income and real income per worker rises to 1.39% and 1.02%, respectively. In other words, when endogenous externalities are allowed, real earnings grow slower. This is driven mainly by changes in the price index. In the full model, the price index decreased by 1.78%, whereas with no externalities it decreased by 3.02%. This is despite average productivity across the seven sectors grew by 0.53% in the full model. The explanation is that agglomeration externalities make the labor demand more elastic. Then, shifts in the labor supply have milder effects on wages, which prevents the price index to fall. In fact, males and female wages at destinations decreased by 1.61% and 2.28% in the full model, whereas they decreased by 2.52% and 3.17% in the model without externalities. Finally, the impact on the aggregate gender gap remains around of -2.00%, although the impact on the gender gap in earnings per worker becomes -0.84% rather than -1.05% as it was in the full model.

The third column keeps the distribution of households across locations fixed at its 2017 value. In other words, it assumes that households cannot reallocate in response to the removal of the transit infrastructure. Compared to column (1), the impacts on real income and on real income per capita are 42% and 79% lower, which suggest that mobility of households is an important mechanism. Furthermore, while the impact on the aggregate gender gap remains quite constant, the impact on the gender gap in terms of average earnings becomes -0.78% instead of -1.05%. This is driven by singles for which the gap increases by 0.83% rather than 0.48% as in the full model. Thus, households' mobility allows single women to better adjust to improvements in commute times.

Column (4) assumes that married couples cannot endogenously change their labor force participation. This reduces the impact on aggregate real income by $1-0.0096/0.0107 = 10\%$ which speaks to the importance of this margin in the aggregate. Moreover, preventing households to change their labor participation choice has some distributional consequences through the general equilibrium. In particular, when this margin is activated, increased supply in female labor tends to decrease females wages relative to male wages. This is reflected on the gender gap in earnings per worker. When married couples have the possibility of changing their labor supply choice, the overall gender gap decreases by 1.05% as a consequence of the new transit infrastructure. Preventing this choice also prevents female wages to decrease even further, leading to a steeper shrinking of the gender gap in earnings per worker, as it decreases by 1.59%.

Finally, Column (5) turns off the three mechanisms above. Doing so decreases the growth in aggregate real income from 1.07% to 0.75%. So, between the three they explain 30% of the growth. However, earnings per worker remains almost unchanged. While the mobility margin is an important mechanism through which improved commute times increase real income per worker, the LFP and externalities tended to have the opposite effect. Turning to the gender gap, without the three mechanisms, the reduction in the aggregate earnings gap becomes 1.14% instead of 2.15%. However, the reduction in gender gap in earnings per worker increases from 1.05% to 1.49%. This is mainly driven by the LFP margin. Increased female supply decreases women's average earning since the labor demand is downward sloping.

6.2 Independent choices.

6.2.1 Impact across locations

How different would the results be if, instead of implementing this paper's model, I use a model in which commute choices are independent within the couple?[26] This is shown in Figure 6. Panel A reveals that married households experienced a decrease in the gap in aggregate earnings. However, Panel B shows that this is not due to a decrease in the gap in earnings per worker. Rather, the decrease shown in Panel A is driven by the fact that the improvement in commute times induced male breadwinner households to become dual-earner households, thereby increasing the mass of income accumulated by married women relative to married men.

6.2.2 Aggregate impact

Panel B of Table 4 shows the aggregate impact when using a model with independent commute choices. Three observations are in order. First, this model overestimates the impact of the new transit infrastructure on aggregate real income by $1 - 0.0107/0.0137 = 22\%$ and on real income per worker by $1 - 0.0070/0.0105 = 33\%$. Second, while the gender gap in aggregate earnings in married households closes by 2.01%, this is mainly due to the labor force participation margin leading to an overall increase in the mass of income accumulated by females. When looking at earnings per worker, this model suggests that the gap in married households increased by 0.23% instead of shrinking by 2.54%. Third, this model underestimates the impact on the gender gap in aggregate earnings by $1 - 0.0128/0.0215 = 40\%$, and the gender gap in earnings per worker by $1 - (0.0008/0.0105) = 92\%$, leading to a switch in the sign.

6.2.3 Decomposition

Panel B of Figure 5 shows the decomposition of the effects into two channels: the direct use channel and the general equilibrium channel. First, results for singles in both models are qualitatively similar, with the general equilibrium channel tending to increase the gap and the direct use channel tending to decrease it. Second, in the model with independent choices, the results for singles and dual-earners are quantitatively similar. However, in the model with interdependent choices, the results for dual-earner households, especially those derived from the direct use channel, were stronger than for singles. This means that the direct use channel

[26] Maximizing utility function: $U^{mf}_{i\ell jj'}(\omega) = u^{mf}_i \nu^{mf}_i(\omega) \cdot \xi^{mf}_{i\ell}\alpha^{mf}_\ell(\omega) \cdot \frac{\epsilon^h_j(\omega)}{d^h_{ij}} C^h_{i\ell j}(\omega)^{\beta^{mf}} H_{R^h_{i\ell j}}(\omega)^{1-\beta^{mf}} \cdot \left[\frac{\epsilon^w_{j'}(\omega)}{d^w_{ij'}} C^w_{i\ell j'}(\omega)^{\beta^{mf}} H_{R^w_{i\ell j'}}(\omega)^{1-\beta^{mf}}\right]^\ell$ subject to budget constraints $PC^h_{i\ell j}(\omega) + r_{R_i} H_{R^h_{i\ell j}}(\omega) = w_{jm}$ and $PC^w_{i\ell j'}(\omega) + r_{R_i} H_{R^w_{i\ell j'}}(\omega) = w_{j'f}\ell_i$ delivers a model with independent commuting probabilities. In this model, I keep the property that married men and women locate together to give it the best chance to replicate the data. Although, it is fairly simple to set up an alternative model where preferences are defined for males and females irrespective of their marital status. By definition, in this alternative model commuting choices would be independent since there would not be any notion of married households.

as inferred by the two models is not the same. This is sensible because the direct use channel depends on commute probabilities, changes in wages, and changes in commute time. While commute time changes are the same in both models as they are data, wages and probabilities are inferred based on the structure of the models and the observed data. Finally, in the model with independent choices, when comparing women in dual-earner households to men in male breadwinner households, the gap decreased mainly due to general equilibrium effects, which are entirely due to the labor force participation choice. Once again, the direct use channel plays no role.

All in all, allowing for interdependent commute choices is quantitatively important when evaluating not only the impact of the new transit infrastructure on the gender gap and overall efficiency, but also when understanding the margins through which infrastructure affects households. Without accurate data on commute probabilities, the model with independent choices would not have been able to accurately measure married women's exposure to the new infrastructure.

7 Policy Exercise: Completing the Metro's Network

In this section, I use the model to evaluate what would happen if the Lines 2 and 4 of the Metro are completed (see Appendix B.5). To do so, I assume that speeds in these lines are similar to those of Line 1. I then keep 2017 exogenous characteristics constant and incorporate Lines 2 and 4 to the city. I compare this counterfactual scenario against (a) a scenario where the Line 1 of the Metro and the BRT are active, and (b) a scenario where neither Metro Lines or the BRT are active. The first comparison informs us about the incremental impact of completing the network, whereas the second comparison informs us about the overall impact of the Metro and the BRT.

Results are shown in Table B.5. Panel A reveals that on average real income would grow an additional 0.95% compared to the situation where only the Line 1 and the BRT are active. Also, income per worker would increase by 0.56%. Moreover, the gap would decrease by 1.87%. The gap in average earnings would shrink by 0.56%. The effect on the gap is driven by married couples. For these households, the gender earnings gap would decrease by 4.05%. In terms of income per worker, the gap would decrease by 2.26%. Overall, impacts are comparable in magnitude and sign to those of the Line 1 of the Metro and the BRT. The main difference is that in this case, the gap among singles increases in a non-negligible way, i.e. by 1.12%, or 1.31% if looking at the gap per worker.

Panel B exhibits the overall impact of the Metro and the BRT. The complete Metro network plus the BRT increases real income by 2.03%, and average earnings per worker by 1.26%. Also, the gap decreases by 3.98% on aggregate. The gap in income per worker decreases by 1.60%. Unsurprisingly, this is due to a decrease in the gap among married. In these households, the gap in aggregate earnings decreases by 8.01%, whereas the gap in earnings per worker decreases by 4.75%. However, among singles the gap increases by 1.61%. The gap in earnings per worker increases by 1.88%. Figure B.14 shows the decomposition of these aggregate impacts. Compared to the analysis of the impact of the Line 1 and the BRT, I observe similar patterns. Finally, in Figure B.15 I show average impacts across locations. Once again, I find that impacts on the gap are concentrated on areas closer to remote stations.

8 Conclusion

Commuting choices are interdependent across spouses. In particular, as the wage of one of the spouses increases, households are willing to give up more of the other spouses' income to decrease commute costs. Thus, improving commute times can affect households through two channels: the direct use channel and the indirect use channel.

My main results show that the model with interdependent commuting choices fits better the data on bilateral commuting flows of dual-earner households than the model without interdependence. They also show that reduced commute times can reduce the gender gap, especially in places were access increased the most.

Policymakers should take into account the interdependence of commuting choices within households when designing and implementing transit infrastructure projects in order to maximize the positive impact on reducing the gender earnings gap and improving overall economic outcomes. For example, governments could prioritize improving infrastructure and services in less developed areas of cities, which tend to be farther from job opportunities. However, it's important to note that through the indirect use channel in commuting choices, improving one spouse's prospects could negatively affect the other spouse's earnings.

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Table 1: Commuting Elasticity

	Single HH		Breadwinner HH		Dual-Earner HH	
	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)
Travel Time	-0.0514	-0.0617	-0.0466	-0.0634	-0.0480	-0.0673
	(0.0034)***	(0.0038)***	(0.0033)***	(0.0041)***	(0.0032)***	(0.0041)***
Origin FE	X	X	X	X	X	X
Destination FE	X	X	X	X	X	X
Gap (Female/Male-1)		20%		36%		40%
N	2500	2500	2500	2500	2500	2500

Notes: Observations are at the district-by-district level. The independent variable in all regressions is the median travel time between origin i and destination j is t, with origin and destination fixed effects included. Column (1) of the regression analysis uses the share of single male workers who reside in origin district i and work in destination district j as dependent variable. Column (2) uses the corresponding share for single female workers. Columns (3) and (4) focus on households where only the male or female breadwinner works, respectively. In columns (5) and (6), the shares are defined for dual-earner households, specifically for males and females separately. The difference between coefficients in column (1) and (2), between column (3) and (4), and between column (5) and (6) is statistically significant at the 1 percent level.

Table 2: Estimation from Aggregate Data, Calibration, and Gravity Equation

Parameter	Description	Value	Source
Panel A: Estimation from Aggregate Data			
$[\alpha_{f1}, \alpha_{f2}, \alpha_{f3}, \alpha_{f4}, \alpha_{f5}, \alpha_{f6}, \alpha_{f7}]$	Female input share by industry	$[0.21, 0.42, 0.41, 0.35, 0.29, 0.29, 0.20]$	ENAHO
$[1-\beta_m, 1-\beta_f, 1-\beta_{mf}]$	Household expenditure in housing	$[0.212, 0.208, 0.171]$	ENAHO
Panel B: Calibration			
σ	Male-female elasticity of substitution	2	Johnson and Keane (2013)
σ_D	Elasticity of substitution of demand	5	Freenstra et al. (2018)
α_s	Labor input share by industry	1-0.2 $\forall s$	Ahlfeldt et al. (2015)
Panel C: Commuting Elasticity			
$[\kappa^m, \kappa^f, \kappa^h, \kappa^w]$	Iceberg disutility	$[0.01, 0.01, 0.01, 0.01]$	Tsivanidis (2021)
$[\hat{\theta}^m, \hat{\theta}^f, \hat{\theta}^h, \hat{\theta}^w]$	Shape parameter in commuting preferences	$[5.14, 6.17, 4.66, 6.34]$	Gravity Equation. See Section 5.3.

Notes: Considered industries are (in order): Manufacture (w/o textiles), Textiles, Services, Business Services, Wholesale Trade, Retail Trade, Transportation. ENAHO stands for the 2007-2018 waves of the national household survey.

Table 3: Estimation of Parameters

Panel A: Agglomeration Externalities (ϕ_{F_s})

	OLS	2SLS	F - Weak Id
	(1)	(2)	(3)
Manufacture (w/o textiles)	0.6230	0.1057	43.54
	(0.0146)***	(0.0877)	
Manufacture (textiles)	0.4836	0.1668	19.02
	(0.0184)***	(0.0968)*	
Services	0.7255	0.0590	19.72
	(0.0126)***	(0.1561)	
Business Services	0.5991	0.1837	30.98
	(0.0200)***	(0.0888)**	
Wholesale Trade	0.6261	0.1591	39.43
	(0.0158)***	(0.0814)*	
Retail Trade	0.8204	0.2435	30.09
	(0.0126)***	(0.0924)***	
Transportation	0.6112	0.1573	42.37
	(0.0138)***	(0.0798)**	

Panel B: Labor Supply and Location Elasticities

	OLS	2SLS	F - Weak Id
	(1)	(2)	(3)
Labor Supply Elasticity (ν)	0.3644	1.2809	57.84
	(0.0776)***	(0.2418)***	
Location Single Females (η^f)	0.1801	2.0458	30.47
	(0.0707)***	(0.4363)***	
Location Single Males (η^m)	0.2046	1.8154	31.13
	(0.0733)**	(0.4121)***	
Location Married (η^{mf})	0.1106	1.0155	42.71
	(0.0519)***	(0.1853)***	

Notes: Panel A of the analysis estimates agglomeration externalities for each industry at the zone level. The study focuses on Lima, which is made up of 1500 zones. The dependent variable is the log change in TFP between 2017 and 2007. TFP is the productivity residual that ensures the definition for industry sales holds given observable data. The independent variable is the log change in sectoral employment. To address endogeneity concerns, the analysis employs IV estimation using Bartik-style instruments that leverage the change in commuting times. I include the euclidean distance to the closest BRT station, the euclidean distance to the closest Metro station, and the euclidean distance to the Central Business District and its square, the physical size of the block and its square, its size in terms of the number of households in 2007, its slope, its elevation, and the number of dual-earner households as a share of married couples in 2007, the average market access across household-types as measured in 2007, and the dependent variable at its value in 2007. Panel B estimates labor supply and location elasticity. For the labor supply elasticity, the dependent variable is the log difference in the odds ratio in female labor force participation in each zone, while the independent variable is the log difference between the utility when participating and when staying at home. The analysis leverages changes in TFP to construct instruments and controls for a complete set of euclidean distances (to the BRT, to the Metro, to the CBD). Additionally, the analysis controls for the physical size of the block, its size in terms of the number of households in 2007, total employment in 2007, the number of dual-earner households as a share of married couples in 2007, and the block's slope and area. For the location elasticity, the dependent variable in the final regression is the log difference in the share of workers of a specific gender-civil status living in a particular zone, while the independent variable is a measure of indirect utility backed out from the model. The analysis exploits changes in TFP to construct instruments and includes controls such as the euclidean distance to the Metro, to the BRT, and to the CBD. The study also includes the size of the block, its slope and elevation, 2007 rents, and the dependent variable at its value in 2007.

Table 4: The Aggregate Impact of the Line 1 of the Metro and the BRT

Panel A: Interdependent Commuting Choices

	Singles		Married			All		
	Males	Females	Males in BW HH	Males in D.E. HH	Females in D.E. HH	Males	Females	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Real Income	0.0060	0.0039	-0.0161	0.0292	0.0396	0.0070	0.0213	0.0107
Real Income per Worker	0.0060	0.0039	0.0066	0.0117	0.0219	0.0070	0.0122	0.0070
Gender Gap	0.0048			-0.0413		-0.0215		
Gender Gap (per Worker)	0.0056			-0.0254		-0.0105		
# D.E. / # Married				0.0174				

Panel B: Independent Commuting Choices

	Singles		Married			All		
	Males	Females	Males in BW HH	Males in D.E. HH	Females in D.E. HH	Males	Females	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Real Income	0.0097	0.0097	-0.0072	0.0273	0.0261	0.0114	0.0196	0.0137
Real Income per Worker	0.0097	0.0097	0.0123	0.0124	0.0112	0.0114	0.0118	0.0105
Gender Gap	0.0000			-0.0201		-0.0128		
Gender Gap (per Worker)	0.0000			0.0023		-0.0008		
# D.E. / # Married				0.0148				

Notes: I conduct a counterfactual exercise where I remove the Metro and the BRT from the city, while keeping exogenous characteristics fixed at their 2017 values. I perform this counterfactual exercise for two cases, one in which one spouse's choice is dependent on the other spouse's choice, and one in which spouses perform their commuting choices independently from each other. To perform these counterfactual exercises, I use observed data to recover unobservables under the two models. Then, I solve each model conditionally on the corresponding unobservables. Panel A shows the results of using the full model. Panel B shows the aggregate impact using the model with independent commute choices.

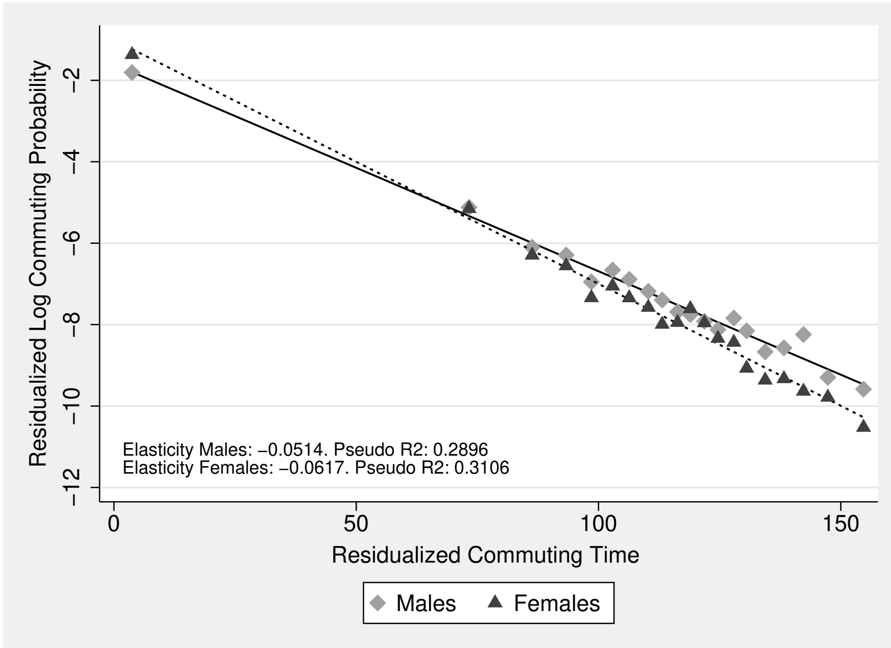
Table 5: The Aggregate Impact of the Line 1 of the Metro and the BRT - Mechanisms

	Full	No Externalities	No Mobility	No LFP	Neither of the three
	(1)	(2)	(3)	(4)	(5)
Real Income	0.0107	0.0139	0.0062	0.0096	0.0075
Real Income per Worker	0.0070	0.0102	0.0015	0.0099	0.0075
Gender Gap	-0.0215	-0.0200	-0.0233	-0.0112	-0.0114
Gender Gap (per Worker)	-0.0105	-0.0084	-0.0078	-0.0159	-0.0149
Gender Gap, Singles	0.0048	0.0089	0.0083	-0.0018	0.0058
Gender Gap (per Worker), Singles	0.0056	0.0104	0.0098	-0.0022	0.0068
Gender Gap, Married	-0.0413	-0.0401	-0.0457	-0.0200	-0.0227
Gender Gap (per Worker), Married	-0.0254	-0.0237	-0.0230	-0.0285	-0.0303
# DE/# Couples	0.0174	0.0174	0.0223	0	0

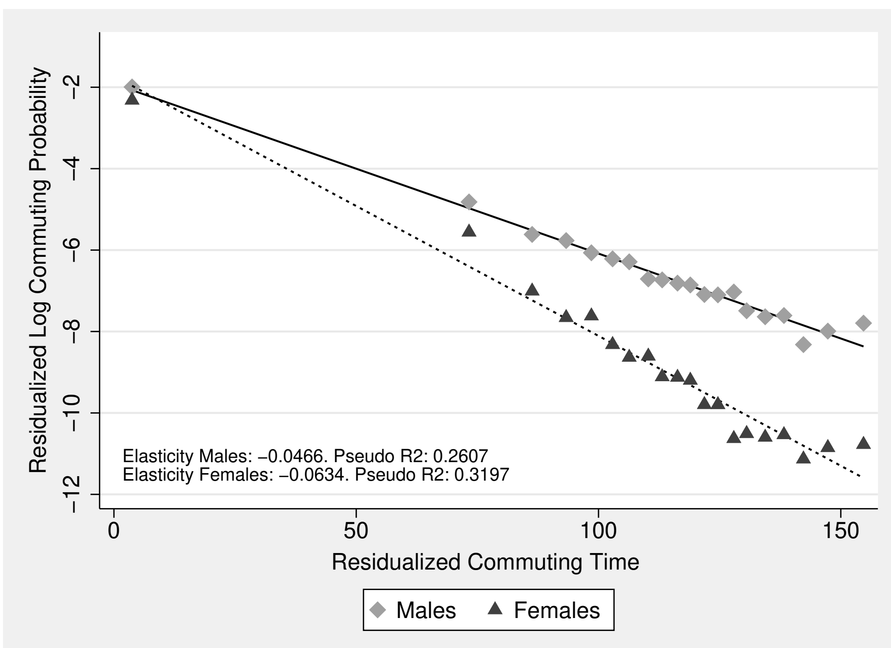
Notes: To assess the significance of individual mechanisms, I disable them from the full model and present their impacts in separate columns. The first column reports the overall effect on real income and the gender gap using the complete model. The second column eliminates externalities and assumes that productivity and amenity terms remain constant at their 2017 levels. The third column fixes the distribution of households across locations at the 2017 level. The fourth column assumes that married couples cannot change their labor force participation in response to economic changes.

Figure 1: Gravity in Commuting Flows among Singles and Married

Panel A: Singles



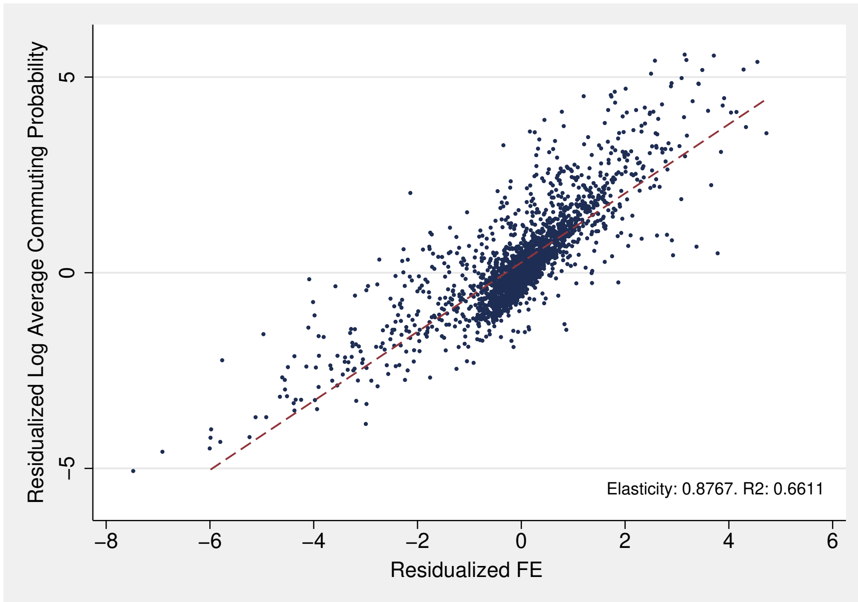
Panel B: Married



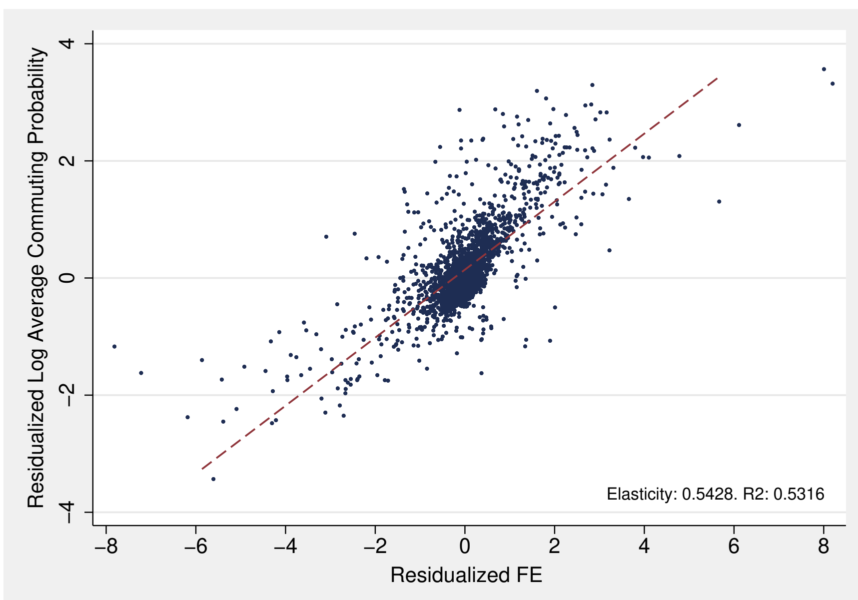
Notes: Columns (1) to (4) of Table 1.

Figure 2: Interdependence in Commuting Choices within Dual-earner Households

Panel A: Husband

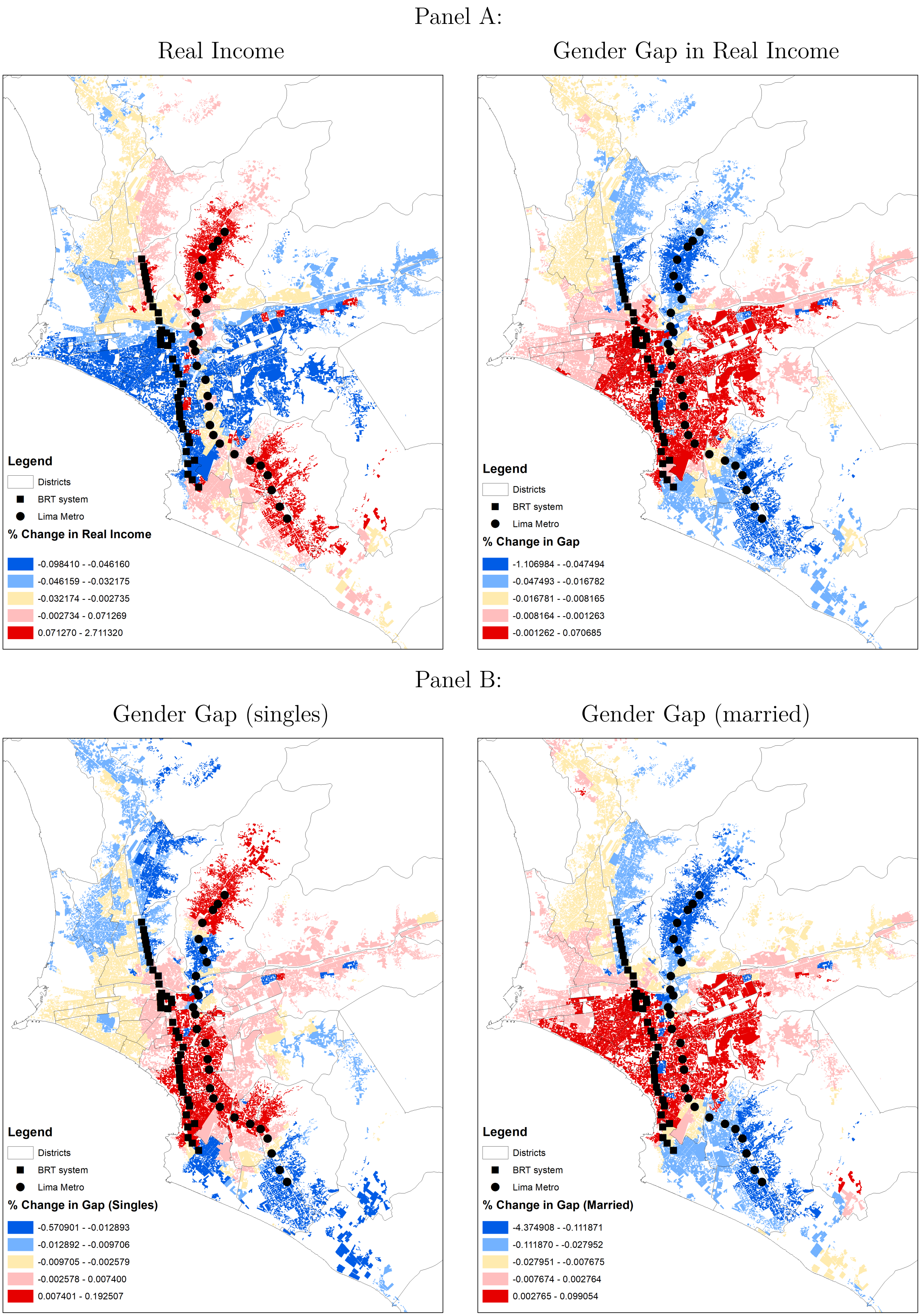


Panel B: Wife



Notes: I estimate $\log \pi_{j|ij',g} = \beta time_{ij} + FE_{i,j',g} + FE_{j,j',g} + \varepsilon_{ijj',g}$ for males and females in dual-earner households. Then, I recover the estimates of $FE_{j,j',g}$. I also control for the time it takes to go from workplace in j to workplace in j' to take into account that couples may decide destinations partially based on the distance between jobs. Finally, I estimate the coefficient ψ from $\log \pi_{j|j',g} = \psi_g \hat{FE}_{j,j'} + FE_j + FE_{j'}$. This figure depicts a scatter plot between residualized commuting probabilities and the residuals of $FE_{j,j'}$. Panel A depicts this plot for husbands while Panel B, for wives.

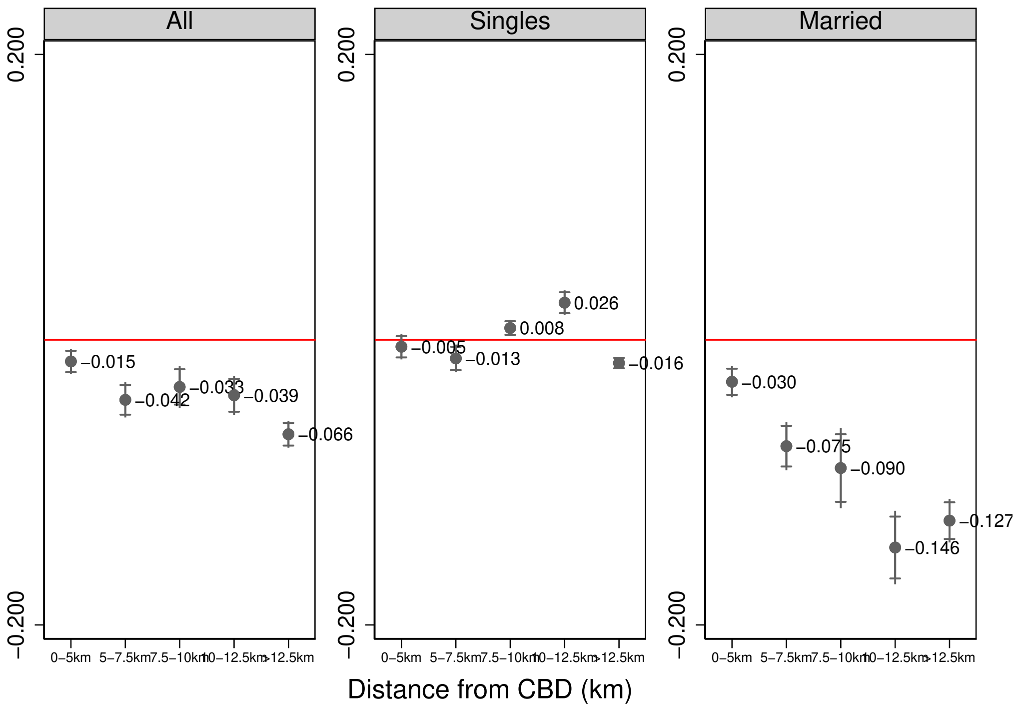
Figure 3: Quantitative Impact of Transit Infrastructure on Earnings and the Earnings Gender Gap with Interdependent Commute Choices



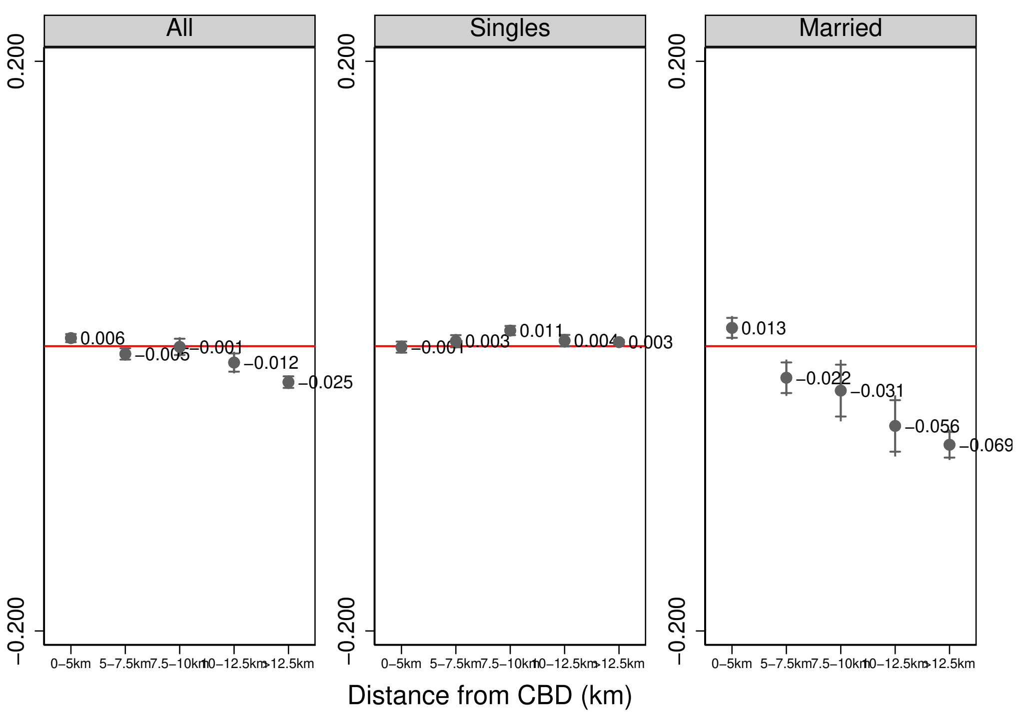
See Section 6.1.1.

Figure 4: Impact with Interdependent Commute Choices by Distance to the CBD

Panel A: Gap in Aggregate Real Earnings



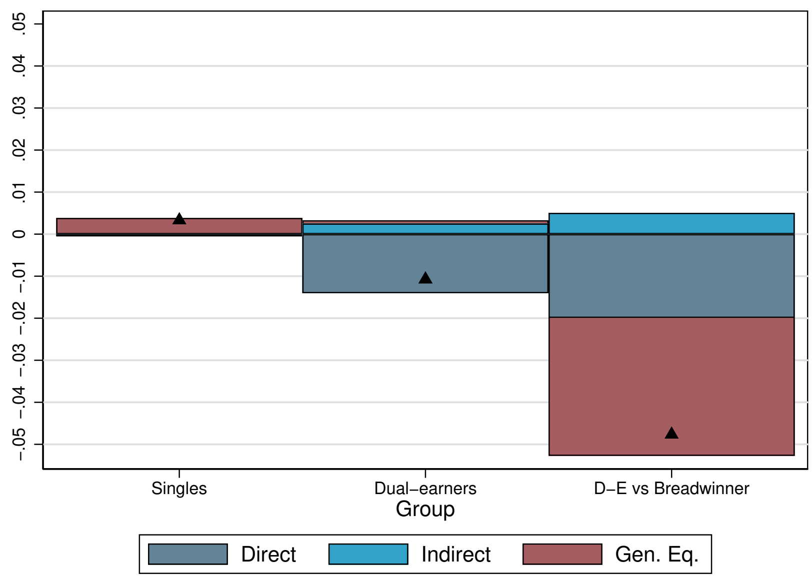
Panel B: Gap in Real Earnings per Worker



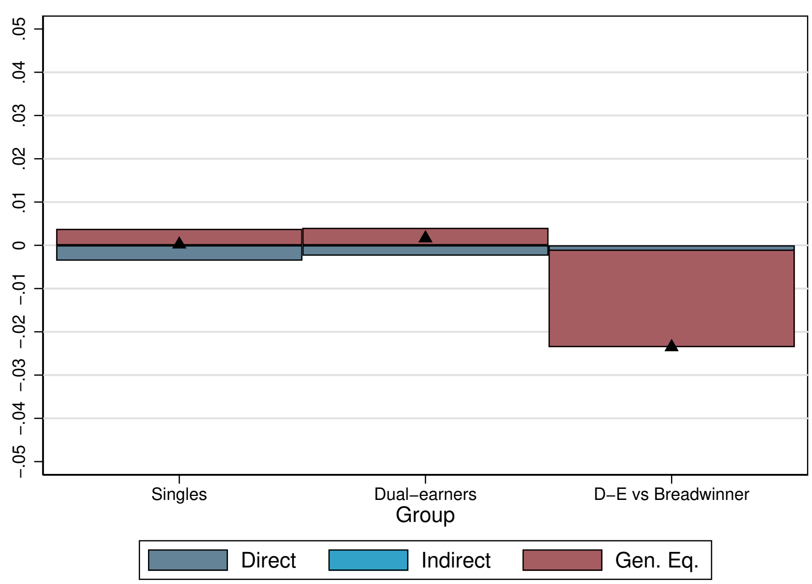
See Section 6.1.1.

Figure 5: Decomposition of the Aggregate Impacts

Panel A: Interdependent Commute Choices



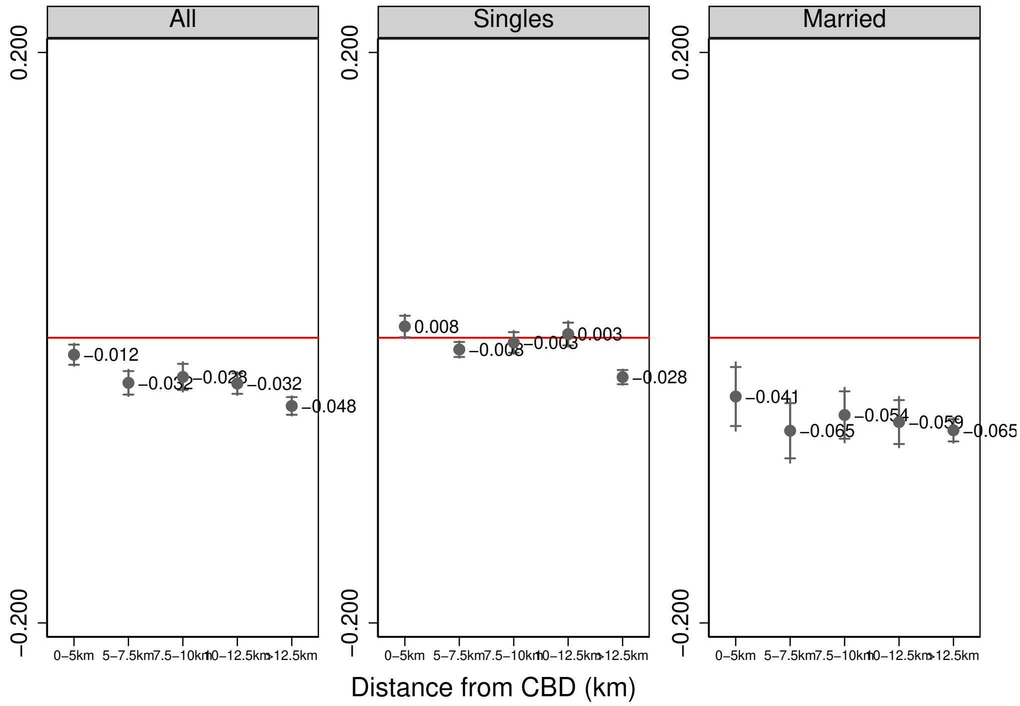
Panel B: Independent Commute Choices



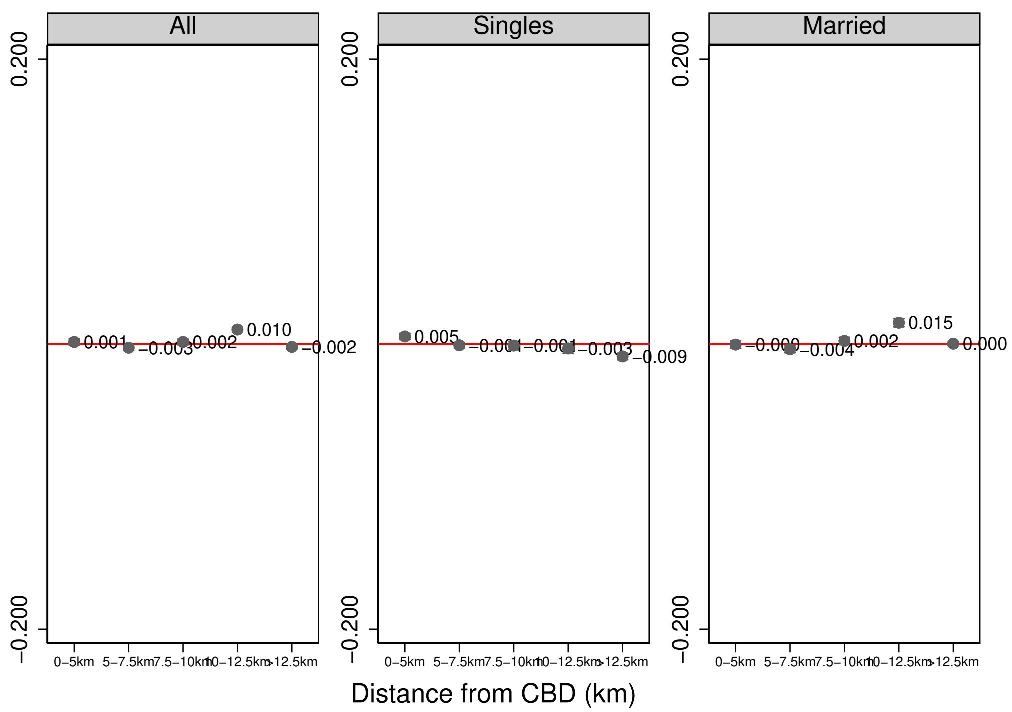
Panel A: see section 6.1.3. Panel B: see section 6.2.3.

Figure 6: Impact with Independent Commute Choices by Distance to the CBD

Panel A: Gap in Aggregate Real Earnings



Panel B: Gap in Real Earnings per Worker



See Section 6.2.1.

A1 Data Appendix

In this section, I explain the choices I made when processing the datasets available in this setting.

A1.1 Population and Household Census, 1993, 2007 and 2017

Household Classification. The primary source of population data is the Population and Household Census of 1993, 2007 and 2017. These were conducted by the National Institute of Statistics and Informatics (INEI). Crucially, these data sets contain the population in each block by gender and civil-status. Moreover, the household's roster is observed. Hence, I can observe who lives with whom.

I define a couple as a male and a female adult living in the same two-members-household. In 2017 around 77% of households had two or fewer adult members. In 2007, 75% of households had two or fewer adult members. So, these account for the majority of households. I also include the restriction that at least one of the two should work. For singles, I consider households with one adult member. This lone member should work.

For simplicity, I treat individuals living with two or more additional adults as singles (i.e. as if they were roommates and therefore not sharing their income). I make this simplification because if more than two adults live together, then it is hard to infer who is the couple of whom, and I require this knowledge to compute conditional commute probabilities. However, in some cases, it could potentially be inferred. For example, when the household head lives with his or her partner. Or if only two of the $N > 2$ members report to be married. One can also make some assumptions about the average age gap between the spouses. To avoid further complications, I make the choice of simply treating these individuals as singles. If anything, this choice makes singles to look a bit more alike to couples since I am potentially misidentifying some couples in multi-members households as singles.[27] By considering singles and couples in this simple way I am already improving on what the literature has done. In any case, results are similar if I drop those that report to be married among multi-members households. Finally, my main results consider as adults those between 25 and 65 years old, but results are robust to alternative definitions.

This classification leads to the following distribution of households: (i) single females (31.9% of households in 2017, 29% of households in 2007), (ii) single males (35.9% and 36.1%), (iii) male breadwinner households, that is, households where the wife stays at home while the husband goes to work (13.3% and 17.3%), (iv) female breadwinner households (1.3% and 1.5%), and (v) dual-earner households (17.6% and 16.2%). I calculate the number of households for each of these five groups for each block.

[27] Less than 50% of individuals in these households report to be married.

For consistency, I use the same classification across databases.

Commuting Flows. In the 2017 Census, employed individuals were asked to provide the district in which they work. Using this information, along with data on the locations where these individuals reside, I calculate commute probabilities as follows:

$$\pi^g_{j|i} = \frac{N^g_{j|i}}{\sum_k N^g_{k|i}}$$

where $N^g_{j|i}$ is the number of workers of group g that live in district i and work in district j. For conditional commute probabilities in dual-earner households,

$$\pi^g_{j|il} = \frac{N^g_{j|il}}{\sum_k N^g_{k|il}}$$

where $N^g_{j|il}$ is the number of dual-earner workers of gender g working in j, living i, and whose partners work in l.

A1.2 Economic Census, 2008

The 2008 Economic Census of Peru was conducted by the National Institute of Statistics and Informatics (INEI). This database covers firms of all sizes and all industries, except agriculture and financial services, even those that had not filed their taxes. It focuses exclusively on the firms' operations in 2007. Information and consistency checks were collected by census officers visiting business establishments. To my convenience, the location of the businesses were recorded at a very detailed level, including the specific census block they were located in. I aggregate sectors into seven sectors so that it is easier to match to the Firms' Administrative Data of 2015. In particular, I consider textiles, other manufacture, services, business services, wholesale, retail trade, and transportation services. I aggregate employment counts at the block level for each of the seven industries described above. This way, I get the distribution of economic activity per industry across locations for the first period of the analysis. I scale-up employment by the ratio of employment in the Economic Census to total employment in Lima according to the Population Census in 2007.

A1.3 Firms' Administrative Data, 2015

The Ministry of Production used their raw data and classified more than 1 million firms by industry, geographic location, sales, and number of workers. The database is available at this link. The information relevant to my analysis is the one concerning the industrial classification, the geographic location and the number of workers. Firms were classified into seven categories: 0-5 workers, 6-10 workers, 11-20 workers, 21-50 workers, 51-100 workers, 101-200 workers, and more than 200 workers. To compute the number of workers per firm I simply impute the lower bound of each interval.[28] Then, I aggregate these counts at the block level for each of the following broad industries: textiles, other manufacture, services, business services, wholesale, retail trade, and transportation services. This way, I get the distribution of economic activity per industry across locations for the second period of the analysis. I scale-up employment by the ratio of employment in the Economic Census to total employment in Lima according to the Population Census in 2017.

A1.4 Road Network Data and Commute Times

Road network data. I use road network data from Open Street Map. Open Street Map (OSM) is a free, editable map of the world that is created and maintained by a community of volunteer contributors. The project was started in 2004 with the goal of creating a free and open alternative to proprietary mapping services, such as Google Maps. The data in OSM is collected from a variety of sources, including GPS tracks, aerial imagery, and manual surveying. The data is then added to the OSM database and is available for anyone to use. The quality of OpenStreetMap data can vary depending on the region and the level of community engagement. In general, OSM data tends to be more accurate and up-to-date in areas with a high level of community engagement, such as densely populated urban areas and regions with a strong OSM community. In these areas, the map is regularly updated with new data and errors are quickly corrected. Importantly, the OSM data contains information on road type or classification, which I use to impute road speeds.

Commute times. I use the data on road type to input speeds during rush hour according to the following classification: motorway (50 km/h), primary (30 km/h), residential (15 km/h), secondary (20 km/h), and tertiary (10 km/h). This classification is based on a report for the Ministry of Transport and Communications done by the Japan International Cooperation Agency in 2013 (JICA, 2013). Additionally, I manually input speeds in certain roads, the BRT, and the Metro following the same report (see Table 6). Then, I run ArcGis's Network Analyst tool to compute the optimal route from origins to destination to generate an origin-destination matrix at the block level. I utilize this tool to compute commute times in absence of the Metro and the BRT and when the two are functional. Sometimes, I aggregate these times to the district level by taking the median value across zones within districts. I show that these times are well correlated with times reported in commuting surveys (see Figure B.3).

[28] Results are similar if I instead use the midpoint between the two bounds.

The matrix of commute times used in the analysis is an approximation of actual commute times. Ideally, the routes of public buses and road speeds would be used to calculate how long it takes to travel between locations using public transportation. However, data on bus routes is not readily available in this context. Despite this limitation, the commute elasticities, which link commute times to costs, are still estimated using the approximation of commute times and probabilities. These elasticities already take into account any potential differences between the estimated and actual commute times. For example, if actual commute times are twice as long as the estimated times, the estimated elasticities would be half as large. The only concern would be if the error in the approximation of commute times is correlated with a blocks' location or some characteristic, which could lead to problems.

Table 6: Manually imputed speeds

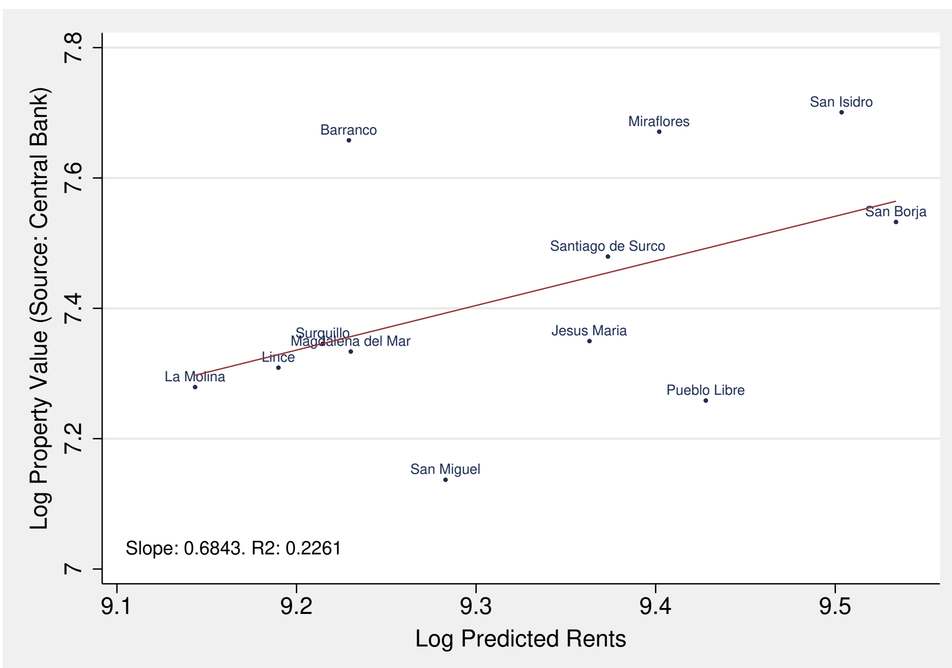
Road	Speed
Avenida Brasil	15 km/h
Avenida Javier Prado Oeste	15 km/h
Avenida La Marina	15 km/h
Avenida Faustino Sanchez Carrión	15 km/h
Avenida Almirante Miguel Grau	15 km/h
Avenida Abancay	15 km/h
Avenida Arequipa	15 km/h
Avenida de Tomás Marsano	15 km/h
Avenida República de Panamá	15 km/h
Avenida Arica	15 km/h
Avenida Aviación	15 km/h
Avenida República de Venezuela	15 km/h
Avenida Bolognesi	15 km/h
Avenida Prolongación Paseo de la República	15 km/h
Avenida Defensores del Morro	15 km/h
Avenida Universitaria	15 km/h
Metro Lines	45 km/h
Bus Rapid Transit System	35 km/h

A1.5 National Household Survey, 2007-2017

The National Institute of Statistics and Informatics (INEI) in Peru conducts the Peruvian National Household Survey (ENAHO) annually. The sample size of the survey varies each year, with a range of 26,000 to 40,000 households. The survey provides a wealth of information on individual income and demographics, including details on primary and secondary activities such as wages and hours worked. One of the survey's key benefits is that households are geocoded at the cluster level, with each cluster containing about 140 households. This level of granularity allows for accurate assignment of households to census blocks. Additionally, the survey collects valuable information from household heads, such as the estimated rental value of their home, total household income, and expenditures.

I use this data to predict how property values vary with centrality, and other block and dwelling characteristics.[29] Then, I use the estimated coefficients to project property values into census' blocks. I assign data on years 2007-2010 to the first period considered in the analysis, and data on years 2014-2017 to the second period. In Figure 7, I compare the log of the average value of predicted rents by district to data on the log of property values compiled by the Central Bank of Peru for a subset of districts. These averages are computed over years 2014-2017. Figure 7 shows that the two measures are well correlated. Finally, since geocoded data on rents by firms is not available in this setting, I assume that there are no differential rents due to land regulations, and so, the returns to floorspace use in residential and commercial activities are the same, conditional on a block's location.

Figure 7: Property Values versus Predicted Rents by District



[29] I achieve and R^2 of around 60% across the two periods considered in the analysis.

A1.6 Land Use Data, 2020

The Metropolitan Planning Institute collects actual land use data, but it is only available for the year 2020 and not for previous years. As a result, when required, I am assuming that land use in 2007 is the same as it was in 2017.[30] Despite this assumption, it does not have any impact on the estimation of any parameters in the model. This is because this data is only used to recover unobservables on the housing side, which is modeled in a straightforward manner following Tsivanidis (2021). These unobsevables are not an input in the estimation of any of the parameters. Additionally, the counterfactual analysis is not affected as I am using 2017 data as a baseline when removing the Metro and BRT from Lima. Therefore, the lack of land use data for 2007 does not affect this exercise. The lack of this data would be of significance if I were to perform a counterfactual analysis using the year 2007 as baseline.

[30] An alternative option would be to use data on floor space zoning, which is available for earlier years.

A2 Reduced-form evidence

As it will become clear in the theoretical section of the paper, the new transit infrastructure can impact households through many channels. The main channel is the improvement in commuting times leading to greater access to jobs. However, the Metro and BRT can also affect local exogenous amenities, for instance by bringing more crime or noise, and the price of the land (Brinkman and Lin, 2022). In this section, I explore these issues in the context of reduced-form specifications.

A2.1 Planned stations

I perform a reduced-form analysis by exploiting the planned network of Metro lines. Specifically, I leverage Line 2 and Line 4 of the Metro.[31] I compare locations closer to Line 1 of the Metro or the BRT (treatment locations) against locations closer to Line 2 and Line 4 (control locations). The basic idea is that we can account for location selection effects by comparing treated locations to locations closer to planned-but-not-constructed stations. Thus, these should constitute a better control group than other locations.

To illustrate how I define the treatment and control groups, Figure B.5 depicts the map of the constructed and planned stations, in addition to buffers around each station. In practice, I define the treatment group as all locations that are within 1.5 kilometers of any Line 1 or BRT station. Then, I define the control group as all locations that are within 3.2 kilometers from any Line 2 or Line 4 station. To avoid contamination from the treated group, I add the restriction that all locations in the control group should also be at least 2 kilometers away from all Line 1 and BRT stations. I use a bigger radius to define the control group because some locations are lost due to contamination which hurts statistical power. However, results are robust to alternative definitions.

[Figure B.5 here]

A2.2 Empirical strategy

I estimate time-event studies by comparing outcomes in locations close to the Metro and BRT stations to outcomes in locations close to yet-to-be-constructed stations. I utilize two data sources: the 1993, 2007 and 2017 Population Censuses, and the 2007-2017 waves of the National Household Survey.

The 1993, 2007 and 2017 Population Censuses. First, due to data limitations I start by

[31] I leave out Line 3 because it will run over the same locations as the BRT.

performing a time event study with a subset of the data.[32] Then, after showing that pre-trends are parallel, I move to a differences-in-differences specification employing only the 2007 and 2017 data, which allows me to fully leverage the cross-sectional variation of the data.

I start by running the following time event study:

$$\log y_{lt} \quad = \quad \sum_k \beta_k \left[Treat_l \cdot Year_t^k \right] + FE_l + FE_t + \epsilon_{it}$$

where y_{lt} is an outcome constructed from Census data, $Treat_l$ is a treatment dummy taking the value of one if the location l is closest to either the Metro or the BRT station. I interact these variables with year dummies and so β_{2017} measures the effect of the new transit infrastructure on locations that are closer to the stations, relative to locations that are closer to yet-to-be-constructed stations. $\beta_{1993} = 0$ would be indicative of parallel pre-trends. Finally, I introduce a set of location fixed effects FE_l, in addition to year fixed effects FE_t.

Next, I use the whole sample of locations in 2007 and 2017 to fully leverage the cross-sectional variation and estimate a differences-in-differences model. First, I break the treatment dummy into two: $Treat_l^{Metro}$, which takes the value of one if location l's closest station is a Metro station, and $Treat_l^{BRT}$ if the closest station is a BRT station.[33] Second, I argue that being closer to a station does not guarantee greater access to relevant destinations. Gains in access should be higher in the fringe of the city since these areas were more isolated at the beginning of the sample. Conversely, gains in access in locations closer to the CBD may be less pronounced since workers were already close to valuable destinations. Also, impacts on amenities and other outcomes could potentially be heterogeneous across locations. Thus, I allow for the treatment effects to vary by the distance of households to the CBD. I construct five dummies indicating if the household is located within 0-5, 5-7.5, 7.5-10, 10-12.5 kilometers, and more than 12.5 kilometers.

The 2007-2017 waves of the National Household Survey. I use 2007-2017 rounds of the Peruvian National Household Survey, georeferenced at the block level, to precisely locate households and classify them into treatment and control groups. Then, I run the following

[32]To perform the time-event study I need a panel of locations identified in 1993, 2007, and 2017. The problem is that the match between the 1993 data and the 2007 data is imperfect, partially, because many locations that existed in 2007 did not exist in 1993. Out of 605 locations in either the treatment or control group, I can correctly match 125. Matched locations tend to be at a lower altitude, and are closer to the CBD than unmatched locations, as expected. However, there are no statistically significant differences in the size of the block, in the slope, nor in the overall treatment status. I argue that while this subset of the data is non-random and might introduce a selection effect, it is still reassuring to find parallel pre-trends. Also, out of the 605 locations, I can match 600 in years 2007 and 2017.

[33]To control for differential trends among a set of covariates, I include a set X_{lt} of block-level controls, i.e. the physical size of the block (i.e. the area), the elevation of the block, the median slope, a continuous measure of distance to the central business district, and a continuous measure of distance to the closest station (either constructed or planned) each interacted with year dummies FE_t.

time-event study at the household level i and block level l at year t:

$$\begin{aligned}\log y_{il(i)t} &= \sum_k \beta_k \left[Treat^{Metro}_{l(i)} \cdot Time^k_t\right] + \sum_k \beta_k \left[Treat^{BRT}_{l(i)} \cdot Time^k_t\right] \\ &+ \gamma' X_{il(i)t} + FE_{l(i)} + FE_t + \epsilon_{it} \end{aligned} \tag{21}$$

where y_{it} is a household-level outcome such as rents and income.[34] $Treat^{Metro}_{l(i)}$ and $Treat^{BRT}_{l(i)}$ are treatment dummies taking the value of one if the location l is closest to either the Metro or the BRT station. $Time_t$ are a set of time dummies indicating if the data comes from (i) any year preceding 2009 i.e. 2007 or 2008, (ii) the year just before the introduction of the new transit infrastructure i.e 2009, or (iii) any year after the introduction of the new transit infrastructure, i.e. 2010 or after. I set the base category to be the year 2009 since the Metro and the BRT started operating in 2010. X_{1it} is a set of household-level controls comprising age, years of education, civil status, mother's language, and moving history. Finally, X_{2lt} is a set of block-level controls, i.e. the physical size of the block (i.e. the area), the elevation of the block, the median slope, a continuous measure of distance to the central business district, and a continuous measure of distance to the closest station (either constructed or planned) each interacted with year dummies FE_t.

The impact of being close to a station can hide substantial heterogeneity. In fact, gains in access are not uniformly distributed across stations. I allow for the treatment effects to vary by the distance of households to the CBD. I construct five dummies indicating if the household is located within 0-5, 5-7.5, 7.5-10, 10-12.5 kilometers, and more than 12.5 kilometers. As we will see, pre-trends do not seem to be an issue. Hence, I simplify equation 21 by replacing the time dummies with a dummy variable taking the value of one if the data comes from any year after 2009 and zero otherwise.

A2.3 Results

Fact 3: Rents and household expenditures tended to increase in the fringe, especially due to the BRT. Table B.2 shows the results of estimating equation 21 using survey data. Column (1) depicts the results on a variable constructed by the Bureau of Statistics which considers paid rents plus hypothetical rents. I show that on average there were no statistically detectable pre-trends, but also no average impacts of either the Metro or the BRT.[35]

Moving to measures of household income and expenditure (columns 2 and 3 of Table B.2), I find no detectable pre-trends of either the Metro or the BRT. Furthermore, I find that, on

[34] Unfortunately, the size of the sample does not allow me to have enough statistical power to explore the heterogeneity in the impact across different types of households.

[35] I obtain similar estimates if I use only paid rents instead.

average, locations closer to the Metro increased their expenditures by 10.6%. I find a similar coefficient when looking at the effect on income, but it is not statistically different from zero. I do not find any average impact of the BRT. In column 4 of Table B.2, I complement previous outcomes with dummies indicating whether household i is poor.[36] Once more, I do not find any pre-trends. Furthermore, I find that the Metro decreased poverty in nearby locations by 4.96 percentage points.

Next, I explore the heterogeneity of the effect across locations. Regarding rents, Panel A of Figure B.4 reveals that the estimated treatment effects are greater the farther away you move from the CBD. This is true for both the Metro and especially for the BRT.[37] Panel B of Figure B.4 shows the heterogenous impact on expenditures. Regarding the Metro, point estimates tend to be quite homogeneous across locations. For the BRT, I find that expenditures increased especially in locations farther away from the CBD.[38]

[Table B.2 here]

[Figure B.4 here]

Fact 4: On average, people moved out from the stations. This effect is reinforced in the fringe for the BRT, and in the CBD for the Metro. The basic intuition is that location choices can summarize to some extent the impact of the new infrastructure on households. As it will become clear in the theoretical section of the paper, new transit infrastructure can impact households through many channels. The main channel is the improvement in commuting times leading to greater access to jobs. However, the metro can also affect local amenities, for instance by bringing crowds, crime, and noise, and thus can also affect the price of the land. All of these will impact the location chosen by households. If we observe population decreasing in treated locations relative to control locations, it would be indicative that the new infrastructure is harming welfare in some way in these locations (e.g. by worsening amenities).

Results for the time-event study utilizing Census data are reported in Table B.3. Column (1) of Panel A shows the impact on overall population living in each block. We can see that relative to locations near yet-to-be-constructed stations, population in locations closer to stations shrunk by 12%. Importantly, I do not find evidence for differential pre-trends. In Table B.4, I show the corresponding differences-in-difference specification using the whole sample of 2007 and 2017 locations. Results are similar albeit coefficients are somewhat smaller.

[36] A household is defined as poor if it is unable to consume 2318 kilocalories per day as well as spend on basic services such as clothing, rent, health, transportation, and education, among others (INEI, 2000).

[37] See Panel A of Figure B.8 for impacts on actual paid rents.

[38] See Figure B.8 for impacts on income and poverty rates.

While the negative impact may seem surprising given the improvement in commuting times, it is not if we consider that rents were increasing especially in the fringe, and that amenities could be deteriorating.

Next, Figure B.6 shows the heterogeneity of the impact across locations. On the one hand, estimates reveal that the Metro decreased the population located in the CBD. On the other, the BRT had a negative impact on locations in the fringe. This could be because the BRT and the Metro affected access to opportunities, rents, and amenities in different magnitudes across locations. For instance, given that rents increased mainly in the fringe but not in the CBD, and that the Metro had a negative impact on population only in the CBD, this would imply that the Metro deteriorated amenities in the CBD.

[Table B.3 here]

[Figure B.6 here]

Fact 5: Males are better off in intermediate locations (between the CBD and the fringe) but married women are better off in the fringe. In Panel A of Table B.3, I exhibit the impact on other outcomes. Column (2) shows the impact on the ratio of singles to married, while column (3) shows the impact on the ratio of female to males. Estimates indicate that singles were more benefited than married households: in locations closer to stations relative to locations near yet-to-be-constructed stations, the population of singles relative to married increased by 8.1%. However, on average, the ratio of males and female stayed constant. Finally, column (4) shows the impact on the number of dual earner households relative to male breadwinner households. On average I do not find any impact. Also note that, importantly, pre-trends are always statistically indistinguishable from zero.[39]

Panel B of Figure B.6 reveals that locations around 7.5-10 km from the CBD experienced a decrease of singles relative to married for both the Metro and the BRT. However, both at the CBD and at the fringe, some increases were detectable for the BRT. Panel A of Figure B.7 shows the impact on the ratio of females to males. I find that women were more prone to leave locations around 7.5-10 km from the CBD. This implies that males were better off in intermediate locations. Finally, in Panel B of Figure B.7 the ratio of dual-earners to male breadwinner households increased in the fringe. So, while single households are equally or better off in the fringe (and worse off between 7.5-10 km from the CBD), dual-earner households are better off compared to male breadwinner households, implying that opportunities to women—and in particular to married women—expanded in the fringe.

[Figure B.7 here]

[39] In Table B.4, I show the corresponding differences-in-difference specification using the whole sample of 2007 and 2017 locations.

In conclusion, first, these results reveal that the new transit infrastructure fostered households to move out from areas closer to the stations. However, this impact was heterogeneous across household groups. For instance, results suggest that males' welfare expanded in intermediate locations, whereas females' welfare did so in the fringe, especially married women's welfare. Second, as it will become clear with the model, this rich heterogeneity comes from a combination of facts related to the geography of improvements in commuting times, the initial distribution of households and jobs across space, potential changes in amenities, and other general equilibrium impacts such as on rents and on wages. The model allows me to tease out the impacts that come exclusively from having better commute times (and the resulting GE impacts). Third, comparing stations to yet-to-be-constructed stations seems to take care of some endogeneity concerns since I do not find strong evidence for pre-trends. Not a single pre-trend coefficient is significant. Fourth, these results point towards the need of a model that takes the geography of Lima very seriously since impacts vary across locations.[40]

Finally, another word of caution when interpreting these impacts is that the introduction of the new transit infrastructure may have induced households to relocate to other parts of the city, as the Census data seems to suggest. In other words, the impacts I estimate are conflating partial and general equilibrium effects. It is hard to extract definitive conclusions from this analysis since the introduction of these transit investments have potentially affected the whole city, blurring the lines between what control and treatment groups are. To better understand these issues and tease out the different forces that are interacting in this context, in the following sections I start building intuition by developing a partial equilibrium model of commuting in married households. Then, in the quantitative section of the paper I set up a general equilibrium model of city structure based on Ahlfeldt, et al. (2015) and Tsivanidis (2021) but with the addition of interdependent commuting choices within couples.

A2.4 Understanding the reduced-form results in light of the model

In the reduced-form section of the paper, I explained that, while location choices might be indicative of overall welfare, they conflate changes in market access and amenities. In this section, I re-estimate the differences-in-differences framework using location outcomes comparing locations closer to stations against yet-to-be-constructed stations before and after the commute times were improved. These capture the effect of the new transit infrastructure that goes through better commuting times, but not through exogenous characteristics changing. Thus, I also estimate the differences-in-differences specification using backed-out exogenous amenities from 2007 and 2017 as dependent variable.

Results are shown in Figure B.11. These results show that amenities worsened in locations

[40] One could argue that Lima cannot be fully described by a monocentric model were only one CBD exists. Hence, the geographical dimension in the model should be flexible enough to account for this heterogeneity.

near to station. This explains apparent divergence between the counterfactual exercise and the data in terms of total population. While better commuting times fostered households to move closer to stations, amenities pushed households out. For completeness, I also show this exercise by civil status and gender and a similar pattern emerges: exogenous amenities for singles and married changed in non-negligible ways. In Figure B.12, I estimate the differences-in-differences specification but allowing heterogeneous impacts by distance to the CBD. These results reveal that amenities worsened especially in areas farther away from the CBD. However, when comparing singles to married, females to males, and dual-earners to male breadwinner households, counterfactuals and data moved in similar ways.

Finally, I solve the model keeping 2017 commute times constant but with 2007 amenities. The objective of this exercise is to evaluate whether differential changes in amenities in locations close to stations had an impact on the gender gap in earnings per worker. In Figure B.13, I show the results using as outcome the gender gap in earnings per worker in a one difference specification.[41] This figure reveals that earnings per worker remain virtually unchanged for singles and married.

[41] I compare outcomes with 2017 amenities against outcomes with 2007 amenities.

A3 Solution Algorithm

Corner solutions and observed prices

Given that I have agglomeration forces in the model, it is possible to have corner allocations for some locations. Without these externalities it is only possible if the exogenous component of productivity or of amenities is equal to zero. With externalities, even if the exogenous component of productivity or of amenities is positive, I can have corner solutions as the endogenous part, which enters multiplicatively, can be equal to zero when either employment or residence are equal to zero.

This implies that the groups $\mathcal{I}_{FR}$, $\mathcal{I}_F$, and $\mathcal{I}_R$ are endogenously determined:

$$
\begin{aligned}
\mathcal{I}_{FR} &= \{i : u_{ik} > 0, A_{is} > 0 \text{ for some } k \in mf, m, f \text{ and for some } s\} \\
\mathcal{I}_{R} &= \{i : u_{ik} > 0, A_{is} = 0 \text{ for some } k \in mf, m, f \text{ and for all } s\} \\
\mathcal{I}_{F} =& \quad \{i : u_{ik} = 0, A_{is} > 0 \text{ for all } k \in mf, m, f \text{ and for some } s\}
\end{aligned}
$$

Following Ahlfeldt et al. (2015), we can define the observed price of floor space (r_i). We can summarize the relationship between the observed price of floor space (r_i), the price of commercial floor space (r_{F_i}), the price of residential floor space (r_{R_i}), and land use as (ϑ_i):

$$
\begin{aligned}
r_i &= \begin{cases} \zeta_{F_i} r_{F_i} & \zeta_{F_i} = 1, \qquad i \in \mathcal{I}_F = \{i : u_{ik} = 0 \text{ for all k}, A_{is} > 0 \text{ for some s}\} \\ \zeta_{F_i} r_{F_i} & \zeta_{F_i} = 1 - \tau_i, \quad i \in \mathcal{I}_{FR} = \{i : u_{ik} > 0 \text{ for some k}, A_{is} > 0 \text{ for some s}\} \end{cases} \\
r_i &= \begin{cases} \zeta_{R_i} r_{R_i} & \zeta_{R_i} = 1, \qquad i \in \mathcal{I}_R = \{i : u_{ik} > 0 \text{ for some k}, A_{is} = 0 \text{ for all s}\} \\ \zeta_{R_i} r_{R_i} & \zeta_{R_i} = 1, \qquad i \in \mathcal{I}_{FR} = \{i : u_{ik} > 0 \text{ for some k}, A_{is} > 0 \text{ for some s}\} \end{cases}
\end{aligned}
\tag{22}
$$

where ζ_{F_i} and ζ_{R_i} relate observed floor prices to commercial and residential floor prices. $\mathcal{I}_F$ is the set of locations specialized in commercial activity $(1 - \vartheta_i = 1)$, $\mathcal{I}_R$ is the set of locations specialized in residential activity $(\vartheta_i = 1)$, and $\mathcal{I}_{FR}$ is the set of locations with both commercial and residential activity $(\vartheta_i \in (0, 1))$. Note that according to equation 22, the relationship between he observed price of floor space (r_i), the price of commercial floor space (r_{F_i}), the price of residential floor space (r_{R_i}), and land use as (ϑ_i), are a function only of the exogenous locational characteristics given by the vector defined by A_{is}, u_{ig}, and τ_i.

Algorithm

The system of equations defined above can be solved using the following algorithm.

1. Guess vector $w_g^0, r^0, \vartheta^0, u_{mf}^0, u_m^0, u_f^0, A_s^0, \mu^0$.

- Vector of prices should have normalization, e.g. $w_{1m} = 1$, so divide the vector of wages and rents by w_{1m}.

2. Given a vector $w_g^t, r^t, \vartheta^t, u_{mf}^t, u_m^t, u_f^t, A_s^t, \mu^t$:

   (a) Given our guess for productivity and amenities, we can determine the group indicator variables:

$$\begin{aligned}
\mathcal{I}_{FR} &= \{i : u_{ik} > 0, A_{is} > 0 \text{ for some } k \in mf, m, f \text{ and for some } s\} \\
\mathcal{I}_{R} &= \{i : u_{ik} > 0, A_{is} = 0 \text{ for some } k \in mf, m, f \text{ and for all } s\} \\
\mathcal{I}_{F} = & \quad \{i : u_{ik} = 0, A_{is} > 0 \text{ for all } k \in mf, m, f \text{ and for some } s\}
\end{aligned}$$

   (b) Construct rents for this iteration:

$$r_{R_i} = \begin{cases} r_i \times (1 - \tau_i) & \text{if} i \in \mathcal{I}_{FR} \\ r_i & \text{if} i \in \mathcal{I}_{R} \\ . & \text{if} i \in \mathcal{I}_{F} \end{cases} \quad r_{F_i} = \begin{cases} r_i & \text{if} i \in \mathcal{I}_{FR} \\ . & \text{if} i \in \mathcal{I}_{R} \\ r_i & \text{if} i \in \mathcal{I}_{F} \end{cases}$$

   (c) Compute total rents:

$$E = \sum_i r_{R_i} H_{R_i} + r_{F_i} H_{F_i}$$

   (d) Compute residence market access for single households:

$$\Psi_{R_i^g} = \sum_{l'} \left(\frac{d_{il'}^g}{w_{l'g}} \right)^{-\theta^g}, \forall g \in \{m, f\}$$

   (e) Compute residence market access for couples:

      i. In male breadwinner households:

$$\Phi_{R_{i,\ell=0}}^h = \sum_{l'} \left(\frac{d_{il}^h}{w_{lm}} \right)^{-\theta^h}$$

      ii. In dual-earner households:

$$\begin{aligned}
\Phi_{R_{i,\ell=1,j'}}^h &= \sum_l \left(\frac{d_{il}^h}{w_{lm} + w_{j'f}} \right)^{-\theta^h} \\
\Phi_{R_{i,\ell=1}}^w &= \sum_l \left(\frac{\left(\Phi_{R_{i,\ell=1,l}}^h \right)^{1/\theta^h}}{d_{il}^w} \right)^{\theta^w}
\end{aligned}$$

iii. On average:

$$\Psi_{R_i^{mf}} = \left[\left(\Phi_{R^w_{i,\ell=1}}\right)^{\frac{\nu}{\theta^w}} + \left(\xi^{mf}_{i\ell=0}\right)^{\nu}\left(\Phi_{R^h_{i,\ell=0}}\right)^{\frac{\nu}{\theta^h}}\right]^{1/\nu}$$

(f) Compute supply of residents to each location for each gender-by-household type:

$$\begin{aligned} N_{R_i^{k,k}} &= \pi_i^{k,k} N^{k,k}, k \in \{m, f\} \\ N_{R_i^{mf}} &= \underbrace{(1-\mu_i)\,\pi_i^{mf} N^{mf}}_{N_{R^{mf}_{i,0}}} + \underbrace{(\mu_i)\,\pi_i^{mf} N^{mf}}_{N_{R^{mf}_{i,1}}} \end{aligned}$$

where

$$\pi_i^g = \frac{\left(\frac{r_{R_i}^{1-\beta^g}}{u_i^g \Psi^{1/\theta^g}_{R_i^g}}\right)^{-\eta^g}}{\sum_l \left(\frac{r_{R_l}^{1-\beta^g}}{u_l^g \Psi^{1/\theta^g}_{R_l^g}}\right)^{-\eta^g}}$$

and

$$\pi_i^{mf} = \frac{\left(\frac{r_{R_i}^{1-\beta^{mf}}}{u_i^{mf} \Psi^{1/\nu}_{R_i^{mf}}}\right)^{-\eta^{mf}}}{\sum_l \left(\frac{r_{R_i}^{1-\beta^{mf}}}{u_l^{mf} \Psi^{1/\nu}_{R_l^{mf}}}\right)^{-\eta^{mf}}}$$

(g) Compute commuting probabilities:

i. For singles:

$$\pi^g_{j|i} = \frac{\left(\frac{d^g_{ij}}{w_{jg}}\right)^{-\theta^{\cdot g}}}{\Phi_{R_i^g}}$$

ii. For males in male-breadwinner households:

$$\pi^h_{j|i,\ell=0} = \frac{\left(\frac{d^h_{ij}}{w_{jm}}\right)^{-\theta^h}}{\Phi^h_{R_{i,\ell=0}}}$$

iii. For females in dual-earner households:

$$\pi^w_{j'|i,\ell=1} = \frac{\left(\frac{d^w_{ij'}}{\left(\Phi^h_{R_{i,\ell=1,j'}}\right)^{1/\theta^h}}\right)^{-\theta^w}}{\Phi^w_{R_{i,\ell=1}}}$$

iv. For males in dual-earner households:

$$\pi^h_{j|i,\ell=1} = \sum_l \pi^h_{j|i,\ell=1,l} \cdot \pi^w_{l|i,\ell=1}$$

where

$$\pi^h_{j|i,\ell=1,j'} = \frac{\left(\frac{d^h_{ij}}{w_{jm}+w_{j'f}}\right)^{-\theta^h}}{\Phi^h_{R_{i,\ell=1,j'}}}$$

(h) Compute labor supply:

$$\begin{aligned}
L_{F_{jm}} &= \sum_i \left\{\pi^{m,m}_{j|i} N_{R^{m,m}_i}\right\} + \sum_i \left\{\pi^h_{j|i,\ell=0} N_{R^{mf}_{i,0}}\right\} + \sum_i \left\{\pi^h_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} \\
L_{F_{jf}} &= \sum_i \left\{\pi^{f,f}_{j|i} N_{R^{f,f}_i}\right\} + \sum_i \left\{\pi^w_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\}
\end{aligned}$$

(i) Compute total income:

$$\begin{aligned}
y^{mf}_{i,\ell=1} &= \underbrace{\sum_j \left(w_{j,m}\pi^h_{j|i,\ell=1}\right) N_{R^{mf}_{i,1}}}_{y^h_{i,\ell=1}} + \underbrace{\sum_j \left(w_{j,f}\pi^w_{j|i,\ell=1}\right) N_{R^{mf}_{i,1}}}_{y^w_{i,\ell=1}} \\
y^{mf}_{i,\ell=0} &= \sum_j \left(w_{j,m}\pi^h_{j|i,\ell=0}\right) N_{R^{mf}_{i,0}} \\
y^g_i &= \sum_j \left(w_{j,g}\pi^g_{j|i}\right) N_{R^g_i}
\end{aligned}$$

(j) Compute price index:

$$\begin{aligned}
p_{js} &= W^{\alpha_s}_{js} r^{1-\alpha_s}_{Fj} / A_{js} \\
P &= \left(\sum \left(W^{\alpha_s}_{js} r^{1-\alpha_s}_{Fj} / A_{js}\right)^{1-\sigma_D}\right)^{\frac{1}{1-\sigma_D}} \\
W_{js} &= \left(\sum_g \alpha^\sigma_{sg} w^{1-\sigma}_{jg}\right)^{\frac{1}{1-\sigma}}
\end{aligned}$$

(k) Update guesses using demand side:

i. Update labor force participation:

$$\mu^{t+1}_{i,mf} = \frac{\left[\left(\Phi^w_{R_{i,\ell=1}}\right)^{-1/\theta^w}\right]^{-\nu}}{\Psi_{R^{mf}_i}}$$

ii. Update endogenous productivities:

$$A_{js}^{t+1} = \bar{A}_{js} \left(L_{F_{js}}\right)^{\phi_{Fs}}$$

iii. Plugging labor supply into labor demand to update new wages:

$$\tilde{w}_{jg} = \left(\frac{\sum_s \left(\frac{1}{\alpha_{sg} W_{js}}\right)^{-\sigma} M_{js}}{L_{F_{jg}}} \right)^{1/\sigma}$$

where:

$$\begin{aligned}
M_{js} &= \alpha_s \frac{X_{js}}{W_{js}} \\
X_{js} &= \frac{p_{js}^{1-\sigma_D}}{P^{1-\sigma_D}} X \\
X = PC &= \sum_i PC_i + \sum_i \left(H_{R_i} r_{R_i} + H_{F_i} r_{F_i}\right) \\
&= \beta^m y_i^{m,m} + \beta^f y_i^{f,f} + \beta^{mf} y_{i,\ell=1}^{mf} + \beta^{mf} y_{i,\ell=0}^{mf} + E
\end{aligned}$$

iv. Update observed rents. To do so, note that aggregate expenditure on housing in location i by households is:

$$\begin{aligned}
E_{Ri} &= r_{R_i} H_{R_i} \\
&= (1-\beta^m)\, y_i^{m,m} + \left(1-\beta^f\right) y_i^{f,f} + \left(1-\beta^{mf}\right) y_{i,\ell=1}^{mf} + \left(1-\beta^{mf}\right) y_{i,\ell=0}^{mf}
\end{aligned}$$

Similarly, note that aggregate spending on floorspace by firms is:

$$H_{F_i} = \sum_s (1-\alpha_s) \frac{X_{js}}{r_{F_j}}$$

Therefore, our new guess for observed rents would be as follows:

$$\begin{aligned}
\text{if i} \in \mathcal{I}_R, \text{ then} r_i^{t+1} &= E_{Ri}/H_i \\
\text{if i} \in \mathcal{I}_F, \text{ then} r_i^{t+1} &= X_i/H_i \\
\text{if i} \in \mathcal{I}_{FR}, \text{ then} r_i^{t+1} &= \frac{\frac{E_{Ri}}{(1-\tau_i)} + X_i}{H_i}
\end{aligned}$$

v. Update land allocation:

$$\begin{aligned}
\text{if i} \in \mathcal{I}_R, \text{ then} \vartheta_i &= 1 \\
\text{if i} \in \mathcal{I}_F, \text{ then} \vartheta_i &= 0 \\
\text{if i} \in \mathcal{I}_{FR}, \text{ then} \vartheta_i &= \frac{\frac{E_{Ri}}{(1-\tau_i)}}{\frac{E_{Ri}}{(1-\tau_i)} + X_i}
\end{aligned}$$

(l) Normalize new vector of prices.

(m) If $|| \left(w_g^{t+1}, r^{t+1}, \vartheta^{t+1}, u_{mf}^{t+1}, u_m^{t+1}, u_f^{t+1}, A_s^{t+1}, \mu^{t+1}\right) - \left(w_g^t, r^t, \vartheta^t, u_{mf}^t, u_m^t, u_f^t, A_s^t, \mu^t\right) || \leq tolerance$, then stop. Otherwise, set:

$$\begin{aligned}
\left(w_g^{t+1}, r^{t+1}, \vartheta^{t+1}, u_{mf}^{t+1}, u_m^{t+1}, u_f^{t+1}, A_s^{t+1}, \mu^{t+1}\right) &= \rho \left(w_g^{t+1}, r^{t+1}, \vartheta^{t+1}, u_{mf}^{t+1}, u_m^{t+1}, u_f^{t+1}, A_s^{t+1}, \mu^{t+1}\right) \\
&+ (1-\rho)\left(w_g^t, r^t, \vartheta^t, u_{mf}^t, u_m^t, u_f^t, A_s^t, \mu^t\right)
\end{aligned}$$

where $\rho \in (0,1)$.

(n) Return to step 2.a

A4 Proofs

A4.1 Proposition 1

Proposition: *Given data on residence by gender and household type, $N_{R^k_{i,\ell}}$, employment by gender $L_{F_{jg}}$ and commute costs d^k_{ij}, and parameters θ^k, there exists a vector of wages w_{jg} up to scale that rationalizes the observed data as a model equilibrium. Additionally, if one does not observe $L_{F_{jg}}$ but rather employment by industry $L_{F_{js}}$ and parameters α_{sg} and σ, there exists a vector of wages w_{jg} up to scale that rationalizes the observed data as a model equilibrium.*

Proof. Recall that labor supply is:

$$\begin{aligned} L_{F_{jm}} &= \sum_i \left\{\pi^{m,m}_{j|i} N_{R^{m,m}_i}\right\} + \sum_i \left\{\pi^h_{j|i,\ell=0} N_{R^{mf}_{i,0}}\right\} + \sum_i \left\{\pi^h_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} \\ L_{F_{jf}} &= \sum_i \left\{\pi^{f,f}_{j|i} N_{R^{f,f}_i}\right\} + \sum_i \left\{\pi^w_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} \end{aligned}$$

Or

$$\begin{aligned} L_{F_{jm}} &= w^{\theta^m}_{jm} \sum_i \left[\frac{N_{R^m_i}\left(d^m_{ij}\right)^{-\theta^m}}{\sum_{l'} w^{\theta^m}_{jm}\left(d^m_{il'}\right)^{-\theta^m}}\right] + w^{\theta^h}_{jm} \sum_i \left[\frac{N_{R^{mf}_{i,0}}\left(d^h_{ij}\right)^{-\theta^h}}{\sum_l w^{\theta^h}_{lm}\left(d^h_{il}\right)^{-\theta^h}}\right] \\ &+ \sum_i \left[\frac{N_{R^{mf}_{i,1}}\left(d^h_{ij}\right)^{-\theta^h}}{\sum_{l'}\left(\sum_n\left(\frac{d^h_{in}}{w_{nm}+w_{l'f}}\right)^{-\theta^h}\right)^{\theta^w/\theta^h}\left(d^w_{il'}\right)^{-\theta^w}} \times \right. \\ &\times \left. \sum_l \frac{\left(d^w_{il}\right)^{-\theta^w}\left(\sum_n\left(\frac{d^h_{in}}{w_{nm}+w_{lf}}\right)^{-\theta^h}\right)^{\theta^w/\theta^h-1}}{\left(w_{jm}+w_{lf}\right)^{-\theta^h}}\right] \end{aligned}$$

and

$$\begin{aligned} L_{F_{jf}} &= w^{\theta^f}_{jf} \sum_i \left[\frac{N_{R^f_i}\left(d^f_{ij}\right)^{-\theta^f}}{\sum_{l'} w^{\theta^f}_{jf}\left(d^f_{il'}\right)^{-\theta^f}}\right] \\ &+ \sum_i \left[\frac{N_{R^{mf}_{i,1}}\left(d^w_{ij}\right)^{-\theta^w}}{\sum_{l'}\left(\sum_n\left(\frac{d^h_{in}}{w_{nm}+w_{l'f}}\right)^{-\theta^h}\right)^{\theta^w/\theta^h}\left(d^w_{il'}\right)^{-\theta^w}} \left(\sum_n\left(\frac{d^h_{in}}{w_{nm}+w_{jf}}\right)^{-\theta^h}\right)^{\theta^w/\theta^h}\right] \end{aligned}$$

Inuitively, if one could observe residence supply by gender and household type, $N^{\ell}_{R_{i,k}}$, and employment by gender, $L_{F_{jg}}$, then one could solve the system defined above.

Additionally, if one does not observe $L_{F_{jg}}$ but rather $L_{F_{js}}$ and knows parameters α_{sg} and

σ, from FOCs of the firm, one gets:

$$L_{F_{jg}} = \sum_s \frac{(w_{jg}/\alpha_{sg})^{-\sigma}}{\sum_{h\in m,f}(w_{jh}/\alpha_{sh})^{-\sigma}} L_{F_{js}}$$

We can plug this expression to the equations above, and solve the system. In what is next, I follow Mas-Collel, Whinston, and Green (1995) and Allen, and Arkolakis (2015) to prove existence. While existence is assured, uniqueness is not unless additional conditions are imposed. Let $\mathcal{Z}_{jm}$ and $\mathcal{Z}_{jf}$ be defined as:

$$\begin{aligned}
\mathcal{Z}_{jm} &= \sum_s \frac{(w_{jm}/\alpha_{sm})^{-\sigma}}{\sum_{g\in m,f}(w_{jg}/\alpha_{sg})^{-\sigma}} L_{F_{js}} - \sum_i \left\{\pi^m_{j|i} N_{R^m_i}\right\} + \sum_i \left\{\pi^h_{j|i,\ell=0} N_{R^{mf}_{i,0}}\right\} + \sum_i \left\{\pi^h_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} \\
\mathcal{Z}_{jf} &= \sum_s \frac{(w_{jf}/\alpha_{sf})^{-\sigma}}{\sum_{g\in m,f}(w_{jg}/\alpha_{sg})^{-\sigma}} L_{F_{js}} - \sum_i \left\{\pi^f_{j|i} N_{R^f_i}\right\} + \sum_i \left\{\pi^w_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\}
\end{aligned}$$

Part I: Existence. $\mathcal{Z}_z = [\mathcal{Z}_{jm}, \mathcal{Z}_{jf}]$ can be decomposed into $\mathcal{Z}_z(w) = \sum_s \mathcal{L}_{sj}(w) - \sum_k \mathcal{N}_{kj}(w)$ where $\mathcal{L}_{sj}(w) \geq 0$ and $\mathcal{N}_{kj}(w) \geq 0$ are, respectively, homogeneous of degree ζ_s and $\varkappa_k$ with $\zeta_s = \varkappa_k = 0$. Since I am stacking $\mathcal{Z}_{jm}$ and $\mathcal{Z}_{jf}$, then the index z corresponds to each location. So, there is a mapping between the index z in vector $\mathcal{Z}_z$, and the index of a location j in $\mathcal{Z}_{jm}$ and $\mathcal{Z}_{jf}$:

$$j = \begin{cases} z & z \leq J \\ z - J & z \geq J+1 \end{cases}$$

First, notice that

$$\mathcal{L}_{sz}(w_m, w_f) = \begin{cases} \frac{(w_{jm}/\alpha_{sm})^{-\sigma}}{\sum_{g\in m,f}(w_{jg}/\alpha_{sg})^{-\sigma}} L_{F_{js}} & z \leq J \\ \frac{(w_{jf}/\alpha_{sf})^{-\sigma}}{\sum_{g\in m,f}(w_{jg}/\alpha_{sg})^{-\sigma}} L_{F_{js}} & z \geq J+1 \end{cases}$$

is homogeneous of degree zero. Second,

$$\mathcal{N}_{kz}(w_m, w_f) = \begin{cases} \sum_i \left\{\pi^m_{j|i} N_{R^m_i}\right\} & z \leq J, k = s \\ \sum_i \left\{\pi^h_{j|i,\ell=0} N_{R^{mf}_{i,0}}\right\} & z \leq J, k = mf0 \\ \sum_i \left\{\pi^h_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} & z \leq J, k = mf1 \\ \sum_i \left\{\pi^f_{j|i} N_{R^f_i}\right\} & z \geq J+1, k = s \\ \sum_i \left\{\pi^w_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} & z \geq J+1, k = mf1 \end{cases}$$

When $k = s$, it is easy to see that either $\sum_i \left\{\pi^m_{j|i} N_{R^m_i}\right\}$ and $\sum_i \left\{\pi^f_{j|i} N_{R^f_i}\right\}$ are homogeneous of degree zero. Similarly, when $k = mf0, \sum_i \left\{\pi^h_{j|i,\ell=0} N_{R^{mf}_{i,0}}\right\}$ is homogeneous of degree zero. Finally, by inspection,

$$\sum_i \left\{\pi^w_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} = \sum_i \left[\frac{N_{R^{mf}_{i,1}} \left(d^w_{ij}\right)^{-\theta^w}}{\sum_{l'} \left(\sum_n \left(\frac{d^h_{in}}{w_{nm}+w_{l'f}}\right)^{-\theta^{mf,m}}\right)^{\theta^w/\theta^h} \left(d^w_{il'}\right)^{-\theta^w}} \left(\sum_n \left(\frac{d^h_{in}}{w_{nm}+w_{jf}}\right)^{-\theta^h}\right)^{\theta^w/\theta^h} \right]$$

and

$$\sum_i \left\{\pi^h_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} =$$

$$\sum_i \left[\frac{N_{R^{mf}_{i,1}} \left(d^h_{ij}\right)^{-\theta^h}}{\sum_{l'} \left(\sum_n \left(\frac{d^h_{in}}{w_{nm}+w_{l'f}}\right)^{-\theta^h}\right)^{\theta^w/\theta^h} \left(d^{mf,f}_{il'}\right)^{-w}} \sum_l \frac{\left(d^w_{il}\right)^{-\theta^w} \left(\sum_n \left(\frac{d^h_{in}}{w_{nm}+w_{lf}}\right)^{-\theta^h}\right)^{\theta^w/\theta^h - 1}}{k^{-\theta^h} \left(w_{jm}+w_{lf}\right)^{-\theta^h}} \right]$$

are homogeneous of degree zero. Thus, we can normalize the vector w. Since Walras' Law is satisfied, and the excess demand function is continuous, existence is assured by Brouwer's fixed point theorem.

$\square$

Next I discuss why the uniqueness proof fails.

Part II: Uniqueness. If $\mathcal{Z}_z$ satisfies gross substitution, that is $\frac{\partial \mathcal{Z}_z}{\partial w_z} < 0$ and $\frac{\partial \mathcal{Z}_z}{\partial w_{-z}} > 0$, where $w_z = \begin{cases} w_{jm} & z \leq J \\ w_{jf} & z \geq J+1 \end{cases}$, then uniqueness is assured. We need to compute the derivative of labor supply and labor demand to wages. Starting with labor demand, we get that:

$$\begin{aligned} \frac{\partial \sum_s \mathcal{L}_{s1m}(w)}{\partial \log w_{1m}} &= \sum_s \frac{\partial}{\partial \log w_{1m}} \frac{\left(w_{1m}/\alpha_{sm}\right)^{-\sigma}}{\sum_{g\in m,f} \left(w_{1g}/\alpha_{sg}\right)^{-\sigma}} L_{F_{1s}} \\ &= -\sigma \sum_s \left(1 - \frac{\left(w_{1m}/\alpha_{sm}\right)^{-\sigma}}{\sum_{g\in m,f} \left(w_{1g}/\alpha_{sg}\right)^{-\sigma}}\right) L_{F_{1sm}} < 0 \end{aligned}$$

And

$$\begin{aligned} \frac{\partial \sum_s \mathcal{L}_{s1m}(w)}{\partial \log w_{1f}} &= \sum_s \frac{\partial}{\partial \log w_1} \frac{\left(w_{1m}/\alpha_{sm}\right)^{-\sigma}}{\sum_{g\in m,f} \left(w_{1g}/\alpha_{sg}\right)^{-\sigma}} L_{F_{1s}} \\ &= \sigma \sum_s \frac{\left(w_{1f}/\alpha_{sf}\right)^{-\sigma}}{\sum_{g\in m,f} \left(w_{1g}/\alpha_{sg}\right)^{-\sigma}} L_{F_{1sf}} > 0 \end{aligned}$$

And,

$$\frac{\partial \sum_s \mathcal{L}_{s1m}(w)}{\partial \log w_{jm}} = \frac{\partial \sum_s \mathcal{L}_{s1m}(w)}{\partial \log w_{jf}} = 0$$

Now, focusing on labor supply of single households, we get that:

$$\begin{aligned}
\frac{\partial \log \sum_i \left\{\pi^f_{1|i} N_{R^f_i}\right\}}{\partial \log w_{1f}} &= \sum_i \frac{\pi^f_{1|i} N_{R^f_i}}{\sum_i \left\{\pi^f_{1|i} N_{R^f_i}\right\}} \left(1 - \pi^f_{1|i}\right) \theta^f > 0 \\
\frac{\partial \log \sum_i \left\{\pi^f_{1|i} N_{R^f_i}\right\}}{\partial \log w_{jf}} &= -\sum_i \frac{\pi^f_{1|i} N_{R^f_i}}{\sum_i \left\{\pi^f_{1|i} N_{R^f_i}\right\}} \pi^f_{j|i} \theta^f < 0 \\
\frac{\partial \log \sum_i \left\{\pi^f_{1|i} N_{R^f_i}\right\}}{\partial \log w_{1m}} &= \frac{\partial \log \sum_i \left\{\pi^f_{1|i} N_{R^f_i}\right\}}{\partial \log w_{jm}} = 0
\end{aligned}$$

For males in dual-earner households we get a similar expression. For women in dual-earner households we get that:

$$\frac{\partial \log \sum_i \left\{\pi^w_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}}{\partial \log w_{1f}} = \sum_i \frac{\pi^w_{1|i,\ell=1} N_{R^{mf}_{i,1}}}{\sum_i \left\{\pi^w_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}} \left(1 - \pi^w_{1|i,\ell=1}\right) \sum_l \pi^h_{l|i,\ell=1,1} \frac{w_{1f}}{(w_{lm} + w_{1f})} \theta^w \geq 0$$

$$\frac{\partial \log \sum_i \left\{\pi^w_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}}{\partial \log w_{1m}} = \sum_i \frac{\pi^w_{1|i,\ell=1} N_{R^{mf}_{i,1}}}{\sum_i \left\{\pi^w_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}} \left\{\pi^h_{1|i,\ell=1,1} \frac{w_{1m}}{(w_{1m} + w_{1f})} - \pi^h_{1|i,\ell=1} \tilde{\omega}_{1m}\right\} \theta^w$$

with

$$\tilde{\omega}_{1m} = \sum_l \frac{\pi^w_{l|i,\ell=1} \pi^h_{1|i,\ell=1,l}}{\pi^h_{1|i,\ell=1}} \frac{w_{1m}}{(w_{1m} + w_{lf})}$$

$$\frac{\partial \log \sum_i \left\{\pi^{mf,f}_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}}{\partial \log w_{jf}} = -\sum_i \frac{\pi^w_{1|i,\ell=1} N_{R^{mf}_{i,1}}}{\sum_i \left\{\pi^w_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}} \pi^w_{j|i,\ell=1} \sum_l \pi^h_{l|i,\ell=1,j} \frac{w_{jf}}{(w_{lm} + w_{jf})} \theta^w < 0$$

$$\frac{\partial \log \sum_i \left\{\pi^{mf,f}_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}}{\partial \log w_{jm}} = \sum_i \frac{\pi^{mf,f}_{1|i,\ell=1} N_{R^{mf}_{i,1}}}{\sum_i \left\{\pi^{mf,f}_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}} \left\{\pi^{mf,m}_{j|i,\ell=1,1} \frac{w_{jm}}{(w_{jm} + w_{1f})} - \pi^{mf,m}_{j|i,\ell=1} \tilde{\omega}_{jm}\right\} \theta^{mf,f}$$

with

$$\tilde{\omega}_{jm}=\sum_{l}\frac{\pi^{mf,f}_{l|i,\ell=1}\cdot\pi^{mf,m}_{j|i,\ell=1,l}}{\pi^{mf,m}_{j|i,\ell=1}}\frac{w_{jm}}{(w_{jm}+w_{lf})}$$

I stop here because it should be already clear where the gross-substitution property fails to hold. In particular, it can be shown that $\frac{\partial\log\mathcal{Z}_z}{\partial\log w_{-z}}>0$ may not always hold. For instance, taking the derivative of excess demand for women in location 1 with respect to wages of men in location 1, that is $\frac{\partial\log\mathcal{Z}_z}{\partial\log w_{-z}}$, with $z=J+1,-z=1$ we get:

$$\begin{aligned}\frac{\partial\log\mathcal{Z}_z}{\partial\log w_{-z}} &= \underbrace{\sigma\sum_s\frac{(w_{1m}/\alpha_{sm})^{-\sigma}}{\sum_{g\in m,f}(w_{1g}/\alpha_{sg})^{-\sigma}}L_{F_{1sm}}}_{>0}-\underbrace{\frac{\text{single women}_j}{\text{all women}_j}\left(\frac{\partial\log\sum_i\left\{\pi^f_{1|i}N_{R^f_i}\right\}}{\partial\log w_{1m}}\right)}_{=0}\\ &\quad-\underbrace{\frac{\text{married women}_j}{\text{all women}_j}\left(\sum_i\frac{\pi^w_{1|i,\ell=1}N_{R^{mf}_{i,1}}}{\sum_i\left\{\pi^w_{1|i,\ell=1}N_{R^{mf}_{i,1}}\right\}}\left\{\pi^h_{1|i,\ell=1,1}\frac{w_{1m}}{(w_{1m}+w_{1f})}-\pi^h_{1|i,\ell=1}\tilde{\omega}_{1m}\right\}\theta^w\right)}_{?}\end{aligned}$$

The supply of women to location 1 can increase even if male wages increase when

$$\frac{\pi^w_{1|i,\ell=1}N_{R^{mf}_{i,1}}}{\sum_i\left\{\pi^w_{1|i,\ell=1}N_{R^{mf}_{i,1}}\right\}}\left(\pi^h_{1|i,\ell=1,1}\frac{w_{1m}}{(w_{1m}+w_{1f})}-\pi^h_{1|i,\ell=1}\tilde{\omega}_{1m}\right)$$

is negative enough such that the positive effect coming from other origins and from the downward-sloping demand get both offset.

A4.2 Proposition 2

Proposition: *Given data on residence by gender and household type, $N_{R^k_{i,\ell}}$, employment by gender $L_{F_{jg}}$, rents r_{F_j},and commute costs d^k_{ij}, and parameters θ^k, α_s, σ_D there exists a vector of sales X_{js} and productivities A_{js} that rationalizes the observed data as an equilibrium of the model. Additionally, we get the same result if instead of employment by gender we observe employment by industry $L_{F_{js}}$ and parameters σ, α_{sg}.*

Proof. From proposition 1, we get wages. Afterwards, we obtain the total wage bill:

$$W_{js}N_{js}=w_{jm}\left[L_{F_{jm}}\right]+w_{jf}\left[L_{F_{jf}}\right]$$

Or if one observes employment by industry and parameters α_{sg} and σ:

$$W_{js}N_{js} = w_{jm}\left[\frac{(w_{jm}/\alpha_{sm})^{-\sigma}}{\sum_h (w_{jh}/\alpha_{sh})^{-\sigma}} L_{F_{js}}\right] + w_{jf}\left[\frac{(w_{jf}/\alpha_{sf})^{-\sigma}}{\sum_h (w_{jh}/\alpha_{sh})^{-\sigma}} L_{F_{js}}\right]$$

where first to second line comes from FOC: $\frac{\tilde{L}_{F_{jhs}}}{\tilde{L}_{F_{jgs}}} = \left(\frac{\alpha_{sh}/w_{jh}}{\alpha_{sg}/w_{jg}}\right)^{\sigma}$ and by summing over h and rearranging, I get $\frac{\tilde{L}_{F_{jgs}}}{\tilde{L}_{F_{js}}} = \frac{(w_{jg}/\alpha_{sg})^{-\sigma}}{\sum_h (w_{jh}/\alpha_{sh})^{-\sigma}}$.

Then, we can gets sales X_{js} from the firm's FOCs because: $\alpha_s X_{js} = W_{js}N_{js}$.

Once we obtain sales, we can recover productivity:

$$X_{js} \propto \left(\frac{W_{js}^{\alpha_s} r_{F_j}^{1-\alpha_s}}{A_{js}}\right)^{1-\sigma_D} \rightarrow A_{js} \propto \left(\frac{W_{js}^{\alpha_s} r_{F_j}^{1-\alpha_s}}{X_{js}^{\frac{1}{1-\sigma_D}}}\right)$$

□

A4.3 Proposition 3

Proposition: *Given data on residence by gender and household type, $N_{R^k_{i,\ell}}$, employment by gender $L_{F_{jg}}$, available floorspace H_i, floorspace allocation ϑ_i, rents r_{R_i} and r_{F_j} and commute costs d^k_{ij}, and parameters θ^k, η^k, ν, σ^D, α_s, β^k, there exists a vector of amenities u^k_i, productivities A_{js}, household productivity $\xi_{i\ell=0}$, sales X_{js}, floorspace wedge τ_i, and total rents E that rationalizes the observed data as an equilibrium of the model. Additionally, we get the same result if instead of employment by gender we observe employment by industry $L_{F_{js}}$ and parameters σ, α_{sg}.*

Proof. From proposition 1, we get wages. Then, we can compute residential market access:

- For single households: $\Phi_{R^g_i} = \sum_{l'}\left(\frac{d^g_{il'}}{w_{l'g}}\right)^{-\theta^g}, \forall g \in \{m, f\}$
- For couples in male breadwinner households: $\Phi^h_{R_{i,\ell=0}} = \sum_{l'}\left(\frac{d^h_{il}}{w_{lm}}\right)^{-\theta^h}$
- In dual-earner households: $\Phi^h_{R_{i,\ell=1,j'}} = \sum_l \left(\frac{d^h_{il}}{w_{lm}+w_{j'f}}\right)^{-\theta^h}$ $\Phi^w_{R_{i,\ell=1}} = \sum_l \left(\frac{d^w_{il}}{\left(\Phi^h_{R_{i,\ell=1,l}}\right)^{1/\theta^h}}\right)^{-\theta^w}$
- On average:

$$\Phi_{R^{mf}_i} = \left\{\left[\frac{1}{\gamma^w}\left(\Phi_{R^w_{i,\ell=1}}\right)^{-1/\theta^w}\right]^{-\nu} + \left[(\xi_{i\ell=0})^{-1}\left(\Phi_{R^h_{i,\ell=0}}\right)^{-1/\theta^h}\right]^{-\nu}\right\}$$

where $\gamma^w = \Gamma\left(\frac{\theta^w-1}{\theta^w}\right)(T^w)^{1/\theta^w} = 1$

Using data on labor force participation choices, we can use the following equation to recover household productivities:

$$\frac{\mu_i^{mf}}{1-\mu_i^{mf}} = \left(\frac{\left(\Phi^w_{R_{i,\ell=1}}\right)^{-1/\theta^w}}{(\xi_{i\ell=0})^{-1}\left(\Phi_{R^h_{i,\ell=0}}\right)^{-1/\theta^h}} \right)^{-\nu}$$

i,e,

$$\xi_{i\ell=0} = \frac{\left(\Phi^w_{R_{i,\ell=1}}\right)^{1/\theta^w}}{\left(\Phi_{R^h_{i,\ell=0}}\right)^{1/\theta^h}} \left(\frac{\mu_i^{mf}}{1-\mu_i^{mf}} \right)^{\frac{1}{-\nu}}$$

Then using the residential supply conditions, from which we can recover implied amenities once that we know wages and rents:

$$\begin{aligned} N_i^g \equiv \pi_i^g N^g &= \sum_l \left(\frac{r_{R_l}^{1-\beta^g}}{u_l^g \Phi_{R_l^g}^{1/\theta^g}} \right)^{-\eta^g} N^g \left(u_i^g \Phi_{R_i^g}^{1/\theta^g} r_{R_i}^{\beta-1} \right)^{\eta^g} \\ N_i^{mf} \equiv \pi_i^{mf} N^{mf} &= \sum_l \left(\frac{r_{R_i}^{1-\beta^{mf}}}{u_l^{mf} \Phi_{R_l^{mf}}^{1/\nu}} \right)^{-\eta^{mf}} N^{mf} \left(u_i^{mf} \Phi_{R_i^{mf}}^{1/\nu} r_{R_i}^{\beta-1} \right)^{\eta^{mf}} \end{aligned}$$

Then we need to solve for unobservables on the housing side. First, we need to get back sales using proposition 2. Then, it is needed to introduce a new pair of location characteristics since the floorspace market clearing condition $E_{Ri} = r_{R_i} H_{R_i}$ will not necessarily hold at the values for data and wages. Therefore, we need to introduce an additional unobservable that can be interpreted as quality of housing $\tilde{H}_{R_i} = H_{R_i} q_{R_i}$ where H_{R_i} are the physical units of floorspace. From the housing market clearing condition we get that $E_{Ri} = r_{R_i} \tilde{H}_{R_i} = r_{R_i} H_{R_i} q_{R_i} \rightarrow q_{R_i} = \frac{E_{Ri}}{r_{R_i} H_{R_i}}$. Similar residuals can be defined for commercial floorspace: $q_{F_i} = \frac{X_i}{r_{F_i} H_{Fi}}$.

Finally, we just need to solve for land use wedge, which can be identified from:

$$(1-\tau_i) = \frac{r_{R_i}}{r_{F_i}}$$

for locations with mixed land use. For locations with single land use, these wedges cannot be identified but are rationalized by zero productivities for all sectors or zero amenities for all worker groups. □

B Appendix Tables and Figures

B.1 Tables

Table B.1: Commuting and Wages

	Husband in D.E. Households	Wife in D.E. Households
	(1)	(2)
Wage at one's destination	2.5647	1.6135
	(0.3202)***	(0.1699)***
Wage at one's destination ×	-0.4466	-0.2744
HH income at destination pair	(0.0588)***	(0.0297)***
Origin-spouses' destination FE	X	X
Destination-pair FE		
Min Elasticity	1.856	1.178
St.Dev	(0.2288)	(0.1242)
Max Elasticity	3.054	1.914
St.Dev	(0.3839)	(0.2019)
N	90477	94773

Table B.2: Reduced Form Impact of New Transit Infrastructure on Rents and Income

	A+H Rents	HH Income	HH Exp.	Poverty
	(1)	(2)	(3)	(4)
$Treat_l^M \times Before2009_t$	-0.0010	0.0311	0.0687	-0.0152
	(0.0698)	(0.0781)	(0.0468)	(0.0325)
$Treat_l^M \times After2009_t$	-0.0216	0.0809	0.1059	-0.0496
	(0.0671)	(0.0651)	(0.0464)**	(0.0275)*
$Treat_l^{BRT} \times Before2009_t$	-0.0229	0.0376	-0.0651	0.0448
	(0.0830)	(0.0937)	(0.0516)	(0.0307)
$Treat_l^{BRT} \times After2009_t$	-0.0414	0.1052	-0.0183	-0.0380
	(0.0686)	(0.0900)	(0.0486)	(0.0249)
Block FE	X	X	X	X
Controls	X	X	X	X
N	24246	24246	24246	24246
Est. Method	PPML	PPML	PPML	OLS

Table B.3: Time-Event Study of New Transit Infrastructure on Census Outcomes

Panel A:	Total Population	Singles to Married	Females to Males
	(1)	(2)	(3)
$Treat \times (Year = 1993)$	0.0938	0.0396	0.0234
	(0.1070)	(0.0444)	(0.0256)
$Treat \times (Year = 2017)$	-0.1242	0.0812	-0.0033
	(0.0354)***	(0.0276)***	(0.0063)

Panel B:	Single to Married (Males)	Single to Married (Females)	Dual-Earners to Male Breadwinner
	(1)	(2)	(3)
$Treat \times (Year = 1993)$	0.0287	0.0461	-0.0073
	(0.0502)	(0.0442)	(0.0491)
$Treat \times (Year = 2017)$	0.0894	0.0764	-0.0516
	(0.0298)***	(0.0288)***	(0.0315)
Block FE	X	X	X
Year FE	X	X	X
N	375	375	375

Table B.4: Differences-in-Differences of New Transit Infrastructure on Mobility

Panel A:	Total Population	Singles to Married	Females to Males
	(1)	(2)	(3)
$Treat \times (Year = 2017)$	-0.0964	0.0477	-0.0041
	(0.0212)***	(0.0137)***	(0.0030)
Panel B:	**Single to Married (Males)**	**Single to Married (Females)**	**Dual-Earners to Male Breadwinner**
	(1)	(2)	(3)
$Treat \times (Year = 2017)$	0.0534	0.0418	-0.0070
	(0.0147)***	(0.0142)***	(0.0135)
Block FE	X	X	X
Year FE	X	X	X
N	1190	1190	1190

Table B.5: The Aggregate Impact of Completing the Metro Network

Panel A: Incremental Impact of Metro Lines 2 and 4								
	Singles		Married			All		
	Males	Females	Males in BW HH	Males in D.E. HH	Females in D.E. HH	Males	Females	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Real Income	0.0039	-0.0011	-0.0175	0.0295	0.0386	0.0063	0.0185	0.0095
Real Income per Worker	0.0039	-0.0011	0.0072	0.0112	0.0201	0.0063	0.0090	0.0056
Gender Gap	0.0112			-0.0405		-0.0187		
Gender Gap (per Worker)	0.0131			-0.0226		-0.0056		
# D.E. / # Married				0.0181				

Panel B: Overall Impact of Metro Lines (1,2, 4) and the BRT								
	Singles		Married			All		
	Males	Females	Males in BW HH	Males in D.E. HH	Females in D.E. HH	Males	Females	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Real Income	0.0099	0.0028	-0.0333	0.0596	0.0797	0.0133	0.0402	0.0203
Real Income per Worker	0.0099	0.0028	0.0139	0.0230	0.0424	0.0133	0.0213	0.0126
Gender Gap	0.0161			-0.0801		-0.0398		
Gender Gap (per Worker)	0.0188			-0.0475		-0.0160		
# D.E. / # Married				0.0358				

B.2 Figures

Figure B.1: The Line 1 of Lima's Metro

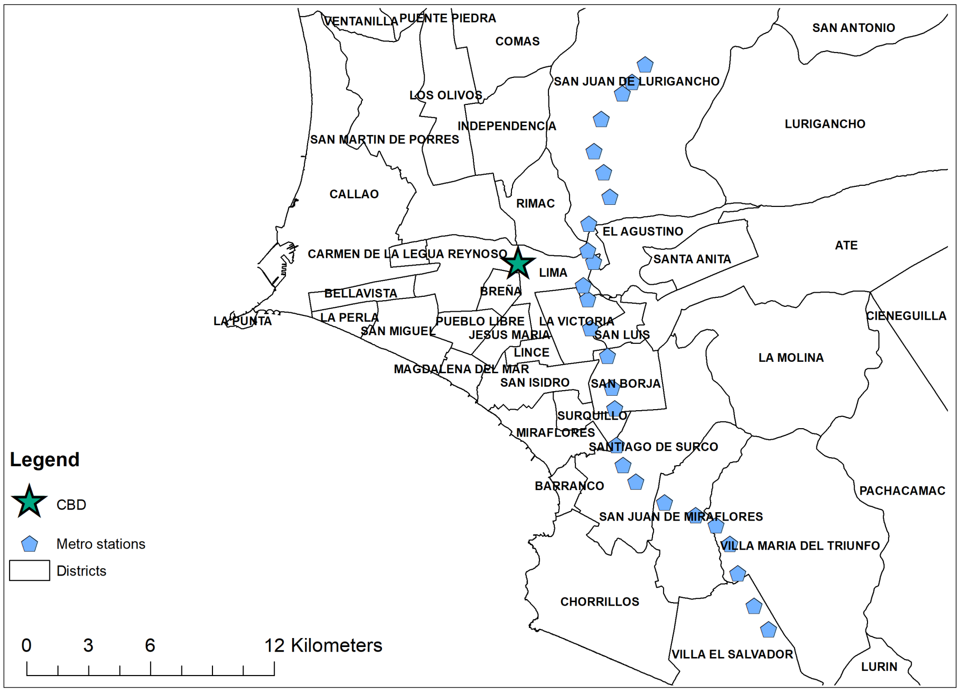


Figure B.2: The Bus Rapid Transit System

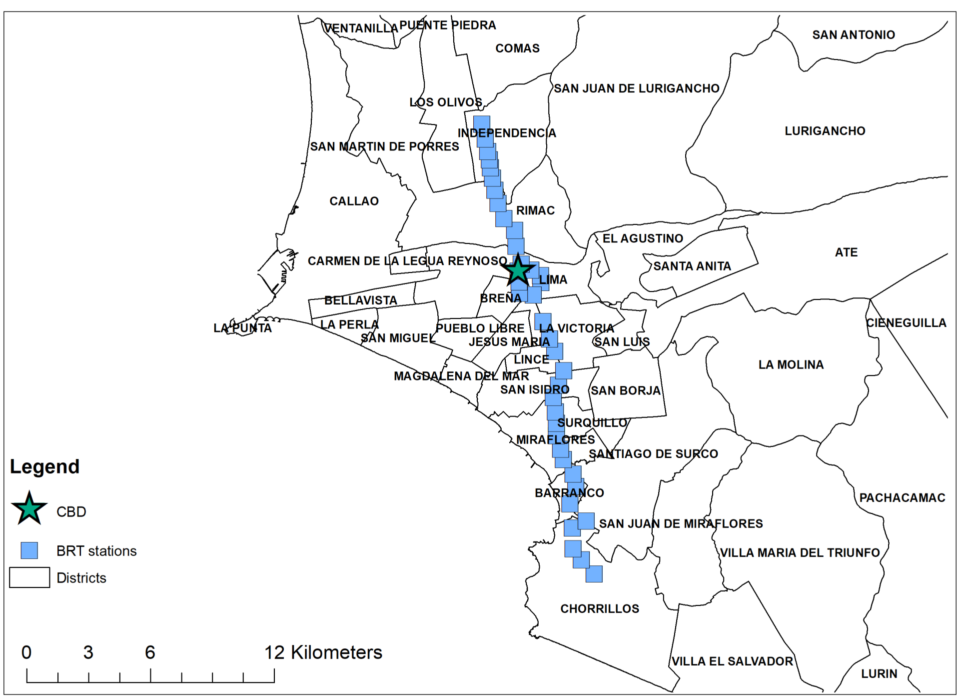
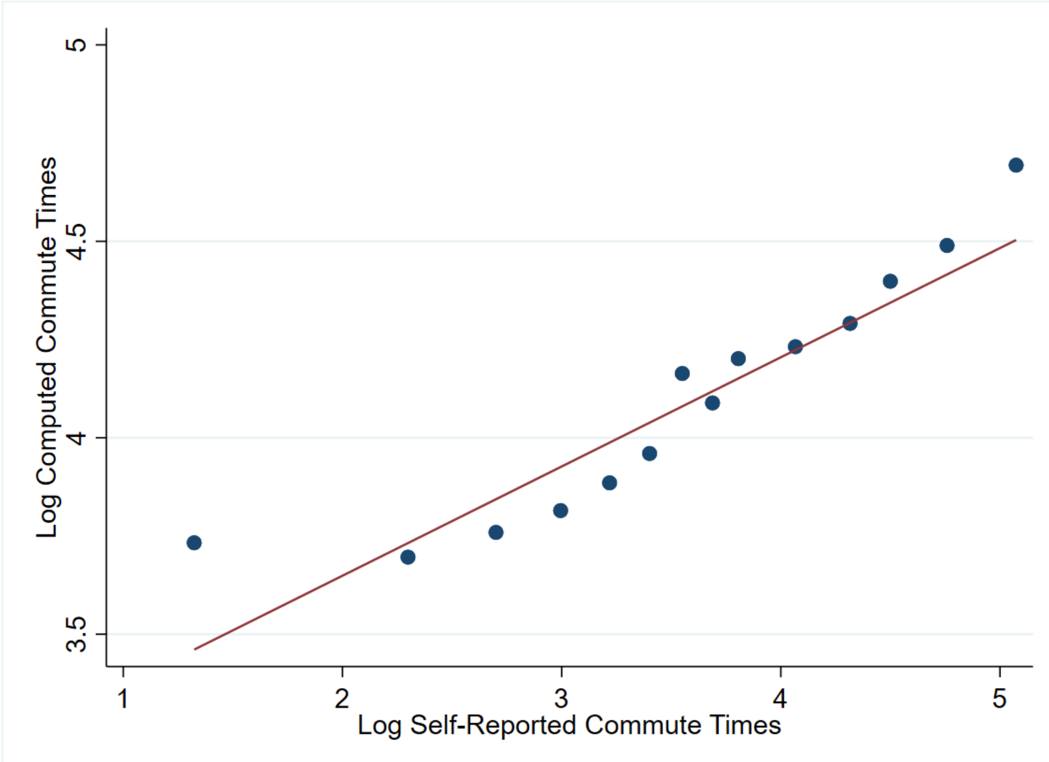


Figure B.3: Imputed versus reported commuting times

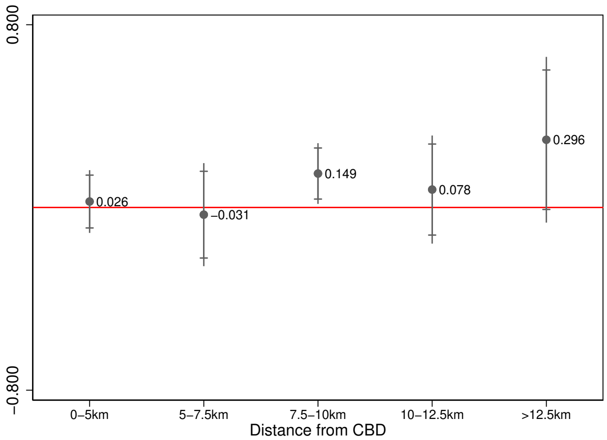


Self-reported commute times, at the district level, come from the 2010-2018 waves of the Commuting Surveys. Imputed commute times come from the Open Street Road Network data in par with Imputed speeds. Imputed commute times were computed at the zone level, and then aggregated to the district level using median values. Scatter was generated using the *binscatter* command in Stata. The correlation between the two measures of commute times is of 53%.

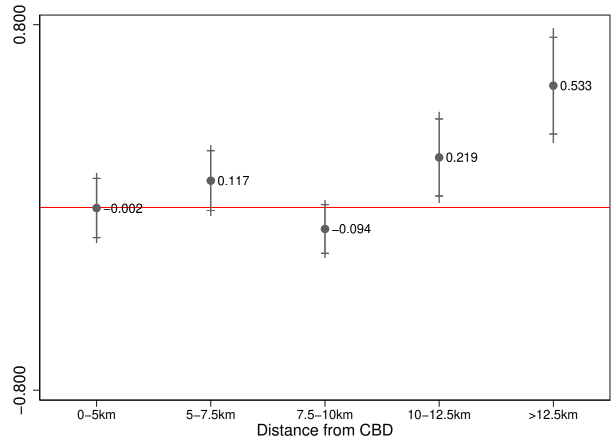
Figure B.4: The Reduced Form Impact of Transit Infrastructure on Rents and Expenditure by Distance to the CBD

Panel A: Actual + Hypothetical Rents

Metro

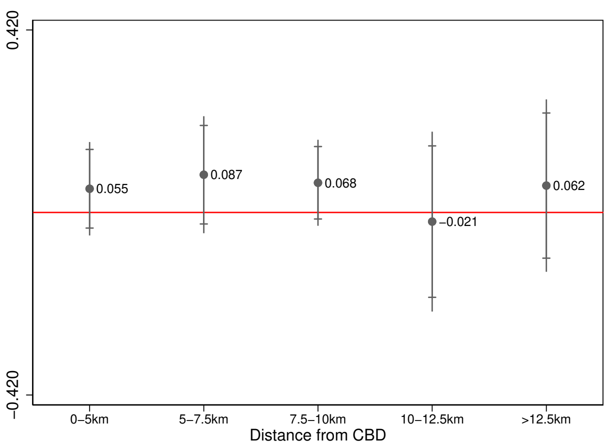


BRT



Panel B: Expenditure

Metro



BRT

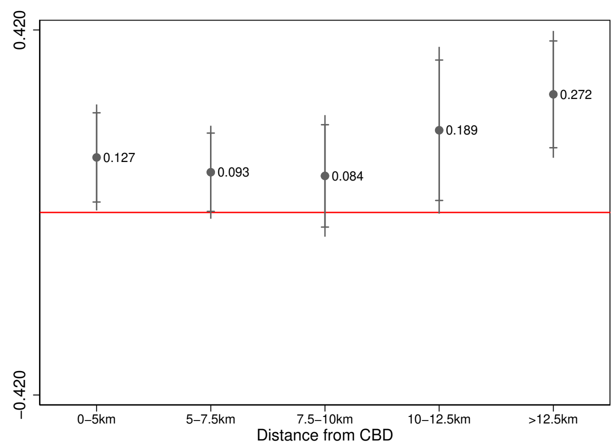


Figure B.5: Constructed and Planned Lines

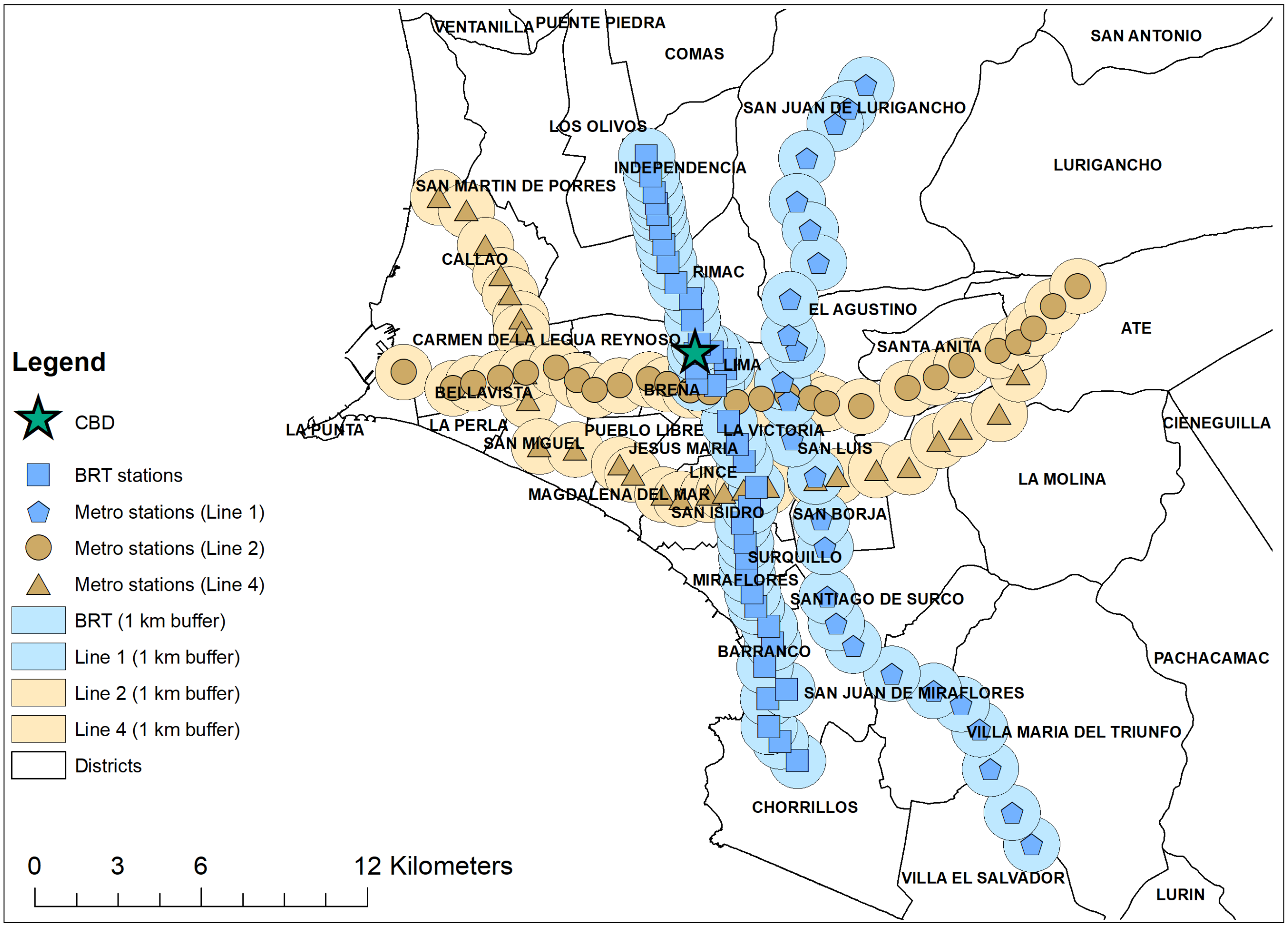
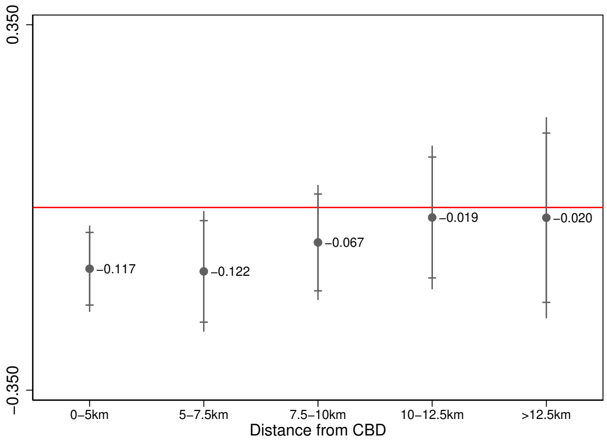


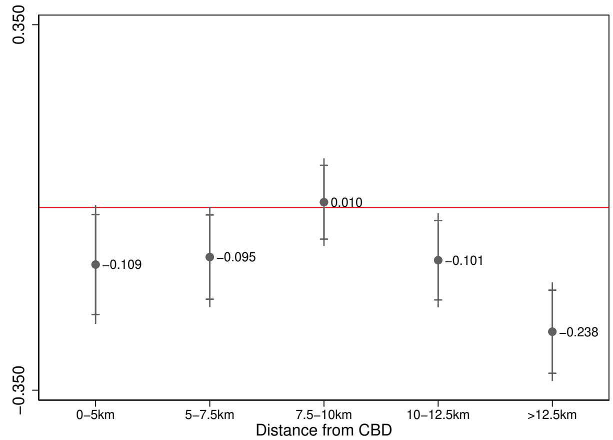
Figure B.6: The Reduced Form Impact of Transit Infrastructure on Census Outcomes by Distance to CBD, Part 1

Panel A: Total Population

Metro

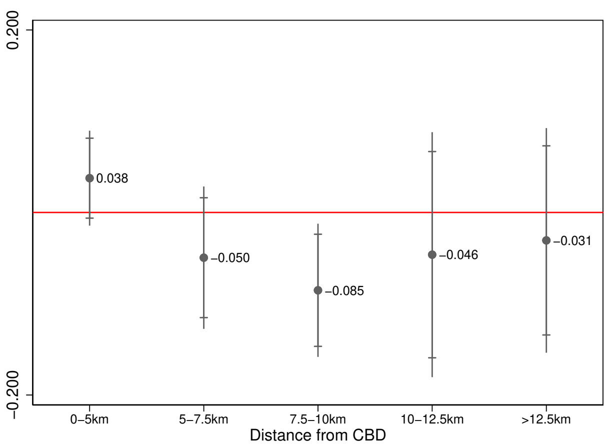


BRT



Panel B: Singles to Married

Metro



BRT

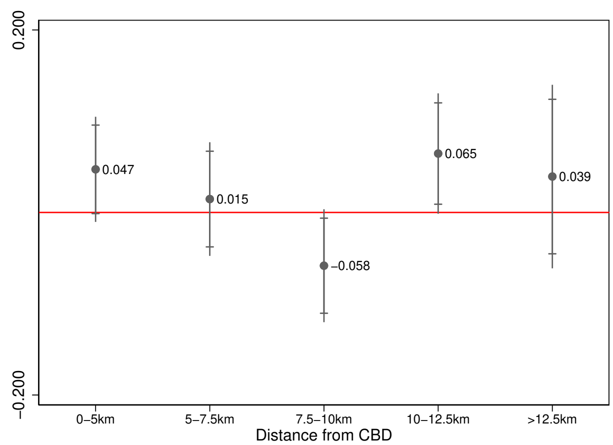
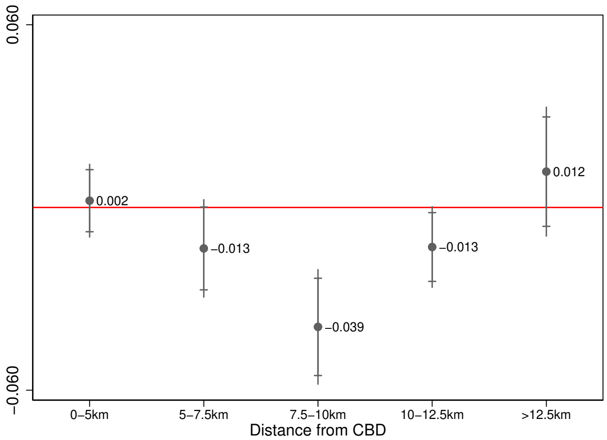


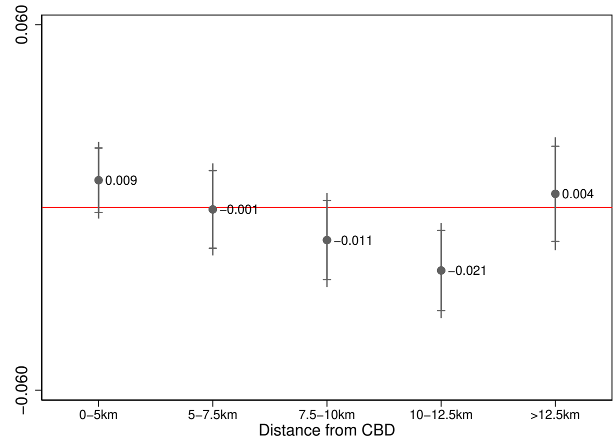
Figure B.7: The Reduced Form Impact of Transit Infrastructure on Census Outcomes by Distance to CBD, Part 2

Panel A: Females to Males

Metro

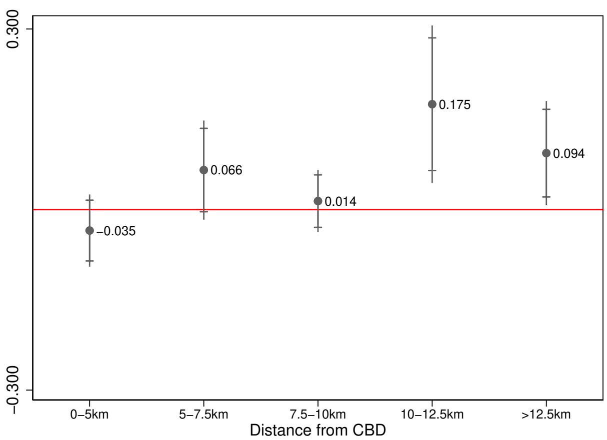


BRT



Panel B: Dual-Earners to Male Breadwinner

Metro



BRT

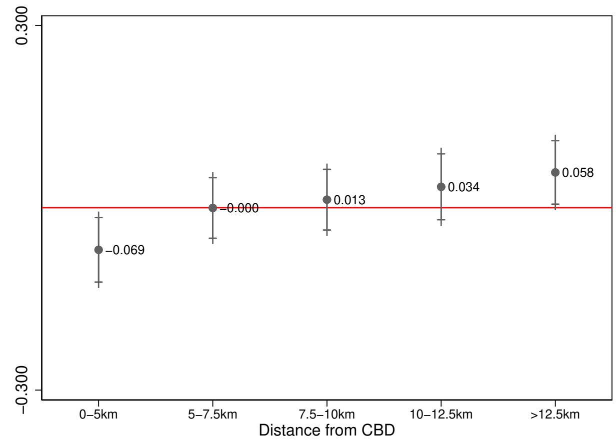
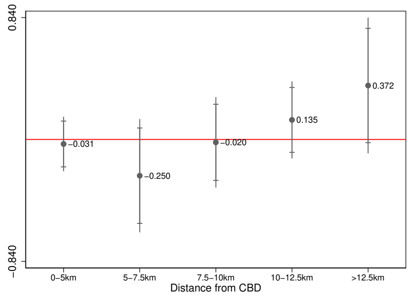


Figure B.8: The Reduced Form Impact of Transit Infrastructure on Rents, Income, and Extreme Poverty

Panel A: Actual Rents

Metro



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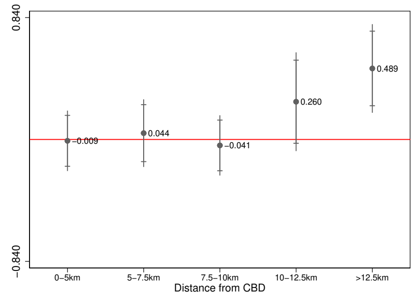
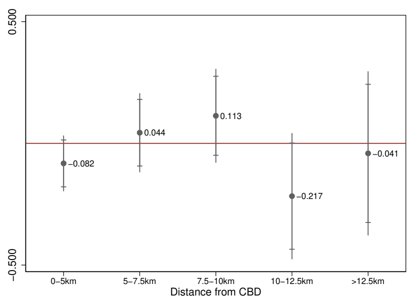
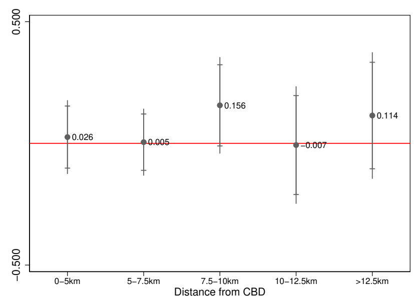


Panel B: Income

Metro

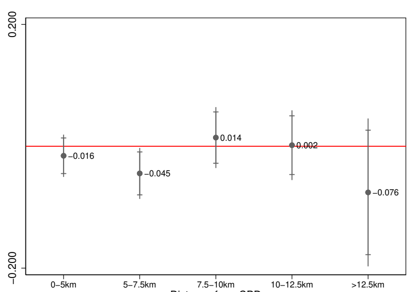


BRT



Panel C: Poverty

Metro



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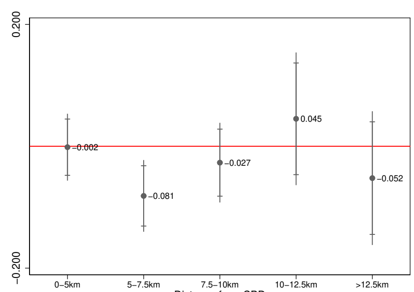
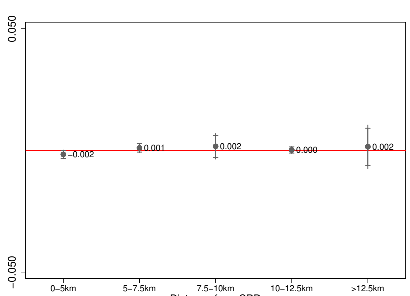


Panel D: Extreme Poverty

Metro



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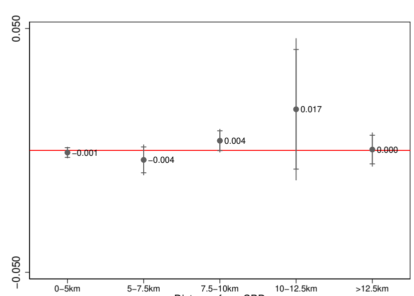
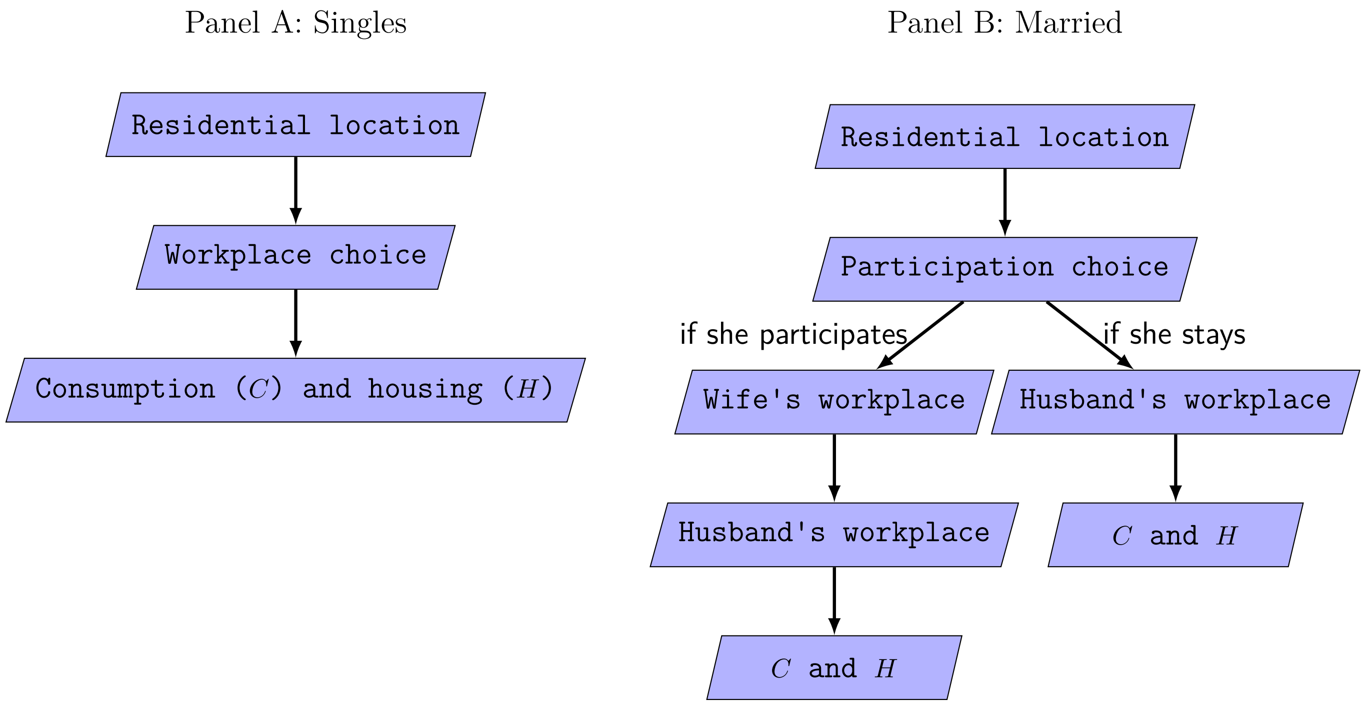


Figure B.9: Timing Assumptions



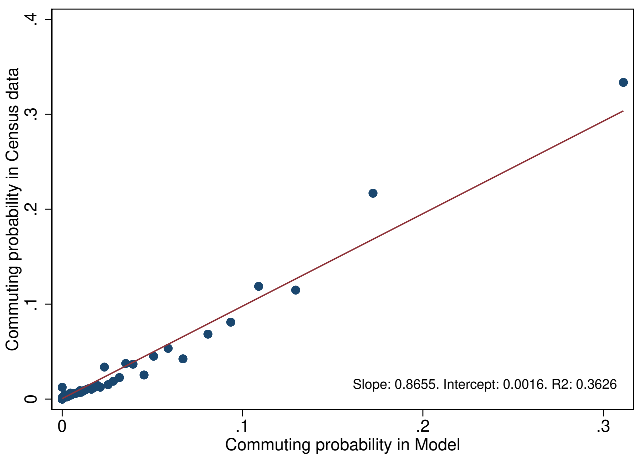
Panel A: Solving backwards, conditional on the locations that singles live and work, they choose their consumption and housing allocations. Afterwards, conditional on their residence location, they choose their workplace location. Finally, they decide where to live.

Panel B: Solving backwards, married households start by deciding how much they consume in the final good and in residence floorspace, conditional on the workplace location of both spouses and the residential location. Afterwards, conditional on the wife's labor status and the wife's workplace location, households decide the workplace of the husband. Then, they decide the workplace of the wife. If the wife does not participate, households only decide the workplace location of the husband. Next, conditional on households residence location, households compare the utility they would receive if the wife works against the utility they would receive if the wife stays at home performing household production. Based on this comparison, households decide the labor status of the wife. Finally, households choose their residence location.

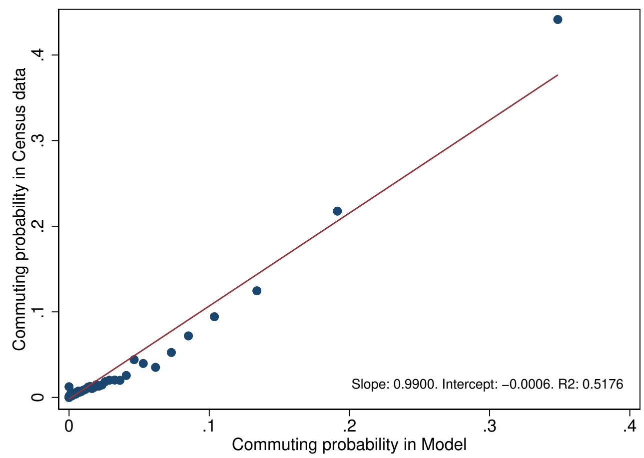
Figure B.10: Commuting and Over-identification

Panel A: Females in Dual-Earner Households

Independent Commute

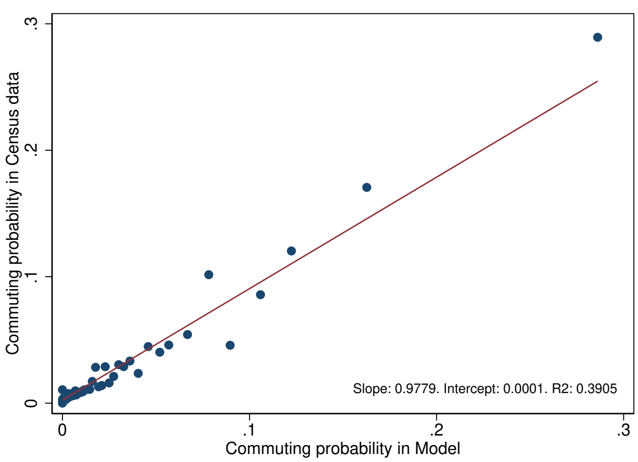


Interdependent Commute



Panel B: Males in Dual-Earner Households

Independent Commmte



Interdependent Commute

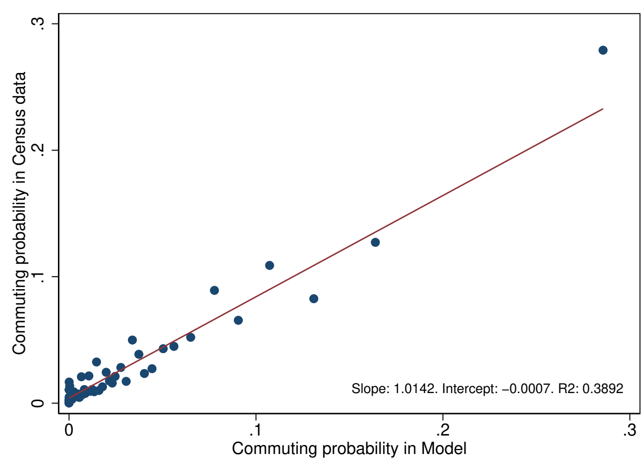


Figure B.11: The Reduced-form Impact of Transit Infrastructure, Data and Model

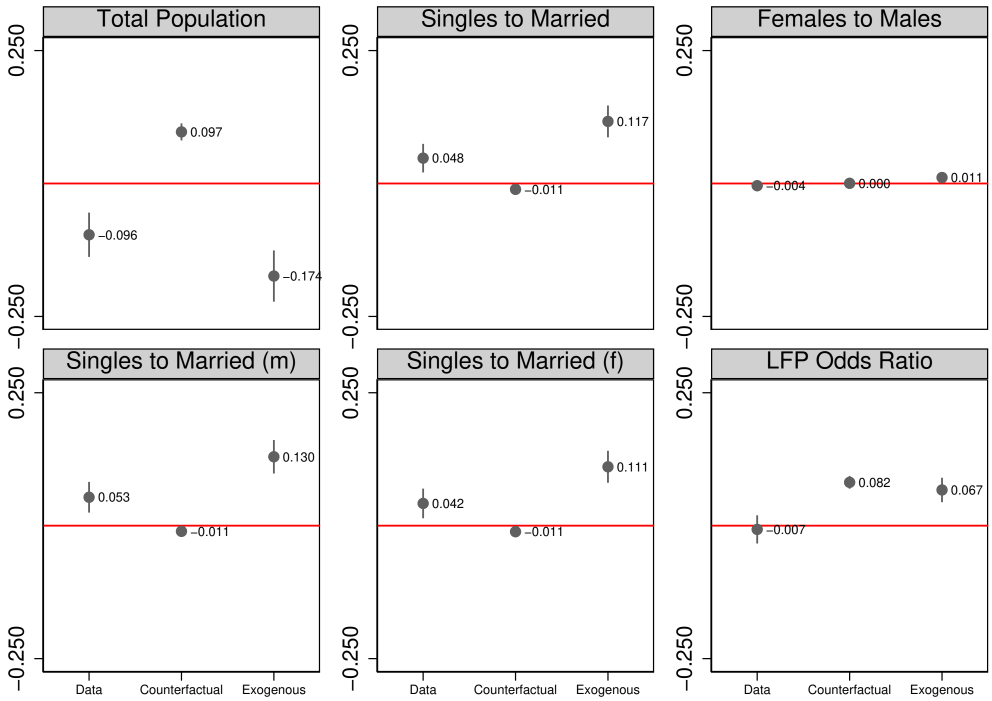


Figure B.12: Reduced-form Impact by Distance to the CBD, Data and Model

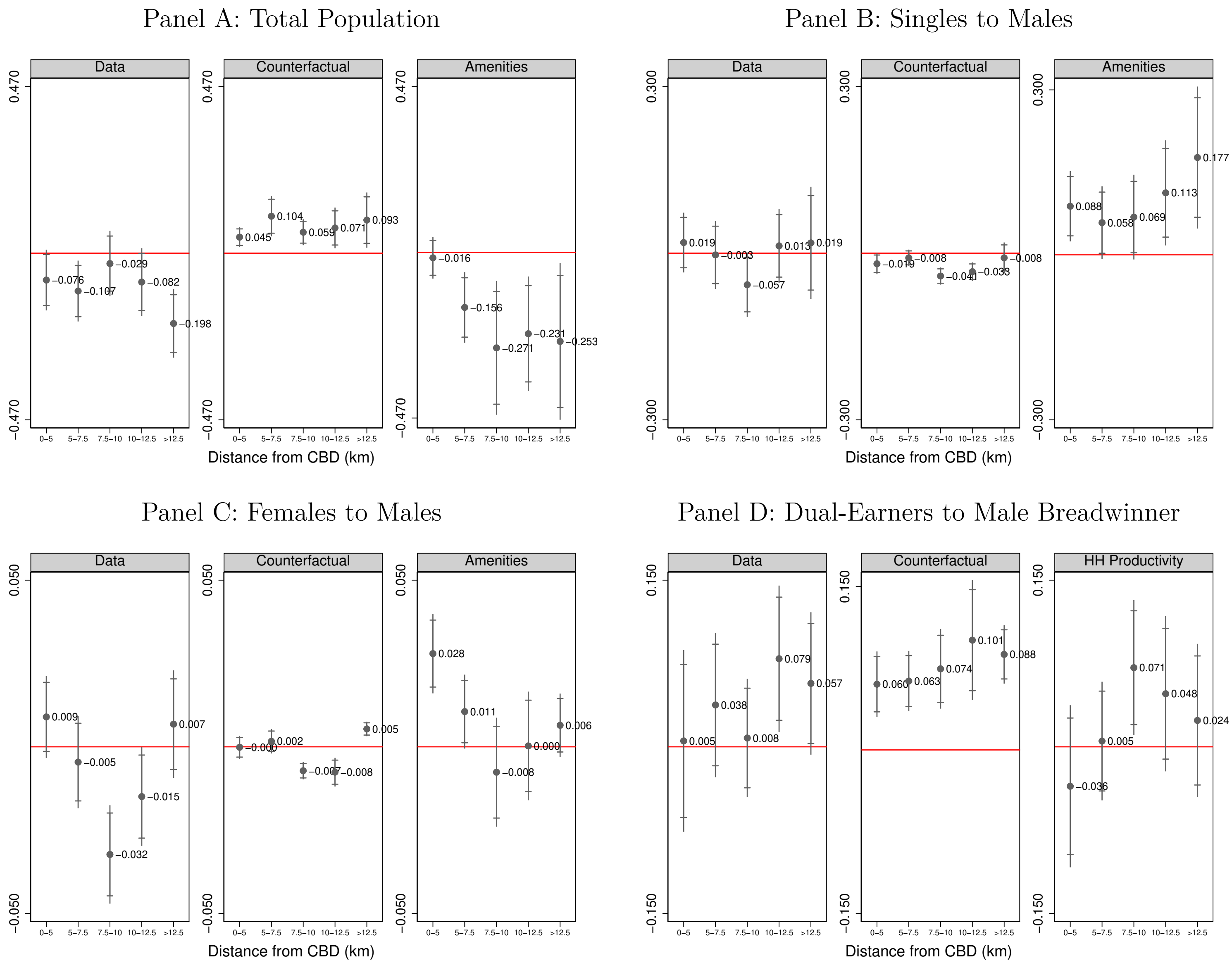


Figure B.13: Reduced-form Impact with Independent Commute Choices by Distance to the CBD

Gap in Real Earnings per Worker

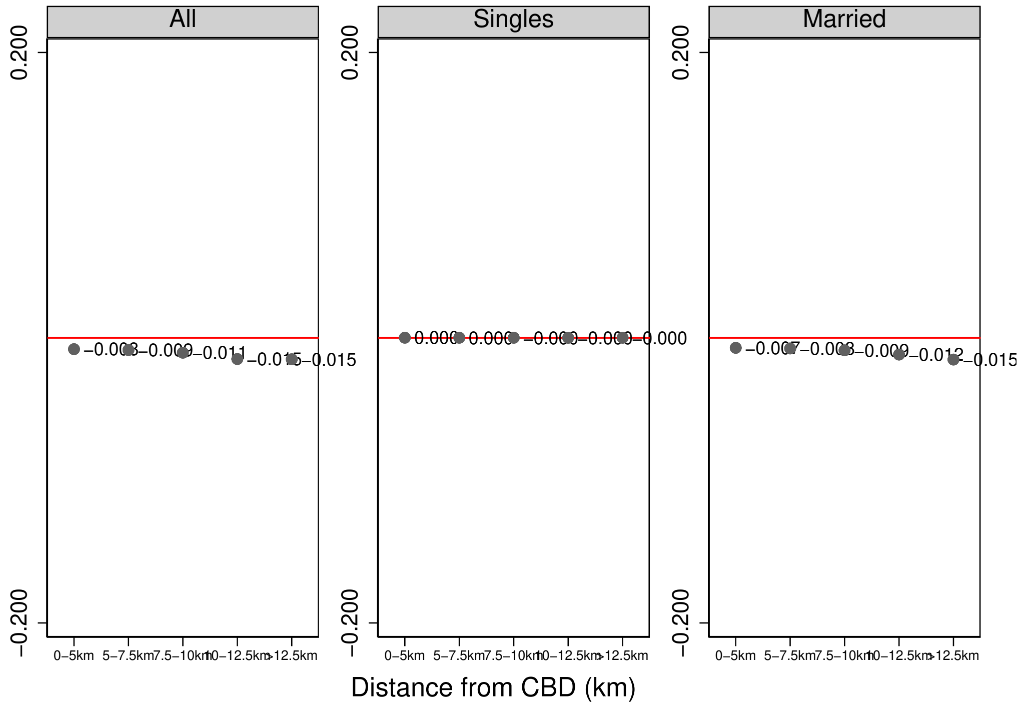
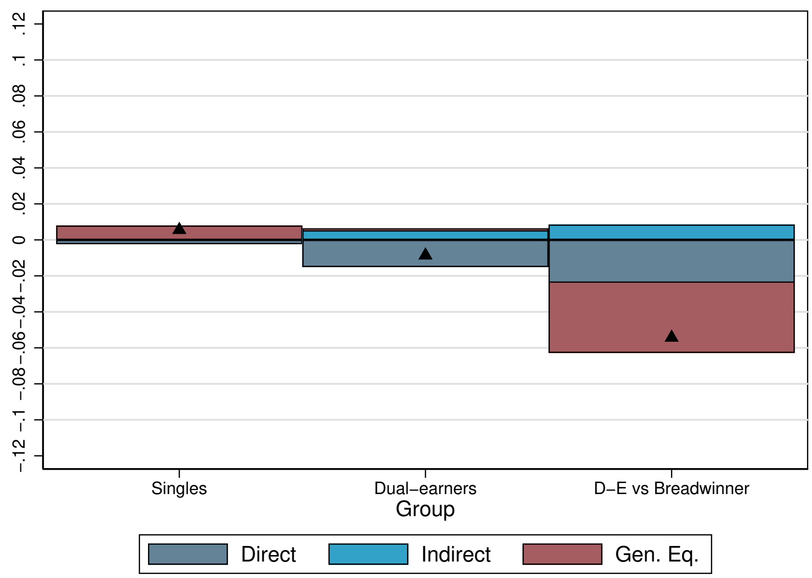


Figure B.14: Decomposition of the Aggregate Impacts

Panel A: Incremental Impact of Metro Lines 2 and 4



Panel B: Overall Impact of Metro Lines (1, 2, 4) and the BRT

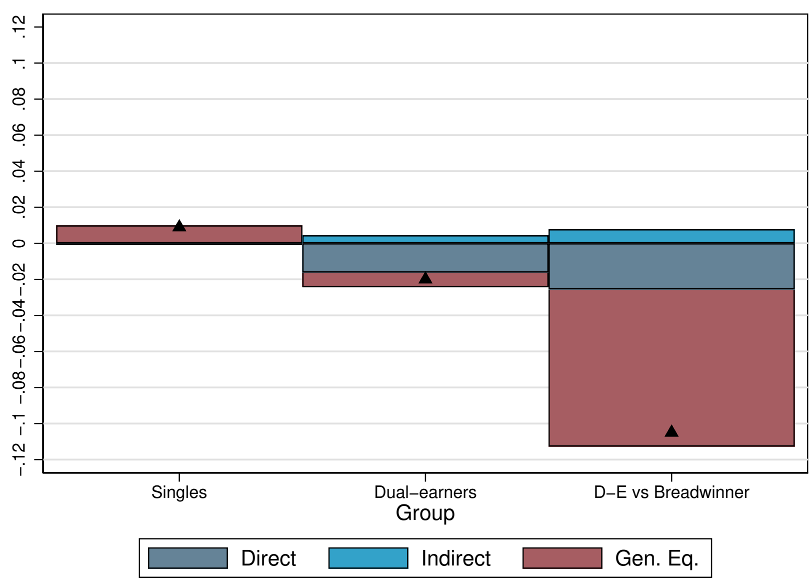
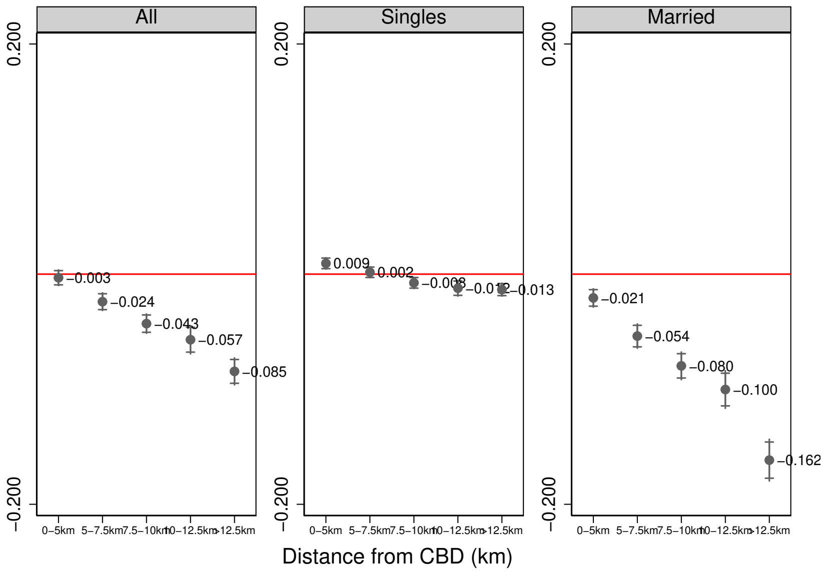


Figure B.15: Incremental Impact of Metro Lines 2 and 4 by Distance to the CBD

Panel A: Gap in Real Aggregate Income



Panel B: Gap in Real Earnings per Worker