Transit Infrastructure and Couples' Commuting Choices in General Equilibrium

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Abstract: What is the impact of improving transit infrastructure on the gender earnings gap? How family structure matters to understand the impact of new transit infrastructure? Recent models on spatial economics hinge on the assumption that households are comprised of a single type of person making commuting and location choices. In reality, an important share of the population live in households comprised of more persons, whose commuting choices might be interlinked through the household's budget constraint. I set up an estimate a quantitative model of city structure featuring single and married households leveraging on the introduction of a Metro line and the Bus Rapid Transit System in Lima, Peru. My model delivers interdependent commuting choices within dual-earner households. This way, reduced commute times impact commuting patterns not only by affecting one spouse's prospects, but also those of her spouse. I show that this mechanism is quantitative important. If I ignore this mechanism, I would underestimate gains in real income by 42% and reductions in the gender earnings gap by 72%.

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1 Introduction

What is the impact of improving transit infrastructure on the gender earnings gap? How does family structure matter to understand the impact of new transit infrastructure? Policymakers in developing countries are increasingly concerned with recent population growth pressuring urban transport systems and exacerbating inequalities in access to opportunities for different segments of the population. Since poor infrastructure constraints mobility for men and especially women due to additional socio-cultural constraints, a natural response is to invest in the improvement of the transit system.

Recently, a class of models has been developed to study how new transit infrastructure can improve overall welfare (Tsivanidis, 2019), reduce informality (Zarate, 2021), and limit crime (Khanna et al., 2022). A common feature in these models is that locations within a city are interconnected through the transport system. Thus, they predict that time savings from new infrastructure improve welfare proportionally to a labor-income weighted average of the commute time reductions (Tsivanidis, 2019). General equilibrium forces can subsequently reinforce welfare effects. However, these predictions hinge on the assumption that households are comprised of a single person making consumption, housing, commuting and location choices. In reality, an important share of the population live in households comprised of more persons, whose choices are interlinked through the household's budget constraint. For instance, my spouse's commuting choice might affect my commuting choice through an income effect; if he or she is already commuting to a high wage location, then my initial response to the sudden availability of high wage locations may be less pronounced. In this paper, I ask whether the composition of households matters when quantifying the impact of new transit infrastructure on the gender earnings gap.

In this research I focus on two infrastructure investments that were introduced around 2011 in Lima Peru: the Line 1 of the Metro and the Bus Rapid Transit system (BRT). I assemble a data set consisting of population censuses, an economic census, a cadastre of firms, and rich survey data, and document three empirical facts suggesting that the Lima's Metro and the BRT may have had not only gendered impacts, but that family structure might matter.

First, commuting elasticities differ by household type. Women are more reactive to improvements in commuting times than men, especially when cohabiting with a partner. Second, the choice of where to work depends on the spouse's commuting choice. I employ Census data on dual earner households to compute conditional commuting probabilities and test whether destination pairs are predictive of commuting probabilities once that I partial out each members' independent reasons to work in a particular destination. In a world with independence, destination pairs should not be predictive of conditional commuting probabilities after controlling for the fact that certain destinations are more desirable than others. Third, I show that the reduced form impact of the new transit infrastructure on households' location choice is heterogeneous on household type (i.e. singles and married households). I find that in locations closer to stations married households moved out, whereas single males stayed. I complement these findings by showing that pre-trends in income and the value of rent were parallel in locations closer to stations relative to locations farther away.

To quantify how commuting times affect men and women heterogeneously, I develop a quantitative model of city structure. The model has four key elements. First, commuting is costly. I assume iceberg costs. Second, households are differentiated by Frechet shocks to their preferences over commuting destinations for each of their members. Similarly, they are also differentiated by Frechet shocks to their preferences over residential locations. Shocks are drawn from different distributions according to household-type, i.e. single males, single females, males in married households, females in married households. Additionally, married households are also differentiated by Frechet shocks to their preferences over stay-at-home wives so that wives' labor force participation choice is endogenous. Third, couples have the possibility of pooling their income to attain higher levels of consumption. This feature interlinks their commuting choices since preference shocks enter utility directly making each member to consider his or her spouse's income when making their commuting choices. Finally, from the production side, multiple sectors employ workers of each gender with a certain degree of substitution. Together, these elements determine gender-specific sensitivities of commuting probabilities with respect to reductions in commuting times, and are crucial explaining gender differences in welfare gains.

I calibrate and estimate the model using Peruvian data. To estimate commuting elasticities, I exploit data on bilateral flows and the gravity structure of the model for commuting probabilities. Moreover, to estimate the remaining parameters, I rationalize the observed data as a model equilibrium to recover the model's observables. I then use these unobservables to estimate: location elasticities, the labor supply elasticity of females in married households, agglomeration externalities and amenity eternalities.[1] To estimate these parameters I leverage on the Lima's road network and the introduction of the new transit infrastructure to construct

[1]The latter two might be quantitative important as recent applications have shown. For instance, see Ahlfeldt et al (2015) and Tsivanidis (2019).

Bartik-style instruments weighting either changes in commute time or inferred productivity as explained in Section 5.3. Once parameters are estimated I show that the model with interdependent commuting choices within couples fits better the data on bilateral commuting flows of dual-earner households than the model where commuting choices are independent.

I simulate how would Lima look like in absence of the Metro and the BRT under income pooling (or interdependent commuting choices) and under a model without income pooling (or independent commuting choices). First, my results reveal that aggregate real income increased by 1.19% in the full model but only 0.69% in the model with independent choices. Second, I show that the model with independent choices underestimates the impact on the gender gap in earnings per worker by 72% compared to the model with interdependent commuting choices. In particular, under the full model, the gender gap in earnings per worker decreased by 1.04% whereas in the model with independent choices it decreased by 0.29% only. Third, this aggregate figure hides some heterogeneities. For instance, according to the full model the new transit infrastructure decreased the gender gap in earnings per worker among married households by 2.52% whereas it increased the gap for singles by 0.58%. Instead, the model with independent commuting choices concludes that the gap among singles and married increased by 0.20% and 0.25%, respectively. Fourth, I show that allowing for income pooling is quantitative important not only on the aggregate but also when studying the distribution of gap changes across space. For example, the correlation between changes in the earnings gap in the full model and in the model without income pooling is of 32.06%. Finally, decomposing the sources of aggregate results, I find that households' mobility across residential locations mould both aggregate efficiency and distributional outcomes, and that the labor force participation choice mainly has distribution consequences although it also modestly influences aggregate efficiency.

This paper contributes to the literature in many ways. First, my work speaks to the recent literature on economic geography models,[2] and in particular of cities.[3] This literature examines the impact of transit infrastructure on economic outcomes accounting for spillovers through the transit network in a general equilibrium framework. I incorporate the fact that labor supply responses to improvements in commuting times is not only heterogeneous across genders but also across household types due to the interconnection in commuting choices and income pooling within couples.

[2]See Allen and Arkolakis (2014), Behrens et al. (2017), Bartelme (2018), Monte et al. (2018), Bryan and Morten (2019), Allen and Arkolakis (2020), Fajgelbaum and Schaal, (2020), Adao et al. (2020), Kwon (2020).

[3]See Ahlfeldt et al. (2015), Allen and Arkolakis (2015), Tsivanidis (2019), Owens et al. (2020), Heblich et al. (2020), Severen (2021), (Zarate) 2021, Khanna, et al. (2022).

Second, this paper relates to the literature that examines gender differences in urban labor markets. This literature documents that there are gender differences in location choices and commuting choices. These gender differences tend to intensify among the married. For instance, Black et al. (2014) documents a very large variation in the labor supply of married women across US cities due to differences in commuting times. Kawabata and Abe (2018) examines the relationship between commute times and female labor force participation within Tokyo, showing that it differs markedly across household types.[4] Carta and De Philippis (2018) explore the relationship between husband's commuting times and wives' employment and family time allocation. Their findings reveal that a 1% increase in the husband's commuting distance reduces his wife's employment probability by 0.016.[5] Moreover, recent experimental evidence reveals that reducing mobility constraints has a large impact on job searching for women (Field and Vyborny, 2022). Also, there is a literature on the trade off between wages and non wage job attributes.[6] My contribution to these literatures is to incorporate many of these features into a single tractable framework allowing me to quantify the aggregate impact of new transit infrastructure. As a by-product, this framework also provides me with the means to quantify the importance of female labor force participation in shaping the aggregate impact of transit infrastructure.

Third, recent work in macroeconomics suggest that family and decision making in families should be an integral part of economic models since family structure have repercussions for the aggregate labor supply (Doepke and Tertlit, 2016). My work contributes to this debate by showcasing that, even in a static model, family structure may have important implications on the determination of aggregates once that we account for the spatial distribution of economic activity. Finally, this research contributes to the literature on the estimation of agglomeration effects and their quantitative importance. In particular, most estimates of agglomeration forces exploits variation of *overall* employment *across regions* for identification.[7] Rather I estimate *sectoral* agglomeration forces *within a city*.[8]

[4] Mehmood et al. (2021) document similar findings for India.

[5] Other relevant papers include Clark et al. (2002), Rosenthal and Strange (2012), Gutierrez (2018), Farré et al. (2020), Kwon (2020), Gu et al. (2021).

[6] See Becker (1985), Cha and Weeden (2014), Goldin (2014), Angelov et al. (2016), Lundborg et al. (2017), Adda et al. (2017), Reuben, Wiswall and Zafar (2017), Cubas et al. (2019), Kleven et al. (2019), Mas and Pallais (2020), Liu and Su (2020), Le Barbanchon et al. (2021).

[7] Rosenthal and Strange, 2004; Combes et al., 2008; Greenstone, Hornbeck, and Moretti, 2010; De la Roca and Puga, 2017.

[8] There are only a few papers estimating sectoral agglomeration forces within a city (e.g. Zarate, 2021). Examples of estimates within city are Ahlfeldt et al. (2015), Tsivanidis, (2019), and Heblich et al. (2020).

The paper is distributed as follows. Section 2 briefly describes the Metro and the Bus Rapid Transit system. Section 3 describes my data sources and shows a three stylized facts. Section 4 develops the structural model, while Section 5 explains choices regarding calibration and estimation of the model's parameters. Section 6 performs counterfactual analysis, and Section 7 concludes.

2 Lima's Metro and Bus Rapid Transit System (BRT)

Both transit investments were introduced around 2011 in Lima Peru, and since then, they have contributed to shape the city's landscape. The Metro is 34.4 km long, and serves more than 500,000 passengers every day. The first 22 km of the Metro were finished in 2011, while the remaining 12.4 km were finished in 2014. Although the Metro does not cross through the CBD, it does cross through some high demand areas, and in particular, through one of the most important commercial areas in the city, that is, the market of "Gamarra" (see Figure B.1). Moreover, thanks to the Metro, commuting times were greatly improved. For example, from one end to the other one, commuting times were reduced from 2 hours and 45 minutes to just 54 minutes.

The BRT was introduced around 2010. It is 26 km long, serving around 700,000 passengers on a daily basis. Typically, a BRT system is comprised by a system of roadways that are dedicated to buses. They have been successfully implemented in cities like Bogota and Buenos Aires. As it can be seen in Figure B.2, the Lima's BRT system connects the fringe to the modern districts, in addition to the central business district (CBD). The idea of a BRT system is to provide better speeds, while keeping the simplicity of a system of buses. In line with this, a study of the World Bank reports that commuting times were cut by around 25-45%.

3 Data Sources, Stylized Facts, and Pre-Trends

3.1 Data

To estimate the model I require several sources of data geographically identified at a fine scale. In particular, (i) I use the Population Census from 1993, 2007 and 2017 to get residence counts

Examples of sectoral estimates of agglomeration forces across regions are Kline and Moretti (2014), Adao, et al. (2017), Bartelme et al. (2019).

at the zone level for men and women.[9] (ii) I also use the Economic Census of 1994, 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 of 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 georeferenced at the block level, 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 stylized facts. Using my data set, I document three stylized facts that motivate my empirical design and modelling approach.

3.2 Facts

Fact 1: Commuting elasticity differs by household type. Using the Population Census, I classify households into five different types. The first two types consist of (i) *single females* and (ii) *single males*, which consist of 31.9% and 35.9% of households. Then I consider (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 type of household I run the following reduced form regression:

$$\log \pi_{j|i,g,k} = \beta time_{ij} + FE_i + FE_j + \varepsilon_{ij} \tag{1}$$

where $\pi_{j|i,m,k}$ is the share of members of gender g in households of type k that live in origin location i that commute to location j. $time_{ij}$ is the time that takes to commute from i to j. Moreover, FE_i and FE_j are fixed effects by origin i and destination j. Finally, β 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.

[9] 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 in more than 30,000 blocks and more than 1500 zones. Since I never use the 30,000 blocks in the analysis and rather focus only on zones, throughout the paper, I refer to zones as blocks for convenience

To compute commuting probabilities I rely on the 2017 population Census, aggregating the data at the district level.[10] 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 in order 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. 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%. 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.

All in all, these results show that women are more reactive to improvements in commuting 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.[11] Hence, the model should allow for heterogeneity in commuting elasticities.

[Table 1 here]

Fact 2: Choice of where to work depends on spouse's choice. In dual earner households, the choice of where to work may depend on the spouse's destination choice through an income effect caused by the pooling of resources. 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). In this paper, rather than focusing on an intensive margin defined over the number of working hours, I study the distance one commutes and so a similar logic applies.

I can test these ideas by leveraging on the fact that I observe each member's commuting choice in dual-earner households allowing me to compute *conditional* commuting probabilities. In turn, this permits me to test whether the interaction of destinations (i.e. the destination of

[10] The data records in which district individuals commute to, and so I realize the analysis at this level.

[11] See Becker, 1985; Cha and Weeden, 2014; Goldin, 2014; Angelov et al., 2016; Lundborg et al., 2017; Adda et al., 2017; Reuben, Wiswall and Zafar, 2017; Cubas et al., 2019; Kleven et al., 2019; Mas and Pallais, 2020.

each member) is predictive of conditional commuting probabilities once that I partial out each member's independent reasons to work in such locations. 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 working in location j given the spouse's choice of working in location j' as $\pi_{j|ij',g,k}$. Thus, if the city has say 50 locations, this object would have $50 \times 50 \times 50$ cells as one spouse living in i can commute to j, while the other spouse can commute to j'. I then estimate the following reduced-form regression for each member in dual-earner households:

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

where $FE_{i,j'}$ 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 $FE_{j,j'}$, which are a set of destination pairs fixed effects controlling for the fact that certain destination pairs might be more desirable than others, for example, because they pay higher wages. I allow for the interaction of the spouse's commuting choice and one's own choice as this interaction is informative about the degree of interdependence in commuting choices within couples.

My procedure goes as follows. First, I estimate the previous equation. Then, I recover the estimates of $FE_{j,j'}$. If one's choice depends on the other spouse's choice, then the residual of $FE_{j,j'}$—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.[12] That is, the coefficient ψ from $\log \pi_{j|j',g,k} = \psi \hat{FE}_{j,j'} + FE_j + FE_{j'}$ should be different than zero.[13]

I show that this is in fact true. Figure 1 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.

[Figure 1 here]

[12] 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.

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

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 in regards to their commuting. I now provide suggestive evidence of the income effect explained above.[14] As such, I lose the destination-pair fixed effect in equation 2 and instead add the average male wage at destination j and the average female wage at destination j' and interact each spouse's wage with total labor income they would obtain at a destination pair.[15] I show the results of this specification in Table 2. These results show that there is some heterogeneity around the average own-gender wage elasticity.[16] In the case of males in dual-earner households, this elasticity goes between 1.856% and 3.054% (column 1), whereas for females this elasticity goes between 1.178% and 1.914% (Column 2).

To sum up, the evidence I provide points toward the need of accounting for the interconnection of choices in dual earner households which stems from the fact that couples may pool their income. Since this leads to commuting choices being quite heterogeneous across income profiles, and hence across locations, then to adequately quantify the impact of the new transit infrastructure I should account for said heterogeneity in commuting choices.

[Table 2 here]

Fact 3: Reduced form impacts on the location of households differ by household type. I employ 2007 and 2017 Census data to document how the new transit infrastructure introduced in 2010 have affected different types of households. In particular, I run the following differences-in-differences model:

$$\begin{aligned} \log y_{it} &= \sum_b \rho_b^M \cdot \left(D_{ib}^M \times t\right) + \sum_b \rho_b^{BRT} \cdot \left(D_b^{BRT} \times t\right) + \\ &\quad + \alpha' X_{it} + FE_{it}^M + FE_{it}^{BRT} + FE_i + \varepsilon_{it} \end{aligned}$$

where y_{it} is an outcome constructed from Census data, D_{ib}^M are dummies that take the value of one whenever zone i is close to a Metro station. I measure how close to stations zones are using distance bins (within 1 km, between 1 km and 3 km, and more than 3 km). Similarly, D_{ib}^{BRT} are dummies based on the distance to the closest BRT station. I interact these variables with year

[14] Income pooling would generate couples to interrelate their decisions. I explain how in the theoretical section of the paper.

[15] I get average wages for each gender from the 2015-2017 waves of the national firm-level survey data.

[16] I have demeaned the variable for log total income, hence the coefficient reveals the average elasticity with respect to own gender wages.

dummies and so ρ_b^M and ρ_b^{BRT} measure the effect of the new transit infrastructure on locations that are closer to the stations relative to locations that are farther away. Moreover, I control for a set of zone fixed effects FE_i, in addition to stations-by-year fixed effects, $FE_{it}^M + FE_{it}^{BRT}$.[17] Finally, X_{it} is a set of covariates including 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 the outcome variable y_i in 2007, each interacted with year dummies. This is to control for differential trends among these dimensions. With the objective of comparing locations that are similar, I only include locations that are at most within 9.7 kilometers from stations, which is the percentile 75 of the distance distribution.

Results by PPML are reported in Table 3. I estimate the impact on six outcomes that are telling of how mobile each type of household is relative to each other. Columns (1) and (2) of Panel A show the impact on overall population living in each block. The first one reports the effects without the set of controls X_{it}, while the second column reports the effects after conditioning on X_{it}. We can see that relative to locations farther away, population in locations closer to Metro stations shrunk by 13.9%. The impact on locations closer to BRT stations was of -8.8%. As we move away from stations, impacts start declining.

Even though total population seems to be decreasing, mobility might be heterogeneous across household types, and hence there is potential for a shift in the composition of households that remain closer to stations. This is in fact the case, as columns (4) and (6) seem to suggest. Column (4) shows that the share of single relative to married households increases in areas closer to stations. Furthermore, column (6) suggests that the share of women relative to men is decreasing in neighborhoods closer to stations, albeit this result is less robust. Moreover, when looking on the ratio of singles to married but conditioning on gender we see that most of the impact is driven by single males. Column (2) of Panel B shows that the share of single males relative to married males increases as one gets closer to the stations. Also, if anything, column (4) of Panel B reveals that the share of single females relative to married females is declining in areas closer to stations. Finally, in column (6) we see that the share of dual-earner households relative to male breadwinner households rises in neighborhoods closer to stations, i.e. female labor force participation might be increasing.

In conclusion, 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 types which I should account for in the model. In particular, I find that those moving

[17] I define each zone's station as the one that is closest as measured by the euclidean distance.

out were mainly married households and those staying were mostly single males. I also find evidence pointing towards an increase in labor force participation in neighborhoods closer to stations, as the ratio of dual-earner to male breadwinner households rose. Finally, impacts were heterogeneous across transit modes, which is consistent with the fact that the Metro and BRT connect different areas within the city.

[Table 3 here]

3.3 Pre-trends and other reduced-form impacts

To test whether pre-trends are parallel I now exploit survey data. In particular, I leverage on the fact that the Peruvian National Household Survey is georeferenced at the block level, which allows me to compute a precise measure of distance to stations. Then, I run the following regression at the household level i and zone level l at year t:

$$\begin{aligned}\log y_{it} &= \sum_t \rho_t^M \cdot \left(d_l^M \times year_t\right) + \sum_t \rho_t^{BRT} \cdot \left(d_l^{BRT} \times year_t\right) + \\ &\quad + \alpha_1' X_{1it} + \alpha_2' X_{2lt} + FE_i + \varepsilon_{it}\end{aligned}$$

where y_{it} is a household-level outcome such as rents and income. d_l^M and d_l^{BRT} measure the distance in kilometers from block l to the closest Metro and BRT station, respectively. $year_t$ are a set of year dummies. I set the base category to be the year 2009 since the BRT started operating on 2010. X_{1it} is a set of household-level controls comprised by age, years of education, civil status, mother's language, and moving history. Finally, X_{2lt} is a 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, each interacted with year dummies $year_t$. The main difference between these specifications and the one I ran for the census data (i.e. in Fact 3) is that to gain statistical power I am now using a continuous measure of distance instead of distance bins.

I estimate this time-event study by PPML and report the results in Figure 2 and 3. In Panel A of Figure 2 I show the time-event study for actual rents paid by households. In the left-hand side I show the coefficients associated to the distance to Metro stations, while in the right hand side I show the coefficients on distance to BRT stations. First and foremost, I cannot statistically differentiate the alternative of pre-trends from the null of no pre-trends for both distances. Second, albeit quite noisy, rents decreased in areas closer to the Metro stations relative to areas farther away.[18] The opposite is true for areas closer to BRT stations. These observations are also true when I use a variable constructed by the Bureau of Statistics which considers hypothetical rents as per Panel B.[19] In Figure 3 I depict the time-event study for outcomes related to household income. Panel A shows the impact on total income, whereas Panel B shows the impact on total expenditures. The former is based on a question asking how much each household member earns, while the latter is based on several questions asking for specific expenditures in different items which is then aggregated to the household level.[20] Using both measures I conclude that there were no pre-trends correlated with distance to stations. Moreover, my results indicate that the introduction of the Metro had a limited impact in locations nearby. Nonetheless, the introduction of the BRT seems to have increased total income in households located closer to the BRT stations.

[Figure 2 here]

[Figure 3 here]

Given that my sample is quite small and thereby my results noisy I estimate a more parsimonious time event study. I replace the year dummies interacted with the distance to stations in equation 3 with 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. Panel A of Table 4 shows the results of estimating this model. Columns (1) and (2) confirm that pre-trends are parallel. They also confirm that rents decreased in areas closer to Metro stations, but raised in neighborhoods closer to BRT stations. Columns (3) and (4) corroborate that pre-trends in income-related outcomes are parallel. They additionally demonstrate once again that the impact of Metro stations on household income was very limited and that household expenditures increased in areas closer to BRT stations.

Since pre-trends does not seem to be an issue I further simplify equation 3 by replacing the year dummies with a dummy variable taking the value of one if the data comes from any year after 2009, and zero otherwise. The results of estimating this model are shown in Panel B of Table 4. They further support the patterns I have already established.

[18] Since coefficients are positive after 2010, households farther away from stations experienced an increase in their rents.

[19] i.e. How much would homeowners have paid would they be renting their homes.

[20] It is usually argued that people are more willing to reveal their expenditures in this kind of surveys thereby this might be a more precise measure of income.

Before concluding this section, one important aspect to consider when interpreting these results is that, as Fact 3 shows, the introduction of the new transit infrastructure may have induced households to relocate to other parts of the city. In other words, the impacts I am estimating are conflating partial and general equilibrium effects. It is hard to extract definite 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 section I develop a model of city structure based on Ahlfeldt, et al. (2015) and Tsivanidis (2019) but with the addition of household-types and income pooling within couples.

[Table 4 here]

4 Quantitative Model of City Structure and Couples

4.1 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, negative residential externalities and an inelastic supply of land). This tension is heterogeneous across household types, that is, among single males and females, and especially among married couples.

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, household productivity, amenities and industry productivities as I will 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.[21] Households have to make different choices. Single households have to decide where to live, where to work, and how much to consume of a final good and housing. Couples have to make these same decisions, in addition to deciding whether the wife will work, and in case she does, where she is going to work. For simplicity, singles and husbands always work in this model. Thus there are five types of workers: single

[21] Couples are comprised of a male and a female.

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 final good using labor and commercial floorspace. 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. In the following section, I describe the model.

4.2 Households

4.2.1 Preferences

Preferences in single households. A household ω of gender g chooses a location i in which to live and a location j in which to work. 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 $1-\beta^g$; 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 income against housing costs and amenities. Concretely, indirect utility is given by:

$$V_{ij}^g(\omega) \quad = \quad (\beta^g)^{\beta^g}(1-\beta^g)^{1-\beta^g} u_i^g \nu_i^g(\omega) P^{-\beta^g} r_{R_i}^{\beta^g-1}\left[\frac{w_{jg}\epsilon_j^g(\omega)}{d_{ij}^g}\right] \tag{3}$$

where P is the price of the freely traded final good, and r_{R_i} is the rental value of residential floorspace.

Preferences in married households. A couple ω perform the same choices as single households but now have the possibility of pooling their resources.[22] In addition 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.

[22] This is a model of unitary households.

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 $\xi_{i\ell}^{mf}$. Married households may also prefer a stay-at-home wife for idiosyncratic reasons which are captured in their preference for stay-at-home wives $\alpha_{\ell}^{mf}(\omega)$. Second, each member experiences disutility from commuting in an iceberg fashion, $d_{ij}^{mf,m} \geq 1$ and $d_{ij}^{mf,f} \geq 1$, where $d_{ij}^{mf,m} = \exp(\kappa^{mf,m} t_{ij})$ and $d_{ij}^{mf,f} = \exp(\kappa^{mf,f} t_{ij})$, and they are heterogeneous in their preference for working in location j, $\epsilon_j^{mf,m}(\omega)$ and j', $\epsilon_j^{mf,f}(\omega)$.[23] Since couples have the possibility of pooling their resources, this creates an additional income effect that was not present for singles. In particular, if one of the spouses is already commuting to a high-wage location, then the other spouse's response to the sudden availability of high wage locations may be less pronounced. This is akin to the income effect present in standard models of labor and working hours. Hence couples based on these considerations should allocate the husband and the wife to a particular destination such that household utility is maximized.

Specifically, indirect utility of a couple living i, where the husband works at j and the wife in j' is given by:

$$\begin{aligned} V_{i\ell jj'}^{mf}(\omega) \quad = \quad & \left(\beta^{mf}\right)^{\beta^{mf}} \left(1-\beta^{mf}\right)^{1-\beta^{mf}} u_i^{mf} \nu_i^{mf}(\omega)\, \xi_{i\ell}^{mf} \alpha_{\ell}^{mf}(\omega) \\ \cdot \quad & \frac{\epsilon_j^{mf,m}(\omega)}{d_{ij}^{mf,m}} \left(\frac{\epsilon_{j'}^{mf,f}(\omega)}{d_{ij'}^{mf,f}}\right)^{\ell} P^{-\beta^{mf}} r_{R_i}^{\beta^{mf}-1} y_{\ell jj'}^{mf}(\omega) \end{aligned} \tag{4}$$

where household ω's income is $y_{\ell jj'}^{mf}(\omega) = w_{jm} + w_{j'f}\ell(\omega)$.

4.2.2 Workplace and residence location choices

Single households

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

$$\pi_{j|i}^g \quad = \quad \frac{\left(\frac{w_{jg}}{d_{ij}^g}\right)^{\theta^g}}{\Psi_{R_i^g}} \tag{5}$$

[23]The superscript mf, m stands for males and mf, f for females in married couples.

where the probability singles g choose j given i is: $\pi^g_{j|i}$, and $\Xi_{R^g_i} = \sum_{l=1}^{S} \left(\frac{w_{lg}}{d^g_{ij}}\right)^{\theta^g}$. Thus, one key trade-off is that individuals are attracted to locations paying a high wage but dislike commuting long distances. 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. Expected utility, conditional on residence i is:

$$\mathcal{E}_j \left[V^g_{ij}(\omega)\,|i\right] = \text{Constant}^g u^g_i \nu^g_i(\omega)\, P^{-\beta^g} r^{\beta^g - 1}_{R_i} \Psi^{1/\theta^g}_{R^g_i} \tag{6}$$

where $\text{Constant}^g = (\beta^g)^{\beta^g} (1-\beta^g)^{1-\beta^g} (T^g)^{1/\theta^g}\, \Gamma\left(\frac{\theta^g - 1}{\theta^g}\right)$. Note that the expected utility is directly related to $\Psi_{R_{ig}}$, a multilateral access term. In other words, utility for singles of gender g is higher in expected value in locations with better access to jobs.

B. Residence Location. Before singles draw a value for $\epsilon^g_j(\omega)$, they draw a value for $\nu^g_i(\omega)$ and decide where to live. $\nu^g_i(\omega)$ 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:

$$\pi^g_i = \frac{\left(\frac{r^{1-\beta^g}_{R_i}}{u^g_i \Psi^{1/\theta^g}_{R^g_i}}\right)^{-\eta^g}}{\sum_l \left(\frac{r^{1-\beta^g}_{R_l}}{u^g_l \Psi^{1/\theta^g}_{R^g_l}}\right)^{-\eta^g}} \tag{7}$$

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. This is another key trade-off in the model.

Married households

Let us start with the case where the wife participates in the labor market.[24] Afterwards, I solve for the case where the wife stays at home. Knowing expected welfare in these two cases households can then choose whether she stays at home. Finally, after learning about the expected utility of living in each location, couples can decide where to live.

[24]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 just turn off this margin as it does not seem to be quantitative important but would add greater complexity to the model.

A. Husbands' Commuting Choice in Dual-Earner Households. I assume for simplicity that husbands are to some extent the household head and choose knowing first what their wife chooses. 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. $\pi^{mf,m}_{j|i,\ell=1,j'} = P\left[V^{mf}_{i,\ell=1,j,j'}(\omega) \geq \max_{l\neq j} V^{mf}_{i,\ell=1,l,j'}(\omega)\right]$. Simple manipulations result in the following expression:

$$\pi^{mf,m}_{j|i,\ell=1,j'} = \frac{\left(\frac{w_{jm}+w_{j'f}}{d^{mf,m}_{ij}}\right)^{\theta^{mf,m}}}{\sum_l \left(\frac{w_{lm}+w_{j'f}}{d^{mf,m}_{il}}\right)^{\theta^{mf,m}}} = \frac{\left(\frac{w_{jm}+w_{j'f}}{d^{mf,m}_{ij}}\right)^{\theta^{mf,m}}}{\Phi^{mf,m}_{R_{i,\ell=1,j'}}} \tag{8}$$

where $\Phi^{mf,m}_{R_{i,\ell=1,j'}} = \sum_l \left(\frac{w_{lm}+w_{j'f}}{d^{mf,m}_{il}}\right)^{\theta^{mf,m}}$. As in single households, married men are more likely to commute to a location when it pays a high wage net of commute cost. Moreover, the sensitivity of employment decisions to commute costs is governed by the dispersion of taste shocks. So, differences in tastes control the extent to which individuals are willing to bear high commuting costs. The key difference with respect to commuting probabilities in single households—which is a natural result from the income pooling assumption—is that the husband's conditional commuting probabilities do not only depend on their his own wage but also on his wife's wage. This is akin to a standard and multiple times tested result in labor models whereas an increase in household income make spouses less sensitive to further increases in wages (Blundell et al., 2007). In this context, the income effect operates through the distance he commutes rather than the hours he allocates to work.

Further exploiting the Frechet properties I can compute the household income deflated by the disutility of commuting given the wife's workplace choice:

$$\mathcal{E}_j\left[\frac{\epsilon^{mf,m}_j(\omega)}{d^{mf,m}_{ij}} y^{mf}_{i\ell=1jj'} | i, \ell = 1, j'\right] = \Gamma\left(\frac{\theta^{mf,m}-1}{\theta^{mf,m}}\right)\left(T^{mf,m}\right)^{1/\theta^{mf,m}}\left(\Phi^{mf,m}_{R_{i,\ell=1,j'}}\right)^{1/\theta^{mf,m}}$$

Hence, conditional on the wife's choice, the expected household utility becomes:

$$\begin{aligned}\mathcal{E}_j\left[V^{mf}_{i,\ell,j,j'}(\omega) | i, \ell = 1, j'\right] &= \text{Constant}^{mf,m}_{\ell=1} u^{mf}_i \nu^{mf}_i(\omega)\, \xi^{mf}_{i1} \alpha^{mf}_1(\omega) \frac{\epsilon^{mf,f}_{j'}(\omega)}{d^{mf,f}_{ij'}} \\ &\cdot \quad P^{-\beta^{mf}} r^{\beta^{mf}-1}_{R_i}\left(\Phi^{mf,m}_{R_{i,\ell=1,j'}}\right)^{1/\theta^{mf,m}}\end{aligned} \tag{9}$$

where $\text{Constant}_{\ell=1}^{mf,m} = \left(\beta^{mf}\right)^{\beta^{mf}} \left(1-\beta^{mf}\right)^{1-\beta^{mf}} \Gamma\left(\frac{\theta^{mf,m}-1}{\theta^{mf,m}}\right) \left(T^{mf,m}\right)^{1/\theta^{mf,m}}$.

<u>*B. Wives' Commuting Choice in Dual-Earner Households.*</u> Wives choose before their husbands have decided where to work. So, they take as given the expected behavior of their spouse when deciding their destination. In particular, we need to compute:

$$\pi_{j'|i,\ell=1}^{mf,f} = P\left[\mathcal{E}_j\left[V_{i,\ell,j,j'}^{mf}(\omega)\,|i,\ell=1,j'\right] \geq \max_{l\neq j'} \mathcal{E}_j\left[V_{i,\ell,j,l}^{mf}(\omega)\,|i,\ell=1,l\right]\right]$$

Plugging equation 9 and simplifying terms in both sides we get that:

$$\begin{aligned}
\pi_{j'|i,\ell=1}^{mf,f} &= P\left[\frac{\epsilon_{j'}^{mf,f}(\omega)}{d_{ij'}^{mf,f}}\left(\Phi_{R_{i,\ell=1,j'}}^{mf,m}\right)^{1/\theta^{mf,m}} \geq \max_{l\neq j|i,\ell=1} \frac{\epsilon_{l}^{mf,f}(\omega)}{d_{il}^{mf,f}}\left(\Phi_{R_{i,\ell=1,l}}^{mf,m}\right)^{1/\theta^{mf,m}}\right] \\
&= \frac{\left(\frac{\left(\Phi_{R_{i,\ell=1,j'}}^{mf,m}\right)^{1/\theta^{mf,m}}}{d_{ij'}^{mf,f}}\right)^{\theta^{mf,f}}}{\sum_l\left(\frac{\left(\Phi_{R_{i,\ell=1,l}}^{mf,m}\right)^{1/\theta^{mf,m}}}{d_{il}^{mf,f}}\right)^{\theta^{mf,f}}} = \frac{\left(\frac{\left(\Phi_{R_{i,\ell=1,j'}}^{mf,m}\right)^{1/\theta^{mf,m}}}{d_{ij'}^{mf,f}}\right)^{\theta^{mf,f}}}{\Phi_{R_{i,\ell=1}}^{mf,f}}
\end{aligned} \tag{10}$$

where $\Phi_{R_{i,\ell=1}}^{mf,f} = \sum_l\left(\frac{\left(\Phi_{R_{i,\ell=1,l}}^{mf,m}\right)^{1/\theta^{mf,m}}}{d_{il}^{mf,f}}\right)^{\theta^{mf,f}}$. This expression says that wives will commute to locations where they expect a higher conditional household income deflated by their husband's disutility of commuting, $\Phi_{R_{i,\ell=1,j'}^{mf,m}}$, net of their own disutility of commuting, $d_{ij'}^{mf,f}$. Finally, after noting that

$$\mathcal{E}_{j'}\left[\frac{\epsilon_{j'}^{mf,f}(\omega)}{d_{ij'}^{mf,f}}\left(\Phi_{R_{i,\ell=1,j'}}^{mf,m}\right)^{1/\theta^{mf,m}}|i,\ell=1\right] = \Gamma\left(\frac{\theta^{mf,f}-1}{\theta^{mf,f}}\right)\left(T^{mf,f}\right)^{1/\theta^{mf,f}}\left(\Phi_{R_{i,\ell=1}}^{mf,f}\right)^{1/\theta^{mf,f}}$$

then dual-earner households' expected utility conditional on their residence is:

$$\begin{aligned}
\mathcal{E}_{j'}\left[\mathcal{E}_j\left[V_{i,\ell,j,j'}^{mf}(\omega)\,|i,\ell=1,j'\right]|i,\ell=1\right] &= \text{Constant}_{\ell=1}^{mf}\cdot u_i^{mf}\nu_i^{mf}(\omega)\,\xi_{i1}^{mf}\alpha_1^{mf}(\omega) \\
&\cdot\quad P^{-\beta^{mf}} r_{R_i}^{\beta^{mf}-1}\left(\Phi_{R_{i,\ell=1}}^{mf,f}\right)^{1/\theta^{mf,f}}
\end{aligned} \tag{11}$$

where $\text{Constant}_{\ell=1}^{mf} = \Gamma\left(\frac{\theta^{mf,f}-1}{\theta^{mf,f}}\right)\left(T^{mf,f}\right)^{1/\theta^{mf,f}} \Gamma\left(\frac{\theta^{mf,m}-1}{\theta^{mf,m}}\right)\left(T^{mf,m}\right)^{1/\theta^{mf,m}} \left(\beta^{mf}\right)^{\beta^{mf}} \left(1-\beta^{mf}\right)^{1-\beta^{mf}}$.

C. Husbands' Commuting Choice in Male Breadwinner Households. A similar logic as in single households delivers the following expressions for commuting probabilities:

$$\pi_{j|i,\ell=0}^{mf,m} = \frac{\left(\frac{w_{jm}}{d_{ij}^{mf,m}}\right)^{\theta^{mf,m}}}{\sum_{l'}\left(\frac{w_{lm}}{d_{il}^{mf,m}}\right)^{\theta^{mf,m}}} \equiv \frac{\left(\frac{w_{jm}}{d_{ij}^{mf,m}}\right)^{\theta^{mf,m}}}{\Phi_{R_{i,\ell=0}}^{mf,m}} \tag{12}$$

Furthermore, households' indirect utility conditional on their residence becomes:

$$\begin{aligned}\mathcal{E}_j\left[V_{i\ell=0j}^{mf}(\omega)\,|i,\ell=0\right] &= \text{Constant}_{\ell=0}^{mf} u_i^{mf}\nu_i^{mf}(\omega)\,\xi_{i0}^{mf}\alpha_0^{mf}(\omega) \\ &\cdot\ P^{-\beta^{mf}} r_{R_i}^{\beta^{mf}-1}\left(\Phi_{R_{i,\ell=0}}^{mf,m}\right)^{1/\theta^{mf,m}}\end{aligned} \tag{13}$$

where $\text{Constant}_{\ell=0}^{mf} = \left(T^{mf,m}\right)^{1/\theta^{mf,m}}\Gamma\left(\frac{\theta^{mf,m}-1}{\theta^{mf,m}}\right)\left(\beta^{mf}\right)^{\beta^{mf}}\left(1-\beta^{mf}\right)^{1-\beta^{mf}}$. So, in terms of commuting, married males in breadwinner households and single males behave quite similarly, although with potentially different commuting elasticities.

D. Labor Force Participation. Conditional on their residence, households compare the expected utility they would obtain if the wife works (equation 11) or if she stays at home (equation 13). Since households are heterogeneous in their preference for a stay-at-home wife, and we assume this heterogeneity is distributed Frechet with shape parameter ν, we are able to compute the probability that a couple will become a dual-earner household. That is:

$$\begin{aligned}\mu_i^{mf} &= P\left[E_{j'}\left[\mathcal{E}_j\left[V_{i,\ell=1,j,j'}^{mf}(\omega)\,|i,\ell=1,j'\right]|i,\ell=1\right] \geq \mathbb{E}_j\left[V_{i\ell=0j}^{mf}(\omega)\,|i,\ell=0\right]\right] \\ &= P\left[\xi_{i\ell=1}^{mf}\alpha_1^{mf}(\omega)\left[\left(\Phi_{R_{i,\ell=1}}^{mf,f}\right)^{1/\theta^{mf,f}}\right] \geq \xi_{i\ell=0}^{mf}\alpha_0^{mf}(\omega)\left(\Phi_{R_{i,\ell=0}}^{mf,m}\right)^{1/\theta^{mf,m}}\right] \\ &= \frac{\left[\left(\Phi_{R_{i,\ell=1}}^{mf,f}\right)^{1/\theta^{mf,f}}\right]^{\nu}}{\left[\left(\Phi_{R_{i,\ell=1}}^{mf,f}\right)^{1/\theta^{mf,f}}\right]^{\nu} + \left[\xi_{i\ell=0}^{mf}\left(\Phi_{R_{i,\ell=0}}^{mf,m}\right)^{1/\theta^{mf,m}}\right]^{\nu}}\end{aligned} \tag{14}$$

where household productivity in domestic goods $\xi_{i\ell=1}^{mf}$ has been normalized to one, and hence $\xi_{i\ell=0}^{mf}$ indicate how much more productive are households in location i when the wife stays at home relative to the situation in which she participates in the labor market.[25] This expression

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

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. In this respect, ν measure the inverse of the dispersion in households tastes about wives' labor force participation. When the dispersion of preferences is low (i.e. high ν), choices are more sensitive small changes in the expected utility of having a stay-at-home wife, for instance. Thus, this parameter governs the labor supply elasticity of women's extensive margin in married households. So, average welfare of households living in location i will be:

$$\begin{aligned} \bar{V}_i^{mf}(\omega) &\equiv \mathcal{E}_\ell \left\{ \mathbb{E}_{j'} \left[\mathbb{E}_j \left[V_{i,\ell=1,j,j'}^{mf}(\omega) \,|i, \ell=1, j' \right] |i, \ell=1 \right] |i \right\} \\ &= \Gamma\left(\frac{\nu-1}{\nu}\right) \cdot u_i^{mf} \nu_i^{mf}(\omega) \, P^{-\beta^{mf}} r_{R_i}^{\beta^{mf}-1} \cdot \Psi_{R_i^{mf}}^{1/\nu} \end{aligned} \tag{15}$$

where $\Psi_{R_i^{mf}} = \left[\left(\Phi_{R_{i,\ell=1}^{mf,f}}\right)^{\frac{\nu}{\theta^{mf,f}}} + \left(\xi_{i\ell=0}^{mf}\right)^{\nu} \left(\Phi_{R_{i,\ell=0}^{mf,m}}\right)^{\frac{\nu}{\theta^{mf,m}}} \right]^{1/\nu}$. This equation states that married households will be better off in locations where, net of housing costs and amenities, expected utility is higher, i.e. greater market access for both genders or greater market access for males paired with high household productivity.

<u>*E. Residence Location.*</u> 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:

$$\begin{aligned} \pi_i^{mf} &= P\left[u_i^{mf} \nu_i^{mf}(\omega) \, r_{R_i}{}^{\beta^{mf}-1} \cdot \Psi_{R_i^{mf}}^{1/\nu} \geq \max_{l \neq i} u_l^{mf} \nu_l^{mf}(\omega) \, r_{R_l}{}^{\beta^{mf}-1} \cdot \Psi_{R_l^{mf}}^{1/\nu} \right] \\ &= \frac{\left(\frac{r_{R_i}^{1-\beta^{mf}}}{u_i^{mf} \Psi_{R_i^{mf}}^{1/\nu}} \right)^{-\eta^{mf}}}{\sum_l \left(\frac{r_{R_i}^{1-\beta^{mf}}}{u_l^{mf} \Psi_{R_l^{mf}}^{1/\nu}} \right)^{-\eta^{mf}}} \end{aligned} \tag{16}$$

Thus, not only the location elasticity η is different in single households than in married couples, but also married have other considerations when deciding where to live. That is, they consider locations where on average both spouses would be better off, thereby linking females and males market conditions. For instance, when deciding to move to location i households will balance out locations characterized by a low market access to female jobs against the location's inclination towards household production through a greater ξ_{i0}.

hereafter.

4.2.3 Aggregation

I aggregate the supply of residents and of workers to jobs, and the income spent in consumption of final goods and housing.

Supply of residents

Equation 7 characterizes the location choice of singles, whereas equation 16 does it for married couples. Given the aggregate number of households-by-type we can compute the supply of households in each location i:

$$\begin{aligned} N_{R_i^g} &= \pi_i^g N^g, g \in \{m, f\} \\ N_{R_i^{mf}} &= \pi_i^{mf} N^{mf} = \underbrace{(1-\mu_i)\,\pi_i^{mf} N^{mf}}_{N_{R_{i,0}^{mf}}} + \underbrace{(\mu_i)\,\pi_i^{mf} N^{mf}}_{N_{R_{i,1}^{mf}}} \end{aligned} \tag{17}$$

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 households $N_{R_{i,0}^{mf}}$.

Supply of workers to jobs

After computing how many households-by-type live in block i as given by equation 17, and the probability of commuting to any block as given by equations 5, 8, 10, and 12, we can calculate the supply of workers of gender g to any location:

$$\begin{aligned} L_{F_{jm}} &= \sum_i \left\{\pi_{j|i}^m N_{R_i^m}\right\} + \sum_i \left\{\pi_{j|i,\ell=0}^{mf,m} N_{R_{i,0}^{mf}}\right\} + \sum_i \left\{\pi_{j|i,\ell=1}^{mf,m} N_{R_{i,1}^{mf}}\right\} \\ L_{F_{jf}} &= \sum_i \left\{\pi_{j|i}^f N_{R_i^f}\right\} + \sum_i \left\{\pi_{j|i,\ell=1}^{mf,f} N_{R_{i,1}^{mf}}\right\} \end{aligned} \tag{18}$$

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

$$\pi_{j|i,\ell=1}^{mf,m} = \textstyle\sum_l \pi_{j|i,\ell=1,l}^{mf,m} \cdot \pi_{l|i,\ell=1}^{mf,f} \tag{19}$$

I refer the comparison between singles' and married' aggregate commuting behavior to the section following the explanation of the model.

Household income, consumption and housing

Before computing aggregate consumption and housing, we need to calculate average income by household type and gender. This is done directly by weighting wages by commuting probabilities:

$$
\begin{aligned}
y^{mf}_{i,\ell=1} &= \underbrace{\sum_j \left(w_{jm}\pi^{mf,m}_{j|i,\ell=1}\right) N_{R^{mf}_{i,1}}}_{y^{mf,m}_{i,\ell=1}} + \underbrace{\sum_j \left(w_{jf}\pi^{mf,f}_{j|i,\ell=1}\right) N_{R^{mf}_{i,1}}}_{y^{mf,f}_{i,\ell=1}} \qquad (20)\\
y^{mf}_{i,\ell=0} &= \sum_j \left(w_{jm}\pi^{mf,m}_{j|i,\ell=0}\right) N_{R^{mf}_{i,0}}\\
y^{g}_{i} &= \sum_j \left(w_{jg}\pi^{g}_{j|i}\right) N_{R^{g}_{i}}
\end{aligned}
$$

Then housing demand in location i and the final good demand become:

$$
\begin{aligned}
H_{R_i} &= (1-\beta^m)\frac{y^{m,m}_i}{r_{R_i}} + \left(1-\beta^f\right)\frac{y^{f,f}_i}{r_{R_i}} + \left(1-\beta^{mf}\right)\frac{y^{mf}_{i,\ell=1}}{r_{R_i}} + \left(1-\beta^{mf}\right)\frac{y^{mf}_{i,\ell=0}}{r_{R_i}} \qquad (21)\\
X &= PC = \sum_i PC_i + \sum_i \left(H_{R_i} r_{R_i} + H_{F_i} r_{F_i}\right) \qquad (22)\\
&= \beta^m y^{m,m}_i + \beta^f y^{f,f}_i + \beta^{mf} y^{mf}_{i,\ell=1} + \beta^{mf} y^{mf}_{i,\ell=0} + \sum_i \left(H_{R_i} r_{R_i} + H_{F_i} r_{F_i}\right)
\end{aligned}
$$

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

4.3 Firms

4.3.1 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 a CES aggregator by consumers with elasticity of substitution $\sigma_D > 1$. This aggregated output good is the same final good introduced in the consumer's problem. Following Tsivanidis (2019), firms produce using a Cobb-Douglas technology over labor and commercial floorspace:

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

Industries aggregate workers of different genders using a CES aggregator over each gender's effective labor with elasticity of substitution σ. 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 which is taken as given. Importantly, industries differ in the intensity in which they use different type of workers α_{sg}. The effect of improving access to workers of different genders hinge on which type of jobs they are gaining access to.

4.3.2 Factor demand

To compute factor demands we need to solve the industries' expenditure minimization problem $\min\{\sum_g w_{jg}\tilde{L}_{F_{jgs}} + r_{F_j} H_{F_j}\}$ subject to $p_{js}Y_{js} = X_{js}$, where r_{F_j} is the price of commercial floorspace in location j, X_{js} is the industry's sales, and p_{js} the price at which the industry s in location j sells its goods, yielding

$$\tilde{L}_{F_{jgs}} = \left(\frac{w_{jg}}{\alpha_{sg} W_{js}}\right)^{-\sigma} N_{js} \tag{23}$$

where $W_{js} = \left(\sum_g \alpha_{sg}^{\sigma} w_{jg}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is the cost of labor for industries of industry s in location j. It is straightforward to proof that:

$$N_{js} = \alpha_s \frac{X_{js}}{W_{js}} \tag{24}$$

$$H_{F_{js}} = (1-\alpha_s)\frac{X_{js}}{r_{F_j}} \tag{25}$$

4.3.3 Price index

Finally, perfect competition leads to the price rule: $p_{js} = W_{js}^{\alpha_s} r_{F_j}^{1-\alpha_s}/A_{js}$. Note that sales of each variety j of the industry s, X_{js}, have to be equal to total demand. Hence, we still need to solve the consumer maximization problem with the lower-tier CES demand with elasticity σ_D (paired with an upper-tier Cobb-Douglas). It is straightforward to proof that $X_{js} = p_{js}^{1-\sigma_D} P^{\sigma_D - 1} X$, where X is total spending on goods in the city and is given by equation 22. and P is the price index for final consumption goods:

$$P = \left(\sum_{js} \left(W_{js}^{\alpha_s} r_{F_j}^{1-\alpha_s} A_{js}^{-1}\right)^{1-\sigma_D}\right)^{1/(1-\sigma_D)} \tag{26}$$

4.4 Housing

4.4.1 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 equals demand. This is the same for commercial floorspace.

Then, residential demand, H_{R_i}, is equal to $(1-\beta)$ times total spending in goods and housing from individuals living in i as given by equation 21, divided by price r_{R_i}. Market clearing is given by:

$$
\begin{aligned}
H_{R_i} &= \vartheta_i H_i r_{R_i} \\
\Leftrightarrow \vartheta_i H_i &= (1-\beta^m)\frac{y_i^{m,m}}{r_{R_i}} + \left(1-\beta^f\right)\frac{y_i^{f,f}}{r_{R_i}} + \left(1-\beta^{mf}\right)\frac{y_{i,\ell=1}^{mf}}{r_{R_i}} + \left(1-\beta^{mf}\right)\frac{y_{i,\ell=0}^{mf}}{r_{R_i}} \\
\Leftrightarrow r_{R_i} &= \frac{1}{\vartheta_i H_i}\left[(1-\beta^m)\, y_i^{m,m} + \left(1-\beta^f\right) y_i^{f,f} + \left(1-\beta^{mf}\right) y_{i,\ell=1}^{mf} + \left(1-\beta^{mf}\right) y_{i,\ell=0}^{mf}\right]
\end{aligned}
$$

Similarly, the supply of commercial floorspace, $(1-\vartheta_j)H_j r_{F_i}$, must equal the demand from firms, $H_{F_j} = \sum_s H_{F_{js}}$:

$$
(1-\vartheta_j)H_j \quad = \sum_s (1-\alpha_s)\frac{X_{js}}{r_{F_j}}
$$

4.4.2 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:

$$
\begin{aligned}
\vartheta_i = 1, &\quad \text{if } r_{R_i} > (1-\tau_i)r_{F_i} \\
(1-\tau_i)r_{F_i} = r_{R_i}, &\quad \forall \{i : \vartheta_i \in (0,1)\} \\
\vartheta_i = 0, &\quad \text{if } r_{R_i} < (1-\tau_i)r_{F_i}
\end{aligned}
\tag{27}
$$

4.5 Agglomeration and amenity spillovers

Productivity per sector A_{js} and amenities per gender u_{ig} can be decomposed into two components, one which is exogenous and captures fundamentals, and the other which is endogenous capturing agglomeration forces.

4.5.1 Agglomeration forces

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 employment in industry s in that location. I model endogenous agglomeration allowing agglomeration forces to vary by sector. In other words:

$$A_{js} \quad = \bar{A}_{js} \left(\tilde{L}_{F_{js}} \right)^{\phi_{F_s}} \tag{28}$$

where ϕ_{F_s} measures the overall effect of agglomeration forces in sector s. To the extent that agglomeration economies are higher in male intensive industries, then agglomeration economies may limit the effect of improvements in the transit system on female earnings. Albeit this effect will ultimately depend on the city's geography and the kind of jobs women are gaining access to. The idea of sectoral agglomeration forces (also called external economies) is not new and recently papers have assessed their importance (e.g. Bartelme et al., 2019).

4.5.2 Amenities

Amenities in each location depend on an exogenous component $\bar{u}_{ik}$ and on an endogenous component comprised by the overall population. On the one hand, the residential fundamental $\bar{u}_{ik}$ capture features of the physical geography that make a location more or less attractive to certain genders, independently of economic activity, such as easy access to child care and security. This externality also captures the idea that living in denser areas may generate negative externalities such as contamination, crowding and crime. I do not disentangle positive and negative externalities, rather I estimate a net externality. I allow the strength of this endogenous amenity externality to vary by household type:

$$u_{ik} = \bar{u}_{ik} \left(N_{R_i^{mf}} + N_{R_i^m} + N_{R_i^f} \right)^{\phi_{Rk}} \text{ where } k \in \{m, f, mf\} \tag{29}$$

4.6 Definition of Equilibrium

I assume that $A_{js} > 0$, $u_{ig} > 0$ and $\xi_{i\ell} > 0$ for all locations, sectors, and genders. Corner solutions are taken care off in Appendix A1.

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

The solution algorithm is presented in section A1.

4.7 Income Pooling in Couples, Supply Responses and the Gender Gap

In this section I compare labor supply responses by singles and married couples. This comparison is informative about the importance of income pooling and what would happen in a world where spouses do not pool their resources, but rather act independently from each other. Furthermore, to concentrate on the consequences of income pooling on commuting probabilities, in this exercise I take the distribution of residents on the city and labor force participation rates as given, and so I abstract away from the residential location choice and the participation choice of married women.

4.7.1 Labor supply responses to an increase in wages

To understand what determines the labor supply of singles to j let us pick a gender, say females, $\sum_i \left\{\pi^f_{j|i} N_{R^f_i}\right\} = w^{\theta f}_{jf} \sum_i \left(d^f_{ij}\right)^{-\theta^f} \frac{N_{R^f_i}}{\Psi_{R^f_i}}$. Then, labor supply in general depends on two variables. First, workers prefer destinations paying higher wages. Second, supply to locations is greater when the location enjoys better access through the commuting network captured in the multilateral resistance term $\sum_i \left(d^f_{ij}\right)^{-\theta^f} \frac{N_{R^f_i}}{\Psi_{R^f_i}}$. In this example, the sensibility of single females to these terms is regulated by θ^f. To be concrete, suppose that female wages rises in location 1 by one log point. The effect on labor supply would be:

$$\frac{\partial \log \sum_i \left\{\pi^f_{1|i} N_{R^f_i}\right\}}{\partial \log w_1} = \sum_i \frac{\pi^f_{1|i} N_{R^f_i}}{\sum_i \left\{\pi^f_{1|i} N_{R^f_i}\right\}} \left(1 - \pi^f_{1|i}\right) \theta^f$$

In other words, single females from all origins will commute to location j but proportionally to the share of single females that were not yet working in j. Note that in terms of commuting, males in male-breadwinner households behave very similarly to singles but with a different elasticity $\theta^{mf,m}$. Thus I am going to skip explaining it further.

Now let us turn to females in dual-earner households. Their labor supply to location j, $\sum_i \left\{\pi^{mf,f}_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\}$, can be rewritten as:

$$\sum_i \left\{\pi^{mf,f}_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} = \sum_i \left(\Phi^{mf,m}_{R_{i,\ell=1,j}}\right)^{\theta^{mf,f}/\theta^{mf,m}} \left(d^{mf,f}_{ij}\right)^{-\theta^{mf,f}} \frac{N_{R^{mf}_{i,1}}}{\Phi^{mf,f}_{R_{i,\ell=1}}}$$

where recall $\Phi^{mf,f}_{R_{i,\ell=1}} = \sum_l \frac{\left(\Phi^{mf,m}_{R_{i,\ell=1,l}}\right)^{\theta^{mf,f}/\theta^{mf,m}}}{d^{mf,f}_{il}}$. The first big difference with the supply of single females is that instead of having a term measuring how good income is in location j that is independent from the origin, $w^{\theta^f}_{jf}$, we have a term $\left(\Phi^{mf,m}_{R_{i,\ell=1,j}}\right)^{\theta^{mf,f}/\theta^{mf,m}}$ that measures how much would *total* household income be after accounting for the fact that husbands might affect their commuting behavior if the wife commutes to j rather than some other location. In other words, wives' commuting behavior becomes interlinked to that of their husbands' through the pooling of income happening at the household level. Let us continue the example by supposing that wages for females in location 1 increase by one log point. That is,

$$\frac{\partial \log \sum_i \left\{\pi^{mf,f}_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}}{\partial \log w_{1f}} = \sum_i \frac{\pi^{mf,f}_{1|i,\ell=1} N_{R^{mf}_{i,1}}}{\sum_i \left\{\pi^{mf,f}_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}} \left(1 - \pi^{mf,f}_{1|i,\ell=1}\right) \underbrace{\sum_l \pi^{mf,m}_{l|i,\ell=1,1} \frac{w_{1f}}{(w_{lm} + w_{1f})} \theta^{mf,f}}_{\epsilon^{mf,f}_{i1}}$$

Compared to singles, the main difference is that instead of having a constant θ^f multiplied by the share of females that are not yet working in j, now we have an endogenous elasticity $\epsilon^{mf,f}_{i1}$. Two observations are in order. First, note that $\frac{w_{1f}}{(w_{lm}+w_{1f})}\theta^{mf,f}$ is the elasticity of the probability of commuting to 1 with respect to the wife's own wage, which is less than $\theta^{mf,f}$. This is a direct implication of the pooling assumption which produces an income effect inducing wives to be less sensitive to increases in wages, especially when their husbands' income make up a large share of the households' budget. Second, $\sum_l \pi^{mf,m}_{l|i,\ell=1,1} \frac{w_{1f}}{(w_{lm}+w_{1f})}\theta^{mf,f}$ is a weighted average across l of supply elasticities given origin i, and hence labor supply responses will ultimately depend on the origin location.

Males in dual earner households commute in a similar fashion, although some differences arise because of the assumption that they choose their location once that they know what their wives do. In particular, $\sum_i \left\{\pi^{mf,m}_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\}$ can be rewritten as:

$$
\begin{aligned}
\sum_i \left\{\pi^{mf,m}_{j|i,\ell=1} N_{R^{mf}_{i,1}}\right\} &= \sum_i \sum_l \pi^{mf,m}_{j|i,\ell=1,l} \cdot \pi^{mf,f}_{l|i,\ell=1} N_{R^{mf}_{i,\ell=1}} \\
&= \sum_i \sum_l \left(w_{jm} + w_{lf}\right)^{\theta^{mf,m}} \left(d^{mf,m}_{ij}\right)^{-\theta^{mf,m}} \cdot \frac{\pi^{mf,f}_{l|i,\ell=1} N_{R^{mf}_{i,\ell=1}}}{\Phi^{mf,m}_{R_{i,\ell=1,l}}}
\end{aligned}
$$

This case males decide where they commute based on what their wives do. This is reflected by the sum over l that appears in the equation above. So, for every possible location she could work, a particular share of husbands will decide to commute to j based on how much they would earn there and how much her spouse is earning due to the income pooling assumption. Concretely, say male wages increase in location 1 by one log point, then

$$
\begin{aligned}
\frac{\partial \log \sum_i \left\{\pi^{mf,m}_{1|i,\ell=1} N_{R^{mf}_{i,1}}\right\}}{\partial \log w_{1m}} = \sum_i \sum_l \frac{\pi^{mf,m}_{1|i,\ell=1,l} \pi^{mf,f}_{l|i,\ell=1} N_{R^{mf}_{i,\ell=1}}}{\sum_i \sum_l \pi^{mf,m}_{1|i,\ell=1,l} \pi^{mf,f}_{l|i,\ell=1} N_{R^{mf}_{i,\ell=1}}} \Bigg[\left(1 - \pi^{mf,m}_{1|i,\ell=1,l}\right) & \underbrace{\frac{w_{1m}}{\left(w_{1m} + w_{lf}\right)} \theta^{mf,m}}_{\Delta \text{in supply due to own elasticity}} \\
\underbrace{+ \pi^{mf,m}_{1|i,\ell=1,l} \frac{w_{1m}}{\left(w_{1m} + w_{lf}\right)} \theta^{mf,f} - \sum_{l'} \pi^{mf,m}_{1|i,\ell=1,l'} \pi^{mf,f}_{l'|i,\ell=1} \frac{w_{1m}}{\left(w_{1m} + w_{l'f}\right)} \theta^{mf,f}}_{\Delta \text{in supply due to wives commuting to a different location}} & \Bigg]
\end{aligned}
$$

Husbands from every origin-spouses' destination and that are currently working elsewhere will increase their supply to location 1 by $\frac{w_{1m}}{(w_{1m}+w_{lf})}\theta^{mf,m} < \theta^{mf,m}$. Note that this first order increase in their supply depends on the total household income as we have already established and so it is not constant as it is for singles. Furthermore, there is an additional effect caused by the potential reallocation of spouses to different locations as the terms on top of the second underbrace reveal. The difference with wives is that females account for these effects by looking at the average response of husbands in every origin, whereas males check in every origin-spouse's destination cell. In practical terms this means than final labor supply is a weighted average of $\theta^{mf,m}$ and $\theta^{mf,f}$ where the weights are $\pi^{mf,m}_{1|i,\ell=1,l}$ and $1 - \pi^{mf,m}_{1|i,\ell=1,l}$, plus a negative term.

Altogether, this section highlights the heterogeneity in labor supply responses stemming from the pooling of resources at the household level in dual earner households, which is in contrast to the labor supply of singles who exhibit constant elasticities across space. This implies that general equilibrium responses coming from shifts in the labor supply will be more heterogeneous in a model including married couples.

4.7.2 Household income and commuting times

In this section I explore how improving commuting times affects household income. Starting with singles (and males in breadwinner households), total income in origin can be expressed as $\sum_j \left(w_{jg}\pi^g_{j|i} \right) N_{R^g_i}$. Therefore, if commuting times from origin i to destination j' decrease by one log point, and assuming a fixed market access term $\Phi_{R^g_i}$ and wages, I get:

$$-\frac{\partial \log y^g_i}{\partial \log t_{ij'}} = \theta^g \kappa^g \underbrace{\frac{w_{j'g}\pi^g_{j'|i}}{\sum_j \left(w_{jg}\pi^g_{j|i} \right)}}_{\text{income from destination j'}}$$

That is, to a first order approximation if it is easier to commute from i to j', income increases proportionally to location j''s share of total income in i. Commuting elasticities therefore are key parameters governing how income responds to improvements in the transit infrastructure.

Let us turn to females in dual earner households. Taking the derivative of total income to commuting times and multiplying by minus one I get:

$$-\frac{\partial \log y^{mf,f}_{i,\ell=1}}{\partial \log t_{ij'}} = \theta^{mf,f}\kappa^{mf,f} \underbrace{\frac{w_{j'f}\pi^{mf,f}_{j'|i,\ell=1}}{\sum_l \left(w_{l,f}\pi^{mf,f}_{l|i,\ell=1} \right)}}_{\text{wives' income from j'}} + \theta^{mf,f}\kappa^{mf,f} \underbrace{\frac{w_{j'f}\left\{ \pi^{mf,f}_{j'|i,\ell=1}\pi^{mf,m}_{j'|i,\ell=1,j'} \right\}}{\sum_l \left(w_{l,f}\pi^{mf,f}_{l|i,\ell=1} \right)}}_{\text{husbands reallocating to j'}}$$

where I have assumed for simplicity that $\partial \log \pi^{mf,f}_{j|i,\ell=1} / \partial \log d_{ij'} = 0, \forall j \neq j'$. Thus, improvements in commuting times affect wives' income through two channels. First, since commuting to j' is now easier, then it becomes more likely that married women work there. Second, since the probability that her husband now works in j' conditional on her working also in j' increases due the improvement in commuting times, this reinforces the initial effect, making the labor supply response more pronounced.

Finally, I turn to males in dual earner households. Recall they commute knowing where her spouse commutes. Then, improving commute times leads to:

$$
\begin{aligned}
-\frac{\partial \log y^{mf,m}_{i,\ell=1}}{\partial \log t_{ij'}} &= \theta^{mf,m}\kappa^{mf,m} \underbrace{\frac{w_{j'm}\pi^{mf,m}_{j'|i,\ell=1}}{\sum_j \left(w_{jm}\pi^{mf,m}_{j|i,\ell=1}\right)}}_{\text{husbands' income from j'}} \\
&+ \theta^{mf,f}\kappa^{mf,f}\left\{\underbrace{\frac{w_{j'm}\left\{\pi^{mf,f}_{j'|i,\ell=1}\pi^{mf,m}_{j'|i,\ell=1,j'}\right\}}{\sum_j \left(w_{jm}\pi^{mf,m}_{j|i,\ell=1}\right)} + \frac{\pi^{mf,m}_{j'|i,\ell=1,j'} \cdot \left\{\pi^{mf,m}_{j'|i,\ell=1,j'}\pi^{mf,f}_{j'|i,\ell=1}\right\} w_{j'm}}{\sum_j \left(w_{jm}\pi^{mf,m}_{j|i,\ell=1}\right)}}_{\text{wives reallocating to j'}}\right\}
\end{aligned}
$$

where the first term is the same channel present in singles. The second term is related to the fact that if the commute time from i to j' improves, then wives will be more likely to work in j', reinforcing the initial impact. The additional term comes from the fact that wives commuting probabilities also depend on their spouses commuting probability. So, one has to account for the full impact on wives' commuting probabilities.

How will improvements in commuting times affect the gender earnings gap? Ultimately, it will depend on the labor market equilibrium. Labor supply responses will depend on how much each gender commutes to destinations that the transit infrastructure facilitates commuting to. However, labor supply responses will be very heterogeneous across locations and will depend on the initial distribution of singles and married households on the city. In particular, married tend to be more reactive to improvements in commuting times due to potentially having larger commuting elasticities $\theta\kappa$ and the fact that their commuting choices are interconnected through the household's budget set.

5 Bridging Theory and Data

In this section I describe how I take the model to the data. First, I report which parameters I calibrate and estimate from aggregate data. Second, I exploit the model's gravity equation prediction for commuting flows to estimate commuting elasticities. Finally, I explain how I use the model's structure to define Bartik-style instruments that allow me to estimate the remaining elasticities.

5.1 Calibration and Estimation From Aggregate Data

In the following table I specify which parameters I estimate from aggregate data and which ones I calibrate from the literature, and their respective values. In particular, I estimate from aggregate data the labor input share by industry-gender, and the household expenditures in housing (Panel A). 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).

[Table 5 here]

5.2 Estimation Outside the Model

5.2.1 Commuting elasticities

By taking logs to commuting probabilities in single and breadwinner households I can estimate the parameters of interest by PPML. From equations 5 and 12 I get the following :

$$
\begin{aligned}
\log\left(\frac{L_{R^g_{ij}}}{N_{R^g_i}}\right) &= -\theta^g\kappa^g\cdot t_{ij} + \underbrace{\theta^g\cdot\log\left(w_{jg}\right)}_{\mathrm{FE}_j} - \underbrace{\log\Psi_{R^g_i}}_{\mathrm{FE}_i}\\
\log\left(\frac{L_{R^{mf,m}_{ij,\ell=0}}}{N_{R^{mf}_{i,0}}}\right) &= -\theta^{mf,m}\kappa^{mf,m}\cdot t_{ij} + \underbrace{\theta^{mf,m}\cdot\log\left(w_{jm}\right)}_{\mathrm{FE}_j} - \underbrace{\log\Phi^{mf,m}_{R_{i,\ell=0}}}_{\mathrm{FE}_i}
\end{aligned}
$$

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 and breadwinner households.[26] For dual earner households, I plug in the same commuting elasticities as breadwinner households since I assume that married households share the same elasticity. In part, I make this assumption because equations 10 and 19 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. 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, 2018; Zarate, 2021) and set the iceberg disutility parameter κ^k to $\kappa^k = 0.01$, from which I get

[26]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.

estimates of $\hat{\theta}^m = 5.14$, $\hat{\theta}^f = 6.17$, $\hat{\theta}^{mf,m} = 4.66$, and $\hat{\theta}^{mf,f} = 6.34$, as shown in Panel C of Table 5.

5.3 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 unique values of location productivities, household productivities and amenities that rationalize the observed data as a model equilibrium, even in the presence of externalities. 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 firm-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 (2019). The following propositions formalize these ideas.

Proposition 1: *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 unique 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 unique vector of wages w_{jg} up to scale that rationalizes the observed data as a model equilibrium.*

Proof. See Appendix A2.1. □

Now we can turn to the problem of recovering the rest of unobservable variables.

Proposition 2: *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 unique vector of sales X_{js} and productivities A_{js} that rationalize the observed data as an equilibrium of the model. Additionally, we get the same result if instead of observing employment by gender we observe employment by industry $L_{F_{js}}$ and parameters σ, α_{sg}.*

Proof. See Appendix A2.2. □

Proposition 3: *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_{ij}^k, and parameters θ^k, η^k, ν, σ^D, α_s, β^k, there exists a unique vector of amenities u_i^k, productivities A_{js}, household productivity $\xi_{i\ell=0}$, sales X_{js}, floorspace wedge τ_i, and total rents E that rationalize the observed data as an equilibrium of the model. Additionally, we get the same result if instead of observing employment by gender we observe employment by industry $L_{F_{js}}$ and parameters σ, α_{sg}.*

Proof. See Appendix A2.3. □

5.3.1 Agglomeration economies

By Proposition 2, 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 use Proposition 2 to 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 our definition for agglomeration economies in equation 28 as:

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

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 $\left\{\sum_k \sum_i \pi_{j|i,\ell}^k N_{R_i^k}\right\}$ with respect to commuting times from origin locations we get the following Bartik-style instruments:

$$Z_{Fj}^m = -\theta^m \kappa^m \sum_{i'} \frac{\pi_{j|i'}^m N_{R_{i'}^m}}{\sum_i \left\{\pi_{j|i}^m N_{R_{i'}^m}\right\}} \cdot dt_{i'j} \qquad Z_{Fj}^f = -\theta^f \kappa^f \sum_{i'} \frac{\pi_{j|i'}^f N_{R_{i'}^f}}{\sum_i \left\{\pi_{j|i}^f N_{R_{i'}^f}\right\}} \cdot dt_{i'j}$$

$$Z_{Fj}^{mf,f} = -\theta^{mf,f} \kappa^{mf,f} \sum_{i'} \frac{\pi_{j|i',\ell=1}^{mf,f} N_{R_{i',\ell=1}^{mf}}}{\sum_i \pi_{j|i',\ell=1}^{mf,f} N_{R_{i',\ell=1}^{mf}}} \cdot dt_{i'j} \qquad Z_{Fj\ell=0}^{mf,m} = -\theta^{mf,m} \kappa^{mf,m} \sum_{i'} \frac{\pi_{j|i',\ell=0}^{mf,m} N_{R_{i',\ell=0}^{mf,m}}}{\sum_i \left\{\pi_{j|i,\ell=0}^{mf,m} N_{R_{i',\ell=0}^{mf,m}}\right\}} \cdot dt_{i'j}$$

$$Z_{Fj\ell=1}^{mf,m} = -\theta^{mf,m} \kappa^{mf,m} \sum_{i'} \frac{\pi_{j|i',\ell=1}^{mf,m} N_{R_{i',\ell=1}^{mf}}}{\sum_i \pi_{j|i,\ell=1}^{mf,m} N_{R_{i,\ell=1}^{mf}}} \cdot dt_{i'j} \quad - \quad \theta^{mf,f} \kappa^{mf,f} \sum_{i'} \frac{\pi_{j|i',\ell=1,j}^{mf,m} \pi_{j|i',\ell=1}^{mf,f} N_{R_{i',\ell=1}^{mf}}}{\sum_i \pi_{j|i,\ell=1}^{mf,m} N_{R_{i,\ell=1}^{mf}}} \cdot dt_{i'j}$$

For each destination j, the Bartik-instruments weight the change in commuting times with the share of workers from each origin. We use inferred shares $\pi_{j|i}$ from 2007 data. Since we have many types 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 our 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:

$$Z_{Fjs} = \frac{L_{F_{jfs}}}{L_{Fjs}}(0.5 \cdot Z^{f}_{Fj} + 0.5 \cdot Z^{mf,f}_{Fj}) + \frac{L_{F_{jms}}}{L_{Fjs}}(0.33 \cdot Z^{m}_{Fj} + 0.33 \cdot Z^{mf,m}_{Fj\ell=1} + 0.33 \cdot Z^{mf,m}_{Fj\ell=0})$$

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 $Z^{mf,f}_{Fj}$, and vice-versa.

Results are shown in Panel A of Table 6.[27] 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.

[Table 6 here]

5.3.2 Labor supply elasticity

By Proposition 1, I can recover wages and compute market access measures $\Phi^{mf,f}_{R_{i\ell=1}}$ and $\Phi^{mf,0}_{R_{i\ell=0}}$. Then, by taking logs to the odds ratio of labor force participation in equation 14 and taking

[27] 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.

first differences I get:

$$\Delta \log \frac{\mu_i^{mf}}{1-\mu_i^{mf}} = \nu \left[\frac{\Delta \log \Phi_{R_{i,\ell=1}^{mf,f}}}{\theta^{mf,f}} - \frac{\Delta \log \Phi_{R_{i,\ell=0}^{mf,m}}}{\theta^{mf,m}} \right] + \nu \left(\Delta \log \xi_{i\ell=1} - \Delta \log \xi_{i\ell=0} \right)$$

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 Bartik instruments. Since this is a supply-side parameter, we require variation from the demand. In particular, I use the TFP terms I recover from Proposition 2 to define the following Bartik instruments exploiting destination-level changes in TFP:

$$Z_{R_{is}^{mf}} = \sum_j \left(d_{ij}^{mf,f} \right)^{-\theta^{mf,f}} d \ln A_{js}$$

The identifying assumption is that $\mathbb{E}_i \left[\left(\Delta \log \xi_{i\ell=1} - \Delta \log \xi_{i\ell=0} \right) \cdot Z_{R_{is}^{\mu}} \right] = 0$. Results are show in Panel B of Table 6.[28] I estimate a labor supply elasticity ν of 1.28.

5.3.3 Location elasticity

By Proposition 1 and 3, I can recover wages and household productivity and compute market access measures $\Psi_{R_i^g}$ and $\Psi_{R_i^{mf}}$. Manipulating the equations for location choices in 7 and 16, I get:[29]

$$\Delta \log \frac{N_{R_i^g}}{N^g} = \chi_g + \eta^g \left[\left(\beta^g - 1 \right) \Delta \log r_{R_i} + \frac{1}{\theta^g} \Delta \log \Psi_{R_i^g} \right] + \eta^g \Delta \log u_i^g$$

$$\Delta \log \frac{N_{R_i^{mf}}}{N^{mf}} = \chi_{mf} + \eta^{mf} \left[\left(\beta^{mf} - 1 \right) \Delta \log r_{R_i} + \frac{1}{\nu} \Delta \log \Psi_{R_i^{mf}} \right] + \eta^{mf} \Delta \log u_i^{mf}$$

[28] 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.

[29] Constants are defined as $\chi_g = \log \Delta \sum_l \left(\left(u_l^g \Psi_{R_l^{g,g}}^{1/\theta^{g,g}} \right)^{-1} r_{R_l}^{1-\beta^g} \right)^{-\eta^{g,g}}$ and $\chi_{mf} = \log \Delta \sum_l \left(\left(u_l^{mf} \Psi_{R_l^{mf}}^{1/\nu} \right)^{-1} r_{R_l}^{1-\beta^{mf}} \right)^{-\eta^{mf}}$.

If growth in exogenous amenities is correlated with the growth in market access measures $\Psi_{R_i^g}$ and $\Psi_{R_i^{mf}}$ then the estimation of the location elasticities η^g and η^{mf} would be biased. Once again, I exploit changes in TFP to construct Bartik instruments which then I use as instruments for the growth in market access measures. Results are shown in Panel B of Table 6.[30] My results indicate that singles ($\hat{\eta}^f \approx \hat{\eta}^m \approx 2$) are much more mobile than married couples ($\hat{\eta}^{mf} = 1.02$).

5.3.4 Amenities externalities

After estimating location elasticities, I can use Proposition 3 to recover unobserved amenities and run the following regressions:

$$\Delta \log u_i^g = \phi_{R_g} \Delta \log N_{R_i} + \Delta \log \bar{u}_i^g$$
$$\Delta \log u_i^{mf} = \phi_{R_{mf}} \Delta \log N_{R_i} + \Delta \log \bar{u}_i^{mf}$$

I need an instrument for $\Delta \log N_{R_i}$, so once again I exploit changes in TFP. Results are shown in Panel B of Table 6.[31] While there are no endogenous amenities for singles females, endogenous amenities do seem to be stronger for single males and especially married households.

6 The Impact of the Metro and BRT

This section quantifies how the new transit infrastructure affected the gender earnings gap and aggregate welfare. It also provides evidence of the mechanisms in the paper, and how my quantitative results change under alternative parameterizations.

6.1 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 scenarios, one

[30] I include controls such as the euclidean distance to the Metro, to the BRT and to the CBD. I also include the size of the block, its slope and its elevation, the 2007 rents, and dependent variable at its value in 2007.

[31] I include controls such as the euclidean distance to the Metro, to the BRT and to the CBD. I also include the size of the block, its slope and its elevation, the 2007 rents and the dependent variable at its value in 2007.

in which commuting is independent and one where it depends on the other spouse's behavior. Then, I compare the predicted commuting probabilities with those observed in the 2017 Census.

Figure 4 plots a binscatter of commuting probabilities in the model and in the data. Panel A focuses on females in dual-earner households. The left hand side shows that the model with independent commuting probabilities underestimate commuting flows. For every percentage point that the model predicts, the data display probabilities 24% lower since the slope is 0.76. Moreover, the model is able to predict around 28% of the variation in the data. On the right hand side, Panel A of Figure 4 reveals that on average the model with income pooling 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 relatively well since the slope between the commuting probabilities in the data and in the model is of 0.89. However, the model with income pooling is capable to improve performance, yielding a slope between probabilities in the data and in the model of 1.02. Moreover the R^2 increases from 31% to 39%.

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.

[Figure 4 here]

6.2 Quantitative Importance of Income Pooling

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 married couples perform their commuting choices independently from each other (i.e. no income pooling), and one in which one spouse's choice is dependent on the other spouse's choice (i.e. income pooling).[32]

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

6.2.1 Aggregate impact

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 type pair. 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 $\bar{RY}^k = RY^k / N_{R^k}$, 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: Gap $= RY^{k,m}/RY^{k,f} - 1$ or $\bar{\text{Gap}} = \bar{RY}^{k,m}/\bar{RY}^{k,f} - 1$, where now k indexes single and married households. Finally, I also compute the number of dual-earner households as a share of married households.

Table 7 summarizes my main 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 0.73% and 0.51%. Given that all single workers participate in the labor market, the growth in the real income per worker is the same. Moreover, since males aggregate income grew faster than females', the gender gap in aggregate earnings increased by 0.49%. When looking at average earnings, the gender gap increased by 0.58%. Second, turning to married households, aggregate income from male breadwinner households decreased by 1.37%, but average income increased by 0.77%. 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 1.64%, representing 8.94% of the total growth in labor force participation in the data. Furthermore, the main beneficiaries of the new transit infrastructure were dual earner households, as males' and females' aggregate real income increased by 2.96% and 3.99%, respectively. 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 1.30%, whereas females' average earnings rose by 2.31%. These impacts led to a reduction of the gender gap in aggregate and average earnings, which decreased by 4.00%, respectively. The heterogeneous impacts described above led to an overall decrease of the gender gap of 2.07% in terms of aggregate income, or 1.04% in terms of income per worker. Finally, regarding the overall impact of the new transit infrastructure, aggregate and real income per worker grew by 1.19% and 0.84%.

Panel B of Table 7 exhibits the impacts when using a model where commuting choices within couples are independent between each other, that is, there is no income pooling. Three observations are in order. First, this model underestimates the impact of the new transit infrastructure on aggregate real income by $1 - 0.0069/0.0119 = 42\%$ and on real income per worker by $1 - 0.0030/0.0084 = 64\%$. Second, while the gender gap in aggregate earnings in married households closes by 3.04%, 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 0.25%. Third, while this model modestly underestimates the impact on the gender gap in aggregate earnings by $1 - 0.0176/0.0207 = 15\%$, it largely underestimates the impact on the gender gap in earnings per worker by $1 - 0.0029/0.0104 = 72\%$.

All in all, these results point towards the conclusion that allowing for income pooling is quantitatively important when evaluating not only the impact of the new transit infrastructure on the gender gap, but also when measuring the impact on overall economic activity.

[Table 7 here]

6.2.2 Impact across locations

Figure 5 maps the evolution of real income RY_i and gender gap Gap_i^k across origins i caused by the new transit infrastructure according to the full model. Each color accounts for 20% of observations. First, 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; areas that employ workers from nearby and eastern origins.

[Figure 5 here]

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 the closest locations to stations. However, impacts vary by household-type. 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 gender gap among married tend to be concentrated in the northern and southern fringe, whereas the decreases in the gender gap among singles are present mainly to the south of the Metro Stations and to the North of the BRT.

Figure 6 maps the same outcomes but according to the model without income pooling. Panel A reveals that changes in real income according to this model tend be smaller than in the full model. It also shows that the distribution of gap reductions across locations differs from that of the model under income pooling. In fact the correlation between the two is just 32.06% which is contrast to the correlation of 95.86% between changes in real income in the two models. Finally, Panel B maps the impact on the gender gap among singles and married. While the spatial distribution seems to be similar in comparison to the full model, the main difference is among singles. Gap changes in single households in the complete model just have a correlation of 21.06% with gap changes in the model without income pooling, even though singles' commuting choices work exactly the same in both models. This showcases the importance of getting right the supply responses of married households, as they also affect the gender gap in singles through the law of supply and demand.

[Figure 6 here]

To conclude, this section highlights that allowing for income pooling is quantitative important, not only on the aggregate but also when exploring the distribution of gap changes across space.

6.3 Mechanisms

In this section I subsequently turn off mechanisms from the full model in order to assess their quantitative relevance. Results are shown in Table 8. 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. This negative effect coming from externalities arises despite that productivity increased in every sector as a result of the new transit infrastructure. According to the full model, average productivity across the seven sectors grew by 0.53%. However, the price index markedly decreased in the counterfactual city with no externalities. In the full model, the price index decreased by 1.97%, whereas with no externalities it decreased by 3.06%. 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 1.86% and 2.50% in the full model, whereas they decreased by 2.56% and 3.22% 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 -1.04% as it was in the full model. This is driven by single workers, for which the impact on the gender gap on average earnings doubles from 0.49% to 1.04%.

The third column keeps the distribution of households across locations fixed at its 2017 value.[33] In other words, it assumes that households cannot reallocate in response to the removal of the transit infrastructure. Compared to column (2), the impacts on real income and on real income per capita are 36% and 60% 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 -0.60% instead of -0.84%. This is because, by keeping single households at their initial location, in this counterfactual exercise, it turns out single males are the main beneficiaries of the new transit infrastructure. This is reflected on the impact on the average gender gap, which becomes 1.65% instead of 1.04%.

Column (4) assumes that married couples cannot endogenously change their labor force participation. This reduces the impact on aggregate real income by $1 - 0.0075/0.0089 = 16\%$ 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 their wages in the equilibrium 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 gender gap decreases by 0.60% 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, as it decreases by 1.49%.

Finally, columns (5) to (7) remove remaining margins. Column (5) assumes couples make their commuting choices independently from each other. This, once again reduces the aggregate impact of the transit infrastructure from 0.75% to 0.41%, which constitutes an impact 45% lower. Also, without income pooling, the impact on the gender gap—especially among married—is much smaller. Column (6) assumes that the shape parameter of the commuting preferences shocks is constant across gender-by-household types and equal to an average value of 5.56. Impacts on real income remain almost constant, although impacts on the gender gap in earnings and earnings per worker basically halve. Column (8) makes wages to remain constant

[33] This is on top of turning off externalities.

at their 2017 levels, eliminating the impact from the new transit infrastructure.

In sum, this analysis confirms that income pooling i a quantitatively important feature. Additionally, externalities, household mobility and the labor force participation choice shape the aggregate impact in important ways. Externalities mainly shape the impact on aggregate income. Mobility mould both aggregate efficiency and distributional outcomes. The labor force participation choice mainly has distributional consequences, although it also shapes aggregate efficiency in non-trivial ways.

[Table 8 here]

7 Conclusion

In this paper I study how family structure shapes the aggregate impact of new transit infrastructure. To do so I develop a quantitative model of city structure featuring single and married households, which are differentiated by shocks to their preferences over commuting destinations. This model delivers commuting gravity equations. For dual-earner households, commuting probabilities are interdependent within the couple. One spouse's commuting choice might affect the other spouse's choice through an income effect; if one spouse is already commuting to a high wage location, then the other's response to the sudden availability of high wage locations may be less pronounced. I estimate the model exploiting data from Lima, Peru and leveraging on the construction of the first Metro line and a Bus Rapid Transit system.

I use the model to simulate how would Lima look like in absence of the Metro and BRT under two models: (i) the full model which states that commuting choices are interdependent within couples, and (ii) the model with independent commuting choices. My findings reveal that aggregate real income per worker grew by 1.19% according to the full model, but only 0.69% under model (ii). In other words, the model with independent commuting choices within couples underestimates the aggregate impact of the new transit infrastructure by 42%. Moreover, model (ii) also underestimates the impact on the gender gap in earnings per worker by 72%. All in all, these results point towards the conclusion that allowing for income pooling is quantitatively important when evaluating not only the impact of the new transit infrastructure on the gender gap, but also when measuring the impact on overall economic activity.

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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

Table 2: Commuting and Wages

	Males in D.E. Households	Females in D.E. Households
	(1)	(2)
Own Gender Wage	2.5647	1.6135
	(0.3202)***	(0.1699)***
Own Gender Wage × HH Income	-0.4466	-0.2744
	(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 3: Reduced Form Impact of New Transit Infrastructure on Mobility

Panel A:	Total Population		Singles to Married		Females to Males	
	(1)	(2)	(3)	(4)	(5)	(6)
$D^{M}_{i(0,1)} \times t$	-0.1253	-0.1392	0.0231	0.1028	0.0051	-0.0044
	(0.0230)***	(0.0243)***	(0.0204)	(0.0194)***	(0.0041)	(0.0034)
$D^{M}_{i(1,3)} \times t$	-0.0342	-0.0704	0.0357	0.0661	-0.0056	-0.0089
	(0.0205)*	(0.0208)***	(0.0172)**	(0.0148)***	(0.0034)	(0.0028)***
$D^{BRT}_{i(0,1)} \times t$	-0.1014	-0.0884	-0.0038	0.0616	-0.0033	-0.0052
	(0.0274)***	(0.0271)***	(0.0217)	(0.0184)***	(0.0048)	(0.0039)
$D^{BRT}_{i(1,3)} \times t$	-0.0071	-0.0099	-0.0033	0.0097	-0.0054	0.0009
	(0.0194)	(0.0191)	(0.0164)	(0.0148)	(0.0035)	(0.0031)
Panel B:	Single to Married (Males)		Single to Married (Females)		Dual Earners to Male Breadwinner	
	(1)	(2)	(3)	(4)	(5)	(6)
$D^{M}_{i(0,1)} \times t$	0.0199	0.1115	0.0267	-0.0270	0.0314	0.0200
	(0.0217)	(0.0210)***	(0.0210)	(0.0195)	(0.0191)*	(0.0166)
$D^{M}_{i(1,3)} \times t$	0.0424	0.0782	0.0288	0.0101	-0.0031	0.0127
	(0.0184)**	(0.0162)***	(0.0175)*	(0.0169)	(0.0165)	(0.0147)
$D^{BRT}_{i(0,1)} \times t$	0.0033	0.0627	-0.0123	-0.0526	0.0681	0.0370
	(0.0229)	(0.0200)***	(0.0227)	(0.0216)**	(0.0243)***	(0.0202)*
$D^{BRT}_{i(1,3)} \times t$	0.0038	0.0058	-0.0120	-0.0215	0.0161	0.0071
	(0.0176)	(0.0157)	(0.0166)	(0.0150)	(0.0177)	(0.0156)
Block FE	X	X	X	X	X	X
Station-year FE	X	X	X	X	X	X
Controls		X		X		X
N	2108	2108	2108	2108	2108	2108

Table 4: Reduced Form Impact of New Transit Infrastructure on Rents and Income

Panel A: Parsimonious Time Event Study				
	Actual Rents	A+H Rents	HH Income	HH Expenditures
	(1)	(2)	(3)	(4)
$d_l^M \times Before2009_t$	0.0010	0.0042	0.0054	0.0022
	(0.0119)	(0.0104)	(0.0089)	(0.0062)
$d_l^M \times After2009_t$	0.0217	0.0231	0.0065	0.0084
	(0.0117)*	(0.0103)**	(0.0077)	(0.0062)
$d_l^{BRT} \times Before2009_t$	-0.0077	-0.0017	-0.0159	-0.0075
	(0.0198)	(0.0174)	(0.0185)	(0.0101)
$d_l^{BRT} \times After2009_t$	-0.0342	-0.0323	-0.0251	-0.0245
	(0.0210)	(0.0177)*	(0.0157)	(0.0104)**
Panel B: Differences-in-differences				
	Actual Rents	A+H Rents	HH Income	HH Expenditures
	(1)	(2)	(3)	(4)
$d_l^M \times After2009_t$	0.0209	0.0201	0.0028	0.0068
	(0.0084)**	(0.0074)***	(0.0058)	(0.0039)*
$d_l^{BRT} \times After2009_t$	-0.0287	-0.0310	-0.0143	-0.0194
	(0.0146)**	(0.0119)***	(0.0093)	(0.0069)***
Block FE	X	X	X	X
Controls	X	X	X	X
N	41915	39726	41917	41917

Table 5: Estimation from Aggregate Data, Calibration, and Gravity Equation

Panel A: Estimation from Aggregate Data			
Parameter	Description	Value	Source
$[\alpha_{f1}, \alpha_{f2}, \alpha_{f3}, \alpha_{f4}, \alpha_{f5}, \alpha_{f6}, \alpha_{f7}]$	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			
Parameter	Description	Value	Source
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			
Parameter	Description	Value	Source
$[\kappa^m, \kappa^f, \kappa^{mf,m}, \kappa^{mf,f}]$	Iceberg disutility	$[0.01, 0.01, 0.01, 0.01]$	Tsivanidis (2019)
$[\hat{\theta}^m, \hat{\theta}^f, \hat{\theta}^{mf,m}, \hat{\theta}^{mf,f}]$	Shape parameter in commuting preferences	$[5.14, 6.17, 4.66, 6.34]$	Gravity Equation. See Section 5.2.1.

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

Table 6: Estimation of Remaining 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)	
Financial and 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, Location, and Amenities			
	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)***	
Amenities Single Females (ϕ_{F_f})	0.4043	0.0761	35.04
	(0.0161)***	(0.0736)	
Amenities Single Males (ϕ_{F_m})	0.4690	0.1435	35.04
	(0.0161)***	(0.0692)**	
Amenities Married ($\phi_{F_{mf}}$)	0.9161	0.2279	35.04
	(0.0259)***	(0.1378)*	

Table 7: The Aggregate Impact of the New Transit Infrastructure

Panel A: Full Model								
	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	0.0073	0.0051	-0.0137	0.0296	0.0399	0.0083	0.0220	0.0119
Real Income per Worker	0.0073	0.0051	0.0077	0.0130	0.0231	0.0083	0.0135	0.0084
Gender Gap	0.0049			-0.0400		-0.0207		
Gender Gap (per Worker)	0.0058			-0.0252		-0.0104		
# D.E. / # Married				0.0164				

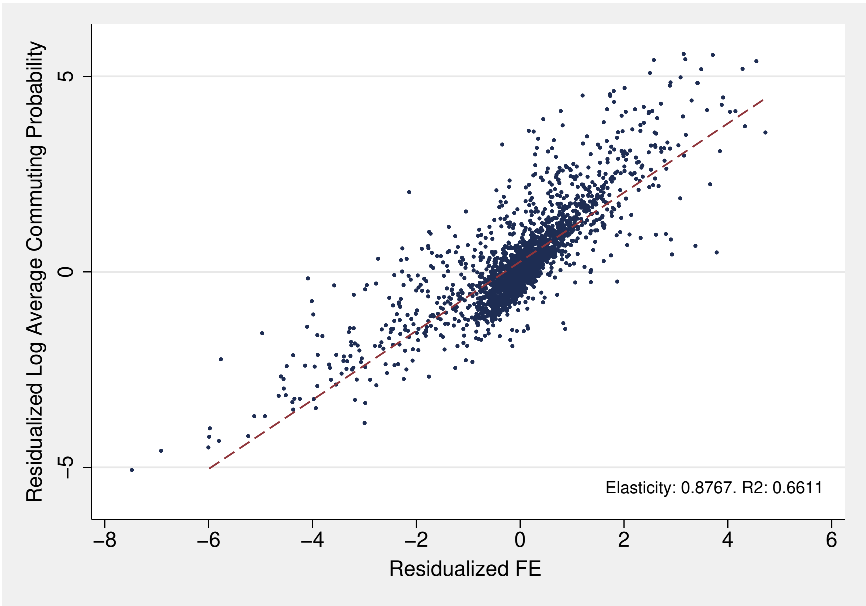
Panel B: Independent Commuting Choices (No Income Pooling)								
	Singles		Married			All		
	Males	Females	Males in BW HH	Males in D.E. HH	Females in D.E. HH	Males	Females	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Real Income	0.0041	0.0033	-0.0128	0.0285	0.0272	0.0039	0.0158	0.0069
Real Income per Worker	0.0041	0.0033	0.0039	0.0041	0.0029	0.0039	0.0052	0.0030
Gender Gap	0.0017			-0.0304		-0.0176		
Gender Gap (per Worker)	0.0020			0.0025		-0.0029		
# D.E. / # Married				0.0243				

Table 8: The Effect of the New Transit Infrastructure - Mechanisms

	Full	No Externalities	No Mobility	No LFP	No Income Pooling	Same θ	Fixed Wages
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Real Income	0.0119	0.0139	0.0089	0.0075	0.0041	0.0045	-0.0002
Real Income per Worker	0.0084	0.0102	0.0041	0.0075	0.0041	0.0043	-0.0002
Gender Gap	-0.0207	-0.0200	-0.0223	-0.0114	-0.0031	-0.0015	-0.0009
Gender Gap (per Worker)	-0.0104	-0.0084	-0.0060	-0.0149	-0.0043	-0.0021	-0.0012
Gender Gap, Singles	0.0049	0.0089	0.0141	0.0058	-0.0014	-0.0024	-0.0012
Gender Gap (per Worker), Singles	0.0058	0.0104	0.0165	0.0068	-0.0016	-0.0027	-0.0014
Gender Gap, Married	-0.0400	-0.0401	-0.0459	-0.0227	-0.0038	-0.0013	-0.0008
Gender Gap (per Worker), Married	-0.0252	-0.0237	-0.0225	-0.0303	-0.0060	-0.0021	-0.0012

Figure 1: Interdependence in Commuting Choices within Dual-earner Households

Panel A: Husband



Panel B: Wife

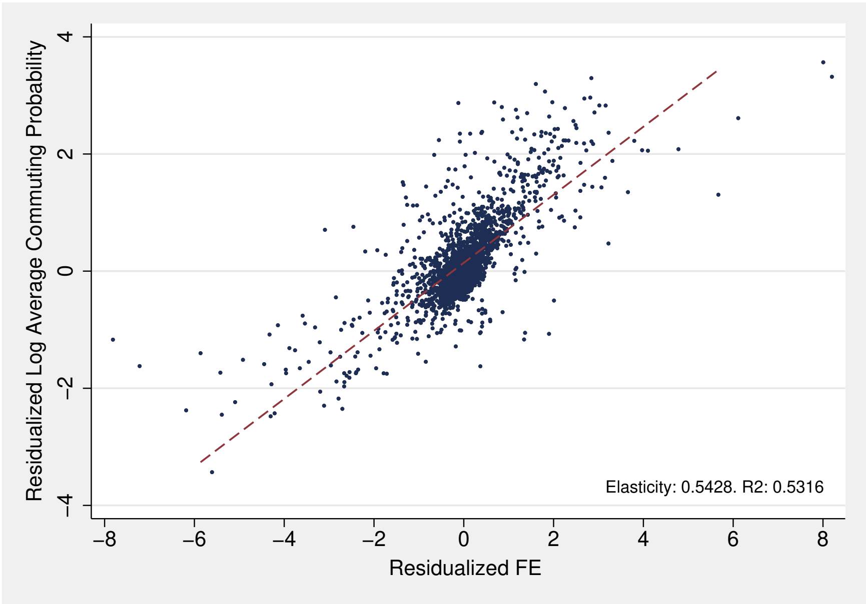
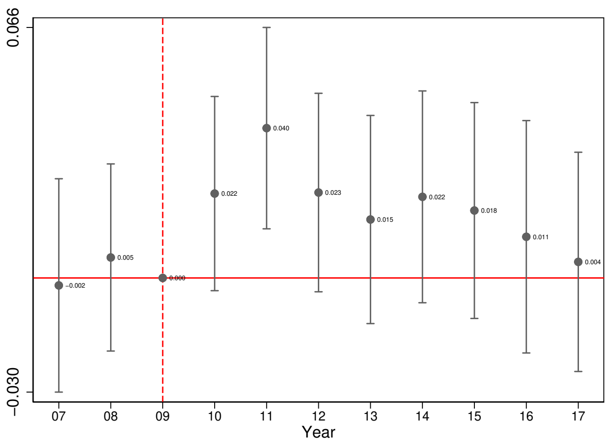


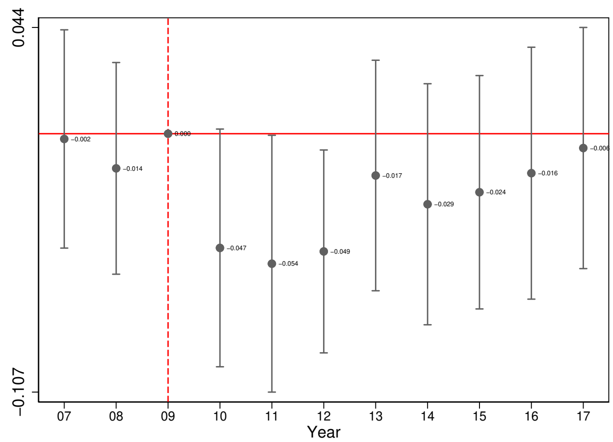
Figure 2: The Reduced Form Impact of Transit Infrastructure on Rents

Panel A: Actual Rents

Metro

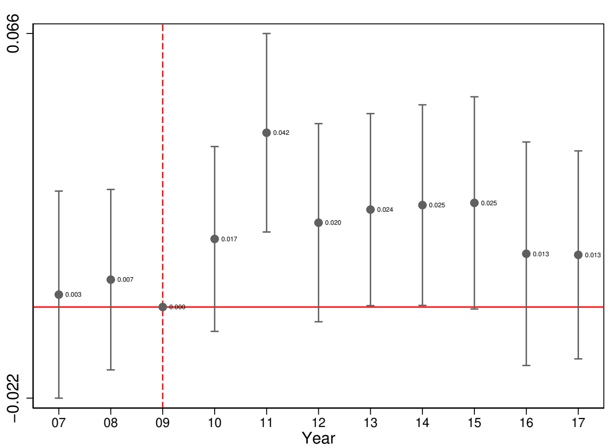


BRT



Panel B: Actual + Hypothetical Rents

Metro



BRT

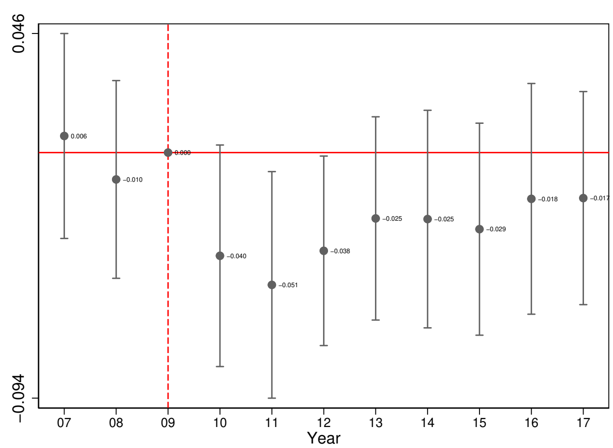
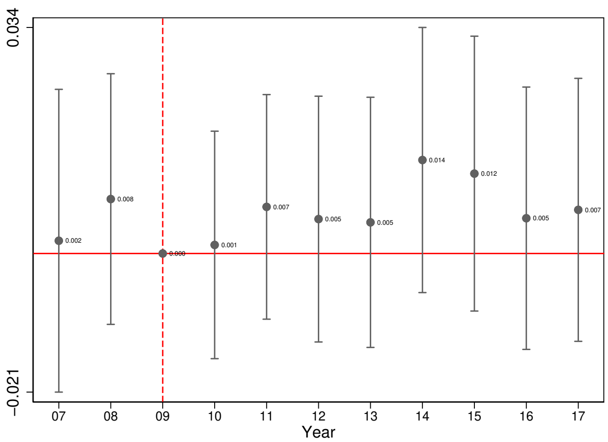


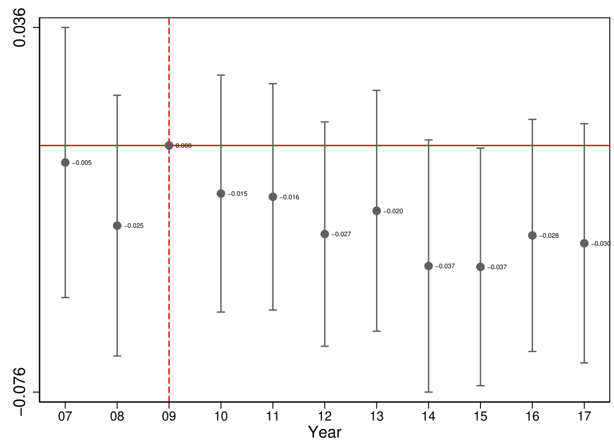
Figure 3: The Reduced Form Impact of Transit Infrastructure on Household Income

Panel A: Total Household Income

Metro

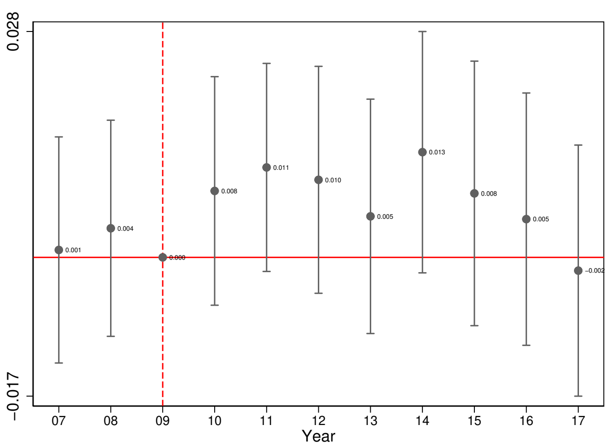


BRT



Panel B: Total Household Expenditure

Metro



BRT

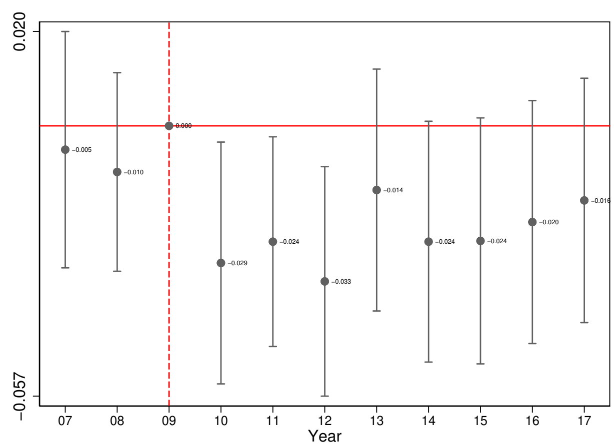
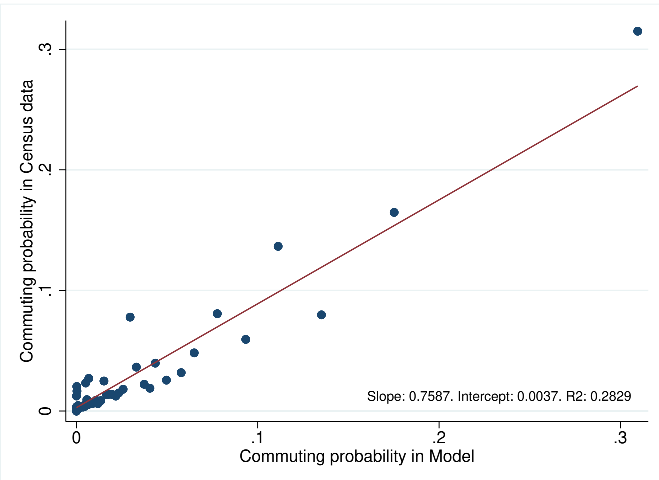


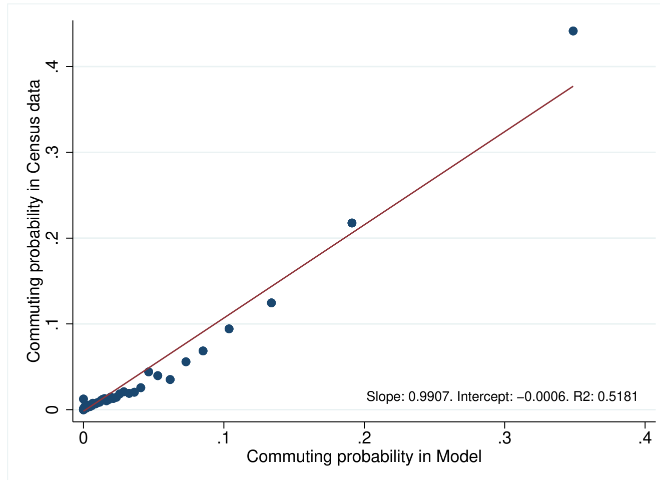
Figure 4: Commuting and over-identification

Panel A: Females in Dual Earner Households

Independence

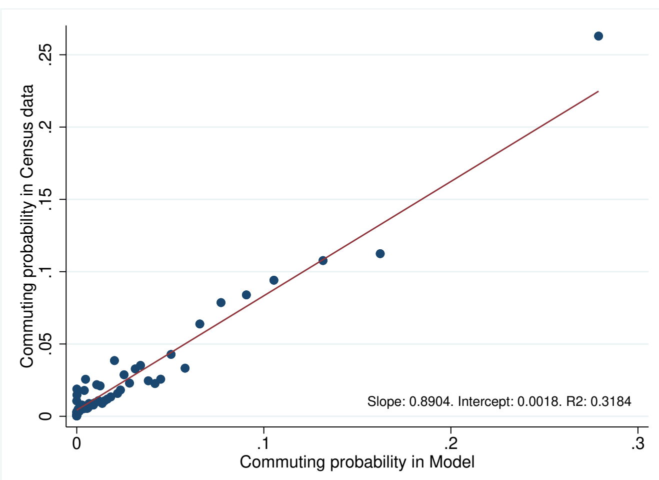


Income Pooling



Panel B: Males in Dual Earner Households

Independence



Income Pooling

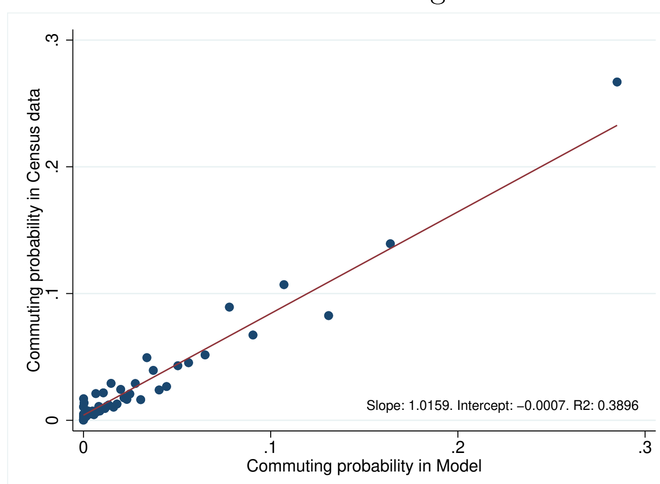
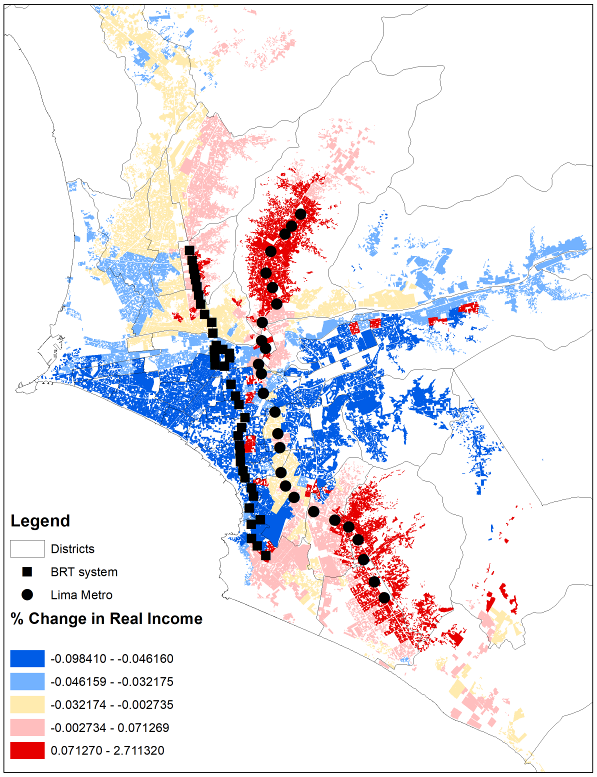


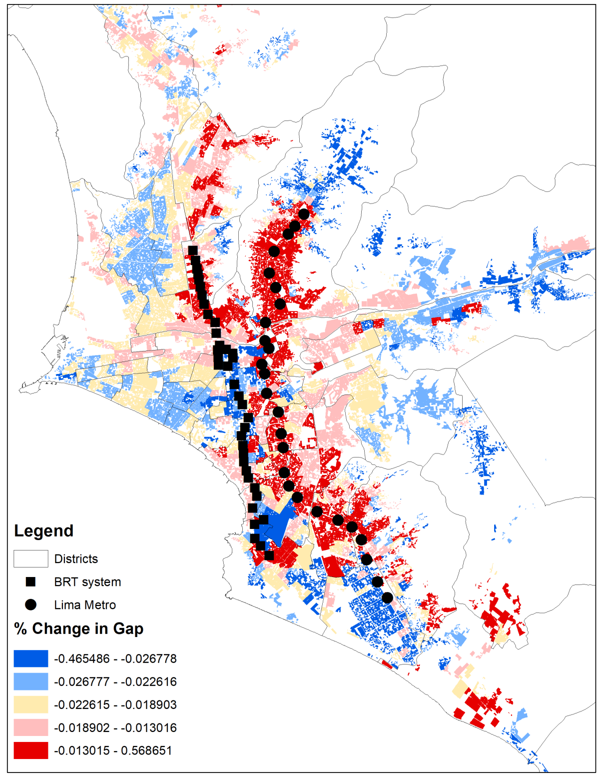
Figure 5: Quantitative Impact of Transit Infrastructure on Earnings and the Earnings Gender Gap Under Income Pooling

Panel A:

Real Income

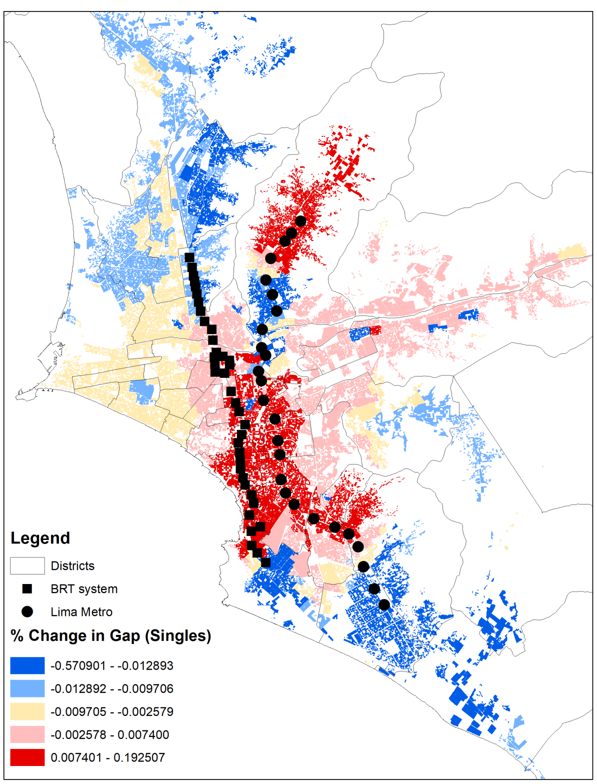


Gender Gap in Real Income



Panel B:

Gender Gap (singles)



Gender Gap (married)

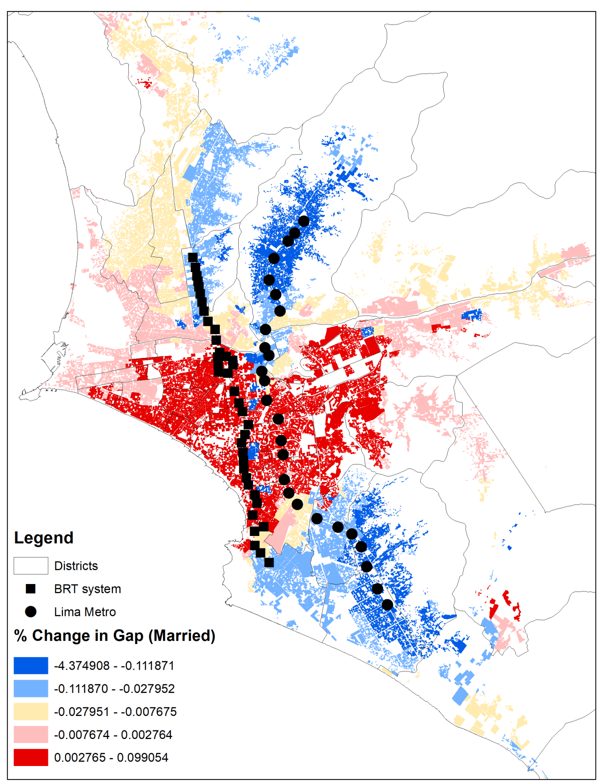
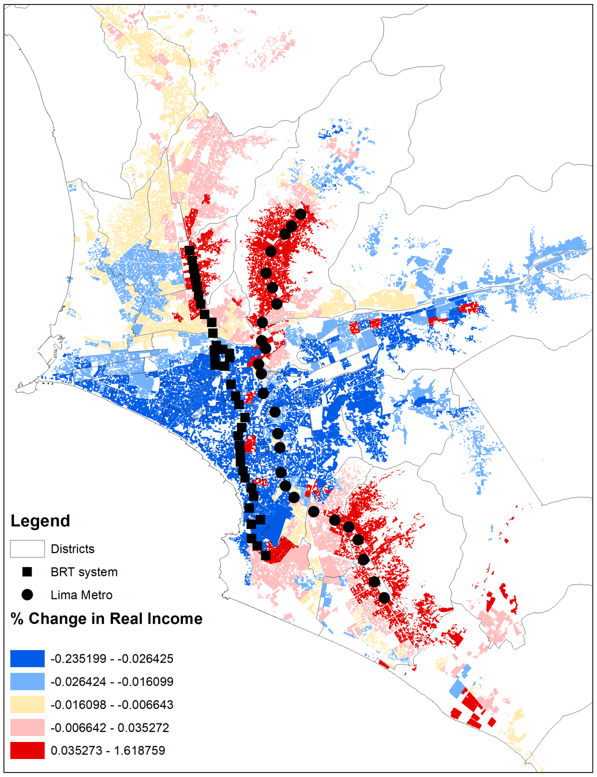


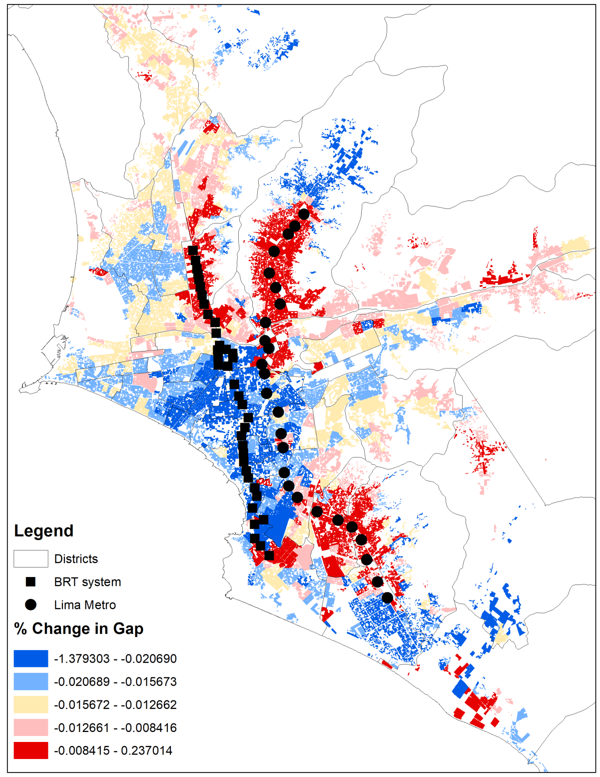
Figure 6: Quantitative Impact of Transit Infrastructure on Earnings and the Earnings Gender Gap Without Income Pooling

Panel A:

Real Income

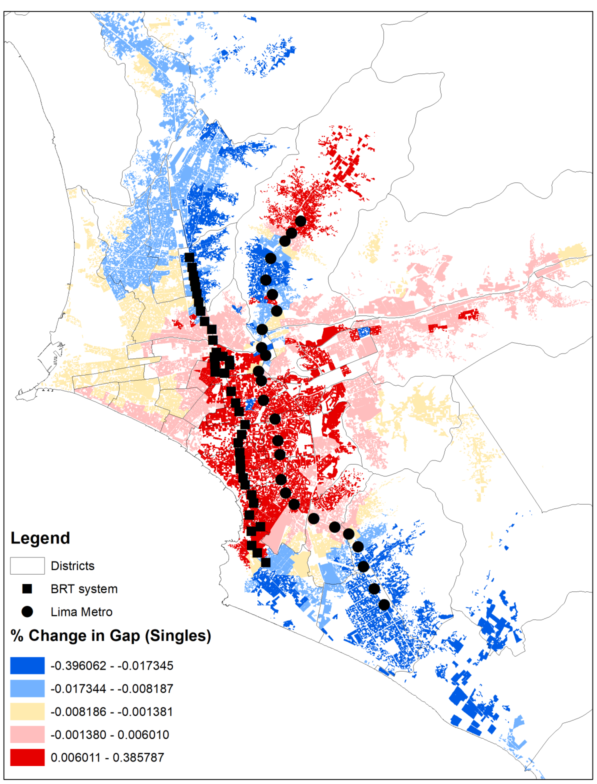


Real Income Gender Gap

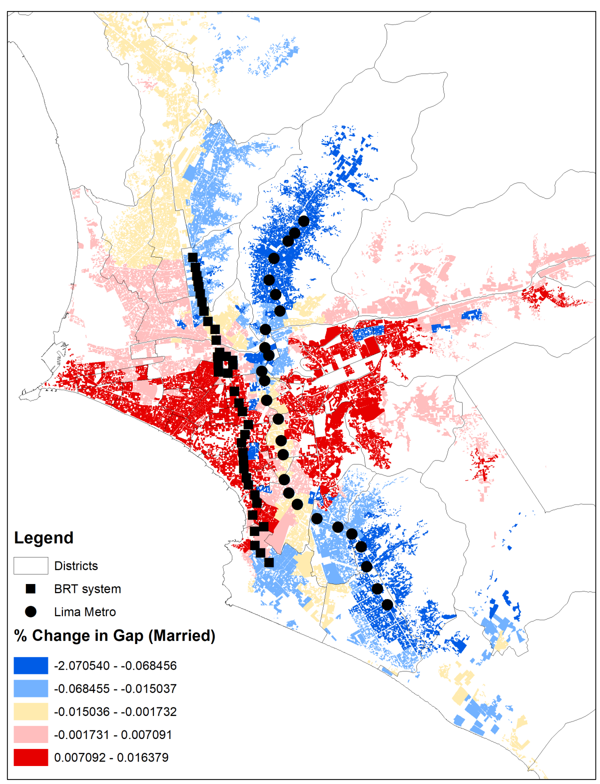


Panel B:

Gender Gap (singles)



Gender Gap (married)



A1 Solution Algorithm

A1.1 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:

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

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):

$$
\begin{aligned}
r_i &= \begin{cases} \zeta_{F_i} r_{F_i} & \zeta_{F_i} = 1, \quad i \in \mathcal{I}_F = \{i : u_{ik} = 0 \text{ for all k}, A_{is} > 0 \text{ for some s}\} \\ \zeta_{F_i} r_{F_i} & \zeta_{F_i} = 1 - \tau_i, \quad i \in \mathcal{I}_{FR} = \{i : u_{ik} > 0 \text{ for some k}, A_{is} > 0 \text{ for some s}\} \end{cases} \\
r_i &= \begin{cases} \zeta_{R_i} r_{R_i} & \zeta_{R_i} = 1, \quad i \in \mathcal{I}_R = \{i : u_{ik} > 0 \text{ for some k}, A_{is} = 0 \text{ for all s}\} \\ \zeta_{R_i} r_{R_i} & \zeta_{R_i} = 1, \quad i \in \mathcal{I}_{FR} = \{i : u_{ik} > 0 \text{ for some k}, A_{is} > 0 \text{ for some s}\} \end{cases}
\end{aligned}
\tag{30}
$$

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 30, 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.

A1.2 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:

$$\Phi^{mf,m}_{R_{i,\ell=0}} = \sum_{l'} \left(\frac{d^{mf,m}_{il}}{w_{lm}} \right)^{-\theta^{mf,m}}$$

ii. In dual earner households:

$$\begin{aligned} \Phi^{mf,m}_{R_{i,\ell=1,j'}} &= \sum_{l} \left(\frac{d^{mf,m}_{il}}{w_{lm} + w_{j'f}} \right)^{-\theta^{mf,m}} \end{aligned}$$

$$\Phi^{mf,f}_{R_{i,\ell=1}} = \sum_{l} \left(\frac{\left(\Phi^{mf,m}_{R_{i,\ell=1,l}}\right)^{1/\theta^{mf,m}}}{d^{mf,f}_{il}} \right)^{\theta^{mf,f}}$$

iii. On average:

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

(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

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

and

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

(g) Compute commuting probabilities:

i. For singles:

$$\pi_{j|i}^{g} = \frac{\left(\frac{d_{ij}^{g}}{w_{jg}}\right)^{-\theta^{,g}}}{\Phi_{R_i^g}}$$

ii. For males in male-breadwinner households:

$$\pi_{j|i,\ell=0}^{mf,m} = \frac{\left(\frac{d_{ij}^{mf,m}}{w_{jm}}\right)^{-\theta^{mf,m}}}{\Phi_{R_{i,\ell=0}}^{mf,m}}$$

iii. For females in dual earner households:

$$\pi_{j'|i,\ell=1}^{mf,f} = \frac{\left(\frac{d_{ij'}^{mf,f}}{\left(\Phi_{R_{i,\ell=1,j'}}^{mf,m}\right)^{1/\theta^{mf,m}}}\right)^{-\theta^{mf,f}}}{\Phi_{R_{i,\ell=1}}^{mf,f}}$$

iv. For males in dual earner households:

$$\pi_{j|i,\ell=1}^{mf,m} = \sum_l \pi_{j|i,\ell=1,l}^{mf,m} \cdot \pi_{l|i,\ell=1}^{mf,f}$$

where

$$\pi_{j|i,\ell=1,j'}^{mf,m} = \frac{\left(\frac{d_{ij}^{mf,m}}{w_{jm}+w_{j'f}}\right)^{-\theta^{mf,m}}}{\Phi_{R_{i,\ell=1,j'}}^{mf,m}}$$

(h) Compute labor supply:

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

(i) Compute total income:

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

(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:

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

ii. Update endogenous productivities:

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

iii. Update endogenous amenities:

$$u_{ik}^{t+1} = \bar{u}_{ik} \left(N_{R_i^{mf}} + N_{R_i^{m,m}} + N_{R_i^{f,f}} \right)^{\phi_{Rk}} \text{ where } k \in \{m, f, mf\}$$

iv. 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:

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

v. 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:

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

vi. 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

A2 Proofs

A2.1 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 unique 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 unique vector of wages w_{jg} up to scale that rationalizes the observed data as a model equilibrium.*

Proof. Recall that labor supply is:

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

Or

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

and

$$
\begin{aligned}
L_{F_{jf}} &= w_{jf}^{\theta^f} \sum_i \left[\frac{N_{R_i^f}\left(d_{ij}^f\right)^{-\theta^f}}{\sum_{l'} w_{jf}^{\theta^f}\left(d_{il'}^f\right)^{-\theta^f}} \right] \\
&+ \sum_i \left[\frac{N_{R_{i,1}^{mf}}\left(d_{ij}^{mf,f}\right)^{-\theta^{mf,f}}}{\sum_{l'}\left(\sum_n\left(\frac{d_{in}^{mf,m}}{w_{nm}+w_{l'f}}\right)^{-\theta^{mf,m}}\right)^{\theta^{mf,f}/\theta^{mf,m}}\left(d_{il'}^{mf,f}\right)^{-\theta^{mf,f}}} \left(\sum_n\left(\frac{d_{in}^{mf,m}}{w_{nm}+w_{jf}}\right)^{-\theta^{mf,m}}\right)^{\theta^{mf,f}/\theta^{mf,m}} \right]
\end{aligned}
$$

If one could observe residence supply by gender and household type, $N_{R_{i,k}}^{\ell}$, 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:

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

We can plug this expression to the equations above, and solve the system.[34] □

A2.2 Proposition 2

Proposition: *Given data on residence by gender and household type, $N_{R_{i,\ell}^k}$, employment by gender $L_{F_{jg}}$, rents r_{F_j}, and commute costs d_{ij}^k, and parameters θ^k, α_s, σ_D there exists a unique 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:

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

[34] Proof is still incomplete.

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:

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

$\square$

A2.3 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 unique 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: $\Phi^{mf,m}_{R_{i,\ell=0}} = \sum_{l'}\left(\frac{d^{mf,m}_{il}}{w_{lm}}\right)^{-\theta^{mf,m}}$
- In dual earner households: $\Phi^{mf,m}_{R_{i,\ell=1,j'}} = \sum_l\left(\frac{d^{mf,m}_{il}}{w_{lm}+w_{j'f}}\right)^{-\theta^{mf,m}}$ $\Phi^{mf,f}_{R_{i,\ell=1}} = \sum_l\left(\frac{d^{mf,f}_{il}}{\left(\Phi^{mf,m}_{R_{i,\ell=1,l}}\right)^{1/\theta^{mf,m}}}\right)^{-\theta^{mf,f}}$

- On average:

$$\Phi_{R_i^{mf}} = \left\{ \left[\frac{1}{\gamma^{mf,f}} \left(\Phi_{R_{i,\ell=1}^{mf,f}} \right)^{-1/\theta^{mf,f}} \right]^{-\nu} + \left[(\xi_{i\ell=0})^{-1} \left(\Phi_{R_{i,\ell=0}^{mf,m}} \right)^{-1/\theta^{mf,m}} \right]^{-\nu} \right\}$$

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

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

$$\frac{\mu_i^{mf}}{1-\mu_i^{mf}} = \left(\frac{\left(\Phi_{R_{i,\ell=1}}^{mf,f}\right)^{-1/\theta^{mf,f}}}{(\xi_{i\ell=0})^{-1}\left(\Phi_{R_{i,\ell=0}^{mf,m}}\right)^{-1/\theta^{mf,m}}} \right)^{-\nu}$$

i,e,

$$\xi_{i\ell=0} = \frac{\left(\Phi_{R_{i,\ell=1}}^{mf,f}\right)^{1/\theta^{mf,f}}}{\left(\Phi_{R_{i,\ell=0}^{mf,m}}\right)^{1/\theta^{mf,m}}} \left(\frac{\mu_i^{mf}}{1-\mu_i^{mf}} \right)^{\frac{1}{-\nu}}$$

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. $\square$

B Appendix Tables and Figures

B.1 Figures

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

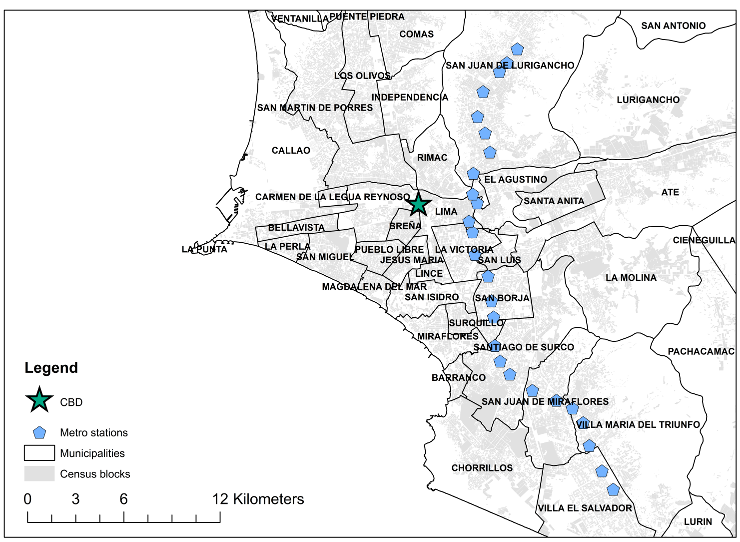


Figure B.2: The Bus Rapid Transit System

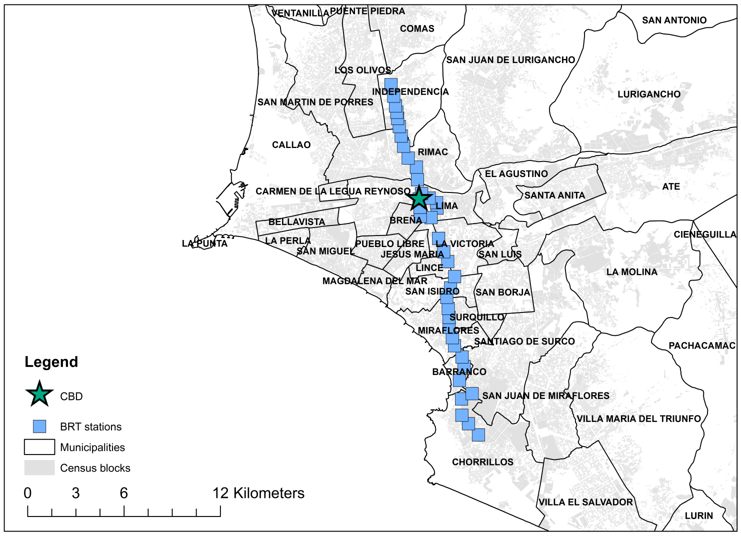
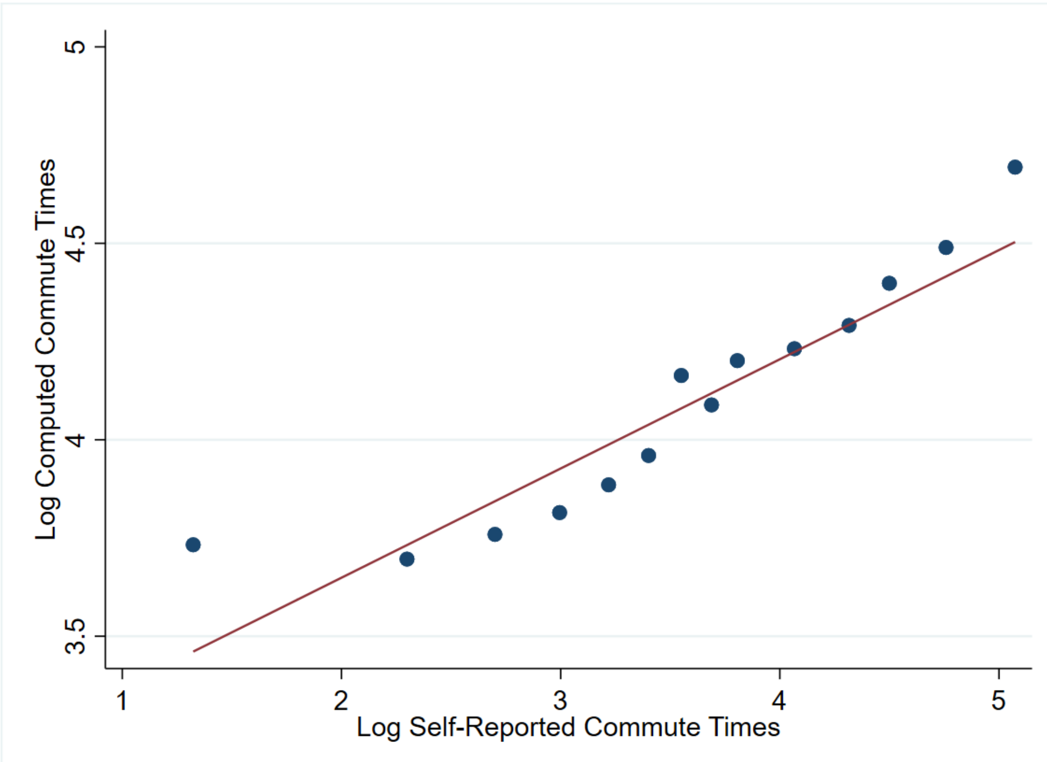


Figure B.3: Imputed versus reported commuting times



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%.