Commuting and the value of marriage

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Job market paper

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Abstract

Over time, as metro-areas sprawled to the suburbs, long commutes became common. In this paper I combine motivating evidence with a structural model to show how policies resulting in long commutes affect singles differently than couples (and men differently than women), if evaluated in a joint housing and marriage market equilibrium. First, I show that the gender gap in commuting among singles is negligible. Second, men in couples (not women) have much longer commutes than single men, and residential choice cannot explain this difference. This suggests that commuting features gains from specialization harnessed within couples, allowing men to take better jobs. I embed this feature in a quantitative spatial model with endogenous marriage and location choices that successfully captures the commuting and location patterns by marital status. In equilibrium, gains from specialization in commuting have the following implications: as metro areas expand in the model, commuting increases most for men in couples and employment falls most for women in couples, widening gender gaps in both outcomes. However, in terms of welfare it is singles who lose the most. Couples are able to partially evade commuting costs through specialization, lower housing costs and redistributing resources within the household.

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1 Introduction

Over the 20th century the geographic footprint of US metropolitan areas grew enormously. Figure 1c shows that the share of U.S. population living in the suburbs increased from 7 percent in 1910 to 50 percent in 2000. Figure 1a illustrates this point within the Panel Study of Income Dynamics (PSID), the primary dataset used in this paper. The distance from a residence to the city center increased from over 13 miles in 1970 to almost 19 miles by 2010, and so did the distance between residence and an average job in the metro area. In this paper I focus on an overlooked aspect of suburban long commutes: the differential impact on couples and singles, and men and women within couples, operationalized through a joint housing and marriage market equilibrium. First, I show that singles and couples differ markedly in their commuting and residential location decisions. I show that men in couples have much longer commutes than all others. Single men and women, both single and in couples, have similar commutes. I show that the choices of residential location cannot explain this difference. Rather the commuting margin plays a role in within couple specialization and the overall value of marriage. I embed this feature in a joint urban spatial housing equilibrium and marriage market equilibrium model, and show that within this framework long potential commutes are most costly to singles. As a result, longer potential commutes can actually incentivize couple formation.

A range of policies can affect commuting.[1] A long policy discussion about the pros and cons of suburban sprawl and long commutes (see Glaeser and Kahn (2004), Ewing and Hamidi (2015), Ehrlich et al. (2018) for reviews) focuses on the trade-off between productivity returns to agglomeration and costs of commuting.[2]. Recently, the COVID pandemic also reignited the discussion on benefits of work-from-home options (Delventhal et al., 2022) and the interaction of working from home with time spent in home productions Leukhina and Yu (2022). The differential effect on the behavior and welfare of singles and couples, the nature of commuting costs within households, and the ways in which housing policy effects can be operationalized through a joint housing and marriage market, are overlooked aspects of this debate.

[1]Bento et al. (2005) discusses how variables that can be affected by policy, such as population density restrictions on new development, public transit supply, density of the road network and distribution of jobs, correlate with average commutes across the Unites States. Gyourko and Molloy (2015) reviews the literature on housing regulations that discourage density, and thus encourage urban sprawl.

[2]See Fu and Ross (2013),Yinger (2021), Boehm (2013), Harari (2020) for examples.

Using a geolocated PSID sample, I first show that men substantially increase their commuting after forming a couple. This is not true for women, especially if they eventually end up having children. Moreover, there is essentially no difference in commuting between single men and women. Thus, gender gaps in commuting cannot be a result of gendered preferences. While it is true that couples are more likely to live in the suburbs than singles, this difference is not big enough to explain the gap in commuting between single men and men in couples. Specifically, I show that the gap reduces only marginally and remains large and statistically significant after controlling for various measures of how much residential location is suburban. Theoretically, couples could achieve short commutes of wives by systematically prioritizing her job access when choosing where to live. However, I find no evidence of this mechanism. Combining the main sample with the geographic distribution of jobs from the LEHD Origin-Destination Employment Statistics (LODES), and assigning individuals to their respective labor markets based on their most common lifetime industry and earnings segment, I show that there is no gender gap in potential commutes within couples. In fact, couples locate weakly closer to the kind of jobs the husband typically works in. Alternatively, a wife might commute less than her husband, because even if most of her potential jobs are far away, she searches for a local alternative or drops out of the labor force if no convenient jobs are available. I show evidence consistent with this second mechanism. Within couples, actual commutes of husbands are more correlated with distances to potential jobs (i.e. potential commutes) then are commutes of wives. On the other hand, labor market participation and hours of wives are more strongly correlated with potential commutes. Thus, overall when jobs in the husband's labor market are further away from the couple's residence, husbands simply commute more. When wives' jobs are further away, they are more likely to work locally, reduce hours, or not work at all. Lastly, I confirm that couples and singles also choose different residential locations within a metro-area. Couples systematically live further away from the city center, and consequently further away from jobs.

With this motivating evidence I add to the literature studying gender gaps in commuting, and the interaction with other labor market outcomes. Despite considerable convergence over the past century, women participate in the labor market less than men, and when they do, they work shorter hours and earn lower wages (for reviews and overall trends see Blau and Kahn (2013), Blau and Kahn (2007), Blau and Kahn (2017),Petrongolo and Ronchi (2020)). Figure 1d illustrates that these gaps tend to be bigger in the suburbs – in couples that live further away from center husbands supply about 2-4% more of the overall household market hours compared to the center of the city.[3] This suggests that compared to men long commutes are more detrimental to labor market outcomes of women when in couples. Similarly, Black et al. (2014) and FarrĂ© et al. (2020) provide descriptive and quasi-experimental evidence suggesting that in metropolitan areas with long commutes women tend to work less. Several early papers document there are substantial gender gaps in commuting, with men commuting more than women (Madden (1981), White (1986), Turner and Niemeier (1997), Tkocz and Kristemen (1994)). Moreover, a streak of recent papers documents that women have a lower willingness to trade off a long commute for a higher wage, contributing to gender wage (and other labor market outcomes) gaps (Rosenthal and Strange (2012), Gutierrez (2018), Liu and Su (2020), Barbanchon et al. (2020), Caldwell and Danieli (2021), Borghorst et al. (2021), Moreno-Maldonado (2022)). With the exception of Gutierrez (2018), the gender gaps in commuting are left unexplained or interpreted as a difference in preferences.[4] I show that gender gaps in commuting are almost solely coming from men and women in couples. Moreover, I provide novel evidence that this difference is not coming from couples prioritizing the wife's job access, rather from men in couples being less sensitive to long potential commutes in their job acceptance behavior.

Motivated by this evidence, I construct and estimate a quantitative urban spatial housing market and marriage market equilibrium model.[5] Singles and couples choose a residential neighborhood within a metropolitan area, accept or reject job offers and choose how to allocate their time. I overlay this structure with a simple marriage market equilibrium. The heterogeneity between singles and couples is a crucial feature of the model motivated by the empirical evidence that both commuting and residential location differ substantially by relationship status. Nevertheless, modeling this heterogeneity is very rare in quantitative urban economics. Most closely related to this paper is Tscharaktschiew and Hirte (2010), who construct a quantitative spatial equilibrium with couples and singles choosing a location. However, their paper has implications that do not square with the evidence presented here (with singles flocking to the suburbs, and higher wage earners within couples commuting less). I model the choices of couples explicitly as a collective

[3] Not including commuting time.

[4] Interestingly, both Barbanchon et al. (2020) and Liu and Su (2020) state that there is heterogeneity in the gender-gap by marital status, with married women being least willing to trade off higher wages for longer commutes.

[5] The spatial equilibrium portion is standard, based on a discrete choice of location as in McFadden (1977), Redding and Rossi-Hansberg (2017), Ahlfeldt et al. (2015) and many others.

decision resulting from bargaining between two partners with potentially conflicting interests, as inBrowning et al. (2014).[6] This again is a methodological contribution, as modeling household bargaining over residential location is rare in quantitative urban economics. With the exception of Chiappori et al. (2018), who show that ignoring the bargaining process within couples in urban models results in biased measures of value of time, the urban economics literature typically relies on a 'unitary' representation of the household.[7][8] Lastly, I endogenize the decision to form a couple and the required within-couple distribution of resources. To the best of my knowledge this is the first paper constructing and estimating a quantitative spatial equilibrium model of a metropolitan area with a combined housing and marriage market equilibrium, showing how the effects of a housing policy can be operationalized through a joint equilibrium.[9]

Several possible mechanisms could explain gender gaps in commuting within couples. However, none of the mechanisms common in the literature can also explain the gap between single and coupled men.[10] I propose that the observed patterns can be rationalized if commuting imposes costs on households in a form that rewards specialization – when one spouse takes a local job or stays at home, the other is freed to work far away, accepting better jobs. I propose a sim-

[6]Thus, I relate to the literature on gender differences in labor market outcomes within the context of household specialization. See Gronau (1977), Chiappori et al. (2002), Cherchye et al. (2012), Blundell et al. (2016), Bertrand et al. (2015), Bianchi et al. (2000)).

[7]Taking the potential conflict between wives' and husbands' location priorities seriously is more common in papers studying cross-metropolitan-area mobility. (Costa and Kahn, 2000) suggest that two-career couples locate in a large metro areas to solve the collocation problem whose career to prioritize. Several papers (Compton and Pollak (2007), Gemici (2008), Chauvin (2018), Venator (2020)) show cross-metro mobility is typically associated with labor market improvements for the husband, and losses for the wife.

[8]Even among unitary representations of the household, those models that consider explicit specialization by gender are not quantitative. Black et al. (2014), Abe (2011) present theoretical illustrative models where a fixed cost of commuting increases labor force participation gaps by gender. Madden (1977) and Gutierrez (2018) present theoretical spatial models where commuting returns increasing with hours (though higher wages) can explain why women in couples commute less. None of these confront their quantitative predictions with the data.

[9]Moreno-Maldonado (2022) constructs a quantitative model of choosing location across metro areas and labor supply, where women's labor supply declines in large cities due to higher commuting costs. Fan and Zou (2021) present a pioneering model of location choice across metro-areas, with joint local marriage and labor market clearing.

[10]For example, Gutierrez (2018) studies only couples and shows that theoretically gender differences in commuting can arise because returns to commuting scale with hours, but commuting itself is a fixed cost with respect to hours. As husbands work longer hours than wives, they are more willing to commute. While I incorporate this mechanism in my model, I argue it is not the principal driving force behind the observed commuting differentials, because it does not explain why men in couples commute so much more than single men.

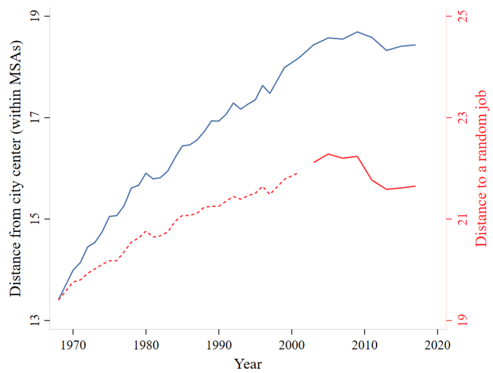
ple parametrization of a household-level cost of commuting that features gains from specialization and show that it allows the model to match the observed patterns of commuting and residential location. The cost captures the intuition that households value if someone is close by, to deal with emergencies, accept packages or pick up children from school. However, one person per household is quite enough, and there is no added benefit when two people are working close to home at the same time. I estimate the model with a moment based procedure, targeting moments summarizing the distribution of people and jobs, labor market behavior of couples and singles, and residential location and commuting behavior patterns presented in the empirical section.

Within this framework, I show how longer potential commutes encourage more marriage while increasing gender gaps in labor market outcomes. Long commutes, while costly to everyone, favor couples over singles. Couples in metro-areas with long commutes become more specialized, with one member (typically the wife) staying home or taking a local job and spending more time in home production. This allows husbands to keep high-value jobs without worrying about commuting. As suburbs are less and less convenient in terms of jobs access, housing rents in the suburbs fall compared to the city. Because singles lack the technological advantage of being able to specialize, they are more incentivized to flock to the city and pay more for housing. While wives lose by not being able to keep jobs they like, within a marriage market equilibrium they are compensated with more consumption and leisure. Thus, when the housing and marriage market equilibrium re-clear, marriages end up being more valuable for both men and women and welfare falls most for those who are single.[11]

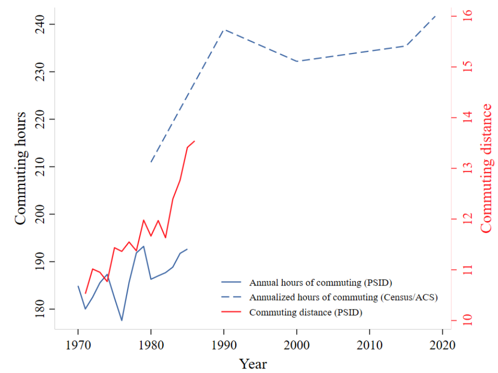
In the next section I describe the commuting and residential patterns of singles versus couples, as well as the evidence that men and women in couples react differently to long potential commutes. In section three I discuss the model, its structure and estimation. Section four presents the results of a counter-factual simulation, changing the urban landscape towards more sprawl that requires longer commutes. Finally, section five compares aspects of the counter-factual simulation with variation across U.S. metro areas, providing further validation for the model mechanisms.

[11]In this paper, I abstract from divorce for the sake of simplicity. If the ability to specialize on the commuting margin adds to the value of marriage, it should also lower the probability of divorce. On the flip side, if an individual (more often the wife) is working close to home, allowing their partner to accept longer commutes, increasing their commute can be especially costly to the couple. Recent evidence by HrehovĂ˘ et al. (2021) shows that when a commute is increased endogenously by the business relocating, the worker is more likely to divorce later. Given the evidence on this paper, commuting increases especially of women

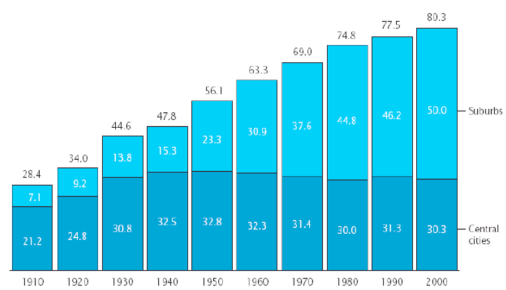
Figure 1: Suburban sprawl and commuting



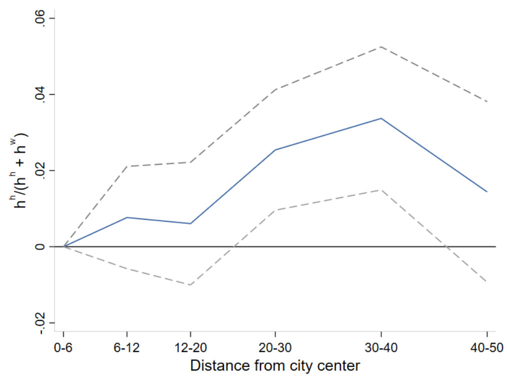
(a) Miles. Sample: PSID 18-50, normalized to white men, 35 years old, in couples. Job distribution: LODES (Bureau, 2021), imputed before 2002.



(b) Sample: 18-50, normalized to white men, 35 years old, in couples. Sources: PSID, Census IPUMS 1980-2000, ACS IPUMS 5-year 2010, 2015, 2019.



(c) Percent of total population living in a metropolitan area: central cities versus suburbs. Source: (Hobbs and Stoops, 2000)



(d) $\frac{H^h}{H^h+H^w}_{t,i} = \sum_{j=2}^{N} \alpha_i^{\text{dist bin } j} + \alpha_i^{ah} + \alpha_i^{aw} + \alpha_i^{educh} + \alpha_i^{educw} + \alpha_t + \alpha_i^{raceh} + \alpha_i^{\#children} + \epsilon_{i,t}$. Source: PSID sample of couples (as defined bellow). The solid line plots the difference between couples living 0-6 miles from the center and the rest of the locations in the share of household market hours performed by husband. The dotted line shows the 95% confidence intervals.

2 Commuting and residential location of couples and singles

2.1 Data and Measurement

The primary data source for this section is the geocoded restricted version of the Panel Study of Income Dynamics (PSID), with residential location data available up to the level of a Census tract. With this information I assign each response to a 2010-defined metropolitan statistical area (MSA) and compute an euclidean distance between the (2010 population weighted) centroid of the tract of residence and the centroid of the largest Census place within the MSA. In addition, the PSID includes four variables allowing us to study commuting. First, in waves 1971-1986 the PSID includes a typical commuting distance for the head and the wife (with 1971-1974 and 1977 only asking the head of the household). This is the primary commuting variable in the analysis, labeled d. Second, in waves 1970-1981 and 1983-1986 the PSID includes annualized hours of commuting for the head and the wife (with 1973, 1974 and 1977 only asking the head of the household).[12] Third, in 2011-2017 both the head and the wife are asked about typical duration of a one way commute (I annualize this report assuming each person works 5 days a week). Lastly, in 2013-2017 the geocoded restricted version includes the census tract of the current job. After restricting only to people whose job is in the same metro area as their residence (thus avoiding distances that are unreasonable to be expected an actual commute), I construct a 'distance to job' measure by computing the euclidian distance between the centroid of the tract of residence and the tract of work. In almost all waves these variables are only asked of people who worked over the last year. I use the alternative commuting measures to confirm robustness of the main results to alternative definitions and time periods.

To study the labor market behavior I use annual hours of work and labor income. To measure time in home production I use annual hours of housework.[13] To study behavior before and after forming a couple I construct tenure within a couple by assigning the first observed year

[12] The timing of this variable is somewhat convoluted - combining a typical commute of the current job with the work-schedule of last calendar year. I keep the timing tied to the year of the wave, as the first component is more relevant.

[13] According to the documentation, this variable should only include hours of housework, not childcare. However, Gayle et al. (2015) and others use this measure to be a combination of plain housework and childcare. Namely, Gayle et al. (2015) show that subtracting typical PSID housework hours of singles from PSID housework hours of women in couples results in a measure of childcare that matches well with childcare hours reported in ATUS.

of cohabitation in the PSID as the year a person stopped being single. For couples that are already observed in the first wave in 1968 I use the year of marriage, whenever available, to represent the year the couple was formed. Throughout this section, single is used to describe people in the PSID who have not been observed in a couple before.[14]

To study the distribution of jobs within metro areas I utilize the publicly available counts of jobs in a census bloc (counting jobs that are part of the unemployment insurance reporting system) per industry (19 categories) and earnings segment (3 categories) provided by the Census Bureau as part of the LEHD Origin-Destination Employment Statistics (LODES) available in 2002-2017 (Bureau, 2021)[15]. To extend the sample size I than backfill the job distribution from 2002 to all pre-2002 waves of the PSID. I compute a matrix of distances from each tract to each tract within all metro areas. Then, by weighting distances by the number of jobs I can compute 1) a distance to an average job in an MSA for each census tract for each year and 2) a distance to an average job in each industry-segment combination in an MSA for each census tract for each year (with pre-2002 years using the 2002 distribution). For each individual in the PSID that works at least in one wave when industry classification is available I select their most common industry and most common earnings segment (normalized to 2002 dollars for pre-2002 waves) and label this their 'labor market'. The associated distance to jobs in their labor market is interpreted as the distance to other potential jobs the individual could get, a potential commute or 'distance to opportunities' (labeled d_o, measured in miles). Distance to an average job across all labor markets is labeled d_j.

In the analysis bellow, I restrict the sample to individuals 18-50 years old who live in a metro area of at least 250 thousand residents per the 2010 Census. Moreover, for each individual I select their most common metro area over their observed lifetime in the PSID and exclude periods when this individual did not live in this MSA, so that all location changes are within the same area. Lastly, I only use single people who have not been in a couple before and couples for whom this is their first match, as far as it can be determined in PSID.[16]

[14]Most importantly, singles do not include divorcees.

[15]2-digit industry categories and 3 earnings segments is the level of differentiation available in the LODES data (Bureau, 2021), which I use to construct distribution of jobs in metro-areas. The segments are separated by monthly earnings at or bellow \$1250, between \$1250 and \$3333, and above \$3333.

[16]Table 13 presents summary statistics for the sample starting in 1969, the first year geographic information is available, and since 1990, a subsample used large parts of the analysis.

2.2 Commuting of couples and singles

This section presents a set of descriptive facts about how commuting behavior changes when men and women move from being single to forming a couple.[17] Tables 2 and 1 show results of regressing commuting outcomes on an indicator of whether an individual is in a couple (this can be a marriage or a cohabitation, to the extent it can be identified within PSID), metro-area, age and time fixed effects and additional demographic controls (with i standing for an individual and t for the wave of PSID). The analysis is done separately for men and women

$$d_{it} = \beta \cdot \text{In couple}_{it} + \alpha_t + \alpha_{age} + \alpha_{msa} + X_i + \epsilon_{it} \tag{1}$$

Consistently, men in couples have considerably longer commutes and spend more time commuting than single men[18] However, for women there is very little difference between couples and singles. The differences are large in scale compared to the baseline. Single men commute about 9 miles on average. Men in couples commute 20 to 30 percent further.[19]

A potential explanation for why men in couples commute more than single men is that couples typically move to the suburbs, thus further away from jobs. In section 2.4 I show that couples do indeed live further away from the city centers (more often in the suburbs) than singles. However, in tables 1 and 2 I show that this difference in residential location cannot account for the observed commuting differences. Specifically, I show that the commuting gap between single and married men reduces only marginally and remains large and statistically significant after controlling for various measures of how much residential location is suburban in 1. In column 3 I include the distance from residential location to the city center d_c as a control. While living further away from the city correlates with longer commutes, the gap between single and coupled men remains well above 2 miles. Column 2 presents the result when d_o, the potential commute constructed with LODES data on jobs distributions, is added as a control instead. This accounts more directly for the job access lost when living in the suburbs. While a longer potential commute is associated

[17] Since commuting is only defined for people with a job, all analysis in this section is done using a subsample of working individuals.

[18] I study both commuting time and commuting distance and treat them as providing information about the same behavior. Table 16 in the appendix shows that this pattern holds in the cross-section using more recent variables in the PSID – typical commuting time (available in waves 2011, 2013, 2015 and 2017) and distance to work (available in waves 2013, 2015 and 2017).

[19] Tthe raw mean of commuting distance in the PSID sample is 10.6 miles with a standard deviation of 11.3 miles.

Table 1: Commuting differences between singles and individuals in couples

	Commuting distance (miles)									
	Men					Women				
Singles (mean)	8.900					8.495				
In couple	2.708	2.555	2.369	2.388	2.238	.297	-.036	-.023	-.086	-.106
	(.674)	(.638)	(.662)	(.633)	(.660)	(.658)	(.646)	(.632)	(.663)	(.628)
d_o		.207					.117			
		(.062)					(.027)			
d_c			.206					.108		
			(0.032)					(.023)		
d_o *bins**				x					x	
d_c *bins**					x					x
N	24299	23243	24299	23243	24299	13641	13238	13641	13238	13641
N clusters	155	153	155	153	155	144	142	144	142	144

SEs statistics in parentheses. SEs clustered at the MSA level.

All regressions include year, age, MSA fixed effects, education and race dummies and cohort of birth.

The sample includes only individuals that are observed in a couple at some point.

* Includes dummies for d_x in intervals of 0-6, 6-12, 12-20, 20-30, 30-40 and over 40 miles.

with a longer actual commute, the gap between single and coupled men is only marginally affected. Columns 4 and 5 repeat the exercise, including instead dummies for several bins of d_o or d_c, showing the results are not driven by linearity of the specification. Moreover, the results are also robust to including polynomials of d_o or d_c instead. Again, for women there is almost no change in commuting before and after forming a couple, with or without controlling for where they live.

Next, I use within-person variation to show how commuting of men and women evolves before entering a couple through spending 5, 10 and more than 15 years in the couple. Figures 2b and 2d plot coefficients $\beta_{(-10)}$,..., β_{15} from the following regression, where α_i stands for a person

Table 2: Commuting differences between singles and individuals in couples

	Commuting time (annual)									
	Men					Women				
In couple	35.253	36.270	33.893	34.010	31.860	-24.027	-24.022	-23.415	-24.138	-23.680
	(8.528)	(8.291)	(8.735)	(8.112)	(8.469)	(6.742)	(7.147)	(7.187)	(7.288)	(7.393)
d_o		.715					-.135			
		(.515)					(.435)			
d_c			.862					-.241		
			(0.294)					(.337)		
d_o *bins**				x					x	
d_c *bins**					x					x
N	24181	22993	24181	22993	24181	15003	14475	15003	14475	15003
N clusters	154	152	154	152	154	147	144	147	144	147

SEs statistics in parentheses. SEs clustered at the MSA level.

All regressions include year, age, MSA fixed effects, education and race dummies and cohort of birth.

The sample includes only individuals that are observed in a couple at some point.

* Includes dummies for d_x in intervals of 0-6, 6-12, 12-20, 20-30, 30-40 and over 40 miles.

fixed effect.

$$\begin{aligned} d_{it} = {} & \beta_{(-10)} \cdot (\text{More than 5 years before forming a couple})_{it} + \beta_{(-5)} \cdot (\text{1-5 years before forming a couple})_{it} \\ & + \beta_5 \cdot (\text{In couple for 5-10 years})_{it} + \beta_{10} \cdot (\text{In couple for 10-15 years})_{it} \\ & + \beta_{15} \cdot (\text{In couple for more than 15 years})_{it} \\ & + \alpha_t + \alpha_a + \alpha_g + \alpha_i + \epsilon_{it} \end{aligned} \tag{2}$$

For men, commuting distance increases after at least 5 years in a relationship at a level 2-3 miles higher than the commute of single men 5-1 years before they enter a relationship and flattens after. Notice, though data is limited for this subsample, there is no evidence of a pre-trend, as commuting is actually higher for men 10-5 years before entering a couple than for men 5-0 years before settling with a partner. The pattern is analogous for commuting time.[20]

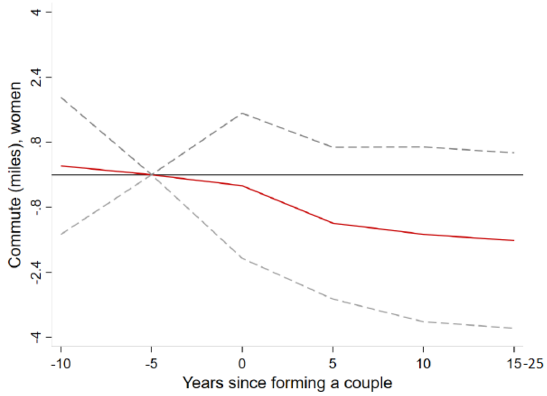
The picture for women, however, is starkly different. In the cross-section, women in couples actually spent fewer hours a year commuting. Using person fixed effects, and as such comparing women who worked both before and after forming a couple, I see that there is essentially no effect of forming a couple on commuting.

A second key observation is that this stark gender difference in commuting behavior that emerges within couples is not present among single people. Table 3 shows that across a variety of measures of commuting, gender differences are stark in couples, but are negligible among singles.[21] This observations disqualifies differential distaste for commuting by gender as the driver of gender gaps in commuting. Since men and women behave similarly as singles, but starkly different within couples, it has to be a dynamic of within household optimization that explains gender differences in commuting.

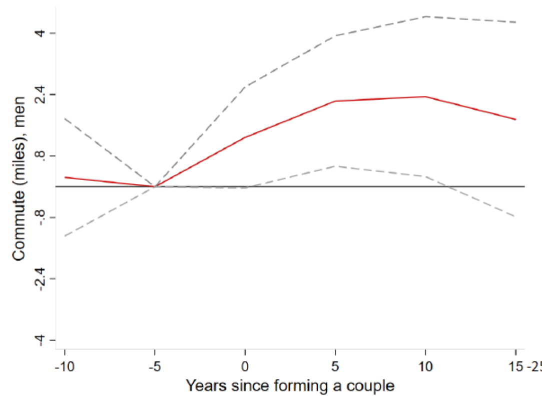
[20]Tables 15 and 14 in the appendix repeat the analysis in tables 2 and 1 with person fixed effects. Qualitatively, the patterns are robust to comparing explicitly men and women before and after they form a couple. Men commute more, while women do not change their commutes. Quantitatively, the differences are smaller. This is not surprising – given the limited number of PSID waves that offer commuting information, there is only a limited number of observations that have have commuting information available before and after forming a couple. Those that do are observed in very fresh couples. The pattern in 2b shows that commuting gaps take 5-10 years to materialize.

[21]Table 21 in the appendix confirms this pattern in the 2000 Census data.

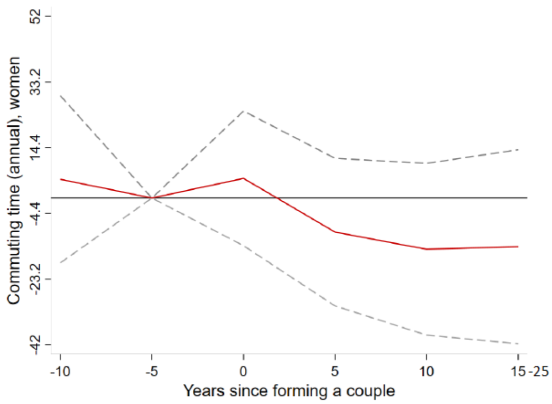
Figure 2: Event studies of commuting with respect to forming a couple



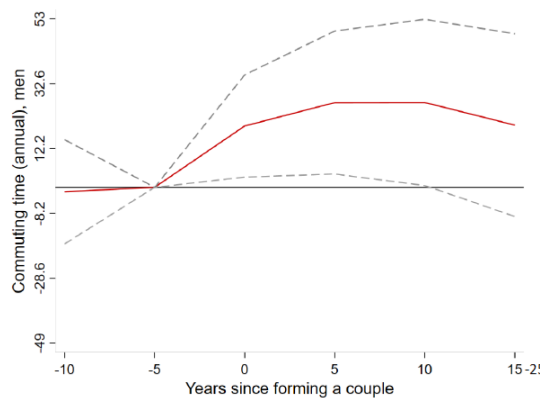
(a) women



(b) men



(c) women



(d) men

Source: PSID. Plotting coefficients $\beta_{(-10)}$, $\beta_{(-5)}$, β_5, β_{10}, β_{15} and the respective 95% confidence intervals from fixed effects regressions of the form 2.2 with the category "in couple for 5 or fewer years" excluded and normalized to 0. Outcomes: commuting distance in miles (one way) and annual hours spent commuting. Notice these regressions include person fixed effects, therefore they are identified from differences in commuting over lifetime as a person moves from being single to living with a partner and from living with a partner for a short versus a longer time, after regressing out age effects. Sample: commuting distance is available in waves 1975-1976, 1978-1986 plus in 1969-1974, 1977 for heads of households only; commuting time is available in waves 1969-1972,1975-1976, 1978-1986 plus in 1973-1074, 1977 for heads of households only.

Table 3: Commuting differences between men and women when single and when in couples

	Commuting distance (typical)	Commuting time (annual)	Commuting time (annualized)	Distance to work (tract to tract)
All (mean)	10.646	173.274	183.402	9.039
Man	**.008**	**-4.656**	**15.550**	**-.773**
	(.697)	(9.220)	(8.791)	(.563)
In couple	-.637	-31.045	-7.600	-.252
	(.542)	(5.931)	(6.383)	(.420)
Man in couple	3.867	74.676	24.197	2.630
	(.775)	(10.060)	(10.582)	(.728)
N	25078	26942	9189	4843
N clusters	145	150	165	148
In couple at some point	x	x		
	1970-1986		2011-2017	2013-2017

All regressions include year, age, MSA, education, race, cohort controls. *SEs* statistics in parentheses. SEs clustered at the MSA level.

2.3 Potential commutes and labor market attachment within couples

The previous section shows that within couples there is a gender gap in commuting. Two sets of mechanical explanations are possible. First, it could be that couples locate close to the chosen job location of the wife, more than that of the husband. Second, when a couple forms and moves to a location with worse accessibility to jobs, women with long potential commutes drop out of the labor market or switch to local jobs, while men keep their jobs with long commutes or switch to potentially better jobs even further away. This is consistent with the dramatic drop in labor market attachment of women after forming a couple, as illustrated in figure 18a, compared to men, who actually slightly increase their labor market attachment after forming a couple, as illustrated by figure 18b).[22] In other words, either couples chose their residential location closer to the wife's

[22]Both figures 18a and 18b are based on regressions with person fixed effects, ruling out any possible explanation of the selection of working men and non-working women into coupling.

jobs, or men and women differ in how they accept jobs given their residential location.

To discriminate between these two proximate causes, I take advantage of the data on the distribution of jobs in a metro-area. By looking within couples (including couple fixed effects) I study differences between husband and wife in their potential commutes, defined as the distance to potential jobs in their typical industry and earnings segment ($d_{o,it}$), by running the following regression $d_{o,it} = \beta \cdot \text{Man}_i + \alpha_{couple} + X_i + \epsilon_{it}$, where α_{couple} stands for couple fixed effects and β measures the within-couple gender gap in job access. Table 4 provides evidence against the residential location channel. There is no statistically significant difference in potential commute within couples. If anything, the point estimates point to shorter potential commutes for husbands.

Table 4: Difference between men and women within couples in potential commutes

	d^o			
Man	-0.039	-0.064	-0.118	-0.109
	(.080)	(.090)	(.074)	(.080)
X_i:				
Industry+segment fixed effects		x		x
Education, race, cohort		x		x
age, year		x		x
N	47482	47130	96412	96023
Sample	$\geq$ 1990		$\geq$ 1969	

SEs in parentheses, clustered at the MSA level.

All regressions include couple fixed effects.

$d_{o,it} = \beta \cdot \text{Man}_i + \alpha_{couple} + X_i + \epsilon_{it}$ where β measures the difference within couples between men and women in their distance to an average job in their assigned industry and earnings segment.

The lack of a gender gap in potential commutes suggests that the gender difference in commuting within couples happens because husbands and wives take jobs differently. Next, I provide more direct evidence of this mechanism. Similar to Gutierrez (2018) I study variation within heterosexual couples, thus comparing one men and one woman living in the same location. I show that men and women in relationships differ in how they react to long potential commutes. Consider the following regression (where i stands for an individual, c stands for a couple, a stands for age and t stands for time)

$$\text{comm}_{it} = \beta_d \cdot d_{oit} + \beta_{wd} \cdot d_{o,it}\text{woman}_i + \beta_w \cdot \text{woman}_i + \alpha_{couple} + \alpha_a + \alpha_t + \alpha_{ind,seg} + \epsilon_{it} \quad (3)$$

Table 5: Actual commutes and potential commutes within couples

	Commuting distance (miles)		Commuting time (annual)		Commuting time (annualized)		Distance to work (tract to tract)	
Distance	0.614	0.706	4.241	5.348	4.614	6.268	0.306	0.570
to jobs (d^{opp})	(0.117)	(0.107)	(1.033)	(0.971)	(0.984)	(1.135)	(0.137)	(0.167)
$d^{opp}\cdot$ Woman	-0.098	-0.106	-1.581	-1.478	-1.681	-1.689	-0.128	-0.121
	(0.047)	(0.050)	(0.612)	(0.649)	(0.324)	(0.378)	(0.046)	(0.032)
Woman	-0.903	-0.083	-21.960	-13.428	-3.363	5.525	0.582	1.091
	(0.557)	(0.610)	(6.462)	(7.361)	(4.927)	(5.404)	(0.485)	(0.404)
X_i:								
'Labor market' fes		x		x		x		x
Couple fes	x	x	x	x	x	x	x	x
N	19836		21244		8824		3350	
N clusters	146		145		159		131	

SEs in parentheses. SEs clustered at the MSA level.

All regressions include year, age, MSA fixed effects.

Sample: all waves when a selected commuting variable is available. For commuting distance in miles and annual commuting time this requires using distribution of jobs from (mostly) 2002 backfilled to the 1970s. Annualized typical commuting time and distance to work use the actual distribution of jobs in the respective wave (2011-2017).

The left-hand side variable is one of the measures of commuting available in the PSID. By including couple fixed effects (α_{couple}) I rely on variation in differences between husband and wife for couples where both of them work and they each work in a different kind of job (industry and/or earnings segment). Table 5 shows the results for commuting distance, annual hours spent commuting, annualized usual time spent commuting and distance to work (euclidean distance. tract to tract). The first row presents the estimate for β_d, showing that for all measures of commuting living further away from potential jobs is associated with longer commutes. This is reassuring as it validates that the chosen measure of access to potential jobs correlates strongly with actual commutes. However, the second row (estimates of β_{wd}) shows that this association is not gender neutral – it is weaker for women. Whenever a couple lives far away from the husband's job opportunities, his commute increases proportionally. Whenever a couples lives further away from the wife's job opportunities, her commute increase less, i.e. her jobs is more likely to be close to her residence anyway.

Notice by using within-couple variation in this regressions I am, by definition, only comparing people who live in the same location, with the location of the job determining commuting. This is important as it eliminates potential differences among people in how one's residential location is convenient for job access in general. Moreover, in columns 2, 4, 6 and 8 I include fixed effects for industry and earnings segment interactions, thereby eliminating concerns that the gender difference is based on the possibility that women work in labor markets where jobs are less concentrated, making their location less associated with the location of an average job for this systematic reason. Overall, there is a strong pattern in couples of women's commutes being less associated with distance to opportunities than men's.

Next I repeat the analysis with labor market behavior on the left hand side. Table 6 presents the results. In the first three columns I see that within couples, for both partners their distance to opportunities is associated with lower hours and a lower probability of labor force participation. This suggests that for both partners a long potential commute disincentivizes work, either because commuting takes out of the time endowment or is costly for other reasons, leaving less time for work, or because jobs that are further away from industry centers are less desirable to spend time in. However, this association is stronger for women, the opposite pattern to what I observe in commuting. Column 4 shows that the distance to potential jobs does correlates negatively with hours of housework for men, but it is positively associated for women. The last column shows that long potential commutes are weakly associated with higher wages. However, this is less true for wives (though this result is only marginally significant).

Overall, a clear pattern emerges. Men and women in couples do not react symmetrically to being far away from potential job opportunities. While husbands generally simply take the desired

Table 6: Work attachment and potential commutes within couples

	Hours	Working	Hours (positive)	Housework hours	log wage
Distance	-5.462	-0.002	-4.935	-1.064	0.00143
to jobs (d^{opp})	(2.221)	(0.001)	(1.911)	(1.236)	(0.00118)
$d^{opp}\cdot$ Woman	-5.146	-0.002	-2.484	3.285	-0.00118
	2.356)	(0.001)	(1.722)	(0.884)	(0.00062)
Woman	-346.370	-0.047	-269.442	258.698	-0.06773
	(27.924)	(0.009)	(19.865)	(10.762)	(0.01268)
X_i:					
'Labor market' fes	x	x	x	x	x
Couple fes	x	x	x	x	x
Both working			x		x
N	59872		49120	58892	47918
N clusters	177		177	177	177

SEs in parentheses. SEs clustered at the MSA level.

All regressions include year, age, MSA fixed effects.

All results are based on waves 1990-2017 to avoid excessive backfilling of the jobs distribution. Table 20 shows analogous analysis of hours spent working over samples when commuting variables are available, providing a more direct link to table 5.

job even when it is far away and spent a long time commuting, wives tend to take a more local job, cut their hours or drop out altogether, spending more time on housework, potentially also settling for a lower paying job. This again suggests that couples behave as if husbands commuting was less costly to them than that of wives.[23]

[23]A potential shortcoming of this analysis is that commuting variables are available only in selected waves, and for commuting distance in miles and annual commuting time the jobs distribution has to be imputed from the first available datapoint, typically from 2002. Table 20 in the appendix repeats the analysis of hours, cutting the sample to only waves when a respective commuting variable is available. While the raw association between distance to opportunities and hours is not robust to using only older waves when commuting information was available, the gender difference is. When using only recent samples that include annualized commuting time and distance to work,

2.4 Residential location of couples and singles

In this section I show that couples and singles also choose differently when picking a residential location within the metro-area. Mimicking the analysis of commuting, table 7 shows the results of regressing distance of the census tract of residence to the center of the MSA in miles (d_{it}^c) on an indicator of whether an individual is in a couple (this can be a marriage or a cohabitation, to the extent it can be identified within PSID), metro-area, age and time fixed effects and additional controls (with i standing for an individual and t for the wave of PSID).[24]

$$d_{it}^c = \beta \cdot \text{In couple}_{it} + \alpha_t + \alpha_{age} + \alpha_{msa} + X_i + \epsilon_{it} \tag{4}$$

Table 7: Distance to the city: couples versus singles

	Distance to center		Distance to center < 10 miles		Distance to jobs		Distance to jobs in own industry and segment	
In couple	1.830	.966	-.071	-.047	1.399	.369	1.754	.436
	(.338)	(.197)	(.0132)	(.0097)	(.312)	(.183)	(.322)	(.192)
X_i: *Education, race, cohort*	x		x		x		x	
Person fes		x		x		x		x
Sample:					≥ 1990		≥ 1990	
N	160549	209337	160549	209337	108662	105099	89873	88970
N clusters	181	181	181	181	183	183	183	183

SEs statistics in parentheses. SEs clustered at the MSA level.
All regressions include year, age, MSA fixed effects.

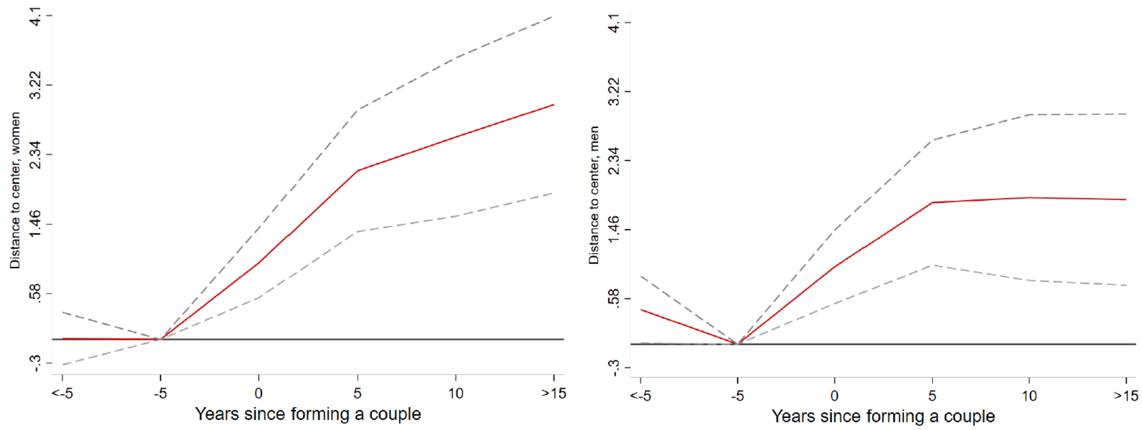
The first and third columns only use people in couples or singles who are later observed in a couple.

In the cross-section, after controlling for education and race, couples live on average almost 2 miles further away from the center than singles. The third column shows that for singles the probability of living less than 10 miles from the center is 7 percent higher. This is not a result of

the gender difference is not significant. This is likely because the sample is substantially smaller, lacking enough variation within couples in their industry-segment combination. When I extend it moderately to include waves from 2000 onward, the result reemerges and is quantitatively similar to using older waves.

[24] Unlike for commuting, analysis in this section is not excluding people who drop out of the labor force.

Figure 3: Event studies of distance to the city with respect to forming a couple



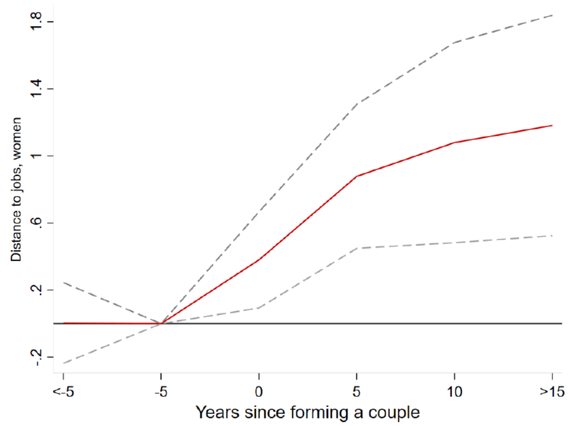
(a) women (b) men

Plotting coefficients β_{-10}, β_0, β_5, β_{10}, β_{15} and the respective 95% confidence intervals from fixed effects regressions of the form: $d^c_{it} = \beta_{-10} \cdot \text{In couple in more than 5 years}_{it} + \beta_0 \cdot \text{In couple less than 5 years}_{it} + \beta_5 \cdot \text{In couple for 5-10 years}_{it} + \beta_{10} \cdot \text{In couple for 10-15 years}_{it} + \beta_{15} \cdot \text{In couple for more than 15 years}_{it} + \alpha_t + \alpha_a + \alpha_g + \alpha_i + \epsilon_{it}$ with the category "in couple for 5 or fewer years" excluded and normalized to 0.

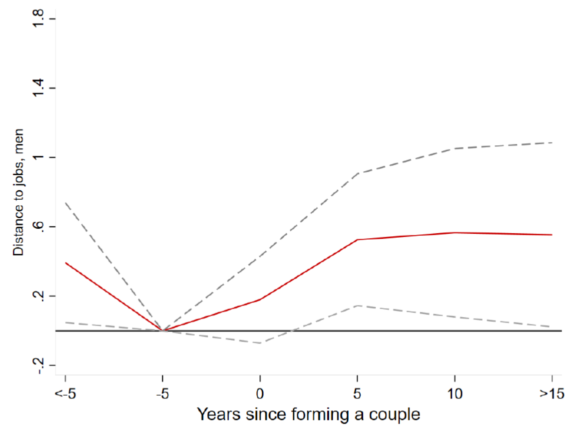
selection into being in a couple, as the first and third column of table 7 exclude singles whom I never observe forming a couple later. Columns 2 and 4 show that selection of singles to the city center is robust to looking strictly at the panel variation, after including person fixed effects. Figures 3a and 3b show that the pattern of moving to the suburbs is comparable for men and women and stabilizes after about 5 years of cohabitation. In metropolitan areas, jobs are more concentrated than people. As a result, when couples move to the suburbs, they are also moving further away from jobs. This is illustrated in columns 4-8 in table 7. People in couples live further away from an average job and further away from an average job in their most typical industry and earnings segment (their labor market, defined as the most common category over their lifetime as observed in the PSID). Figures 4a-4d show this pattern with the within-person variation. Unlike with commuting, the move to the suburbs is very similar for men and women. Therefore, there is no way that the large change in commuting for men when they form a couple contrasted with no change for women can be explained by a differential change in access to jobs between men and women.

To summarize, I show the following facts. First, on average men commute more then women.

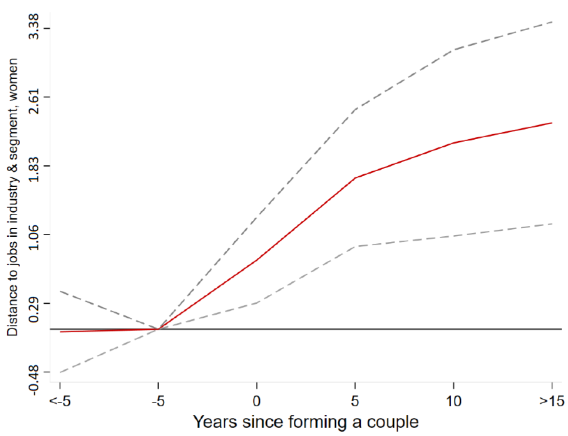
Figure 4: Event studies of job access with respect to forming a couple



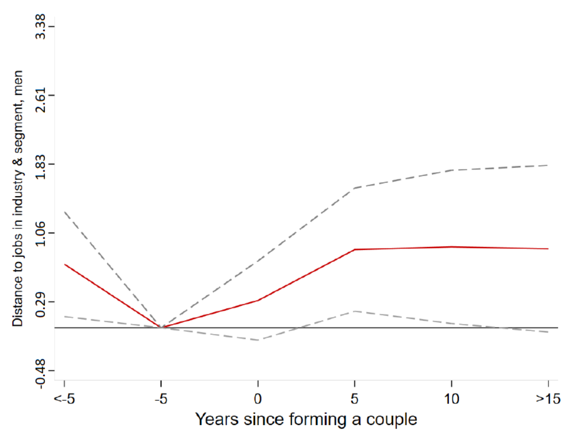
(a) women



(b) men



(c) women



(d) men

Analogous regressions for figures 3a and 3b. With distance to center d^c replaced with the average distance to jobs in the metropolitan area of residence d_j, and the average distance to such jobs restricted to the individuals most common industry and earnings segment d_o. Only data after 1990 are used, to not backfill job location information by more than 12 years. The results, however, are very similar when a shorter or longer samples are used.

Second, this gender gap is not present among singles, but is substantial among couples. Third, men in couples commute much more than single men, while there is little difference for women. Fourth, couples are more likely to live in the suburbs and further away from jobs than singles. However, this difference is not the main driver of the commuting gap between single men and men in couples. In fact, this difference is very robust to controlling for aspects of residential location that measure distance to the city. Fifth, there is no evidence that couples locate further away from the husband's potential jobs. This suggests that gender gaps in commuting within couples are not facilitated by the choice of residential location that prioritizes job access for women. However, I show suggestive evidence that when faced with long potential commutes, couples are willing to accept them for men while women in couples opt for a local job, shorter hours or drop out altogether. Overall, this set of facts suggests that there is something about commuting that makes it less costly when a couple specializes on this margin. This gendered specialization is what allows men in couples to accept potentially better jobs with longer commutes. I use the presented facts in estimating my model and show that especially the commuting gap between single men and men in couples cannot be easily matched unless commuting costs reward specialization.

3 Model

In this section I present a structural spatial equilibrium and marriage market equilibrium model of a metro-area capable of replicating the salient features of commuting and location decisions as presented above. Because gender differences in wages and productivity of time in home production do not lend themselves naturally to explain difference in commuting between men and women in couples, and between single men and men in couples, I posit that working close to home matters to households beyond the time lost commuting and introduce a convenient functional form that matches commuting patterns in the data. This cost of commuting is capturing the intuition that it is convenient if at least one member of the household works close by, but one is quite enough. As a result, couples have a technological advantage over singles in being able to specialize in commuting, with one of them working close by and freeing the other one to accept jobs far away from their the residence.

In its basic structure the model is a spatial equilibrium of a single metro-area with fixed housing supply per neighborhood, where residential rents are clearing the market for housing. Crucially, agents in the model are differentiated by gender and relationship status. This is directly motivated by the data, which show that men and women behave very differently depending on whether they are single or in a couple. To capture the transition from single-hood to forming a couple

I use a simple overlapping generations structure. On an individual level the population consists of three overlapping generations, one of singles and two of living in a couple (1 period represents roughly 10-15 years). Moreover, I include a simple marriage market equilibrium, to endogenize the share of the population who is married and the within-couple distribution of resources.

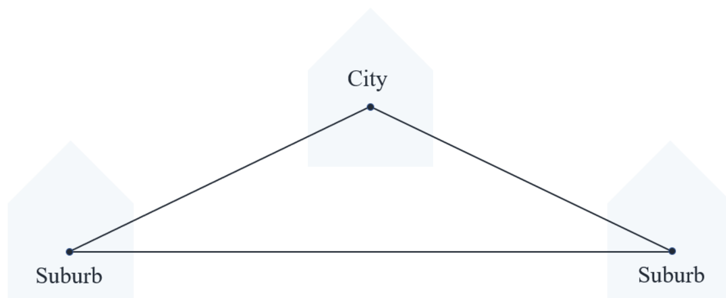
With the focus on the individual decision of households differentiated by relationship status the rest of the model is kept rudimentary. Matching into couples happens at random. The spatial structure is simple. There is a city and suburbs to capture the typical degree of centralization of economic activity and the differences in access to jobs between singles and couples. The suburbs is further differentiated into two locations, one offering more opportunities to men and one to women. This is necessary to capture the potential for disagreement within couples about whose career to prioritize.[25] Thus, the metro-area is composed of three equally-sized neighborhoods organized in a triangle (see figure 5).

The labor market is structured as a distribution of offers that individuals can accept or reject. This distribution captures that locations differ in how many and what kind of jobs they can offer. Each job is a bundle of a location (j), a wage (w) and a utility match shock (ξ) representing non-monetary benefits, where both w and ξ are higher for jobs that are close to other jobs in the same sector. To capture the idea that location choices are shaped by job access, households learn the location j of a job offer before they choose where to live. In the data, however, differences in commuting (between men and women in couples and between couples and singles) are not explained away by differential job access, but by differences in how jobs are accepted. Specifically, there is no evidence that within couples short commutes of women are facilitated by couples locating close to the wife's opportunities. Thus, one job offer would not provide enough flexibility in shaping ones commute to capture the patterns in the data. Therefore, I allow a share π of the population to always get an additional option to work locally. This flexibility gives households more agency to affect their commutes.

I fit the model to match location, commuting and work patterns in metropolitan areas in the United States and study how these patterns change when potential commutes increase and what are the implications for the value of marriage.

[25]There is no robust difference between men and women in how much the kind of jobs they typically work in are offered in the city versus the suburbs. As a result, having only two locations would not be appropriate to capture the potential for disagreement between men and women in couples about where to locate within a metro-area.

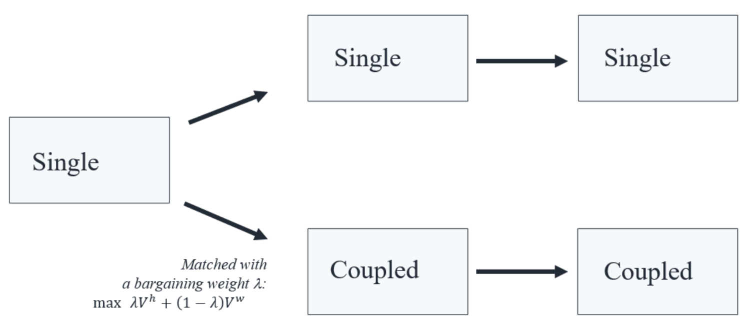
Figure 5: Spatial structure of the model metro-area



3.1 Household choices and timing

There are two types of households choosing where to live and how to spend their time - singles and couples. Each individual goes trough three life stages. Everybody is single in the fist stage. After the first life stage, a person decided whether to marry or stay perpetually single.[26]

Figure 6: Model timing: lifecycle



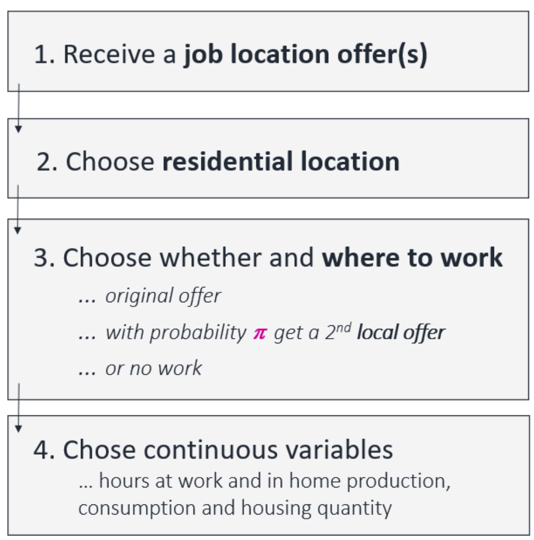
Couples differ from singles on three dimensions. First, couples have a more complex optimization problem. Whereas individuals maximize their own utility, couples maximize a weighted average of the utilities of the husband and the wife. Second, couples derive more value from time

[26]In this paper, I abstract from divorce, for the sake of simplicity.

spent on home production of a public good. This difference is capturing the fact that couples are more likely to bring up children in their households.[27] Third, singles and couples have potentially different preferences over location amenities, with couples appreciating the suburbs more (potentially for better schools and an overall good environment for children).

Within a life stage decisions are made sequentially. Figure 7 presents the timeline. Each period starts with everybody being offered a random job location. With this information in hand (and knowing residential rents in all locations) singles and first-period couples choose where to live. Next, a share of households π learns about another local job and decides whether to take it. Whoever is left without a job learns the match shock of their original offer and decide whether to take it or drop out of the labor force. After jobs are assigned, all households make decisions on time use, consumption and housing demand.[28]

Figure 7: Model timing: within each stage of life



Equation 5 presents the optimization problem of a single person, after they have settled to a location i and a job $(j_**, \xi())$. Notice the model abstracts from borrowing and lending, so each

[27] See figures 20a and 20b in the appendix.

[28] The sequential nature of these decisions is posited for simplicity. The order of receiving a local offer first or second does not meaningfully affect results.

period a household spends all their income. As a result, the decision problem is static.

$$
\begin{aligned}
U^s(i, j_*, \xi()) = \max_{c^s, l^s, h^s, H^s, x^s} & u_c(c^s) + u_l(l^s) + u_H(H) + a^s(i) + \Pi^s + \xi(h^s) \\
\text{s.t. } c &= Y + h^s \cdot w(j_*) - R(i) H^s \\
1 &= h^s + \beta d(i, j_*) + l^s + x^s \\
h^s &\leq \bar{h} \\
\Pi^s &= -F^s(d(i, j_*)) + u^s_x(x^s)
\end{aligned}
\tag{5}
$$

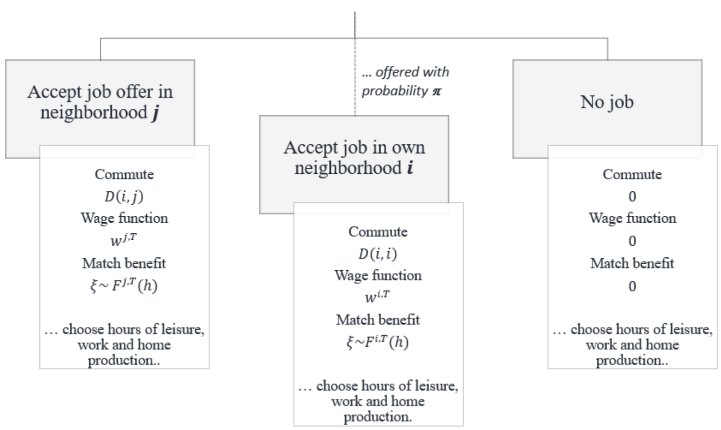
Utility is derived from c consumption, l leisure, H housing quantity, $a^s(i)$ amenity derived from living in a location i, $\xi(.)$ a transitory match shock of a job that is increasing in hours, and more so if the job is close to other similar jobs, and Π^s the value of home production and additional household costs of commuting. Time is constrained to sum up to 1: $1 = h + b \cdot d + x + l$ (where h stands for time spend at work and $b \cdot d$ for commuting). Commuting distance is given by $d(i, j_*)$, where $d(.,.)$ is the matrix of distances between neighborhoods and is $d(i, 0) = 0 \forall i$ (where 0 is indicating not having a job). The value generated at home depends on time put in housework as well as on commuting: $\Pi^s = F^s(d) + u^s_x(x)$, where F is decreasing in d and u_x is increasing in x. The effect of commuting on household value generated at home reflects the costs of commuting beyond time use – the option value of being near home in the case of emergencies in the household (such as accepting packages and letting in maintenance personnel). Section 3.3 includes a detailed discussion of this parametrization choice. There is an upper bound on work hours, reflecting that the labor market typically does not allow for complete flexibility in the kind of employment contracts offered.

Equation 6 presents the optimization problem solved by a single person when choosing a job, given their residential location i, the wage function $w(.)$, residential rents $R(i)$ and a job location offer j (for each labor market sector T, affecting the kind of offers a person gets). $A_j \in \{0, 1\}$ indicates whether a person accepts job location j.

$$
\begin{aligned}
V^s(i|j,T) &= \pi \cdot E_{\xi_{i,T}}\left[\max_{A_i}\ E_{\xi_{j,T}}\left[\max_{A_j} v(A_i, A_j|\xi_i, \xi_j)\right]\right] \\
&\quad + (1-\pi) \cdot E_{\xi_{j,T}}\left[\max_{A_j} v(0, A_j|0, \xi_j)\right] \\
v(A_i, A_j|\xi_i, \xi_j) &= U^s(i, j_*, \xi) \\
\text{where } j_* &= A_i \cdot i + (1-A_i)A_j \cdot j \\
\xi &= A_i \cdot \xi_i + (1-A_i)A_j \cdot \xi_j
\end{aligned} \tag{6}
$$

A single person knows the location of their potential job j and the distribution of matches in these jobs that depends on the location and the labor market sectors T they belong to. First, a share of the population learns about a local job and decides whether to take it. This would give a short commute which is weighed against the potential of a better match. All who did not take the local job accept the offer in j or drop out of the labor force. j_* is the final optimally chosen job location (either i, j or 0). Figure 8 summarizes the job-taking decision. Settling into jobs, each single person

Figure 8: Choice of where and whether to work



decides on hours of leisure, work and home production, on consumption and quantity of housing. At the end of the period job ties are severed.

A couple acts to maximize a weighted sum of the husband's and the wife's utility, with λ representing the bargaining power of the husband. The maximization problem of a couple within each period, given residential location i and jobs $(j_*^g, \xi^g())$ for $g \in \{h, w\}$ is presented in equation 7.

$$
\begin{aligned}
U(i, j_*^h, j_*^w, \xi^h, \xi^w) = \max_{c^h, l^h, h^h, x^h, c^w, l^w, h^w, x^w, H, \Pi} \Big[& \lambda\big[u_c(c^h) + u_l(l^h) + \xi^h(h^h, j_*^h)\big] \\
& + (1-\lambda)\big[u_c(c^w) + u_l(l^w) + \xi^w(h^w, j_*^w)\big] \\
& + u_H(H/2) + a^c(i) + \Pi\Big] \\
\text{s.t. } c^h + c^w &= 2Y + h^h \cdot w^h + h^w \cdot w^w - R(i)H \\
1 &= h^g + b \cdot d(i, j_*^g) + l^g + x^g \text{ with } g \in \{h, w\} \\
h^g &\leq \bar{h} \\
\Pi &= u_x^c(P(x^h, x^w | d^h, d^w)) - F^c(d^h, d^w)
\end{aligned} \tag{7}
$$

The value generated at home depends on time put in housework as well as on commuting: $\Pi^c(x^h, x^w, d^h, d^w) = u_x^c(P(x^h, x^w|d^h, d^w)) + F^c(d^h, d^w)$, where P is an increasing function of x^h and x^w, while F^c is a (weakly) decreasing function of d^h and d^w. Moreover, for couples, there is a complementarity between time and commuting: the productivity of x^h versus x^w is decreasing in $d^h - d^w$. The calibration section includes a detailed discussion parametrization choices.

The optimization problem of a couple choosing jobs is presented in equation 8, given residential location i and job location offers and labor market sector assignments for both partners. A couple knows the locations of their potential jobs j^h, j^w and the distribution of matches in these jobs that depends on the locations and the labor market sectors T^h, T^w they belong to. First, a share of households learns about local jobs (located in i) and decide whether the husband, the wife or both should take it. This would give a short commute which is weighed against the potential of a better match. All who did not take the local job accept their initial offer or settle into non-participation in the labor market. j_*^g is the final optimally chosen job location (either i, j^g or 0). Lastly, the couple chooses housing continuous variables: housing quantity, consumption, hours of work and hours of home production for both partners. At the beginning of second period, old job ties are severed, new offers ar presented, news jobs chosen and continuous variables are re-optimized.

$$
\begin{aligned}
V^C(i|j^h, j^w, T^h, T^w) &= V_1 + E_{j'^h, j'^w}\left[V_2\right] \qquad (8)\\
V_t &= \pi \cdot E_{\xi_i^h, \xi_i^w}\Big[\max_{A_i^h, A_i^w} E_{\xi_{j^h}^h, \xi_{j^w}^w}\big[\max_{A_j^h, A_j^w} v(A_i^h, A_i^w, A_j^h, A_j^w|\xi)\big]\Big]\\
&\quad + (1-\pi) \cdot E_{\xi_{j^h}^h, \xi_{j^w}^w}\big[\max_{A_j^h, A_j^w} v(0, 0, A_j^h, A_j^w|\xi)\big]\\
&\text{with } \xi = (\xi_i^h, \xi_{j^h}^h, \xi_i^w, \xi_{j^w}^w)\\
v(A_i^h, A_i^w, A_j^h, A_j^w|...) &= U(i, j_*^h, j_*^w, \xi^h, \xi^w)\\
&\text{where } j_*^g = A_i^g \cdot i + (1 - A_i^g)A_j^g \cdot j^g\\
&\qquad \xi^g = A_i^g \cdot \xi_i^g + (1 - A_i^g)A_j^g \cdot \xi_j^g\\
&\text{with } g \in \{h, w\}
\end{aligned}
$$

3.2 Job offers

The labor market is structured as a distribution of offers that individuals can accept or reject. The purpose of differentiated job offers is to capture the potential trade-offs between short commutes and better monetary and non-monetary benefits from working. Each job is a bundle of a location (j), a utility match shock (ξ) and a wage (w). Job location together with the location of residence determines commuting time. The match shock is a private utility benefit of a job, that captures differences in job satisfaction, career prospects and other non-monetary benefits. Both non-monetary benefits ξ and wage w is decreasing in distance to other jobs in the labor market. Moreover, wages are exogenously lower for women in couples.

In the data, men and women systematically work in different sectors of the economy. Moreover, similar jobs cluster together within geographic areas. This sets up couples for a potential disagreement about whether to locate closer to the husband's or wife's potential jobs. To capture this tension, I classify all offers into two distinct labor market sectors $T \in \{1, 2\}$. In every period each individual is assigned to one sector, and only draws job offers from that sector. Sector assignments are random, but more men belong to sector one ($T = 1$). At the same time, sectors differ in which geographic locations they concentrate in. Moreover, jobs coming from locations where the sector is concentrated in come with better matches on average. The purpose of this variation is to capture the potential for systematic disagreement within couples in where to locate with respect to commuting, since living close to a job as well as living close to other jobs in your sector is desirable. Specifically match shocks (ξ) of jobs are higher when located near other job offers in the same sector[29]. This benefit to agglomeration has a constant component and a component that scales with hours: $\xi = \xi_0 + \Xi(d'_o(j), h)$, where ξ_0 is stochastic and Ξ is deterministic, h stands for hours of work and d'_o stands for the distance to other first offers[30] in the same labor market).[31] As such this variation captures agglomeration effects, where labor market sector hubs concentrate more productive and more innovative companies that provide their workers with a higher job satisfaction. Each sector has a hub in the city and in one of the suburbs.

The base wage is constant across individuals of the same gender and relationship status. There is a wage benefit to having a job in a hub of own sector (complementing the non-monetary benefit in ξ). Moreover, there is a fixed gender pay gap for men and women in couples. There is no gender wage-gap for singles.[32] Overall, the wage function is defined as $w(d'_o(j), g) = w_a \cdot e^{-w_{(d'_o(j))} + 1_{g==h} w_{gap}/2 - 1_{g==w} w_{gap}/2}$ where $w_{(d'_o(j))} = w_{\Xi} \cdot (b \cdot d'_o(j) - b \cdot \bar{d}'_o)$.

Figure 9 summarizes the spatial distribution of first job offers. Red and green distinguishes sectors 1 and 2, showing that the first suburb has more offers in sector 1. Specifically, $f_T(j)$ is the share of first job offers in a labor market sector T in the location j. $d^i_{o,T}(j)$ is the implied distance in a location j to a random first job offer from a labor market sector T, that influences the benefits (monetary and non-monetary) of a job. The final distribution of jobs is endogenous, depending on which offers are accepted.

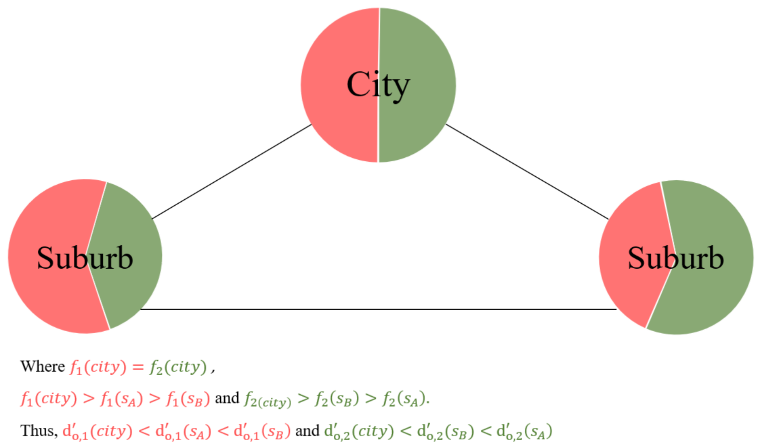
[29] Not including the additional local offers.

[30] I use distance to first offers, not distance to other jobs in the same labor market, because the latter would make this dependency endogenous to the labor market behavior of other people, gravely complicating the solution of the model. Nonetheless, the spatial distribution of jobs and distribution of first offers is closely linked.

[31] With $\Xi(d'_o(j), h) = -\bar{\Xi} \cdot (b \cdot d'_o(j) - b \cdot \bar{d}'_o) \cdot h$ linear and centered at 0.

[32] Including a smaller gender gap for singles would not change any principal conclusions of the paper. Gender gap in couples is imposed on the model to match the wage gap in the data, as this paper does not aim to explain why wage gaps are much larger for people in couples. A wage gap in couples is included to properly capture the incentives for whether a wife or a husband, or both, participate in the labor market.

Figure 9: Job offers in location



Red and green distinguishes sectors 1 and 2, showing that the first suburb has more offers in sector 1. Specifically, $f_T(j)$ is the share of first job offers in a labor market sector T in the location j. $d^i_{o,T}(j)$ is the implied distance in a location j to a random first job offer from a labor market sector T, that influences the benefits (monetary and non-monetary) of a job.

3.3 Value of working close to home that rewards specialization

Men in couples commute much more than single men, and much more than women in general. In this section I propose a functional form for the cost of commuting that rewards specialization on this margin, and allows a model to quantitatively match the differences observed in the data. I posit that working close to home has additional benefits to all households beyond time use. For singles, this is a simple fixed cost of working, that scales with time spent commuting.

$$F(d) = F^c(d, d) = \phi \cdot (b \cdot d) \tag{9}$$

Working close to home can be beneficial for many reasons, for example to accept deliveries or to be around in case of emergencies around the house. Importantly, this benefit does not scale naturally with both partners being involved. If one member of the household is available by working close by, there is little harm in the other one working far away from home. This suggests that couples have an advantage over singles by sharing a household together, and that specialization in one member of the household working close to home is often the efficient option. Equation 10 suggests a functional form that captures this intuition for couples

$$F^c(d^h, d^w) = \phi \cdot \min\Big\{b \cdot d^w, b \cdot d^h\Big\} \tag{10}$$

$F(d^h, d^w)$ implies that one person working close to home benefits the whole household. It is weakly increasing in the commuting time of husband and wife.[33] I impose the scale of the value of working close to home ϕ to be the same for couples and singles. ϕ is identified from the variation in commuting between singles and married men and women.

Standard explanations in the literature for gender differences in the labor market include either hard-wired preferences for women to stay at home, differences in the value of leisure, productivity in home production or differences in compensation in the labor market. None of these lent themselves naturally to explain the observed gaps in commuting, unless commuting has additional costs to households beyond time use that rewards specialization. First, wage gaps actually incentivize a reverse gap in commuting between men and women. Since commuting takes out of the time endowment, if the husband's time is more valuable, the couple is motivated to locate close to the husband's offer or to let him accept a local offer to avoid losing his valuable time. Second, a gender gap in home productivity also does not naturally motivate couples to prefer the wife's commute to be shorter than the husbands. This is because the decline in available time due to commuting $b \cdot D(i, j)$ is offset by a decline in market hours, leaving time in home production and leisure unaffected.

Theoretically, differences in commuting within couples could by caused by differences in bargaining power. If λ is low, husband's interests are not considered. If individual utility is decreasing in commuting time, the couple could prioritize short commutes of wives. However, other features of the data do not support this explanation. If women commute less because couples prioritized their offers when choosing a residential location, we would see couples living systematically closer to the jobs in the wife's sector. In other words, $E({d_o}^h - {d_o}^w)$ would be positive in the data (where ${d_o}^h$ is the distance within MSA to an average job in the wife's most common industry and earnings segment, i.e. the husband's potential commute). However, the husband's potential commute is on average about the same or weakly shorter than the wife's potential commute (see table 4). This is true both when comparing raw means an when controlling for education, age and labor market sector fixed effects. Matching this moment in the data thus disqualifies a bargaining advantage

[33] $1 - F^c(d^h, d^w)$ can be interpreted as a special case of a more general commuting cost structure. See 14 for details.

as the primary factor explaining that women in couples have shorter commutes.[34] Differences in commuting within couples could also come from differential job access to sectors dominated by men versus women (for example, if jobs where men work were concentrated far away from residential areas, it would be less surprising that men commute more). However, the same argument applies – couples do not systematically live closer to the kind of jobs that wives work in. Moreover, this mechanism would create a commuting gap among single men and women as well.

In principle, a gender gap in commuting could be rationalized by assigning men and women different preferences (for example with $b^w > b^h$), as is sometimes implicitly assumed in the literature. This, however, is rejected by the data as there is essentially no difference in commuting between single men and single women.

Both wage gaps and differential productivity in home production do generate a gap in commuting between husbands and wives in the model through selection, motivating women to drop out of the labor force more than men, and with women being more likely to drop out when their potential commute is long. However, this channel alone has no potential in matching the gap between single men and husbands. Similarly, gender gaps in commuting within couples could come from a complementarity between commuting and time in home production. For example, it is conceivable that it is more efficient for the same person to be able to pick up children from school and to take care of them afterwards. To allow for this channel, I extend the model to include an interaction between productivity of time in home production and working close to home (or dropping out of the labor market). The production function is CES where $\kappa_w(d^h - d^w) = \kappa_w^0 + (d^h - d^w) \cdot \kappa_d$:

$$P(x^h, x^w | d^h, d^w) = (\kappa_w(d^h - d^w) x_w^{1-\eta_x} + (1 - \kappa_w(d^h - d^w)) x_h^{1-\eta_x})^{\frac{1}{1-\eta_x}} \tag{11}$$

By making $\kappa_w(d^h - d^w) = \kappa_w^0 + (d^h - d^w) \cdot \kappa_d$ increasing in $d^h - d^w$ I facilitate that commuting in couples leads the individual to put in fewer hours in home production, letting the partner compensate for the loss. Since $\kappa_w > 0.5$, $\kappa_d > 0$ motivates the couple to prioritize short commutes of wives and helps to match the sensitivity of home production hours to differences in the distance to opportunities within couples from table 6. However, again this does little to fit the most salient feature of the data – that men in couples commute more than single men. Within the model, I include gender differences in home productivity and wages, bargaining within couples and the

[34] Moreover, higher bargaining power does not necessarily lead to shorter commutes. Within the household, a long commute if more efficient for the household as a whole can be compensated with shorter hours of work or home production, with consumption or with a better job match.

potential for differences in access to male versus female dominated sectors. However, without costs of commuting that reward specialization within couples on this margin, the husband-wife and husband-single man commuting differences cannot be matched between the model and the data.

3.4 Choosing residential location and marriage

Each single or a new couple chooses a residential location[35], either the city or one of the two suburbs. This is a standard discrete choice as in McFadden (1977), comparing systematic benefits (access to current job offers, access to other potential jobs, amenity values and costs of housing) with idiosyncratic amenity preferences per location ϵ_i. Residential location within the metro area is made knowing the location of potential job j and the distribution of matches in these jobs that depends on the location and the labor market sectors T they belong to (as discussed in section 3.2). For singles:

$$\max_{i=c,s_A,s_B} V^s(i|j,T)+\epsilon_i$$

For couples:

$$\max_{i=c,s_A,s_B} V^c(i|j^h,j^w,T^h,T^w)+\epsilon_i$$

With ϵ_i following the Type-1 extreme value distribution, the choice probabilities can be solved in closed form.

The choice of marriage for a man (h) and a woman (w) is done by comparing the expected value from remaining single for 2 periods and the expected value of being married (given the husband's bargaining weight λ). As in Choo and Siow (2006), I assume that in addition to the systematic component of utility in the married or single state each individual receives an idiosyncratic payoff θ^g that is specific to him or her. The expected value from remaining single for 2 periods is defined by plugging optimal choices of time use, spending, job taking and residential location in the period utility functions

$$u^s+\theta_s=2\cdot E_{T,\epsilon_i,j,\xi_i,\xi_j}\left(u^s_c(c)+u_l(l)+u_H(H)+a^s(i)+\Pi^s(x,d)+\xi\right)+\theta_s$$

where the expectation is taken over job-match shocks for the offered and local jobs ξ_i,ξ_j, draw of job offer location j, the idiosyncratic location preferences ϵ_i, and ultimately the labor market sector assignment T.

[35] All singles choose a residential location each period. Couples only choose location in their first period, reflecting that couples stay in one place for longer periods of time.

Similarly, the expected values in marriage for a man and a woman is defined as

$$u^h(\lambda)+\theta_h = E_{T^g,\epsilon_i,j_t^g,\xi_{i_t}^g,\xi_{j_t^g}^g}\left(\sum_{t=1}^{2} u_c(c_t^h) + u_l(l_t^h) + u_H(H_t/2) + a^c(i) + \Pi(x_t^h, x_t^w, d_t^h, d_t^w) + \xi_t^h\right)+\Theta+\theta^h$$

$$u^w(\lambda)+\theta_w = E_{T^g,\epsilon_i,j_t^g,\xi_{i_t}^g,\xi_{j_t^g}^g}\left(\sum_{t=1}^{2} u_c(c_t^w) + u_l(l_t^w) + u_H(H_t/2) + a^c(i) + \Pi(x_t^h, x_t^w, d_t^h, d_t^w) + \xi_t^w\right)+\Theta+\theta^w$$

Expectations are taken over job-match shocks for the offered and local jobs for two periods and for both partners, draws of job offer locations, the idiosyncratic location preferences ϵ_i, and ultimately the labor market sector assignments T for self and the partner.

In addition to idiosyncratic preferences θ_g (where $g \in \{h, w\}$), I allow for non-economic benefits to marriage (a constant Θ). Note that the Pareto weight does not depend on the realization of uncertainty. This implies full commitment and efficient risk sharing within the household. Moreover, I assume that assignment to a labor market sector T is randomly reshuffled after marriage (preserving the gender composition of each). This way with matching at random there is no differentiation in the incentive to marry by labor market sector T. This is a simplifying assumption that preserves the logic of one common marriage market.

A man decides to enter the marriage market if, given λ,

$$u^h(\lambda) + \theta_h > u^s + \theta_s$$

As with residential location, I assume that the idiosyncratic payoffs θ_g and θ_s, observed prior to the marriage decision, follow the Type-1 extreme value distribution with a zero location parameter and the scale parameter σ_m. Thus the proportion of men or women $g \in h, w$ who would like to be married has a closed form and is given by

$$p^g(\lambda) = \frac{e^{\frac{u^g(\lambda)-u^{g,s}}{\sigma_m}}}{1 + e^{\frac{u^g(\lambda)-u^{g,s}}{\sigma_m}}}$$

Denoting M and F as the supply of men and women in the marriage market, an equilibrium bargaining weight λ satisfies

$$M \cdot p^h(\lambda) = F \cdot p^w(\lambda)$$

Assuming a gender-balanced metro-area, with equal number of men and women, this equation boils down to a simple equilibrium condition.

$$u^h(\lambda) - u^{h,s} = u^w(\lambda) - u^{w,s}$$

3.5 Equilibrium

There are four overlapping markets: three housing markets and one marriage market. With three discrete locations, there are three prices $\{R(i)\}_{i=c,s_A,s_B}$ to clear three housing markets. The bargaining weight λ is endogenous in the model and serves as a price clearing the marriage market. Supplies of housing $\{H_i\}_{i=c,s_A,s_B}$ are fixed in each residential location, and they sum up to 1 (equal to the total population of the metro-area).[36] Individuals are differentiated by gender $g \in \{h, w\}$ (with an equal number of men and women living in the metro-area) and labor market sector assignment $T \in \{1, 2\}$ (with an exogenous distribution $\{s^g(T)\}_{g\in\{h,w\},T\in\{1,2\}}$). Moreover, the location of first job offers is drawn from an exogenous distribution $\{f_T(j)\}_{T\in\{1,2\},j\in\{c,s_A,s_B\}}$. The matching to couples is random with respect to T. However, marrying is a choice, so the share of people married is endogenous. Thus, the overall distribution of different types of households is endogenous in the model.

Definition 1 *Given fixed supplies of housing units per location $\{H_i\}_{i\in\{c,s_A,s_B\}}$, exogenous distributions of individuals to sectors $\{s^g(T)\}_{g\in\{h,w\},T\in\{1,2\}}$, and of job locations of first offers $\{f_T(j)\}_{T\in\{1,2\},j\in\{c,s_A,s_B\}}$, a housing and marriage market equilibrium is a set of* ***rents*** *per location $\{\boldsymbol{R(i)}\}_{i\in\{c,s_A,s_B\}}$ and a* ***bargaining weight $\boldsymbol{\lambda}$****, such that choices are optimal and the choice probabilities to enter the marriage market $\{\boldsymbol{p^h}\}$ are equal for men and women*

$$\boldsymbol{p^h} = \boldsymbol{p^w}$$

and the choice probabilities to live in a location $\{\boldsymbol{P^s_{j,T}(i)}\}$ and $\{\boldsymbol{P^c(i)_{(j^h,j^w),(T^h,T^w)}}\}$ and the housing demands $\{\boldsymbol{H^{s,g}_{i,j,T}}\}$ and $\{\boldsymbol{H^c_{i,(j^h,j^w),(T^h,T^w)}}\}$ are such that the housing markets clear

$$\begin{aligned}
H_i = & \sum_{g\,\in\, h,w}\ \sum_{sector\ T}\ \sum_{offer\ in\ j} N^{s,g}_{i,j,T} \cdot \boldsymbol{H^{s,g}_{i,j,T}} \\
& + \sum_{(T^h,T^w)} \sum_{(j^h,j^w)} N^c_{i,(j^h,j^w),(T^h,T^w)} \cdot \boldsymbol{H^c_{i,(j^h,j^w),(T^h,T^w)}} \\
& + \sum_{(T^h,T^w)} \sum_{(j^h,j^w)} N^c_{i,(j^h,j^w),(T^h,T^w)} \cdot \left(\sum_{(j^h_2,j^w_2)} f_{T^h}(j^h_2) f_{T^w}(j^w_2) \cdot \boldsymbol{H^c_{i,(j^h_2,j^w_2),(T^h,T^w)}} \right)
\end{aligned}$$

[36] In the baseline specification $H_c = H_{s_1} = H_{s_2}$

where

$$N^{s,g}_{i,j,T} = \left(\frac{1}{3} + (1 - \boldsymbol{p^g})\frac{2}{3}\right) \cdot s^g(T) \cdot f_T(j) \cdot \boldsymbol{P^s_{j,T}(i)}$$

$$N^c_{i,(j^h,j^w),(T^h,T^w)} = \boldsymbol{p^h}\frac{2}{3} \cdot s^h(T^h)s^w(T^w) \cdot f_{T^h}(j^h)f_{T^w}(j^w) \cdot \boldsymbol{P^c_{(j^h,j^w),(T^h,T^w)}(i)}$$

Equilibrium prices $\{R(i)\}_{i=c,s_A,s_B}$ are to be interpreted as residential rents per unit of housing in each neighborhood.[37]

3.6 Selecting parameter values

I populate the metro area with a fixed number of individuals equal to the number of housing units, half men and half women. Each location has the same number of housing units. Overall, I fit the model to match moments in the data summarizing the distribution of people and jobs within the urban space, time use of couples and singles, and residential location and commuting behavior patterns presented in section 2. These are created using several data sources as described in the empirical section: the geocoded PSID sample described above, the LODES jobs data and the 2000 Census as well as 2006-2010 ACS IPUMS samples (Ruggles et al., 2019).[38] Table 22 presents the list of targeted data moments $\bar{m}$ used in the estimation routine.

I set preferences over consumption, leisure, housing quantity and home production to have the constant relative risk aversion functional form (with $z \in \{c, l, H, x\}$ and $g \in \{s, c\}$ denoting singles or couples).

$$u_z(z) = \Omega^g_z \cdot \frac{z^{1-\omega_z}}{1-\omega_z}$$

Preferences are imposed to be the same for singles and couples, except for the value of home production and amenities ($\Omega^s_z = \Omega^c_z$ for $z \in \{c, l, H\}$). Since childcare is part of producing value at home and couples are more likely to have young children in their household (see figures 20b and 20a), it is easily imaginable that couples put a higher value on home production (i.e. that $\Omega^s_x < \Omega^c_x$). Time endowment is set to one.

Section C in the appendix describes in detail what parameters are identified by what variation in the data. The spatial structure of the metro-area and the distribution of jobs is identified from distances between two random jobs (any and within the same labor market), share of jobs and of

[37] Section B.1 in the appendix presents details on how the model is solved.

[38] Section C.1 in the appendix describes the details.

people close to city center, and distances to a random job from a place of residence. Moreover, I target average $|d_o^w - d_o^h|$, the average absolute value of the difference between potential commutes of husband and wife. This statistic determines the potential of disagreement within couples – the larger this difference in absolute value, the bigger the challenge for a couple to balance living close to opportunities for both household members. Amenities are identified to match the residential location choices of couples and singles as well as the price gradient between the city and suburbs. The distribution of match shocks ξ_0 matches labor force participation of men and women in couples. To identify the benefits (monetary and non-monetary) to working close to an sector hub I include moments from tables 5 and 6 in the estimation. Hours of work and housework in the PSID, as well as a share of income spent on housing from of Labor Statistics (2020), is used to identify preference parameters over continuous variables. σ_{θ_i} is selected to exactly match the share of men and women staying single. Bargaining weight λ is identified using the model's implied derivative of marriage rates of men versus women with respect to variation in the ratio of men and women, matching that to the equivalent variation in the data across metro-areas. Table 23 presents a complete list of parameters to be estimated.

I estimate the model with a moment based procedure.[39] There are 26 parameters and 44 moments used in estimation. A subset of the parameters α^1 is fit directly within the estimation routine to exactly match a moment condition at each iteration, using guesses of other parameters combined with moments in the data. This partition decreases the number of parameters that are estimated via a grid search, decreasing the computational burden in estimating the model. Letting $\alpha = [\alpha^1, \alpha^2]$ denote the Bx1 parameter vector, the estimation problem may be formally described as

$$[\alpha^1, \alpha^2] = \arg\min_{\alpha^2} \; [m(\alpha) - \bar{m}]^T W [m(\alpha) - \bar{m}] \tag{12}$$

$$\text{s.t. } \alpha^1 = f(\alpha^2, \bar{m}) \tag{13}$$

W is chosen based on the inverse of the variance-covariance matrix of the data[40].

[39] A small subset of the parameters is calibrated outside the estimation routine.

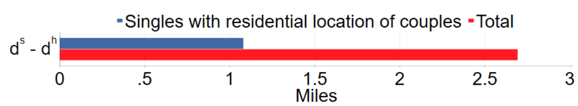
[40] For moments from different samples I set the covariance to zero. For moments within the same sample I compute the variance-covariance matrix using influence functions of individual moments, and clustering at the MSA level.

3.7 Fit of the model

Table 8 highlights that the model matches very well the commuting patterns of couples and singles, for men and women. Specifically, the large difference between the commute of husbands and single men is successfully captured by the model. This is a combination of the couples moving to suburbs (thus further away from jobs in general) and men in couple being more willing to accept long commutes, wherever they live. The move to the suburb alone accounts for over a mile of difference. This success is dependent on including a benefit of working close to home that rewards specialization. Effectively, husbands have a lower cost of commuting compared to single men, because responsibilities around the house are already covered by the wife. C.3 shows that an equivalent model without the specialization-rewarding cost of commuting fails to match the difference between single men and men in couples.

Table 8: Commuting moments data versus model

Moment	Model value	Data value
Average commute of single d^s	8.507	8.667
$\boldsymbol{d_h^s - d^h}$	**-2.698**	**-2.708**
$d_w^s - d^w$	-0.083	-0.297



d^s is the average commuting distance of singles in miles. $d_h^s - d^h$ is the difference in commuting distance between single men and men in couples. $d_w^s - d^w$ is the equivalent for women. The blue bar presents the commuting difference between single men and men in couples that is accounted for by their differences in residential location.

Couples are more likely to live in the suburbs, and suburbs have on average longer commutes. Still this alone cannot account for the difference in commuting between single men and men in couples in the model (as well as in the data). This is because distances between neighborhoods, distribution of jobs and distribution of location choices between city and suburbs of couples and singles in the model are constrained to match corresponding moments in the data. Table 9 presents these moments and their fit. The model, with only three locations, is capable of capturing the distances between jobs and people and between one random job to another, as well as the distribution of jobs and people between suburbs and city. Couples are less likely to live in the city, so they live on average further away from jobs. There are more jobs in the city than in the suburbs. There are also slightly more people in the city (living in smaller units). Moreover, within couples there is systematic potential for disagreement over which suburb to choose. Within couples $|d_o^w - d_o^h|$, the difference in the distance between a random job in the labor market of one spouse versus the other is about 2 miles. Table 22 in the appendix shows the fit on all targeted moments.

Table 9: Moments describing the spatial structure of a metro area: data versus model.

Moment	Model value	Data value
Distance to an average job for a couple (d_j^h)	20.249	20.277
Distance to an average job in own labor market for a husband (d_o^h)	20.156	20.027
Distance between 2 random jobs	15.367	17.300
Distance between 2 random jobs of the husbands labor market	14.849	16.267
Distance between husbands and wifes actual jobs	11.434	9.740
$\|d_o^w - d_o^h\|$	1.875	1.862
$P(city\|couple) - P(city\|single)$	0.094	0.070
$d_o^s - d_o^h$	-1.472	-1.693
$d_j^s - d_j^h$	-1.379	-1.410
$d_o^w - d_o^h$	0.076	0.028
Share of jobs in city	0.608	0.498
Share of population in city	0.332	0.392

Moments describing the spatial structure of a metro area, as well as commuting and location preferences. In the data, a 'city' is defined as a radius around city center of 10 miles.

Table 10 compares a key result from table 1 that is not targeted in estimation, a difference in commuting between single men and men in couples after netting out the potential commute differences d_o, between the model and the data. While the pattern is similar, the model attributes a bigger role to the move to the suburbs in the commuting gap between singles and couples. Therefore, if anything, the model likely underestimates how much specialization in commuting allows husbands to accept long commutes, beyond how far away from jobs the move. Together tables 10 and 25 provide insight into why a move to the suburb alone does not account for how much men commute more after they form a couples. Couples live about 1.5 miles further from a random job in their labor market. So even if jobs were taken entirely randomly, husbands would only commute about 1.5 miles more. However, jobs and locations are not random – people prefer shorter commutes all else equal. Thus an increase of 1.5 miles in the distance from a random job translates to only about a mile of increase in actual commuting distance. The rest has to be accounted for by a change in behavior towards jobs. In other words, the difference between couples and singles in the share of households living in the suburbs is too small to explain this margin.

Table 10: Difference in commuting between husbands and single men, controlling for d_o: data (as in table 1) versus model equivalent.

	Commuting distance (miles) men	
	Data	Model
In couple	**2.525**	**1.641**
	(.638)	
d^o	.331	.788
	(.098)	
N	23243	

Available in 1975-1976, 1978-1986; plus in 1969-1974, 1977 for heads of households only. Sample of only those in a couple, or those that have never been observed in one, but eventually they will be.

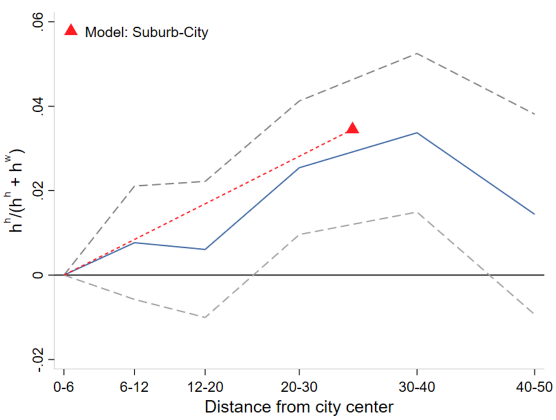
All regressions include year, age, MSA, education, race, cohort controls. *SEs* statistics in parentheses. SEs clustered at the MSA level.

The estimation routine also does not target any differences in labor market outcomes within couples based on whether they live in the city or the suburbs, similar to the behavior presented in figure 1d. Here I present the fit on these non-targeted moments. As in figure 1d, in the data I regress a gender gap measure in a couple on binned distance from city center in a metro area, controlling for dummies for demographic characteristics of the couples. I compare the estimated differences $\alpha^{\text{dist bin } j}$ in gender gaps between those living close to city center and those living further away to the difference between city and suburbs in the model (which in the model presents a distance of over 20 miles). Figure 10 visualizes the comparison between the data and the model, for share of market hours $\frac{h^h}{h^h+h^w}_{t,i}$, share of housework hours $\frac{x^h}{x^h+x^w}_{t,i}$ and difference in commuting distance

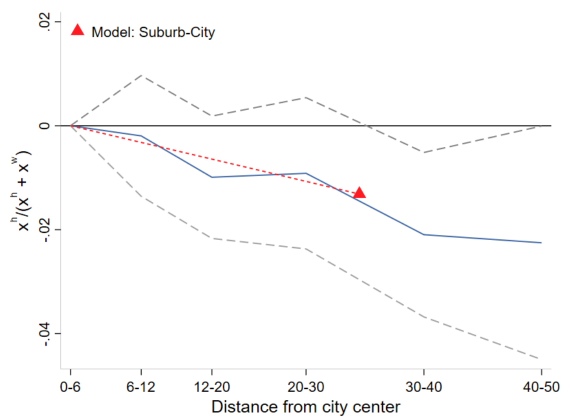
$(d^h - d^w)_{t,i}$. Overall, the model is successful in capturing how much gender gaps are larger in the suburbs.

Figure 10: Gender gaps within couples by distance of residential location from city center: data vs model

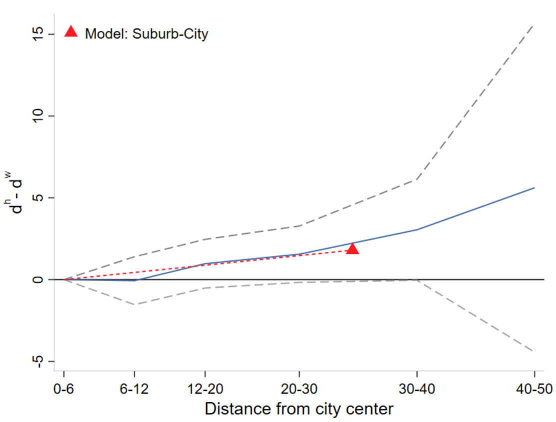
(a) Share of market hours $\frac{h^h}{h^h+h^w}_{t,i}$



(b) Share of housework hours $\frac{x^h}{x^h+x^w}_{t,i}$



(c) Difference in commuting distance $(d^h - d^w)_{t,i}$



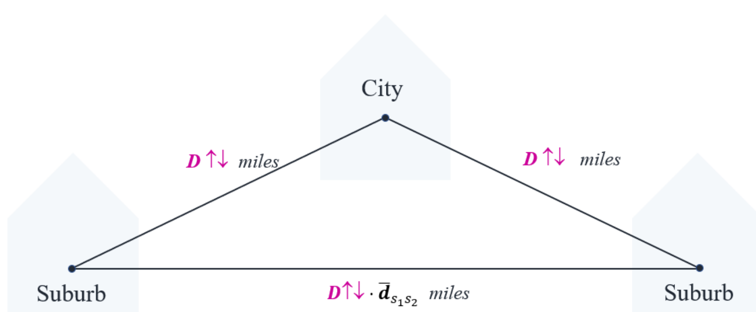
As in figure 1d, I regress a gender gap measure in a couple on binned distance from city center in a metro area, controlling for dummies for age and education of both spouses, race of the head and number of children. $\frac{h^h}{h^h+h^w}_{t,i} = \sum_{j=2}^{N} \alpha_i^{\text{dist bin } j} + \alpha_i^{ah} + \alpha_i^{aw} + \alpha_i^{educh} + \alpha_i^{educw} + \alpha_t + \alpha_i^{raceh} + \alpha_i^{\#children} + \epsilon_{i,t}$

4 Commuting and the value of marriage

I perform counter-factual simulations, changing the spatial characteristics of the metro-area towards more or less commuting. I study the effect on welfare of men and women and singles and couples, asking for whom commuting is ultimately most costly in a combined housing and marriage market equilibrium. All comparisons are between different steady states, alternative scenarios where the metro area would develop differently. I measure welfare for each subgroup (single and married men and women) as period utility averaged over the respective population: $W = \int_i u^*(i)$. Moreover, I show how gender gaps within couples, residential rents and sorting changes.

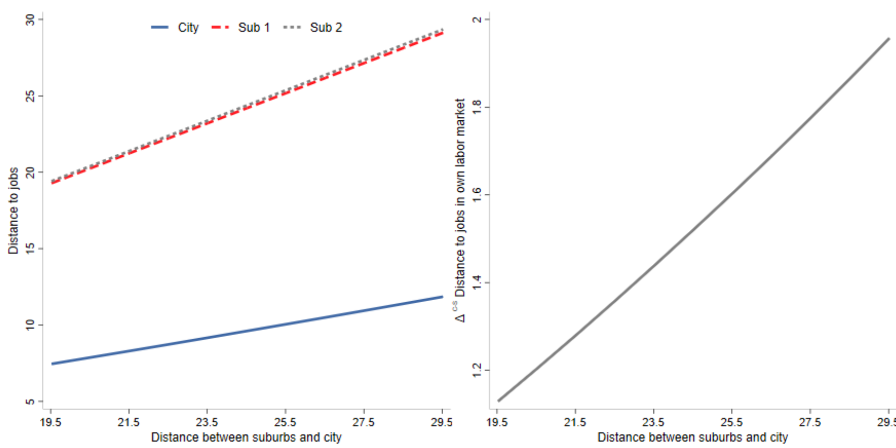
The main experiment mimics a comparison of metro-areas that differ in how long is the commute between suburbs and the city. Specifically, I re-solve the model with different values of $D = D(1,2) = D(1,3)$ (implying $D(2,3) = D \cdot \frac{\bar{D}(2,3)}{\bar{D}(1,3)}$), keeping all the other parameters the same. This means that the metro area is sprawled in space, without any change in amenities or productivity (materialized as wages or non-monetary benefits) at work. Figure 11 summarizes this counter-factual. Lower values of F represent metro-areas with a shorter average distance from suburbs to the center. As such, this counter-factual also mimics a policy intervention that makes suburbs more or less accessible, for example, by dis-investing in public transit.

Figure 11: Connectivity between suburbs and the city



Overall, this is a negative technology shock to the metro-area. Everybody is hurt by it. However, not everybody is affected the same way. Figure 12 presents the first set of results – on the horizontal access is the respective distance between suburbs and city D, with the middle point representing the baseline value. The first figure shows that the distance from a residential location to a random job increases more in the suburbs than in the city. This is both because the city is positioned in the center, and because more jobs are offered in the city. Because couples are more likely to flock to the suburbs, their job access deteriorates more compared to singles. This suggests that without any adjustment to behavior and prices within the housing and marriage market equilibrium, couples are most affected by long commutes.

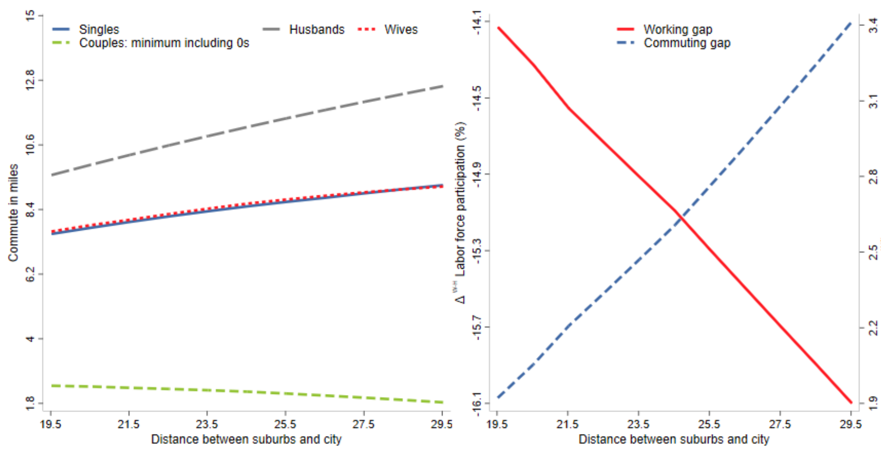
Figure 12: Job access when metro area grows in space



Counter-factual simulations of the model, varying the distances between neighborhoods while keeping the shape of the metro-area fixed. Distance to a random job by location. Distance to a random job: difference between singles and couples

However, jobs are not taken randomly with respect to residential location. Households hustle to make their commutes short – by moving close to jobs and taking jobs close to home. Moreover, couples specialize with one (more often the wife) taking a local job or drops out of the labor force while the other accepts long commutes. Because commuting is in part costly on the household level through only the shortest commute within household, couples are rewarded for their specialization. Figure 13 shows that husband's commutes increases the most. They are the ones living far away from jobs and accepting offers with long commutes. This suggests that husbands are the most affected by long commutes. Wives and singles also increase their commuting, but less. The second figure shows that indeed within couples gender gaps increase, both in labor force participation and in commuting. Overall, women in couples are most sensitive in their labor market outcomes to long commutes. Figure 13 also shows how gender gaps help couples evade part of the commuting

Figure 13: Commuting and gender gaps when metro area grows in space



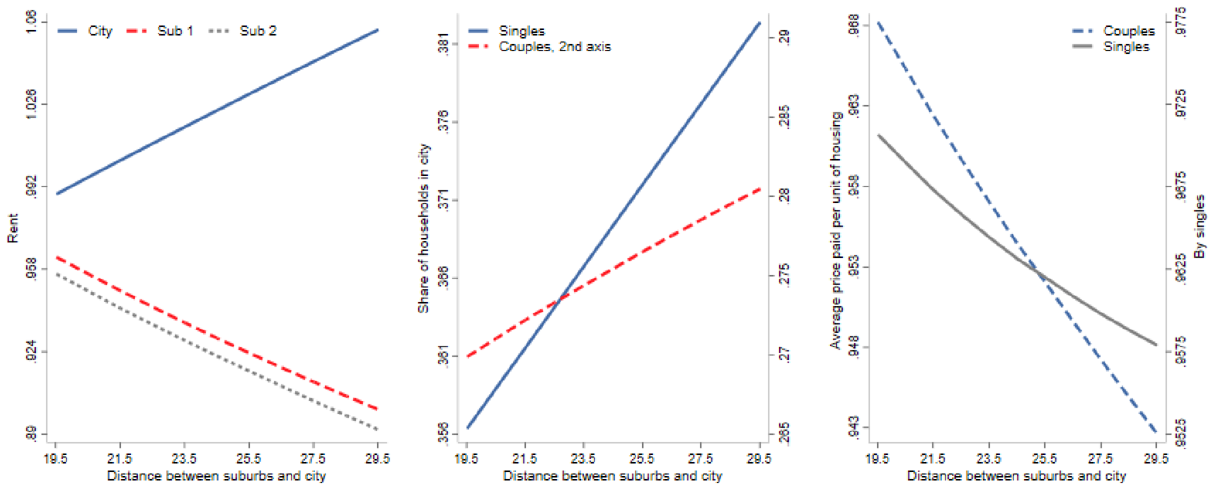
Commuting of all subgroups. Gender gaps within couples.

costs. Even though all groups of people commute more on average, within couples at least one is still often close by (assigning 0 commute to those who drop out of the labor force). The minimum of the commuting distance within households increases only marginally for couples.

On top of the endogenous responses in labor market behavior and specialization within households, the housing market is affected by long commutes from suburbs to the city. Figure 14 presents the results. Housing rents increase in the city, but fall in the suburbs. All households try to flock to the city, however singles are more motivated than couples, because they cannot evade commuting costs through specialization. The spatial segregation of couples and singles within metro area increases. As a result, singles are now forced to overpay more for housing. Overall, housing prices fall, because households have on average less time to work and thus less income to spend.

So who looses the most from long commutes? Husbands commute the most and their commuting increases more. Wives are most affected in terms of their labor market outcomes. However, it turns out it is singles who lose the most when commuting from the suburbs to the city is longer. Both husbands and wives change their behavior more, but in the end they benefit from evading commuting costs through specialization within the household, as housing prices adjust in the housing equilibrium and distribution of resources within the couple adjusts in the marriage market equilibrium. Figure 15 presents this result. While welfare falls for everybody, singles lose the most.

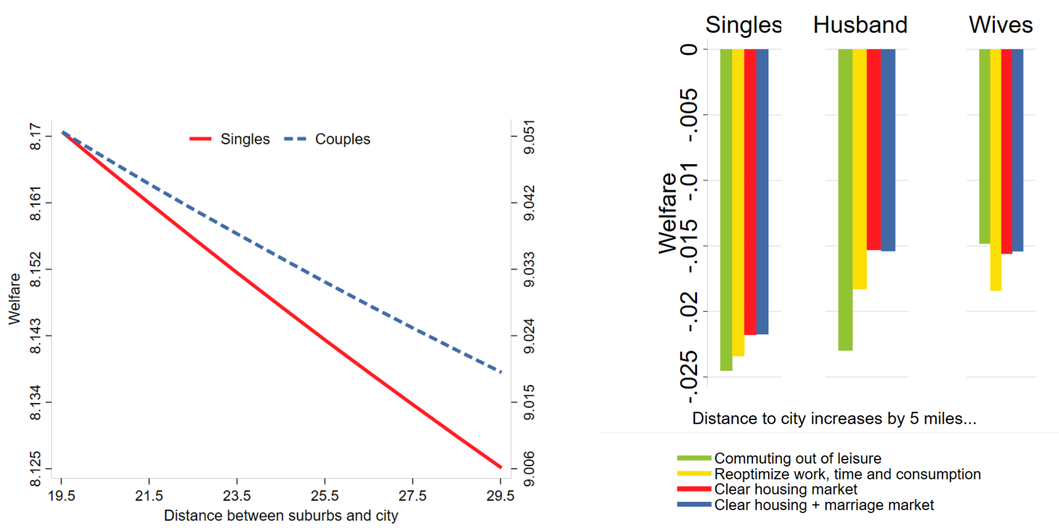
Figure 14: Housing when metro area grows in space



Housing rents, sorting and housing costs of couples and singles.

The role of the joint housing and marriage market equilibrium is pivotal in delivering this result. Figure 15 present the decline in welfare for singles, husbands and wives when the distance between suburb and cities increases by 5 miles. Overall, welfare falls. The green bar shows the welfare effect when longer commutes simply subtract from leisure, without re-solving the housing and marriage market equilibrium. In this case, husbands loose the most, precisely because they are the ones who are locked into the longest commutes. However, the yellow bars show that when households re-optimize but the housing and marriage market does not re-clear, it is the wives who lose the most. This is precisely because they change their labor market behavior the most, dropping out of jobs they liked into worse local jobs or out of the labor force altogether, to diminish the burden of commuting costs on couples. The red bars shows the effect on welfare when the housing market re-clears. This helps couples (both husbands and wives), because they can now enjoy cheaper prices in the suburbs. The blue bars show the final result within a full housing and marriage market equilibrium. Figure 16 presents explicitly the effect of longer distances between suburbs and city on the value of marriage, with limited endogenous responses and in the new full marriage and housing market equilibrium. The value of marriage increases for both men and women. Husbands keep

Figure 15: Welfare when metro area grows in space



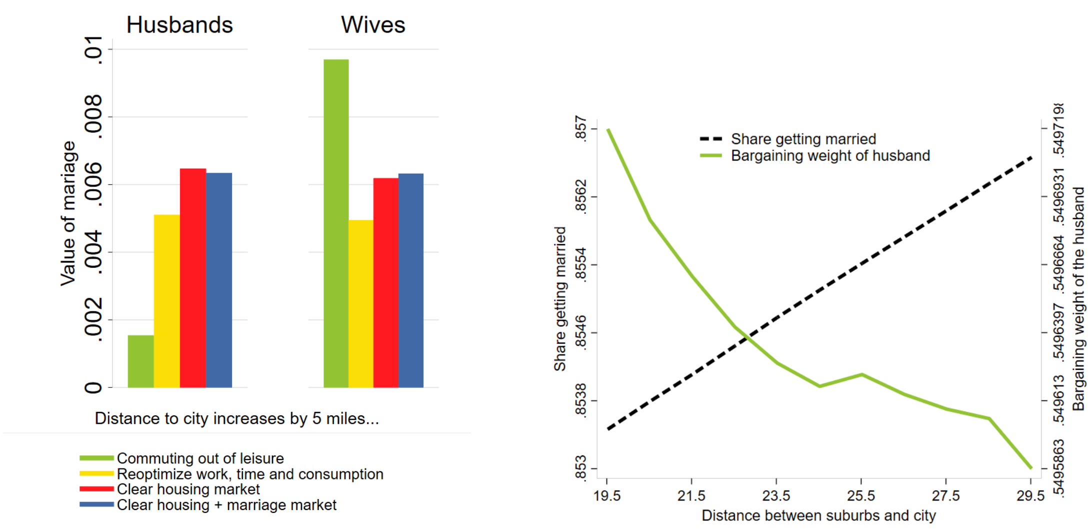
Change in welfare for singles, husbands and wives between the baseline metro area, and a sprawled metro area. The second figure presents a decomposition of the drop in welfare when the suburbs are 5 miles further away from the city, depending on which parts of the model are re-solved.

their long commutes, wives take local jobs or stay at home, but are ultimately compensated with more leisure and consumption within the household. This way couples evade part of the commuting costs, directly and through lower housing prices. Figure 16 shows that the share of people marrying increases, while the bargaining weight of husbands falls.

Figure 17 shows how the distribution of resources within couples is reorganized. The first figure shows that when metro-areas have long commutes, wives gain both leisure and consumption compared to husbands, but loose more on non-monetary benefits from work. Figures 2 and 3 decompose the change in the value of marriage accounted for by different sources of welfare. For both men and women, marriage becomes more valuable partially through home production and the lesser impact on the household value of somebody working close to home. Moreover for husbands, the value of marriage increases most through better jobs that they enjoy more. On the other hand, wives take worse jobs, but their marriage is more valuable for them through more leisure and consumption.

To summarize, the counter-factual simulation shows that if metro-areas spread out and the

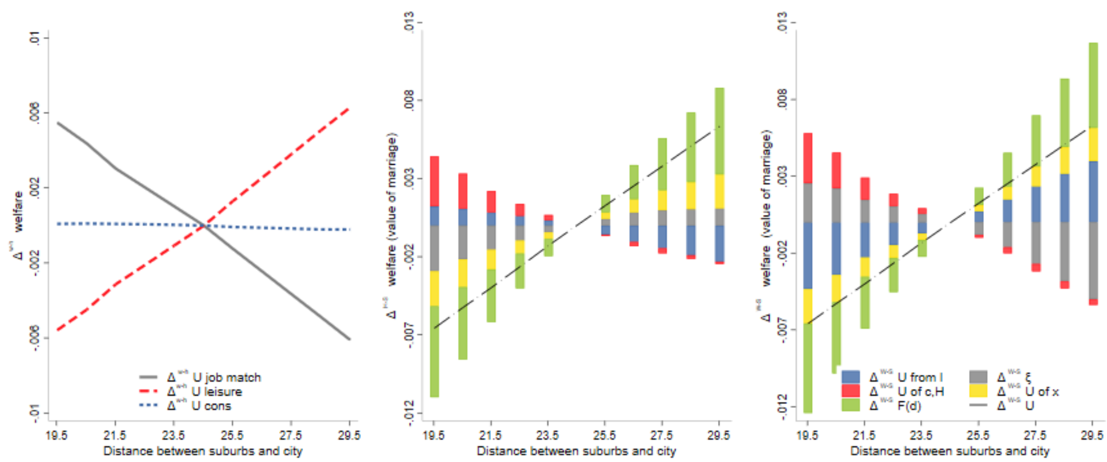
Figure 16: Value of marriage when metro area grows in space



Change in welfare and the value of marriage between the baseline metro area, and a sprawled metro area where the suburbs are 5 miles further away from the city. Value of marriage is defined as the difference in period welfare between a single and a person in a couple $\Delta^{h-s}W$ and $\Delta^{w-s}W$. New marriage market equilibrium: share of people getting married and bargaining weight of husbands, the price in the marriage market.

housing and marriage market re-clears, marriage becomes more valuable for both men and women. This is facilitated through larger gender gaps in the labor market and cheaper housing in the suburbs. While longer potential commutes are costly to all, single people have the most to lose.

Figure 17: Welfare effects decomposed into elements of utility



Decomposing the husband-wife welfare gap: effect of consumption, leisure and non-monetary benefits from work. Decomposing the change in the value of marriage: accounted for by leisure, consumption, household value of having somebody work close to home, non-monetary benefits from work and home production.

5 Testing model predictions with cross metro-area correlations

In this section I provide further validation for the model, by comparing the counterfactual simulations with variation across U.S. metro areas. First I replicate results by Black et al. (2014) showing that metro areas with longer commutes have larger differences in labor force participation between men and women in couples. Using the 2000 IPUMS Census sample I run the following regression

$$Working_{im} = \beta C_m \cdot (\text{woman}) + \gamma X_i + \delta X_m + \epsilon_{i,m}$$

where i stands for an individual, m for a metro are and C_m is the average annualized hours of commuting in a metro m and the sample is restricted to people in couples. β is the coefficient of interest - it shows the differential impact of living in a place of long-commutes on men and women.

Table 11a, shows the results. In metro-areas with 16.5 more average hours of commuting per year (roughly corresponding to 1 mile) the gender gap in labor-force participation in couples is

	Working	Commute (annualized)
$C_m\cdot$ (woman)	-0.0552 (0.0101)	-0.239 (0.0379)
C	x	x
$C\cdot$ *(age, race, educ)*	x	x
1-digit industry		x
Sample :	couples	couples

SEs in parentheses, clustered at the MSA level.

All regressions include age, education, region, race dummies and MSA size polynomial.

(a) Source: IPUMS 2000 Census 5% sample. Sample: 18-50 years old, married or cohabiting, MSAs of at least 250k people. "Working" is equal to one if the person worked at least for 1 week in the past year and is scaled up by 100 so that results are interpreted as percentage point changes. Industry dummies are for 1-digit NAICS codes. D_m is the average of annualized commuting hours for all residents of the MSA that do not work from home.

Commute	Working
-0.726	-0.0582

Implied by the D counter-factual.

(b) Model simulations

higher by almost a whole percentage point.

Next, I repeat the exercise with commuting itself on the left hand side (and using a sample of working individuals).

$$d_i = \beta_c C_m \cdot (\text{in couples}) + \gamma X_i + \delta X_m + \epsilon_{i,m}$$

The results show that in metro-areas with longer average commutes the difference between the time spent commuting of wives and husbands increases. When the average commute in a metro-area increases by an hour, husbands commute increases by an average of 0.24 hours more than that of wives. Qualitatively, this is exactly what happens in the model. Quantitatively, counter-factual exercises above imply a somewhat bigger effect - an increase of 0.58 hours.

Next I test the model prediction that larger average commutes are actually conducive of couple formation, by making single life disproportionately costly compared to being in a couple and being able to specialize. I focus on the sub-population of 30-50 years of age, responding to the

	(Ever married or cohabiting)·100			
C	.00465 (.0097)	.0158 (.0048)		
$C_{husbands}$			.0114 (.0067)	.0134 (.0031)
Politics and church-affiliation proxies		x		x
Sample:	$30 \leq$ age ≤ 50			

SEs in parentheses, clustered at the MSA level.

All regressions include age, education, region, race dummies and MSA size polynomial.

(a) Source: IPUMS 2000 Census 5% sample. Sample: 30-50 years old, MSAs of at least 250k people. The outcome variable is equal to one if the person is married, divorced, separated, widowed or currently cohabiting. Columns 3 and 4 replace C_m with an average commute in an MSA among married men.

	(Ever married)·100	
C	0.00955	
$C_{husbands}$		0.00643

Implied by the D counter-factual.

(b) Model simulations.

population in the model that is either in a couple or perpetually single. Using the 2000 IPUMS Census samples I run the following regression

$$\text{Ever in couple}_{im} = \gamma C_m + \gamma X_i + \delta X_m + \epsilon_{i,m}, \;\; \forall i : \text{age}_i \geq 30$$

Ever in couple$_{im}$ is a dummy variable equal to 1 if the person has ever been married or is currently cohabiting with a partner. C_m, again, is the average annualized hours of commuting in a metro are m. Table 27 shows that, at least when metro-area-level controls X_m include religious participation and proxies for political affiliation, the estimate of $\gamma > 0$. Therefore, across metro areas those with a longer average commute tend to have fewer people staying perpetually single. This correlation in the data could be caused by a selection effect - metro-areas with more couples have higher average commutes because it is the married men who commute most. Columns 3 and 4 in table 27 shows the result is robust to replacing C_m with the average commute among only married men, avoiding this type of selection.

Table 12b again compares the cross-metro area correlations to the change in marriage rates implied by the increase in distances between neighborhoods in the model. As in the data, simulated metropolitan areas with longer average commutes have a higher share of the population eventually marrying.

6 Conclusion

In this paper I show that longer potential commutes make marriages more valuable by making living alone relatively more costly. First, using the geolocated PSID I identify patterns in the data that suggest that commuting plays a role in specialization within couples. I show that there is a large and robust difference in commuting between single men and men in couples beyond what can be accounted for by couples moving to the suburbs. This wide margin cannot be easily explained with usual approaches to modeling the costs of commuting or gender gaps in other labor market outcomes within couples. I argue that this failure of standard models to match this observation in the data reveals that there is likely an aspect to commuting costs that rewards specialization on this margin within a household.

I propose a simple functional form that captures this intuition and when added to a standard labor supply model is capable of matching the large gap in commuting between men in couples and single men, as well as other salient features of the data. I embed this behavior in a quantitative spatial equilibrium model of a metro-area, contributing to the urban economics literature by seriously distinguishing between the incentives of couples and singles in this setting. Moreover, I overlay the spatial equilibrium structure with a simple marriage market clearing, endogenizing both the share of individuals choosing marriage and the distribution of resources between a husband and a wife.

I show how increasing potential commutes, through lower connectivity between neighborhoods or suburban sprawl, affects behavior and welfare of singles and couples. Couples live more in the suburbs, and they face a collocation problem – a residential location with a short commute for one spouse can be very inconvenient for the other. Therefore, their potential commutes are more affected by poor transit or sprawling development. Despite these challenges it is actually singles that lose the most when potential commutes increase. While couples can specialize in who stays home or works close by, singles bear the whole cost of commuting alone. While long potential commutes make marriages more valuable, they also increase the gap in labor market outcomes between married men and women. Lastly, suburban sprawl increases the price differential between city and suburb, again making singlehood costly by making housing that singles prefer less affordable.

As metro-areas grow in size while jobs concentrate in cities, average commutes increase. I argue that there is an aspect of commuting costs that creates a wedge between singles and couples. In section D in the appendix I discuss two additional implications of this result. Recently, the

COVID pandemic reinvigorated the discussion about the benefits of allowing employees to work from home. The results in this paper imply that while women in couples are most likely to be motivated to enter the labor force when more work from home options are available, it is singles who would benefit the most in terms of welfare. Second, in this model as in the data singles are more likely to live in the city, both because they value suburban amenities less and because they appreciate short commutes more. In recent decades we have seen a marked decline in the share of population getting married, especially through increasing the age at first marriage. I show that a natural implication of a decline in marriage is gentrification – a steepening of the distance price gradient in metropolitan areas. Both of these observations touch on timely topics in labor and housing economics and would be a fruitful direction of future research.

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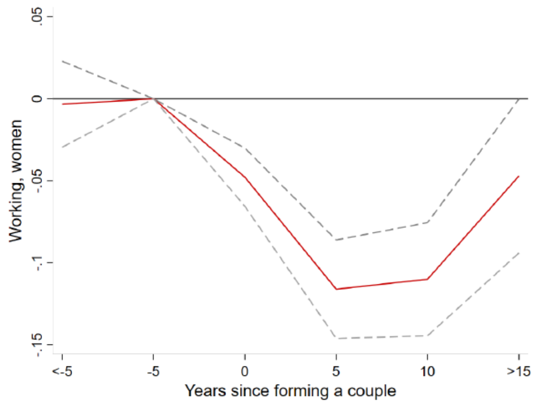
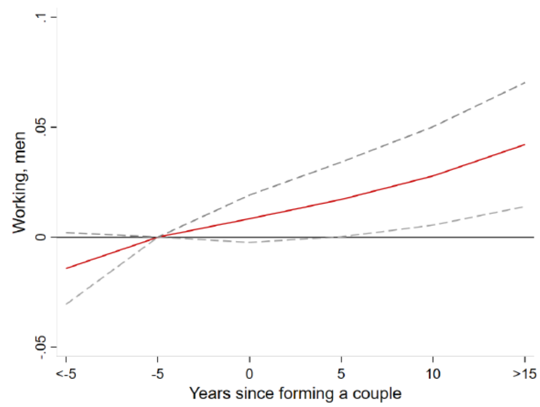
A Supplement to empirical observations



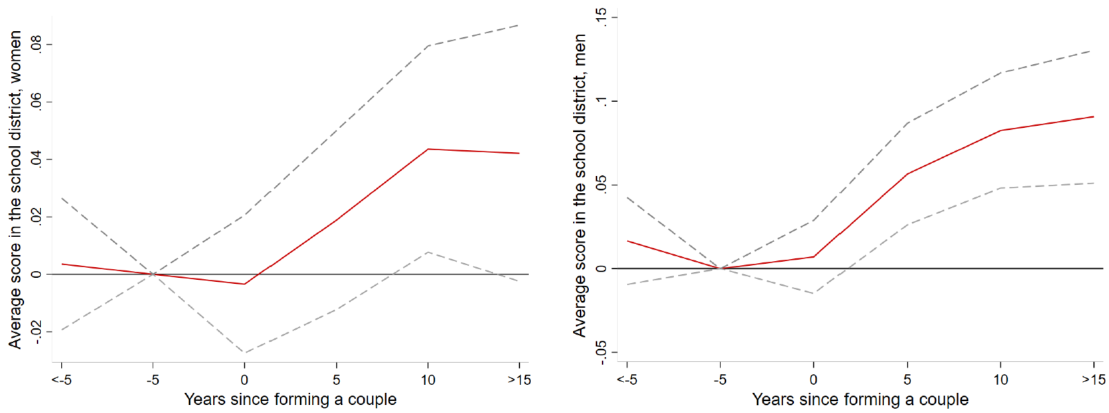
(a) women



(b) men

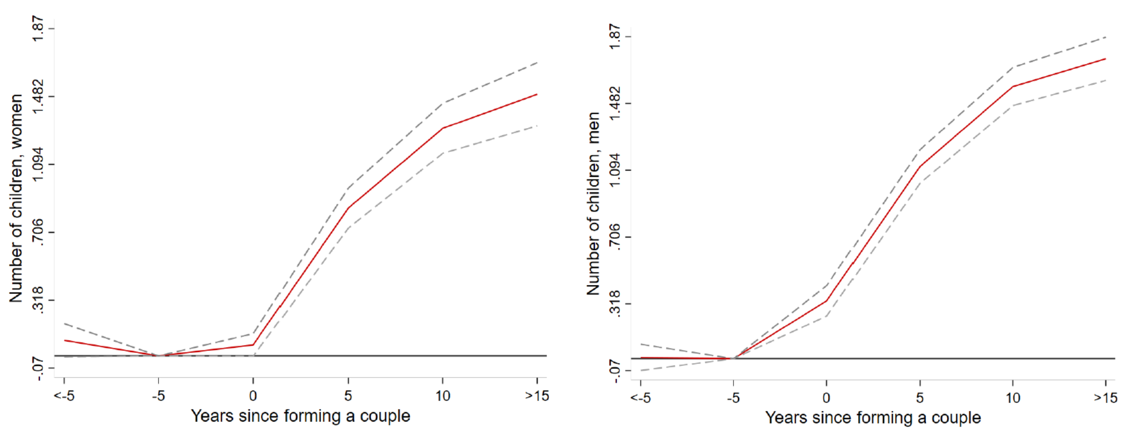
Figure 18: Source: PSID

I hypothesize that an amenity which is more valued by couples than singles can be the quality of schools. As a proxy, I use the averaged standardized test scores in the public school district of residence administered in 3rd through 8th grade in mathematics and reading, language and arts over 2008-2018 school years, normalized to be comparable nationally and to the middle grade of the data as provided by the Education Opportunity Project (Reardon et al., 2021). The lifecycle evolution of this proxy measure with respect to tenure in a couple (controlling for year and age dummies) is plotted in 19a and 19b.



(a) women (b) men

Figure 19: Analogous regressions for figures 3a and 3b. With distance to center d^c replaced with averaged standardized test scores in the public school district of residence averaged over 2008-2018 (only cross-sectional variation in test scores used).



(a) women (b) men

Figure 20: Analogous regressions for figures 3a and 3b. With distance to center d^c replaced with the number of children in the household.

PSID summary statistic	since 1969	since 1990
Age	33	33
Man	49%	50%
2010 Population size of metro-area	4679k	4524k
Having children in the household	62%	58%
Number of children (including zeros)	1.2	1.1
Commuting distance in miles	10.6	
Annual commuting time in hours	173	
Standard deviation of commuting distance in miles	11.3	
Usual annualized commuting time in hours		183
Distance to current job		9
Distance to center in miles	14.7	15.5
'Distance to opportunity'	12.11	12.18
Distance to an average job	12.2	12.3
Share living less than 10 miles from the center	44%	41%
In couple	68%	66%
Tenure in a couple (including negative values for singlehood)	7.8	7.7
Share of men in couples working	98%	97%
Share of women in couples working	76%	82%
Annual hours of work of men in couples (including 0s)	2202	2224
Annual hours of work of women in couples (including 0s)	1201	1415
Annual hours of work of men in couples (when both work)	2249	2293
Annual hours of work of women in couples (when both work)	1578	1724

Table 13: PSID sample summary statistics. Age restrictions 18-50. Geographic restriction: in a metro area of at least 250 thousand residents per the 2010 Census. Moreover, for each individual I select their most common metro area over their observed lifetime in the PSID and exclude periods when this individual did not live in this MSA, so that all location changes are within the same area. Lastly, I only use single people who have not been in a couple before and couples for whom this is their first match, as far as it can be determined in PSID. Metro-area assigned as the most frequent metro area within the sample. Row "Tenure in a couple (including negative values for singlehood)" present the sample mean of $\mathrm{Y} - \mathrm{Y}_{\text{first observed in a couple, or first year of marriage for original sample couples}}$.

Variable	waves
Distance city center	1969-
Commuting distance	1970-1986 with gaps[41]
Commuting time annual	1970-1986 with gaps[42]
Commuting time usual	2011-2017
Distance to a job	2013-2017
Distance to an average job	1990-2017 (1990-2000 backfilled)
Distance to an average job in ind & seg	1990-2017 (1990-2000 backfilled)

	Commuting distance (miles)									
	Men					Women				
In couple	1.079	1.095	.964	1.041	.964	-.050	-.100	-.067	.036	-.224
	(.649)	(.616)	(.632)	(.592)	(.620)	(.731)	(.711)	(.719)	(.739)	(.726)
d_o		.469					.322			
		(.071)					(.068)			
d_c			.365					.309		
			(0.047)					(.058)		
d_o *bins**				x					x	
d_c *bins**					x					x
N	24905	23784	24905	23784	24905	16291	15868	16291	15868	16291
N clusters	154	152	154	152	154	146	144	146	144	146

SEs statistics in parentheses. SEs clustered at the MSA level.

All regressions include year, age and person fixed effects.

* Includes dummies for d_x in intervals of 0-6, 6-12, 12-20, 20-30, 30-40 and over 40 miles.

Table 14

	Commuting time (annual)									
	Men					Women				
In couple	18.781	19.417	16.588	18.802	6.010	5.092	5.782	5.677	5.782	5.134
	(7.9409)	(7.628)	(7.713)	(7.532)	(7.471)	(8.307)	(9.139)	(8.837)	(9.139)	(8.980)
d_o		4.593					2.355			
		(.898)					(.806)			
d_c			3.879					2.309		
			(0.489)					(.623)		
d_o *bins**				x					x	
d_c *bins**					x					x
N	24924	23612	24924	23612	24924	17232	16798	17232	16798	17232
N clusters	154	152	154	152	154	146	143	146	143	146

SEs statistics in parentheses. SEs clustered at the MSA level.

All regressions include year, age and person fixed effects.

* Includes dummies for d_x in intervals of 0-6, 6-12, 12-20, 20-30, 30-40 and over 40 miles.

Table 15

	Commuting time (typical, annualized)		Distance to work (tract to tract)	
In couple	-7.600	-10.443	-.252	-.891
	(6.383)	(6.022)	(.420)	(.341)
Man in couple	24.197	23.536	2.630	2.303
	(10.582)	(10.703)	(.728)	(.703)
Man	15.550	16.464	-.773	-.403
	(8.791)	(8.781)	(.563)	(.562)
X_i:				
Education, race, cohort	x	x	x	x
Distance to center		x		x
N	25078			
N clusters	145			
N observed in both				

t statistics in parentheses. SEs clustered at the MSA level.

All regressions include year, age, MSA fixed effects.

Table 16: $d_{it} = \beta \cdot \text{In couple}_{it} + \beta_{wc} \cdot \text{Man in couple}_{it} + \beta_w \cdot \text{Man}_i + \alpha_t + \alpha_a + \alpha_{msa} + X_i + \epsilon_{it}$

	Commuting distance (miles)	
	men	women
Singles (mean)	8.900	8.495
In couple	**2.525**	.281
	(.638)	(.432)
d^o	.331	.186
	(.098)	(.043)
N	23243	13238

Available in 1975-1976, 1978-1986; plus in 1969-1974, 1977 for heads of households only. Sample of only those in a couple, or those that have never been observed in one, but eventually they will be.

All regressions include year, age, MSA, education, race, cohort controls.*SEs* statistics in parentheses. SEs clustered at the MSA level.

Table 17: Commuting differences by relationship status. Separately by gender. As in 1, including d_o as a control.

	Commuting distance (miles)	
	men	women
In couple	**2.138**	.682
	(.684)	(.653)
children	.969	-1.284
	(.412)	(.394)
N	23243	13238

Available in 1975-1976, 1978-1986; plus in 1969-1974, 1977 for heads of households only. Sample of only those in a couple, or those that have never been observed in one, but eventually they will be.

All regressions include year, age, MSA, education, race, cohort controls.*SEs* statistics in parentheses. SEs clustered at the MSA level.

Table 18: Commuting differences by relationship status. Separately by gender. As in 1, including a dummy for having a child under 18 in the household.

	Commuting distance (miles)			
	men		women	
In couple	**2.392**	**2.691**	.422	.564
	(.687)	(1.248)	(.673)	(1.529)
N	22073	2216	11963	1667
Eventually observed with children	1	0	1	0

Available in 1975-1976, 1978-1986; plus in 1969-1974, 1977 for heads of households only. Sample of only those in a couple, or those that have never been observed in one, but eventually they will be.

All regressions include year, age, MSA, education, race, cohort controls.*SEs* statistics in parentheses. SEs clustered at the MSA level.

Table 19: Commuting differences by relationship status. Separately by gender. As in 1, separately by whether a person ever ends up in a couple living with a child under 18 in their household.

	Hours				
Distance	3.675	5.101	-5.525	-7.118	-4.109
to jobs (d^{opp})	(1.102)	(1.688)	(1.155)	(1.160)	(1.686)
$d^{opp}\cdot$ Woman	-2.990	-3.532	-0.976	-0.643	-3.302
	(1.442)	(1.589)	(0.467)	(0.269)	(1.816)
Woman	-513.876	-536.349	-344.054	-349.910	-323.452
	(7.602)	(7.673)	(5.896)	(5.284)	(5.284)
Sample:					
Waves when commuting variable is available	miles	annual hours	annualized hours	distance to work	
					year $\geq$ 2000
X_i:					
'Labor market' fes	x	x	x	x	x
Couple fes	x	x	x	x	x
N	33300	35838	11586	8488	27378
N clusters	150	150	160	158	171

t statistics in parentheses. SEs clustered at the MSA level.

All regressions include year, age, MSA fixed effects.

Table 20

	Commute (annualized)				
Man	-2.705			29.41	-3.946
	(.874)			(1.798)	(0.863)
In couple	-11.68	17.99	-8.157		
	(2.111)	(1.201)	(2.235)		
Man in couple	31.92				
	(2.208)				
Industry 1-digit NAICS dummies.	x	x	x	x	x
Sample:		men	women	couples	singles
N	2286363	1245988	1040375	1565336	721027

SEs statistics in parentheses, clustered at MSA level.

All samples include only people who are married or never married.

All regressions include age, MSA, education, race, cohort controls.

Table 21: Source: IPUMS 2000 Census 5% sample. Sample: 18-50 years old, married or never married, MSAs of at least 250k people. "In couple" includes married and cohabitation. Industry dummies are for 1-digit NAICS codes.

B Model supplements

B.1 Model solution

For each location of job (determining distance and job match) and rent R, solutions of consumption, time use and housing demand are as follows:

Consumption and housing quantity demand as a function of the budget multiplier and rent for all households can be solved in closed form. For singles:

$$H^s(\mu) = \Big(\frac{\Omega_H}{R \cdot \mu}\Big)^{1/\omega_h}$$

$$c^s(\mu) = \Big(\frac{\Omega_c^S}{\mu}\Big)^{1/\omega_c}$$

With income as a function of labor supply $Y(h^s) = h^s \cdot w$.

For couples:

$$H(\mu) = 2^{1-1/\omega_H}\Big(\frac{\Omega_H}{R \cdot \mu}\Big)^{1/\omega_h}$$

$$c^h(\mu) = \Big(\frac{\lambda \Omega_c^C}{\mu}\Big)^{1/\omega_c}$$

$$c^w(\mu) = \Big(\frac{(1-\lambda)\Omega_c^C}{\mu}\Big)^{1/\omega_c}$$

With income as a function of labor supplies $Y(h^h, h^w) = h^h \cdot w^h + h^w \cdot w^w$.

Leisure can be expressed as a function of home production times:

$$l^s(x^s) = \Big(\frac{1}{\Omega_x^S (x^s)^{-\omega_x}}\Big)^{1/\omega_l}$$

$$l^h(x^h, x^w) = \Big(\frac{\lambda}{\Omega_x^C (P(x^h, x^w))^{(\eta_x - \omega_x)} (x^h)^{-\eta_x}}\Big)^{1/\omega_l}$$

with wife's leisure derived equivalently. Consequently, labor supply as a function of home production time:

$$h^s(x^s) = 1 - l^g(x^s) - x^s - b \cdot d(i, j^s)$$

$$h^g(x^h, x^w) = 1 - l^g(x^h, x^w) - x^g - b \cdot d(i, j^g)$$

Budget constraint multiplier and home production times (the leftover free variables) solve a system of equations (again for each job location and rent). For singles:

$$Y(h^s(x^s)) = c^s(\mu) + H^s(\mu)$$

$$0 = \frac{1}{l^s(x^s)^{\omega_l}} - \mu \frac{\partial Y(h^s(x^s)) + \xi(h^s(x^s))}{\partial h^s}$$

For couples where both work:

$$Y(h^h(x^h, x^w), h^w(x^h, x^w)) = c^h(\mu) + c^w(\mu) + H^c(\mu)$$
$$0 = \frac{\lambda}{l^h(x^h, x^w)^{\omega_l}} - \mu \frac{\partial Y(h^h(x^h, x^w)) + \xi(h^h(x^h, x^w))}{\partial h^h}$$
$$0 = \frac{\lambda}{l^w(x^h, x^w)^{\omega_l}} - \mu \frac{\partial Y(h^w(x^h, x^w)) + \xi(h^w(x^h, x^w))}{\partial h^w}$$

When one in a couple dos not work, an equation equalizing the marginal benefit of an hour of work to the marginal utility of leisure is replaced with a leisure equation:

$$0 = -l^h(x^h, x^w) + 1 - x^g - b \cdot d(i, j^g)$$

With solutions for each continuous variable, consumption, housing quantity, labor supply and home production hours for each location of residence, locations of work and labor force participation decision combination (and given match shocks ξ), I construct the respective values of discrete choices (participation, job acceptance and location). A single person always works, because their utility approaches infinity at 0 consumption. However, each single person given a choices also decides between taking an offered job in location j (with distance $d(i, j)$) and a local job (with distance $d(i, i)$). The match shock ξ has a stochastic component drawn from a uniform distribution and a deterministic component that is dependent on j and is lower if j is far away from other jobs in the individual's sector.

For tractability, decisions on what job to take are made sequentially, as match shocks are revealed one at a time. First the local shock $\xi(i)$ is revealed and a decision is made on whether to take it or not (before knowing $\xi(j)$), calculating the expected value of working in j. Than the offered location shock $\xi(j)$ is revealed.[43]. Therefore, each single person chooses a job location by comparing $U^s(i, i, \xi)$ with $E(U^s(i, j, \xi))$. Before match shocks are revealed (when the residential location choice is made) the probability that a single person with an offer in j living in i works in j is given by $P'_j = \pi + P_j$, where $P_j = P(E(U^s(i, j, \xi_j))) > U^s(i, i, \xi_i))$, and is solved for in closed form. A value for a single person with a j offer in hand for each residential location:

$$V^s(i) + \epsilon_i | t, j$$

[43]This is done to keep matters tractable within couples, avoiding four shocks being realized at once. For singles, the order is without loss of generality, if both shocks come from uniform distributions with the same variance.

where

$$V^s(i) = \pi E(U^s(i,j,\xi_j)) + \\ (1-\pi)\{P_j E(U^s(i,j,\xi_j))) + (1-P_j)E(U^s(i,i,\xi_i) \mid \text{choose j over i})\}$$

In couples, the choices of working or not, and where to work for both, creates nine distinct options. Not working is a non-stochastic option. Match shocks for local jobs are realized first and decisions are made on whether to accept them. Second, the match shocks for offered jobs are realized and those without a job decide on whether to take their offer or drop out of the labor force. Given all four shocks are uniformly distributed, the probability of the nine combinations of work options for husband and wife are calculated in closed form. Conditional expectations of match shocks for all options and overall are also found in closed form and used to compute a within period value function of the couple.

This decision is done in both first and second period (the implicit assumption being that in the second period of being in a couple everybody is offered a new job from a random location and a new local job). A value for a couple with offer from j^h, j^w in hand of each residential location is given by

$$V^C(i) + \epsilon_i | T^h, T^w, j^h, j^w$$

where

$$V^C(i) = V_1(i) + E_{j'^h, j'^w}(V_2(i))$$

Assuming idiosyncratic preferences for locations ϵ_i have a standard extreme value distribution, the share of each type of household choosing a location i can be solved in closed form (see McFadden (1977)). Households are differentiated by being a single or a couple, and than by labor market sector assignment and job offer location of household members. Sector matters, because match shocks for jobs ae higher if the job is located in a sector hub. Summing the housing demand over all types of households gives a total demand for housing in each location. This gives a system of three equations and three unknowns which I solve numerically.

B.2 Commuting costs – general functional form

$F^c(d^h, d^w)$ used in the paper can be interpreted as a special case of a more general commuting cost structure.

$$1 - F^c(d^h, d^w) = \phi(\left(\frac{\delta}{0.5}(1 - \beta \cdot d^h)\right)^{\rho} + \left(\frac{1-\delta}{0.5}(1 - \beta \cdot d^w)\right)^{\rho})^{1/\rho} \tag{14}$$

Parameter ρ governs how much specialization is efficient. If ρ approaches infinity, the benefit collapses to $F(d^h, d^w) = \phi \cdot \max\left\{\frac{\delta}{0.5}(1 - b \cdot d^w), \frac{1-\delta}{0.5}(1 - b \cdot d^h)\right\}$, where with one person working close, commuting of the second partner is not costly at all. With $\rho = 1$, husband and wife working close to home provide an additive benefit. In the estimation, fit on commuting is the best with ρ approaching infinity.

C Identification and estimation

In this section I discuss the construction of moments in the data that are used in calibrating and estimating the model and identification of model parameters from these moments. Table 23 presents a complete list of parameters to be calibrated or estimated. I estimate the model with a moment based procedure. Table 22 presents the list of data moments $\bar{m}$ used in the estimation routine. A subset of the parameters is calibrated outside the estimation routine. Moreover, a subset of the parameters α^1 is fit within the estimation routine – at each iteration using guesses of other parameters and moments in the data to fit an exact specific moment condition. This partition decreases the number of parameters that are estimated via a grid search, decreasing the computational burden in estimating the model. Letting $\alpha = [\alpha^1, \alpha^2]$ denote the Bx1 parameter vector, the estimation problem may be formally described as

$$\begin{aligned} \alpha &= \arg\min_{\alpha^2} \; [m(\alpha) - \bar{m}]^T W [m(\alpha) - \bar{m}] \\ \text{s.t. } \alpha &= [\alpha^1, \alpha^2], \alpha^1 = f(\alpha^2, \bar{m}) \end{aligned}$$

W is chosen to be the inverse of the variance-covariance matrix of the data.

C.1 Constructing moments

In this section I describe in detail the construction of moments used in estimating the model.

PSID main sample moments Most moments used in estimation and calibration come from a common PSID sample. The publicly available PSID data is linked to confidential identifiers of the census tract of residence, and in a few waves the census tract of a job. The sample is than restricted to include only people between 18 and 50 years of age, those about whom I can discern whether they have ever been in a couple, those who currently live in a metro-area of at least 250 thousand residents (by 2010) and for whom this is the metro-area they have spent the most number of periods in the PSID sample. Furthermore, I drop people who have been married (or in a couple as identified in the PSID) before and are later observed as single or in a different couple. This is done so that differences between singles and couples are identified without characterizing divorcees as single, to match the notion of singlehood in the model. All statistics are computed using sample PSID weights.

Average commute of singles d^s is an average commuting distance in miles for those identified as having never been in a couple. $d_h^s - d^h$ and $d_w^s - d^w$ are quantified by running two separate regressions by gender, that control for metro-area, age, education, race and PSID wave dummies. Moreover, in the regressions comparing singles to couples I only use singles that are later (at any point in the future PSID samples) observed in couples. This results in slightly smaller differences between singles and couples, thus choosing a more conservative measure. All hours of work moments ($h^h_{\text{both work}}$-h^s and other) are computed using annual hours of market work. All moments describing hours of home production use data on annual hours of housework as defined in the PSID. Labor force participation is defined as one if an individual worked over the last year at all, and zero otherwise. Differences between two groups are always quantified using a simple regression with the controls as listed above, only using the samples of the two groups being compared.

$P(city|couple) - P(city|single)$ is quantified from a regression of a dummy variable of living in a tract that is less than 10 miles from the center of the biggest city of a metro-area, using a regression with the controls listed above, and again restricting the sample to exclude single people that are never observed to couple up.

Moments describing a distance to jobs d_j and distance to opportunities d_o were also computed using this sample, except only restricting to waves since 1990. Construction of these variables are described in the main text. Distance between two random jobs is first computed on the metro-area/year/industry and earnings segment level using the LEHD Origin-Destination Employment Statistics aggregated to a census tract level. They are than matched to individuals in the PSID sample (on metro-area and year, with 2002 being used for PSID waves where no LODES data are available, most common industry and earnings segment). The statistics are than computed on this sample.

Distance between actual jobs of a husband and wife were computed using the job-location census tract identifiers, computing the euclidean distance between the centroids. This information is only available in waves 2013, 2015 and 2017.

PSID moments identified from within-couple variation This set of moments is computed on the sample described above, except that only couples are used and remarried couples are included to increase sample size. All moments in this section are based on within-couple differences, as they are computed using regressions with couple fixed effects. β^a_b is a set of moments mimicking the analysis in tables 5 and 6, where a denotes the left-hand side variable and b stands for either d or wd, with d marking coefficients on d_o and wd marking coefficients on the interaction term woman $\cdot\, d_o$. a stands for $comm$ (commuting distance in miles), $hours+$ (annual hours of work for those who did any market work last year), $hours$ (annual hours of work including zeros), $work$ (labor force participation), x (annual hours of housework) and $log(w)$ (log of the ratio of annual labor income and annual hours). For all variables except for $comm$ only waves since 1990 were included. The details of this analysis are described in the main text.

$\log(\frac{w^w}{w^h})$ is a measure of gender-wage gap among people in couples computed using within-couples variation. Wage is defined as the ratio of annual labor income and annual hours. The same controls as listed above are included. I also add an interaction between education groups and industries to capture as much as possible the differentiation into different kinds of jobs.

Moments identified in external data $\hat{\lambda}_0$, as described in table 15, is computed using IPUMS 2000 Census and 2006-2010 ACS (Ruggles et al., 2019). The same sample is used to compute the 'share never married', defined as the ratio between people never married and not cohabiting over all people, in the age-range 30-50. The goal is to use a measure describing a share of population that never ends up married, as of a certain age. This matches the nature of singlehood in periods 2 and 3 in the model.

Next I use NHGIS census-tract data (Logan et al., 2016) from the 2010 Census to compute housing rent gradients. I define $\log(p)$ in the data as the log of the ratio between the median rent in the census tract over the median number of bedrooms in the census tract. I than compute the difference between $\log(p)$ for tracts less than 10 miles away from the center and the rest. Moreover, I compute the $\log(p)$ gradient with the distance to an average job (d_j). This sample is also used to compute the share of overall population living less than 10 miles away from city center. For comparability, I use the 2010 slice of the LEHD Origin-Destination Employment Statistics (LODES) available in 2002-2017 (Bureau, 2021) aggregated to the Census-tract level, to compute the share of jobs located less than 10 miles away from the center of the largest city in the metro-area, restricting to metro areas with at least 250 thousand resident.

I match the industry and earnings segment groups as defined in the LODES data with the measures of industry and labor income from 2006-2010 ACS and 2000 Census IPUMS data, restrict the sample to the age group 18-50. To calibrate the level of gender segregation in the labor market I compute the share of one's own gender in ones own industry and earnings segment group.

I take the expenditure share on housing from the 2019 Consumer Expenditures Report (of Labor Statistics, 2020). Share of non-labor income is calibrated to match the Source of Income report from 2010, ages 25-64, as one minus the share of earnings in income (of Labor Statistics and Bureau, 2019).

Moment	Model value	Data value	Directly used to fit a parameter
Average commute of single d^s	8.507	8.667	0
$d^s_h - d^h$	-2.698	-2.708	0
$d^s_w - d^w$	-0.083	-0.297	0
$h^h_{\text{both work}}$	2131.300	2206.542	0
$h^w_{\text{both work}} - h^h_{\text{both work}}$	-721.533	-671.547	0
$h^h_{\text{just husband works}} - h^h_{\text{both work}}$	208.700	63.103	0
h^s	1884.057	1873.126	0
$x^w_{\text{both work}}$	1021.787	973.914	1
$x^w_{\text{just husband works}} - x^w_{\text{both work}}$	670.271	683.003	1
$x^h_{\text{both work}} - x^w_{\text{both work}}$	-631.052	-604.506	1
$x^h_{\text{just husband works}} - x^h_{\text{both work}}$	-114.809	-50.524	1
x^s	494.154	495.341	1
LFP of wives-husbands	-0.151	-0.221	0
LFP of husbands	0.954	0.974	0
$\log(\frac{w^w}{w^h})$	-0.243	-0.244	0
Expenditure share on housing	0.198	0.193	0
Share of population in city	0.332	0.392	0
Share of jobs in city	0.608	0.498	0
Distance to an average job for a couple (d^h_j)	20.249	20.277	0
Distance between 2 random jobs	15.367	17.300	0
Distance between 2 random jobs of the husbands labor market	14.849	16.267	0
$\lvert d^w_o - d^h_o \rvert$	1.875	1.862	0
Distance to an average job in own labor market for a husband (d^h_o)	20.156	20.027	0
$P(city\|couple) - P(city\|single)$	0.094	0.070	0
$\log(p)$ distance to jobs gradient	-0.007	-0.009	0
$\log(p)$ city over suburb	0.100	0.073	0
$d^s_o - d^h_o$	-1.472	-1.693	0
$d^s_j - d^h_j$	-1.379	-1.410	0
$d^w_o - d^h_o$	0.076	0.028	0
Distance between husbands and wives actual jobs	11.434	9.740	0

β_{wd}^{comm}	-0.121	-0.105	0
β_{wd}^{work}	-0.006	-0.002	0
β_{wd}^{hours+}	-2.969	-2.485	0
β_{wd}^{hours}	-8.331	-5.146	0
β_{wd}^{x}	4.961	3.285	0
β_{d}^{comm}	0.998	0.706	0
β_{d}^{work}	-0.004	-0.002	0
β_{d}^{hours+}	-19.478	-4.935	0
β_{d}^{x}	2.396	-1.064	0
$\beta_{wd}^{\log(w)}$	-0.001	-0.001	0
β_{d}^{hours}	-24.390	-5.462	0
Share never married	0.145	0.145	1
$\hat{\lambda}_0$	0.551	0.536	0

Table 22: **Preliminary results.** Moments used in estimation: data versus model. In the data, a city is defined as a radius around city center of 10 miles. In addition, I use a ratio of average commuting time and distance in miles as a scaling factor, I constraint housing prices to be one on average, and I impose that the ratio of men and women in the metro-area is equal to one. Lastly, the distribution of men and women in the two labor market matches that the share of ones own gender in ones labor market in the data is 0.59 percent.

Parameter	Value	Fit directly	SE	t
ϕ	2.718	0	(0.860)	3.161
$D(1,2) = D(1,3)$	24.522	0	(1.139)	21.529
$D(3,2)/D(1,2)$	1.953	0	(0.210)	9.285
$f(1)/f(2)$	5.104	0	(0.744)	6.857
$f(2\|1)/f(3\|1) = f(3\|2)/f(2\|3)$	2.404	0	(0.450)	5.341
$A(1)$	-0.180	0	(0.034)	-5.368
$A^c(3) = A^c(2)$	0.105	0	(0.037)	2.808
σ_{ϵ_i}	0.333	0	(0.105)	3.159
κ_d	0.368	0	(0.401)	0.916
Ω_l	12.914	1	(8.537)	1.513
ω_c	1.184	0	(0.097)	12.194
ω_l	2.075	0	(0.450)	4.613
Ω_x	0.473	1	(0.047)	10.086
$\bar{\kappa}_w$	0.554	1	(0.027)	20.366
η_x	0.475	1	(0.107)	4.434

ω_x	0.660	1	(0.145)	4.554
Ω_x^s	0.381	1	(0.052)	7.348
w_{gap}	-0.232	0	(0.013)	-17.594
π	0.622	0	(0.038)	16.549
$E(\xi_0)$	0.240	0	(0.056)	4.291
$Var(\xi_0)$	0.368	0	(0.074)	4.964
$\bar{\Xi}$	6.050	0	(1.440)	4.202
w_{Ξ}	7.389	0	(0.988)	7.479
λ	0.550	0		
σ_{θ_i}	1.000	1	(0.031)	2.500
Θ	1.637	1		
$\frac{\Omega_H}{\Omega_c}$	0.192	0		
w_a	24.383	1		
b	0.002	1		
T	5.181	1		
$\bar{h}^U$	0.267	1		
$\frac{\bar{N}_{1,1}^C+\bar{N}_{1,2}^C}{\sum_{u,v}\bar{N}_{u,v}^C}$	0.706	1		

Table 23: **Preliminary results.** Baseline parameter values, standard errors when appropriate and t-statistics.

C.2 Identifying parameters

Identification of λ The bargaining weight λ, though technically a price, is treated in practice as a parameter to be estimated (because it is not observed in any form).

I build on the identification argument presented in Gayle and Shephard (2019). Given the assumption that allocations within couples are Pareto efficient and λ is constant, equation 15 presents a useful condition on the value of the bargaining weight

$$\frac{\partial u^h(\lambda)}{\partial \lambda} = -\frac{(1-\lambda)}{\lambda}\frac{\partial u^w(\lambda)}{\partial \lambda} \tag{15}$$

Given marriage market clearing, $\log(M^m) - \log(M - M^m) = \frac{1}{\sigma_{\theta_i}}(u^h(\lambda) - u^{h,s})$ and $\log(F^m) - \log(F - F^m) = \frac{1}{\sigma_{\theta_i}}(u^w(\lambda) - u^{w,s})$. Assume there is a variable X, that has no impact on the value of the single state and only affects the value in marriage through its influence on the Pareto weight, aka a distribution factor in the sense of Bourguignon et al. (2009). A marginal perturbation in the distribution factor thus gives

$$\frac{\partial(\log(M^m)-\log(M-M^m))}{\partial X} = \frac{1}{\sigma_{\theta_i}}\frac{\partial u^h(\lambda)}{\partial \lambda}\frac{\partial \lambda}{\partial X}$$

$$\frac{\partial(\log(F^m)-\log(F-F^m))}{\partial X} = \frac{1}{\sigma_{\theta_i}}\frac{\partial u^w(\lambda)}{\partial \lambda}\frac{\partial \lambda}{\partial X}$$

Notice the left-hand side is potentially observable. Taking a ratio of these two derivatives thus provides an estimate of the ratio of marginal values of husband versus wife. A typical example of such a distribution factor is a variation in the available supply of men and women M/F.[44]

Thus, I collect $\frac{M}{F}_k$ for a set of metro-areas and years as well as the share of both men and women who are single (s_k^g for $g \in m, f$) and run the following regression

$$\log\left(\frac{1}{s_k^g}-1\right) = A \cdot \frac{M}{F}_k + B \cdot 1_{g=m} \cdot \frac{M}{F}_k + u_{k,g}$$

If $\frac{M}{F}_k$ is a distribution factor, $\hat{\lambda} = -\frac{\hat{A}}{\hat{B}}$ could be used as a direct calibration of λ.[45] In this paper, however, $\frac{M}{F}$ affects the relative value of marriage through more than λ. This is because there is a housing market as well as a marriage market. $\frac{M}{F}$ affects the overall share of people being single, thus demand for housing in different locations. Moreover, a change in λ implied by a change in the sex-ratio changes the decisions of couples, impacting their income and thus housing demand.

Specifically,

$$\frac{\partial u^g(\lambda)-u^{g,s}}{\partial X} = \frac{\partial u^g(\lambda)}{\partial \lambda}\frac{\partial \lambda}{\partial X} + \frac{\partial u^g(\lambda)-y^{g,s}}{\partial p}\frac{\partial p}{\partial X}$$

For the exact identification to be preserved, it would have to hold

$$\frac{\frac{\partial u^h(\lambda)}{\partial \lambda}\frac{\partial \lambda}{\partial X} + \frac{\partial u^h(\lambda)-u^{h,s}}{\partial p}\frac{\partial p}{\partial X}}{\frac{\partial u^w(\lambda)}{\partial \lambda}\frac{\partial \lambda}{\partial X} + \frac{\partial u^w(\lambda)-u^{w,s}}{\partial p}\frac{\partial p}{\partial X}} \sim \frac{\frac{\partial u^h(\lambda)}{\partial \lambda}}{\frac{\partial u^w(\lambda)}{\partial \lambda}} = \frac{\lambda-1}{\lambda}$$

Thus, I instead collect $\hat{\lambda}_0 = -\frac{\hat{B}}{A}$ as one of the moments that I recreate withing the model (using a numerical derivative with respect to $\frac{M}{F}$. resolving the housing and marriage market

[44] Gayle and Shephard (2019) use this argument to identify bargaining power from a variation across the population vectors M and F across several marriage markets.

[45] With $c = \frac{\frac{\partial u^h(\lambda)}{\partial \lambda}}{\frac{\partial u^h(\lambda)}{\partial \lambda}} = \frac{A+B}{B}$, $\lambda = \frac{1}{1-c} = -\frac{A}{B}$

	$\log\left(\frac{1}{s^g_k}-1\right)$
$\log(\frac{M}{F}_k)$	1.002
	(.317)
$\log(\frac{M}{F}_k)$ Men	-1.869
	(.162)
$\hat{\lambda}_0$	**0.536**
X_i:	
Polynomials up to 4th order of $\log(\frac{M}{F}_k)$	x
Religious participation by denomination 2000, 2010	x
Vote shares in presidential elections 1996-2012	x
Polynomial of size of MSA, year fes	x
N clusters	166

SEs in parentheses.

Table 24: $s^g_k = 1 - \frac{\text{married or currently in couple}}{all}$ for $g \in h, w$ stands for men or women, in an age range of 25-45. Source of data: 5% IPUMS Census 2000 and 2006-2010 IPUMS ACS, MSAs with at least 250k residents by 2010. $\frac{M}{F}_k = \frac{\text{all men}}{\text{all women}}$, in an age range of 25-45. All controls are also included as interacted with gender

equilibrium, and collecting the implied changes in the share of single men and women) and use it in estimation.

Numerically, $\hat{\lambda}_0$ in the model is very close to the λ used, suggesting that this identification strategy is still sound even with adding housing market clearing.[46]

Identification of the rest of the parameters First, I describe parameters calibrated outside of the estimation procedure. There are two parameters that function as scaling factors. b is a scaling factor between distance in miles and annual hours of time (rescaled to be between 0 and 1). b is calibrated outright to match the ratio between average annual commuting time and average commuting distance in miles in the PSID. Second, I scale the base wage w_a so that prices of housing are around 1 and I rescale time inputs in home production and utility so that the average leisure

[46]First, higher bargaining power of husbands allows them to work less. Households have less income on average, housing demand falls, and prices in all neighborhoods fall. This however affects couples and singles about equally. Second, sex ratio different from 0.5 results in a lower overall marriage rate. More singles put pressure on the housing price in the city, favoring marriage over singlehood. This effect, however, is quantitatively minuscule.

would be close to the average consumption quantity, and both aspects of utility were measured in comparable ranges.[47] Specifically, I use moments describing average hours, share of non-labor income, gender wage-gap in couples, share of couples versus singles, share of couples where both work and share of income spent on housing to have an average demand for housing equal to 1 if price of housing is 1. Since the modeled metro-area has a fixed supply of housing of one unit per person, this ensures equilibrium prices are averaging around 1, whenever the model matches the other moments mentioned. Men and women in the model systematically work in different kinds of jobs. Men work more in the labor market that has more jobs in the first suburb. The extent of gender segregation in the labor market is calibrated to match the share of workers of one's own gender in their industry and earnings segment group (as defined in the LODES dataset, the definition of one's labor market in the data for this paper). The last parameter calibrated outside the estimation routine is an upper bound on annual hours $\bar{h}^U$ equal to 0.2671 rescaled annual hours (equivalent to 9 hours a day, 5 days a week, 52 weeks a year). Having an upper bound on hours allows the model to match the fact that hours of husbands only increase so much when the wife drops out of the labor force.

Out of 9 parameters governing preferences for time, consumption and housing quantity, 5 are calibrated within the estimation routine. η_x, ω_x, Ω_x Ω_x^s and $\bar{\kappa}_w$ (parameters governing home productivity of time and preferences over the resulting public good) can be expressed in closed form first order conditions in the optimization problems of different types of households as functions of allocations of time and other parameters. I replace individual time choices in the first order conditions with their averages from the data and use the current guess of other parameters (ω_l, λ) within the estimation routine. Let L^h, x^h, L^w, x^w be the average leisure and housework hours of husband and wife when both work and $L_0^h, x_0^h, L_0^w, x_0^w$ be the average leisure and housework hours of husband and wife when only husband works.[48] Then combining first order condition of couples where both work versus those where only the husband works, I set

$$\eta_x = \omega_l \cdot \frac{\log(\frac{L_0^w \cdot L^h}{L^w \cdot L_0^h})}{\log(\frac{x^h \cdot x_0^w}{x_0^h \cdot x^w})}$$

[47]Specifically, inputs in u_x and u_l are multiplied by T equal to average income per capita.

[48]Using moments in the data as presented in table 22: $x^w = x^w_{\text{both work}}$, $x^h = x^w + (x^h_{\text{both work}} - x^w_{\text{both work}})$, $x_0^w = x^w + (x^w_{\text{just husband works}} - x^w_{\text{both work}})$, $x_0^h = x^h + (x^h_{\text{just husband works}} - x^h_{\text{both work}})$, $h^h = h^h_{\text{both work}}$, $h^w = h^h + (h^w_{\text{both work}} - h^h_{\text{both work}})$, $h_0^h = h^h + (h^h_{\text{just husband works}} - h^h_{\text{both work}})$, $L^h = 1 - h^h - x^h - b \cdot (-(d^s - d^h) + d^s)$, $L^w = 1 - h^w - x^w - b \cdot (-(d^s - d^w) + d^s)$, $L_0^h = 1 - h_0^h - x_0^h - b \cdot (-(d^s - d^h) + d^s)$, $L_0^w = 1 - x_0^w$.

$$1-\kappa_w = \frac{\frac{\lambda}{1-\lambda}\cdot\left(\frac{x^h}{x^w}\right)^{\eta_x}}{\frac{\lambda}{1-\lambda}\cdot\left(\frac{x^h}{x^w}\right)^{\eta_x}+\left(\frac{L^h}{L^w}\right)^{\omega_l}}$$

From there I get the base level of $\bar{\kappa}_w = \kappa_w - b\cdot\kappa_d\cdot(d^h - d^w)$. Using the above, I compute average values of home production time (when both husband and wife works, and when only husband works): $T = (\kappa_w(x^w)^{1-\eta_x} + (1-\kappa_w)(x^h)^{1-\eta_x})^{\frac{1}{1-\eta_x}}$, $T_0 = (\kappa_w(x_0^w)^{1-\eta_x} + (1-\kappa_w)(x_0^h)^{1-\eta_x})^{\frac{1}{1-\eta_x}}$ to get

$$\omega_x = \frac{\omega_l\cdot\log\left(\frac{L_0^h}{L^h}\right)+\eta_x\cdot\log\left(\frac{T_0^h}{T^h}\right)-\eta_x\cdot\log\left(\frac{x_0^h}{x^h}\right)}{\log(\frac{T_0^h}{T^h})}$$

$$\Omega_x = \frac{1}{1-\kappa_w}T^{(\omega_x-\eta_x)}(x^h)^{\eta_x}\frac{1}{L^h}^{\omega_l}$$

For singles, I allow for a different value of home production derived from time Ω_x^s, calibrated equivalently to Ω_x, and average time allocations of singles from the data. With $L^s = 1-h^s-b\cdot d^s-x^s$

$$\Omega_x^s = (x^s)^{\eta_x}\frac{1}{L^s}^{\omega_l}$$

In table 22 the last column indicates the moments that are implicitly directly targeted by this calibration.

Ω_c, Ω_H, ω_c, ω_l are left to be estimated. Ω_H is identified of the share of income spent on housing. A set of moments pertaining to average hours (of singles, husbands and wives, when both work and when only one works) as well as the fact that preferences of individuals in and out of couples are constrained to be the same (except for the value of home production) allow the identification of Ω_c, ω_c and ω_l.

Non-labor income Y is fit within the estimation routine so that the share of non-labor income in household income equals 0.156 on average. The wage function $w(d_o'(j), g) = w_a \cdot e^{-w_{\Xi}\cdot(b\cdot d_o'(j)-b\cdot\bar{d}_o')+1_{g==h}w_{gap}/2-1_{g==w}w_{gap}/2}$ is decreasing in distance to other jobs in the worker's own labor market, and is lower for women in couples. w_{gap} is estimated to match the observed within-couple gender wage gap in the PSID sample.

Next I describe the parameters governing the spatial structure of the modeled metro-area: the distance matrix D and the distribution of job offers f. It is important to identify these parameters separately from commuting behavior, as the parameters of commuting costs are the focus of this paper. The metro-area has 3 locations and is shaped as a triangle. The parameters to be estimated are the distance between suburbs and city $D(1,2) = D(1,3)$ and the distance between the two suburbs (compared to the distance to the city) $D(3,2)/D(1,2)$. There are two labor markets, one offers more jobs in the first suburb, one in the second. The parameters to be identified are the number of jobs (of both types) offered in the city compared to the suburbs $f(1)/f(2)$ and the degree of specialization of each suburb $f(2|1)/f(3|1) = f(3|2)/f(2|3)$. Share of jobs observed in the city (i.e. located less than 10 miles away from the center of the metro-area) identifies the share of job offers in the city. I use a distance between two random jobs to identify the distance between neighborhoods. In addition, I include the distance between two jobs in the same labor market. The difference identifies the degree of concentration of different kinds of jobs in different parts of the metro-area. Increasing $D(3,2)/D(1,2)$ helps to identify the the variability in access to opportunities $Var(d_o)$ and helps match how much distance to an average job is lower in the suburb than in a city, thus helping to match $d_o^s - d_o^h$. The shape of the metro-area and the distribution of job offers also define the potential for disagreement within couples about whose job offer to locate close to. This is measured by the absolute value of the difference in the distance to opportunities within couples between a husband and a wife $|d_o^w - d_o^h|$, which is also included as a moment in estimation.

Next I describe identification of preferences governing location choices. These include the vector amenity values for singles and couple A^c and A^s, as well as the dispersion of idiosyncratic location preferences σ_{ϵ_i}. Again, it is important to identify these parameters separately from commuting behavior driven by acceptance of different kinds of jobs. First, I constrain $A(2)^s = A(3)^s = 0$ and $A(1)^s = A(2)^c$. Constrains here are necessary. Adding a constant to both A^c and A^s results in exactly the same choices. Similarly, the same differences between couples and singles can be achieved by manipulating any two of the location values. Amenities preferences are identified as residuals – after the value of access to opportunities is taken into account, amenities are chosen to match the difference in the share of singles versus couples who live in the city, and the price gradient between city and suburbs. Specifically, $A^c(3)$ matches $P(city|couple) - P(city|single)$, $A^c(2) - A^c(3)$ makes $d_o^w - d_o^h$ fit and $A(1)$ matches the price-gradient moments. σ_{ϵ_i} can be identified with the difference between the distance to an average job and the distance to an average job in own labor market – lower dispersion in idiosyncratic preferences matches a higher tendency to sort to the offered job location and potential other good offers.

The value of not commuting is governed by two aspects, the value of time (as governed by the preferences identified above) and the value of being close to home that enters public good home production in each household. ϕ is than identified from the difference in commuting between husbands and single men, and between husbands and wives. The overall level of commuting is identifying π, the share of households who get a local job offer in addition to their initial offered job. Intuitively, there has to be a barrier on how many people are offered a local job wherever they live, so that commutes in the model are large enough to match the data.

Moreover, the model includes a specific interaction between commuting and the productivity of time in home production. Specifically, $\kappa_w(d^h - d^w) = \kappa_w^0 + (d^h - d^w) \cdot \kappa_d$, i.e. wives are more productive at home compared to husbands whenever their commute is short compared to their husbands. Note that individuals who do not work have an implicit commute of 0. κ_d is identified from β_{wd}^x and β_d^x, moments in the data that measure how much housework hours change depending on the difference in the distance to opportunities between the husband and the wife, as described in table 6.

Each job comes with a utility match shock $\xi = \xi_0 + e^{-\bar{\Xi} \cdot (b \cdot d_o'(j) - b \cdot \bar{d}_o') \cdot h}$, where ξ_0 is a random variable with a uniform distribution. The parameters to be identified are $\bar{\Xi}$, $E(\xi_0)$ and $Var(\xi_0)$. Moreover, wages are decreasing in the distance to other jobs in your labor-market, through a parameter w_{Ξ}. I include $\beta_{wd}^{\log(w)}$, a coefficient estimate presented in table 6, measuring how much within couples a woman's wage is more affected by the couple living far away from other jobs in the wife's labor market than a husband's wage would be. In the model, women take local jobs more often, not taking an advantage of a job that is in a sector hub. Thus when the couple locates far away from the center of her labor market, her wage does fall more. Similarly, $\bar{\Xi}$ is identified with β_{wd}^{hours+}, a coefficient measuring how much more wife's hours fall when they live far away from opportunities. The higher $\bar{\Xi}$ is, the more jobs outside of sector hubs offer a worse match that scales with hours. Since women in couples are more prone to accept a local job instead of a good job, their hours decrease the more.

Θ is a baseline snifter for the the value of marriage and thus is identified by the share of men and women choosing marriage over perpetual single-hood after the first period (and the fact that the sex-ratio in the metro-area is fixed at 1). At this point, σ_{θ_i} cannot be separately identified and is set to be equal to $\sigma_{\epsilon_i} * 2$.[49][50]

To further help estimate the interlink between access to opportunities and labor market

[49]Importantly, this parameter does not affect any moments used in estimation, except for $\hat{\lambda}_0$, theoretically. However, quantitatively, the effects of σ_{θ_i} on $\hat{\lambda}_0$ are minuscule as well. Thus calibrating this parameter at an arbitrary level does not affect the estimates of the rest of the model.

[50]Alternatively, constraining Θ to 0 would allow identification of σ_{θ_i}.

behavior I also include the average distance between the actual job of husband and wife (when both work), as well as the other estimates of sensitivity to being far away from opportunities for husband and wives, as shown in tables 5 and 6. Lastly, I include a share of overall population in the city as a moment to be matched.

C.3 Fit with alternative commuting cost structures

In this section I evaluate the role of the value of working close to home that rewards specialization $F(d^h, d^w)$ in the ability of the model to fit commuting patterns. I set $F^g() = 0$ for both singles and couples, and partially re-estimate the model. For couples:

$$F^c(d^h, d^w) = 0$$

For singles:

$$F^s(d) = 0$$

This makes commuting overall less costly.

Moment	Model value	Data value
Average commute of single d^s	8.677	8.667
$\boldsymbol{d_h^s - d^h}$	**-1.662**	**-2.708**
$d_w^s - d^w$	-0.115	-0.297

Table 25: **Preliminary results.** Moments data versus model.

D Other counter-factuals

D.1 Work from home

Recently, the COVID pandemic reinvogorated the discussion about the benefits of allowing employees to work from home. In this section, I allow a fixed share of the households to keep whatever job characteristics they were offered, but set their commutes to 0.

Within the joint housing and marriage market equilibrium this generates several endogenous responses. Across all groups there is less commuting. Wives work from home more often than

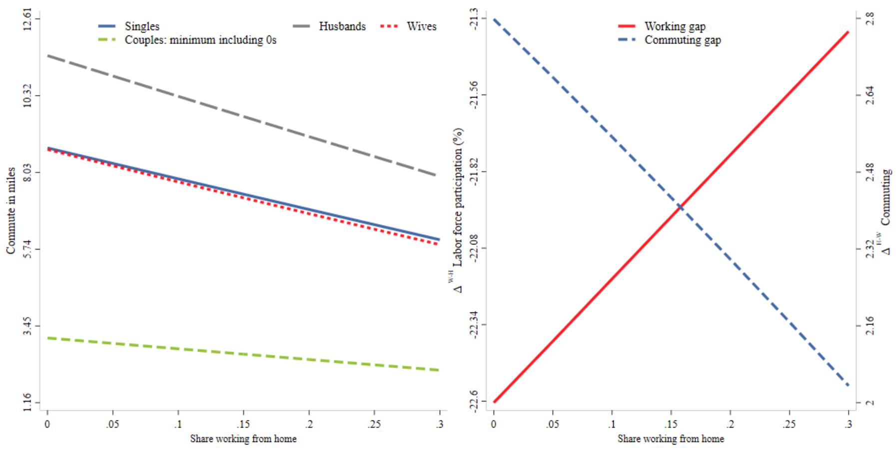


Figure 21: Offering a share of the households a work from home option – commuting and gender gaps Preliminary results.

husbands. However, because at baseline husbands commute the most, their overall commuting falls the most, pushing down gender gaps in commuting. Because commuting costs discourage women in couples from the labor force, work from home options reduce gender gaps in working. As commuting

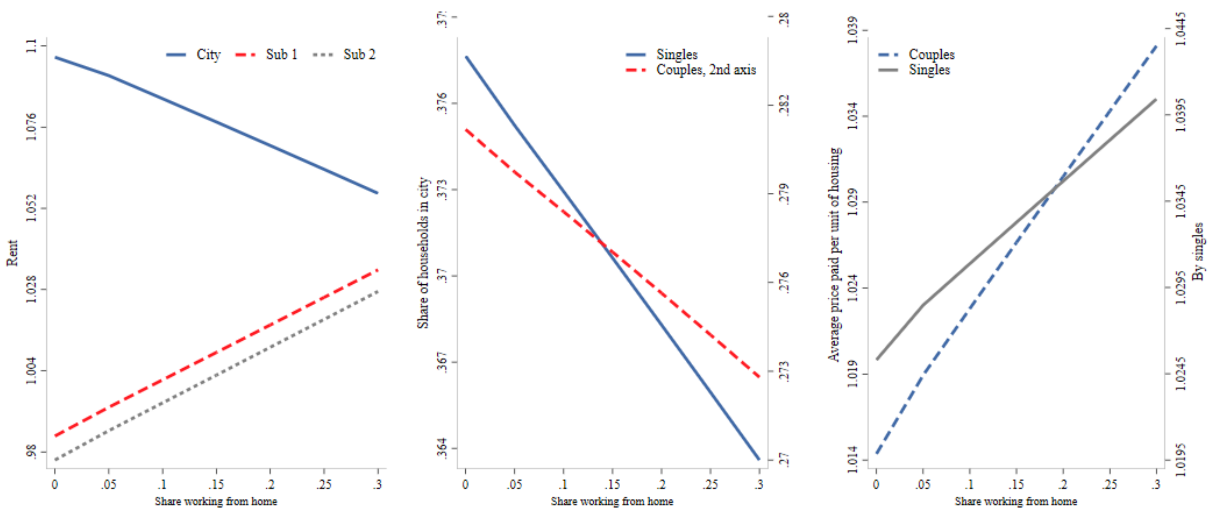


Figure 22: Offering a share of the households a work from home option - housing costs and sorting. Preliminary results.

costs are partially alleviated across households, everybody is more willing to live in the suburbs. The change in incentives is even stronger for singles than couples. As a result, housing costs in the suburb increase and housing costs paid on average by couples increase, compared to singles.

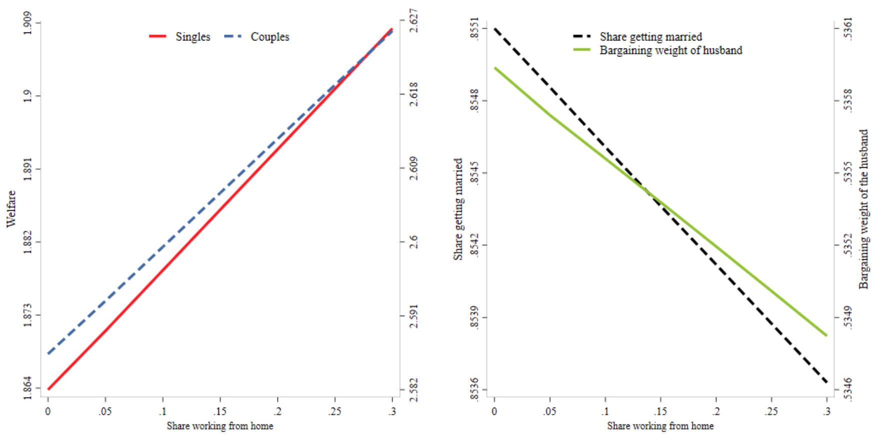


Figure 23: Offering a share of the households a work from home option - change in welfare for singles and couples, the share of people choosing marriage, bargaining weight of husbands. Preliminary results.

All benefit from work from home options, here under the assumption that it does not take away from either your monetary or non-monetary benefits from working. However, an environment with long commutes is comparatively less costly for couples. Therefore, a work from home option is more appreciated by singles than couples. This is true despite the fact that work from home allows women in couples to come back to the labor force more. As a result, fewer people choose marriage in this metro area.

Work from home options present a discrete jump in commuting – a small share of the population can go from a very long commute to a zero commute. However, the rest of the population is still facing the old commuting costs. This heterogeneity implies that some of the women who would like to come back to the labor force still cannot, while some of the women who do come back from the labor force do so even in jobs that are not a good match and bring negative non-monetary benefits. As a result, this policy change is actually not on average appreciated much by wives and results in a renegotiation in the marriage market towards a lower bargaining weight of husbands. If, however, a work from home option was given to everybody but perhaps only for a

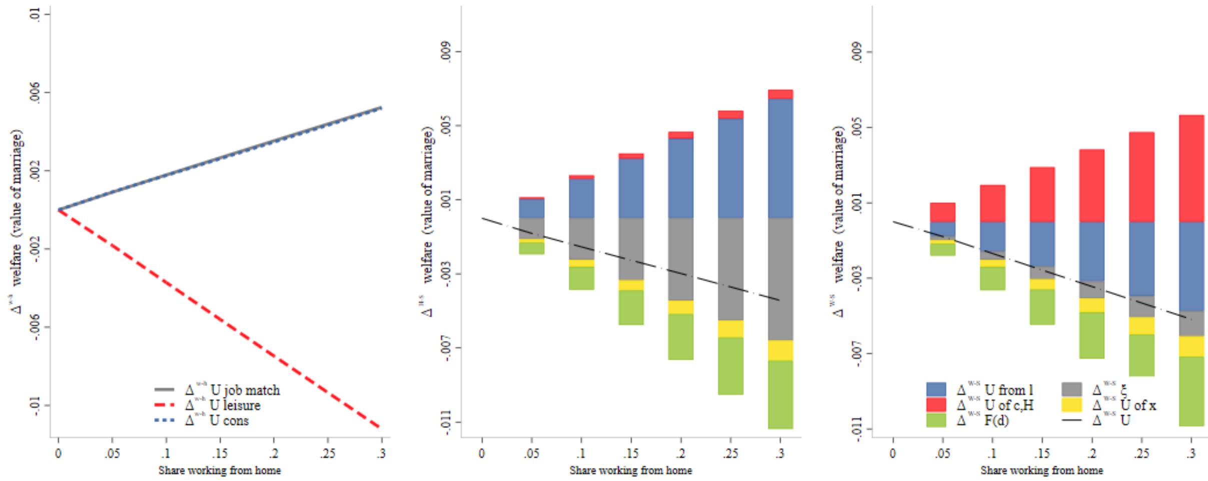


Figure 24: Offering a share of the households a work from home option - change in the value of marriage, decomposed into parts of utility. Preliminary results.

day a week, women could better sort into jobs and the bargaining weight of husbands within the marriage market equilibrium would increase.

Overall, work from home options make marriages less valuable. This is because the technology of specialization that couples possess is less needed, so couples do not benefit as much from specialization and lower housing prices within a housing and marriage market valuable. Figure 24 shows how the decline in the value of marriage for men and women is decomposed into various aspects of utility. Husbands lose some of their privilege of better jobs, because now singles can access them just as easily. Wives lose in terms of leisure compared to single women as they join the labor force, but are somewhat compensated with consumption as they bargain over a higher share of household resources with their husbands.

D.2 Decline in overall willingness to marry – orthogonal to commuting costs

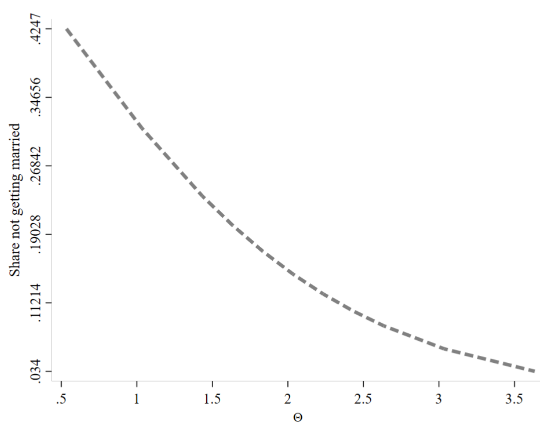
In recent decades we have seen a marked decline in the share of population getting married, especially through increasing the age at marriage. I show that a natural implication of a decline in marriage is gentrification – a steepening of the distance price gradient. Since couples and singles differ in their location choice preferences, a change in the composition of the metro area results in a shift in demand for city versus suburbs. I model an exogenous decline in marriage as a decline in Θ, the constant gender-neutral shifter to the value of marriage. Individual marries if $u^g(\lambda) + \theta^g > u^{s,g} + \theta^s$, with $\theta^g \sim$ EV1 and

$$u^h(\lambda) = E_{T^g,\epsilon_i,j_t^g,\xi_{i_t}^g,\xi_{j_t^g}^g}\left(\sum_{t=1}^{2} u_c(c_t^h) + u_l(l_t^h) + u_H(H_t/2) + a^c(i) + \Pi(x_t^h, x_t^w, d_t^h, d_t^w) + \xi_t^h\right) + \Theta^h$$

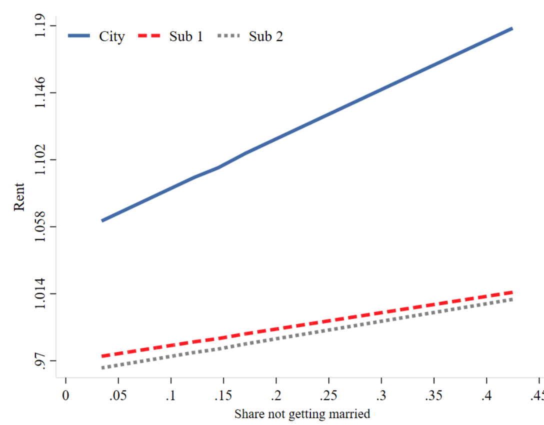
and

$$u^{s,g} = 2 \cdot E_{T,\epsilon_i,j,\xi_i,\xi_j}\left(u_c^s(c) + u_l(l) + u_H(H) + a^s(i) + \Pi^s(x,d) + \xi\right)$$

Lifetime utility in marriage thus has a constant shifter, Θ that is identified to match the share of people married by a certain age. If Θ declines, the share of population wanting to get married declines (proportionally for men and women), as in figure 25a. Figure 25b shows that this is associated with a marked increase in the price of housing in the city, without much change to the price in the suburbs. In other words, an exogenous decline in the willingness to get married causes city centers to become more expensive compared to suburbs.



(a) Share of people not getting married as a function of the exogenous shifter Θ. Preliminary results.



(b) Housing rents per location as a function of the resulting share of people not getting married. Preliminary results.

Figure 25: Counter-factual simulation: declining value of marriage.

D.3 Sprawling into the suburbs

The next counter-factual I study mimics the growth of an existing metro-area by 33% in population and by 33% in housing stock, where this new housing supply is located in a brand new third suburb. Figure 26 presents this experiment. I add a new neighborhood on the outside of the metro-area that mimics the features of the existing suburban neighborhoods. This new neighborhood is gender-neutral in terms of the jobs offered. Share of first offers coming from the new development is the same as in older suburbs, and so are the amenities offered. Job benefits (monetary and non-monetary) within the whole metro area are scaled to have the same average as the baseline (so there is no change in overall productivity in jobs) and vary based on the distance to other first offers in own sector, according ot the new spatial structure.

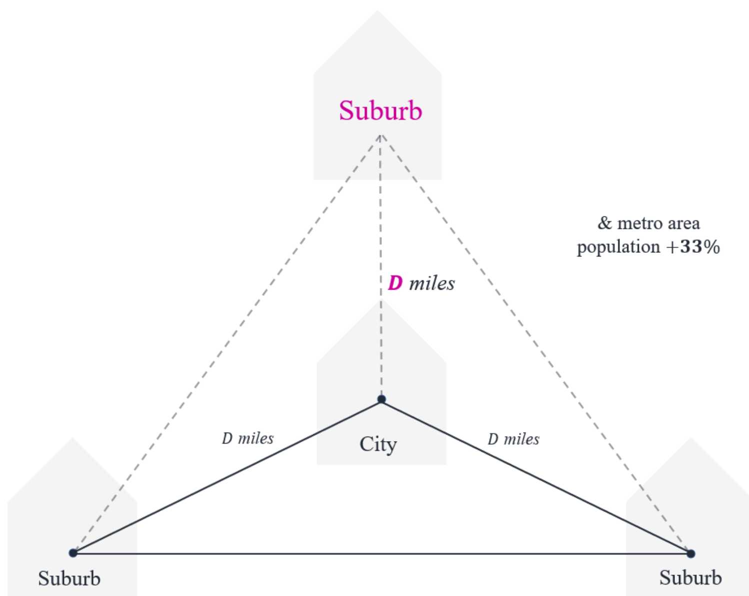


Figure 26: Sprawling into the suburbs – adding a third suburb to grow the metro area (and simultaneously increasing the population by a third).

Similarly to the main sprawl counter-factual, this form of growth of the metro-area into the suburbs increases the value of marriage. Figure 27 shows that in the new metro area, there is more marriage while men lose bargaining power.

Next I examine how the outcomes of the model change when varying the exact location of

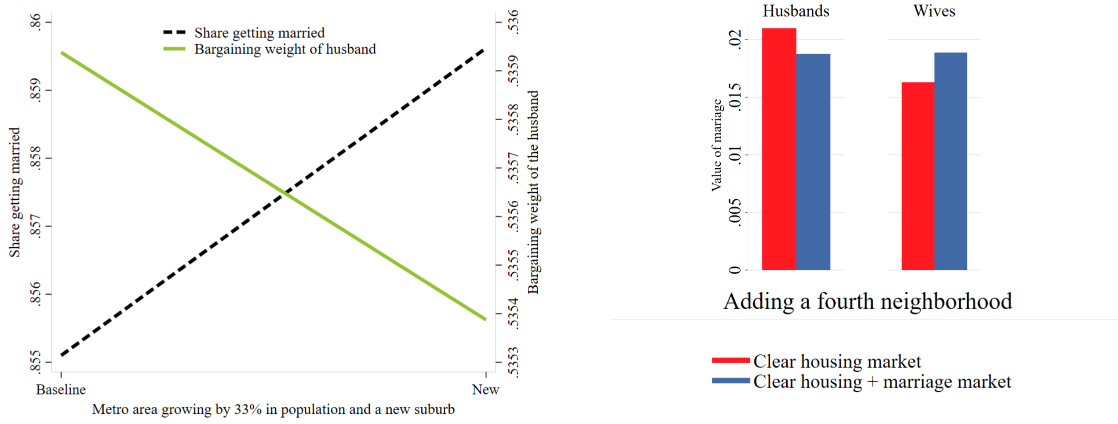
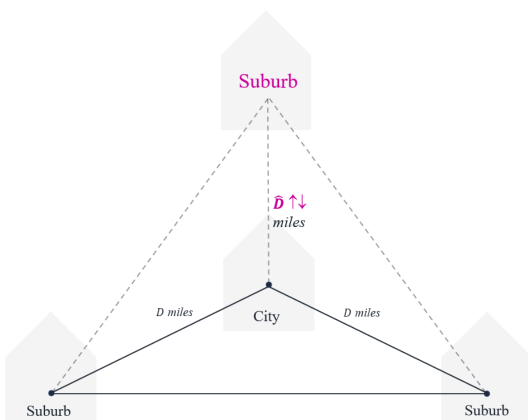
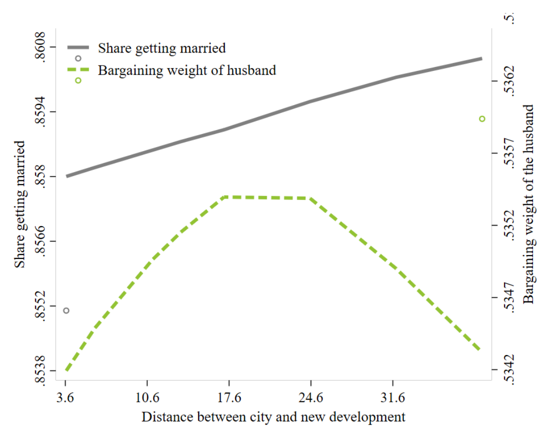


Figure 27: Sprawling into the suburbs – adding a third suburb to grow the metro area (and simultaneously increasing the population by a third). Preliminary results.

the new suburb. Specifically, I change how close or far away the new suburb is the city. Figure 28a presents this counter-factual. Figure 28b shows that the further away from city center the new development is located (the more sprawled the new metro area is), the more people get married.



(a) Sprawling into the suburbs – changing how far away from city center the new suburban development is located. Preliminary results.



(b) Sprawling into the suburbs – changing how far away from city center the new suburban development is located. Preliminary results.

The renegotiation within couples is nonmonotonic with respect to distance. When new development is very close to the city, increasing the distance brings wives more leisure while the job benefits they are losing are small. Therefore, within the marriage market equilibrium, men gain in bargaining weight and are compensated with more consumption. However, at longer distances the gains in leisure for women are not enough to compensate for losing jobs with great benefits. Thus, the bargaining weight starts falling again to result in an overall increase in the value of marriage for women as well as men.

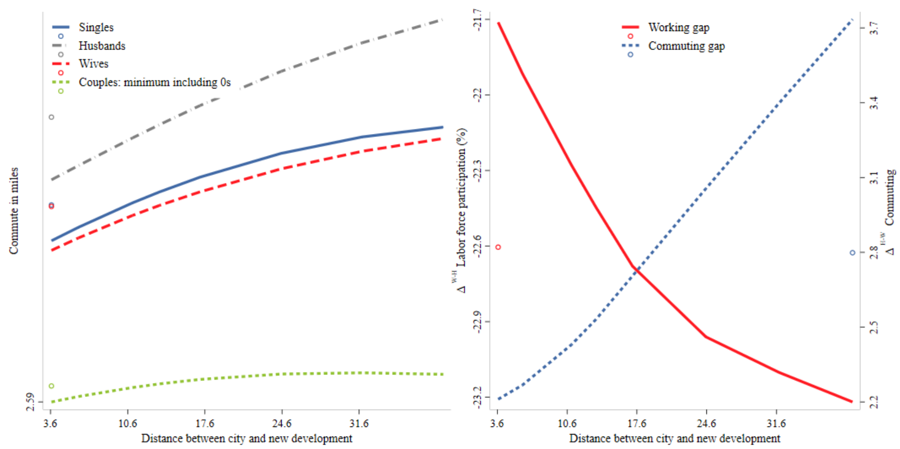


Figure 29: Commuting of all subgroups. Gender gaps within couples. Preliminary results.

As in the main analysis, suburban sprawl increases gender gaps within couples in both commuting and employment. This specialization is a key to the mechanism by which marriage becomes more available in sprawled areas.

D.4 Sprawling into the suburbs with average amenities

The next counter-factual I study mimics the growth of an existing metro-area by 33% of new housing units and new population and adding a fourth neighborhood with average amenities. Figure 30 presents this experiment. I add a new neighborhood on the outside of the metro-area.

By definition, this new neighborhood is gender-neutral in terms of the jobs offered. Share of first offers coming from the new development is the same as in older suburbs. In terms of amenities and job benefits (monetary and non-monetary), the new neighborhood is an average between the existing neighborhoods, suburbs and city, so the overall distribution of amenities and job qualities is kept constant as in the baseline calibration.

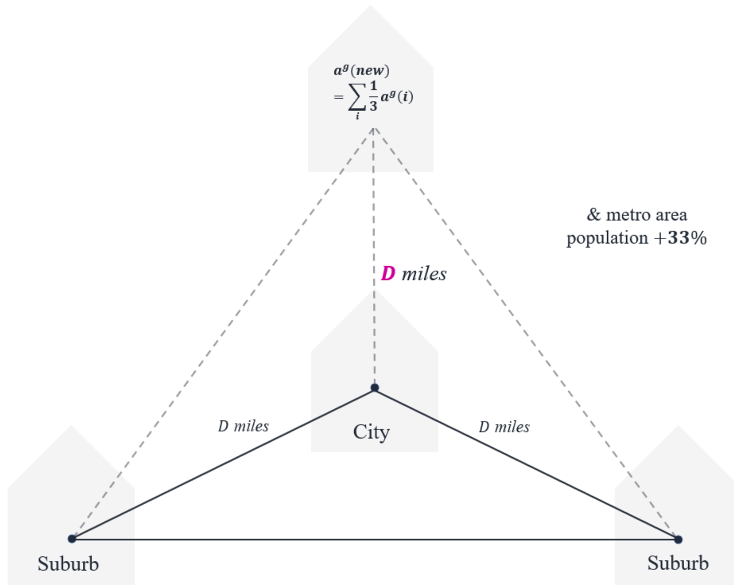


Figure 30: Sprawling into the suburbs – adding a new neighborhood with average amenities (and simultaneously increasing the population by a third). Preliminary results.

Similarly to the main sprawl counter-factual, this form of growth of the metro-area into the suburbs increases the value of marriage. Figure 31 shows that in the new metro area, there is more marriage while men lose bargaining power. This conclusion comes about through a combination of a housing and marriage market equilibrium. Without the marriage market clearing, women in couples would gain less compared to singles or men in couples.

In this version, the value of marriage does increases less than in 27, because the new neighborhood is suburban in terms of job access, but has amenities that are an average of the existing neighborhoods. As a result, this version of suburbanization does not actually increase the share of neighborhoods providing suburban amenities that favor couples. Still, the value of marriage increases because couples specialize and thus partially avoid the increased commuting costs.

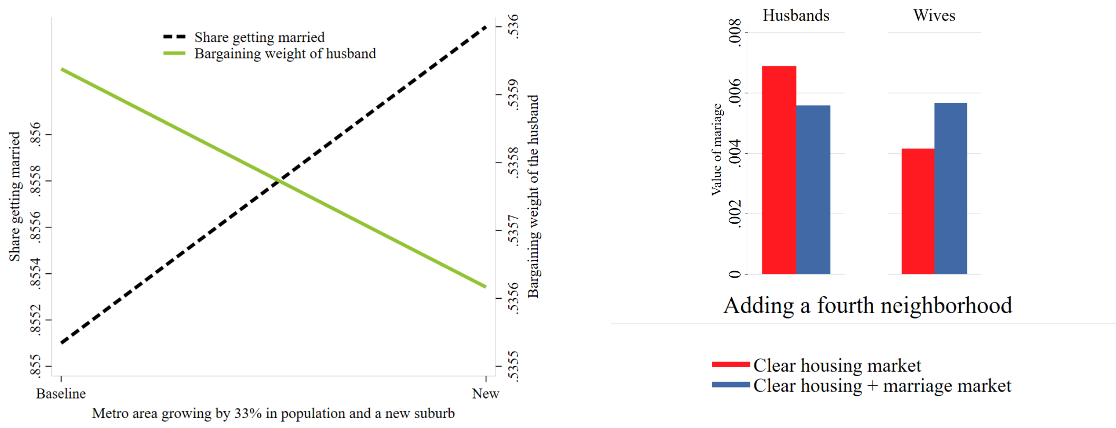


Figure 31: Sprawling into the suburbs – adding a third suburb to grow the metro area (and simultaneously increasing the population by a third). Preliminary results.

E Testing model predictions with cross metro-area correlations

In this section I show that cross-sectional differences between metro-areas in the US match counter-factual simulations of the model. First I replicate results by Black et al. (2014) showing that metro areas with longer commutes have larger differences in labor force participation between men and women in couples. Using the 2000 IPUMS Census sample I run the following regression

$$Working_{im} = \beta C_m \cdot (\text{woman}) + \gamma X_i + \delta X_m + \epsilon_{i,m}$$

where i stands for an individual, m for a metro are and C_m is the average annualized hours of commuting in a metro are m. The sample is restricted to people in couples. β is the coefficient of interest - it shows the differential impact of living in a place of long-commutes on men and women. Table 26, column 6, shows the results. In metro-areas with 16.5 more average hours of commuting per year (roughly corresponding to 1 mile) the gender gap in labor-force participation in couples is higher by almost a whole percentage point.

In column 3 I repeat the same exercise, replacing labor-force-participation with commuting itself on the left hand side (and use a sample of working individuals).

$$d_i = \beta_c C_m \cdot (\text{in couples}) + \gamma X_i + \delta X_m + \epsilon_{i,m}$$

	Commute (annualized)			Working		
$C\cdot$ (in a couple)	0.0667	-0.170		0.0133	-0.0326	
	(10.34)	(-4.66)		(14.94)	(-6.22)	
$C\cdot$ (woman)			-0.239			-0.0552
			(-6.31)			(-5.44)
X_i:						
C	x	x	x	x	x	x
$C\cdot$ *(age, race and education dummies)*	x	x	x	x	x	x
Sex-couple, age, education, region and race dummies. MSA population.	x	x	x	x	x	x
Industry dummies	x	x	x			
N	1194278	990877	1558750	1776688	1750895	2267949
Sample:	men	women	couples	men	women	couples

t statistics in parentheses.

All samples include only people who are married or never married.

Table 26: Source: IPUMS 2000 Census 5% sample. Sample: 18-50 years old, married or never married, MSAs of at least 250k people. "Working" is equal to one if the person worked at least for 1 week in the past year and is scaled up by 100 so that results are interpreted as percentage point changes. "In couple" includes married and cohabitation. Industry dummies are for 1-digit NAICS codes. D_m is the average of annualized commuting hours for all residents of the MSA that do not work from home. Regression in columns 1-2 and 4-5: $d_i = \beta C_m \cdot (\text{in couples}) + \gamma X_i + \epsilon_{i,m}$ for either men or women. Regression in columns 3 and 6: $d_i = \beta C_m \cdot (\text{woman}) + \gamma X_i + \epsilon_{i,m}$ for people in couples.

The results show that in metro-areas with longer average commutes the difference between the time spent commuting of wives and husbands increases. When the average commute in a metro-area increases by an hour, husbands commute increases by an average of 0.24 hours more than that of wives. Qualitatively, this is exactly what happens in the model. Quantitatively, counter-factual exercises above imply a somewhat bigger effect - an increase of 0.58 hours.

Next I repeat the above analysis, this time focusing on the difference between couples and singles using the following regressions.

$$Working_{im} = \beta C_m \cdot \text{(in couples)} + \gamma X_i + \delta X_m + \epsilon_{i,m}$$

$$d_i = \beta_w C_m \cdot \text{(in couples)} + \gamma X_i + \delta X_m + \epsilon_{i,m}$$

If β_w (β_c) is positive, longer average commutes are associated with higher labor force participation (longer commutes) in couples compared to singles. I run this analysis separately for men and women. Columns 1-2 and 4-5 of table 26 show that both β_w and β_c are estimated to be positive for men and negative for women. In metro-areas with long commutes men in couples work and (conditional on working) commute more than single men. However, women in couples work less and (conditional on working) commute less than single women. Qualitatively, this is exactly what happens in the model. Quantitatively, the model predicts a larger effect on commuting of men while the data suggests a larger effect on commuting of women.

Next I investigate the model prediction that larger average commutes are actually conducive of couple formation, by making single life disproportionately costly compared to being in a couple and being able to specialize. I focus on the subpopulation of 30-50 years of age, responding to the population in the model that is either in a couple or perpetually single. Using the 2000 IPUMS Census samples I run the following regression

$$\text{Ever in couple}_{im} = \gamma C_m + \gamma X_i + \delta X_m + \epsilon_{i,m}, \;\; \forall i : \text{age}_i \geq 30$$

Ever in couple$_{im}$ is a dummy variable equal to 1 if the person has ever been married or is currently cohabiting with a partner. C_m, again, is the average annualized hours of commuting in a metro are m. Table 27 shows that, at least when metro-area-level controls X_m include religious participation and proxies for political affiliation, the estimate of $\gamma > 0$[51]. Therefore, across metro areas those with

[51] 32 visualizes the variation in average commuting across metro areas, with and without residualizing with respect to proxies for religious participation and political affiliation.

	(Ever married or cohabiting)·100			
C	0.00465	0.0158		
	(0.47)	(3.26)		
$C_{husbands}$			0.0114	0.0134
			(1.70)	(4.39)
X_i:				
Age, sex-couple, education, region, race dummies. MSA population polynomial.	x	x	x	x
Presidential elestion results 1996-2008, number of religious congregations and adherens by denomination in 2000 (or 2010 if not available earlier).		x		x
N	2754757	2751511	2754757	2751511
Sample:	$30 \leq$ age ≤ 50			

t statistics in parentheses.

Table 27: Source: IPUMS 2000 Census 5% sample. Sample: 30-50 years old, MSAs of at least 250k people. The outcome variable is equal to one if the person is married, divorced, separated, widowed or currently cohabiting. Columns 3 and 4 replace C_m with an average commute in an MSA among married men.

a longer average commute tend to have fewer people staying perpetually single. This correlation in the data could be caused by a selection effect - metro-areas with more couples have higher average commutes because it is the married men who commute most. Columns 3 and 4 in table 27 shows the result is robust to replacing C_m with the average commute among only married men, avoiding this type of selection.

It is important to know these results present descriptive and suggestive evidence, not the causal effect of commuting on marriage rates.

Figure 32: Average annualized commuting time, residualized. Second figure residualizes also with respect to religion and politics proxies. As politics proxies I use county-level shares of votes in presidential elections in 1996-2008 going to the democratic candidate (accessed from Leip (2021)). As religious proxies I use the number of congregations per capita and number of adherents per capita in 2000 (overall and specifically for Evangelical Christian denominations), and number of congregations per capita and number of adherents per capita in 2010 in Black Protestant denominations as provided in Jones et al. (2000) and Grammich et al. (2012).