COMMUTING AND THE VALUE OF MARRIAGE*

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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 that even though long commutes are detrimental to labor market outcomes of women in couples, in terms of welfare couples loose less than singles. First, I show that the gender gap in commuting among singles is negligible. Second, men in couples have much longer commutes than single men, and job access of their residence cannot explain this difference. These facts can be reconciled with commuting featuring gains from specialization that couples unlike singles are able to harness, allowing men to take better jobs. I embed this feature in a quantitative spatial model with endogenous work, residence and marriage choices that successfully captures the commuting and location patterns by marital status. In a joint housing and marriage market equilibrium, as metro areas sprawl, commuting increases most for men in couples and employment falls most for women in couples, contributing to gender gaps in both outcomes. However, in terms of welfare singles lose more than couples, increasing the value of marriage. Couples are able to partially evade commuting costs through specialization, lower housing costs and redistributing resources within the household. Overall, sprawl incentivizes couple formation by increasing gains from specialization.

JEL: J12, J22, R30, R23

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1 Introduction

Over the 20th century the geographic footprint of US metropolitan areas grew enormously. Figure 1 shows that the share of U.S. population living in the suburbs increased from 7 percent in 1910 to 50 percent in 2000. Figure 1 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. I show that while long commutes are most detrimental to married women's labor market outcomes, this does not necessarily mean their welfare is also most affected.

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, Hilber and Schoni (2018) for reviews) focuses on the trade-off between productivity returns to agglomeration and costs of commuting.[2][3] 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.

I start by observing 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 (and thus job access) cannot explain this difference. Rather the commuting margin plays a role in within couple job taking behavior, increasing specialization on commuting as well as time. I then 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, even though observable labor market outcomes of married women are the most

[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.

[3] Recently, the COVID pandemic also reignited the discussion on benefits of work-from-home options (Delventhal, Kwon and Parkhomenko, 2022) and the interaction of working from home with time spent in home productions Leukhina and Yu (2022).

affected. As a result, longer potential commutes actually incentivize couple formation.

The conclusion that long commutes decrease the welfare of singles more than that of married women might come as a surprise. First, there is now a robust body of evidence documenting that long commutes are a contributing factor to gender gaps in the labor market, particularly for married women.[4] For example Black, Kolesnikova and Taylor (2014) and Farre, Jofre-Monseny and Torrecillas (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, Rathelot and Roulet (2020), Caldwell and Danieli (2021), Borghorst, Mulalic and van Ommeren (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.[5] While welfare implications are rarely discussed in this literature, it is often implicit that the increased gender gaps in labor market outcomes are undesirable for women and that policies implying long commutes are worse for women than men. This would be true if gender gaps in commuting were caused by particular distaste for commutes among women. Such a mechanism is, however, not supported by the range of empirical evidence I provide in this paper.

Second, as metro-areas sprawl while jobs are concentrated in the city, suburban neighborhoods lose more access than central ones. At the same time, couples are more likely to live in the suburbs. Thus geographically sprawled areas hurt job access of couples substantially more than job access of singles. Plus long distances exacerbate the collocation issue couples are facing. Yet, in this paper I show that even though sprawl does hurt couple's job access more and the labor market outcomes of women in couples more, it is overall singles who loose most in terms of welfare.

To make welfare conclusions about the impact of long commutes, it is necessary to know more about the underlying motivations for residential and job choices, as they are both endogenous.

[4]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)).

[5]Interestingly, both Barbanchon, Rathelot and Roulet (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.

To this end, I collect a range of motivating evidence about commuting and location choices of singles and couples. The most important and novel observation is that the gender gap in commuting arises solely through men dramatically increasing their commuting after they form couples. Specifically, using a geolocated PSID sample, I first show that men substantially increase their commuting after forming a couple, that this is not true for women and that there is essentially no difference in commuting between single men and single women. Thus, gender gaps in commuting cannot be a result of gendered preferences. Second, 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 in commuting reduces only marginally and remains large and statistically significant after controlling for various measures of how much residential location is suburban or how much job access it has. 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 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 actual commutes of wives. On the other hand, labor market participation and hours of wives are more negatively 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.

Motivated by this evidence, I construct and estimate a quantitative urban spatial housing market and marriage market equilibrium model.[6] Singles and couples choose a residential neigh-

[6]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.

borhood 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 difference 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 (for example singles flocking to the suburbs, and higher wage earners within couples commuting less). I model the choices of couples explicitly as a collective decision resulting from bargaining between two partners with potentially conflicting interests, as inBrowning, Chiappori and Weiss (2014).[7] This again is a methodological contribution, as modeling household bargaining over residential location is rare in quantitative urban economics. With the exception of Chiappori, de Palma and Picard (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.[8][9] 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 outcome.[10]

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.[11] I propose that the observed patterns can be rationalized if commuting im-

[7]Thus, I relate to the literature on gender differences in labor market outcomes within the context of household specialization. See Gronau (1977), Chiappori, Fortin and Lacroix (2002), Cherchye, Rock and Vermeulen (2012), Blundell, Pistaferri and Saporta-Eksten (2016), Bertrand, Kamenica and Pan (2015), Bianchi et al. (2000)).

[8]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.

[9]Even among unitary representations of the household, those models that consider explicit specialization by gender are not quantitative. Black, Kolesnikova and Taylor (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.

[10]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.

[11]For example, Gutierrez (2018) studies only couples and shows that theoretically gender differences in commuting

poses 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 simple 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 benefit couples and encourage more marriage while simultaneously increasing gender gaps in labor market outcomes. 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 accept 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 overpay on housing. While wives lose by not being able to keep jobs they like, within a marriage market equilibrium they are compensated with more 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.[12]

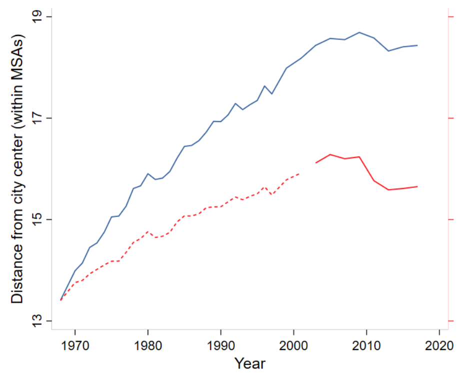
In the next section I describe the commuting and residential patterns of singles versus couples, as well as the evidence that men and women in couples react differently to long potential commutes. In section three I discuss the model, its structure and estimation. Section four presents the results of 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

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.

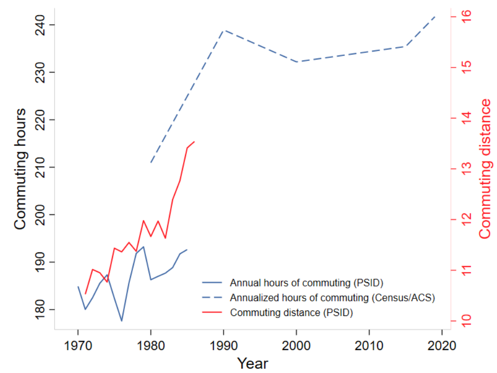
[12]In this paper, I abstract from divorce for the sake of simplicity. If the ability to specialize on the commuting margin adds to the value of marriage, it should also lower the probability of divorce. On the flip side, if an individual (more often the wife) is working close to home, allowing their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

variation across U.S. metro areas, providing further validation for the model mechanisms.

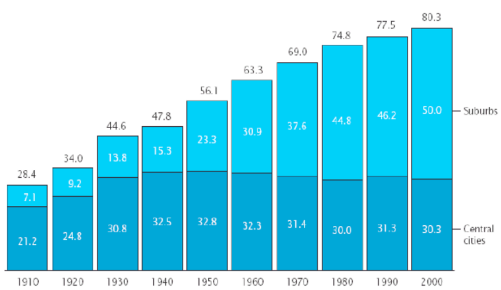
Figure 1: Suburban sprawl and commuting



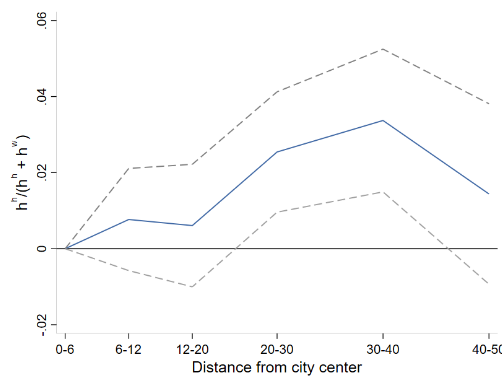
Miles. Sample: PSID 18-50, normalized to white men, 35 years old, in couples. Job distribution: LODES (Bureau, 2021), imputed before 2002.



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.



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



$\frac{H^h}{H^h+H^w}_{t,i} = \sum_{j=2}^{N} \alpha_i^{\text{dist bin } j} + \alpha_i^{ah} + \alpha_i^{aw} + \alpha_i^{educh} + \alpha_i^{educw} + \alpha_t + \alpha_i^{raceh} + \alpha_i^{\#children} + \epsilon_{i,t}$. 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 (distance to center d_c). In addition, the PSID includes four variables allowing me to study commuting. First, in waves 1971-1986 the PSID includes a typical commuting distance in miles 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).[13] 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 an actual daily 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.[14] To study behavior before and after forming a couple I construct tenure within a couple by assigning the first observed year of cohabitation in the PSID as the year a person stopped being single. For couples that are already

[13]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.

[14]According to the documentation, this variable should only include hours of housework, not childcare. However, Gayle, Golan and Soytas (2015) and others use this measure to be a combination of plain housework and childcare. Namely, Gayle, Golan and Soytas (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.

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.[15]

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).[16] 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 would be a good fit for, 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 the PSID.[17]

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

[16] 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.

[17] Table A2 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.[18] Tables 1 and 2 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

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

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.

Consistently, men in couples have considerably longer commutes and spend more time commuting than single men.[19] However, for women there is very little difference between couples and

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

[19] I study both commuting time and commuting distance and treat them as providing information about the same behavior. Table A5 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).

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.

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 more.[20] This is not a result of selection into being in a couple, as the sample excludes singles whom I never observe forming a couple later on.

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 their residential location is suburban (adding additional controls to equation 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,

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

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 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 the linearity of the specification.[21] 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 2 plot coefficients $\beta_{(-10)}$,..., β_{15} from the following regression, where α_i stands for a person fixed effect. β_5 measured the difference in commuting between those who are 5-9 years in a relationship compared to the baseline of between 1 and 5 years before forming a couple.

$$
\begin{aligned}
d_{it} = {} & \beta_{(-10)} \cdot (\text{More than 5 years before forming a couple})_{it} + \beta_0 \cdot (\text{0-4 after forming a couple})_{it} \\
& + \beta_5 \cdot (\text{In couple for 5-9 years})_{it} + \beta_{10} \cdot (\text{In couple for 10-14 years})_{it} \\
& + \beta_{15} \cdot (\text{In couple for 15 and more years})_{it} \\
& + \alpha_t + \alpha_a + \alpha_g + \alpha_i + \epsilon_{it}
\end{aligned} \tag{2}
$$

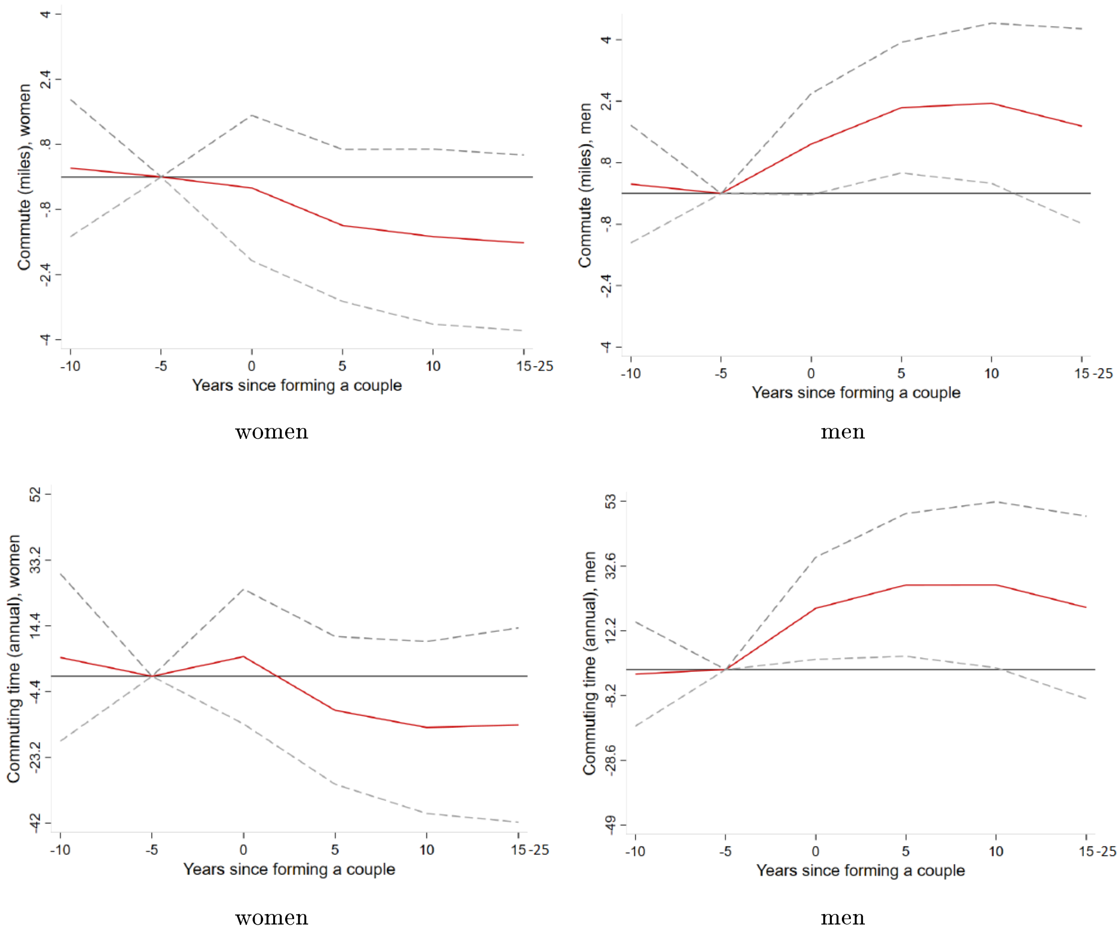
The results mimic the cross-sectional comparison. For men, commuting distance increases after at least 5 years in a relationship to a level 2-3 miles higher than the commute of single men 5-1 years before they enter a relationship and flattens after.[22] The pattern is analogous for commuting time. Tables A4 and A3 in the appendix repeat the analysis in tables 1 and 2 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 commuting information both available before and after forming a couple. Those that do are

[21] Similarly, the results are also robust to including polynomials of d_o or d_c instead.

[22] Notice, though data is limited for this subsample, there is no evidence of a pre-trend, as commuting is actually higher for men 10-6 years before entering a couple than for men 5-1 years before settling with a partner.

observed in only very fresh couples. The pattern in 2 shows that commuting gaps take about 5-10 years to materialize.

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



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.

The picture for women, however, is starkly different. In the cross-section, women in couples spent fewer hours a year commuting (likely confounding working fewer days with commuting shorter daily distances, as the time measure is annual). 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.

Given that one distinct difference between singles and couples is that couples are more likely to take care of small children, one might wonder whether the presented differences are somehow caused by having children instead. Table A8 repeats the analysis in the second columns of table 1 with a dummy variable of having a child living in the household as a control – while the gender gap within couples widens in households with children, the gap between single men and men in couples remains substantial. This suggest that couples with children specialize more across gender lines, but the presence of children is not what lets men in couples commute much more than single men. Moreover, table A9 shows that the even in a sample of men who are never observed within the PSID sample to have a child there the gap between singles and those in a couple is substantial.

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.[23] This observations disqualifies differential distaste for commuting by gender as the primary 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.

[23]Table A6 in the appendix confirms this pattern in the 2000 Census data.

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, 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.[24] In other words, either couples chose their residential location closer to the wife's jobs, or men and women in couples 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. I compute the difference 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. If couples on average systematically prioritized job access of wives, their residential location would be on

[24]This is consistent with the dramatic drop in labor market attachment of women after forming a couple, as illustrated in figure A1, compared to men, who actually slightly increase their labor market attachment after forming a couple).Both figures A1 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.

average closer to the wife's type of job. Table 4 provides evidence against the residential location channel. There is no statistically significant difference in potential commute within couples. If anything, husbands have weakly shorter potential commutes.

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

	d^o			
Man	-0.039 (.080)	-0.064 (.090)	-0.118 (.074)	-0.109 (.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 men and women living in the same location. Consider the following regression (where i stands for an individual, c stands for a couple, a stands for age and t stands for time).

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

The left-hand side variable is one of the measures of commuting available in the PSID. 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 being the one whose potential jobs are further away from the place of residence is associated with longer commutes for men. This is reassuring as it validates that the chosen measure of access to potential jobs correlates strongly

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 to jobs (d^{opp})	0.614	0.706	4.241	5.348	4.614	6.268	0.306	0.570
	(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).

with actual commutes. The second row (estimates of β_{wd}) shows the main coefficient of interest. The association between actual commutes and potential commute within couples is not symmetric by gender – it is weaker for women. Whenever a couple lives further away from the wife's job opportunities, her commute increase less than it would for her husband.

Notice that by including couple fixed effects (α_c) 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). As a byproduct, 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. This way I am netting out systematic gender differences in working in generally more or less accessible industries. 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

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 A10 shows analogous analysis of hours spent working over samples when commuting variables are available, providing a more direct link to table 5.

the results. In the first three columns I see that within couples, for men their distance to opportunities is associated with lower hours and a lower probability of employment. This suggests that 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. The second row shows that this association is again not gender-neutral: it is stronger for women, the opposite pattern to what I observe in commuting. Column 4 shows that the distance to potential jobs 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 poor job access. While husbands go for desired jobs even when they are 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 husband's commuting was less costly to them than that of wives.[25]

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^c_{it}) 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).[26]

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

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 (.338)	.966 (.197)	-.071 (.0132)	-.047 (.0097)	1.399 (.312)	.369 (.183)	1.754 (.322)	.436 (.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

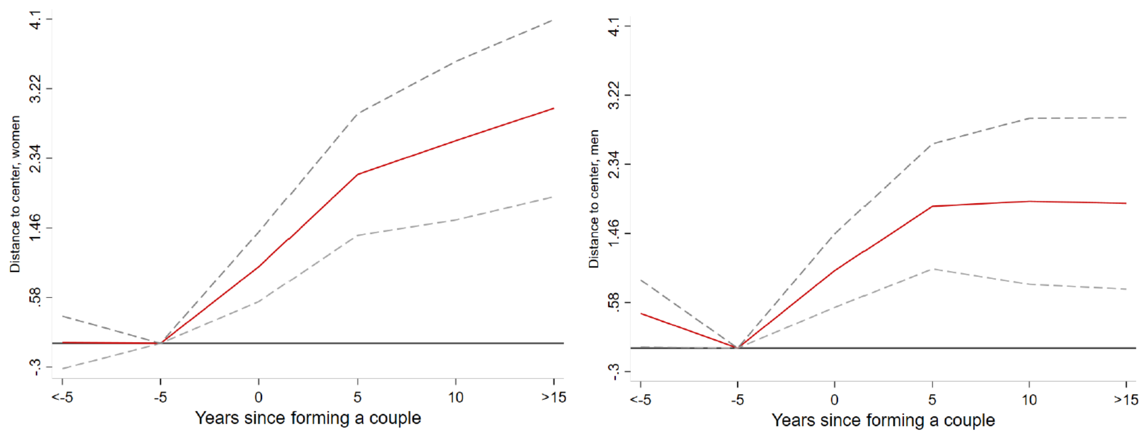
SEs statistics in parentheses. SEs clustered at the MSA level.
All regressions include year, age, MSA fixed effects.

Columns 1,3,5 and 7 only use people in couples or singles who are later observed in a couple.

[25] 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 A10 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, 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.

[26] 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



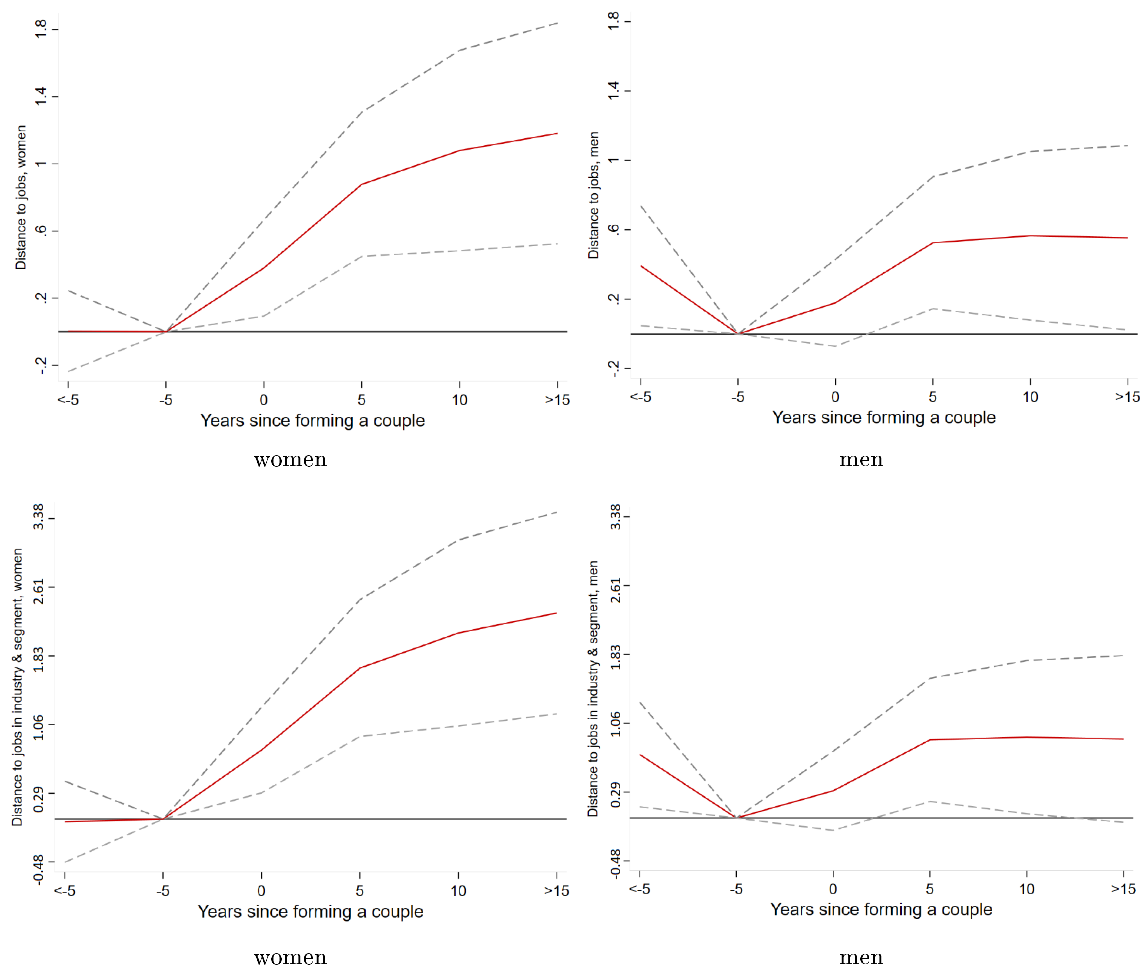
women men

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 "5-1 year before forming a couple" excluded and normalized to 0.

In the cross-section, after controlling for age, education and race dummies, 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 about 7 percent higher. 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 3 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 typically more concentrated than people. 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. Figures 4 show this pattern with the within-person variation. Unlike with commuting, the move to the suburbs is very similar for men and women.

To summarize, I show the following facts. First, on average men commute more then women. Second, this gap arises purely because men increase their commutes substantially after they form couples. This gender gap is not present among singles and men in couples commute much more than single men, while there is little difference for women. Third, couples are more likely to live

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



Analogous regressions for figures 3. 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.

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, the commuting gap is very robust to controlling for aspects of residential location that measure distance to the city or jobs. Fourth, 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. Fifth, I show direct 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 motivates couples to specialize on this margin. Furthermore, this gendered specialization markedly changes the behavior of men. Specialization is allowing men in couples to behave as if commuting is less costly for them than for everyone else, including singles. Through specialization, men in couples can accept potentially better jobs with longer commutes.

3 Model

In this section I present a structural spatial housing market equilibrium combined with a rudimentary marriage market equilibrium model of a metro-area capable of replicating the salient features of commuting and location decisions as presented above.

Crucially, standard explanations for gender differences in wages and time use do not lend themselves naturally to explain differences in commuting within couples and between single men and men in couples (as detailed in section 3.3). Instead the data patterns are consistent with a mechanism that rewards specialization within couples on the commuting margin. I introduce a household cost of commuting 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, where if one of them works close by, the other one is free 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 markets for housing and a bargaining weight clears the marriage market. Agents are differentiated by gender and relationship status. To capture the transition from singlehood to forming a couple I use a simple overlapping generations structure. The population consists of three generations, one of singles and two of potentially 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 in a couple 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 metro-area is composed of three equally-sized neighborhoods – a city and two suburbs – organized in a triangle (see figure 5). There is a city and suburbia to capture the typical degree of centralization of economic activity and the differences in access to jobs between singles and couples. The suburbs are further differentiated into two locations, one offering more opportunities to men and one to women. This is necessary to capture two features: the potential for disagreement within couples about whose career to prioritize and the disadvantage of balancing two job locations that couples face compared to singles.[27]

Individuals get jobs by receiving offers which they can accept or reject. Each job is a bundle of a location (j), hours (h, part time or full time), a wage (w) and a utility match shock (ξ_0) representing non-monetary benefits. The purpose of differentiated jobs is to capture the potential trade-offs between short commutes and better monetary and non-monetary benefits from working. Each individual belongs to one of two job sectors. The purpose of two sectors (one with more men and one with more women) is to capture the potential for disagreement couples are facing in whose job access to prioritize. Each individual is exogenously assigned to a sector T and draws offers only from that sector. Job characteristics are exogenous; there is no firm decision or labor market clearing. To allow for the idea that location choices are shaped by job access, households learn the location j of one job offer before they choose where to live. Beyond their first offer a share π of the population is given an additional option to work locally (in their location of residence). This additional flexibility is necessary, because differences in commuting (between men and women in couples and between couples and singles) in the data are not explained away by differential job access, but by differences in what jobs are actually taken.

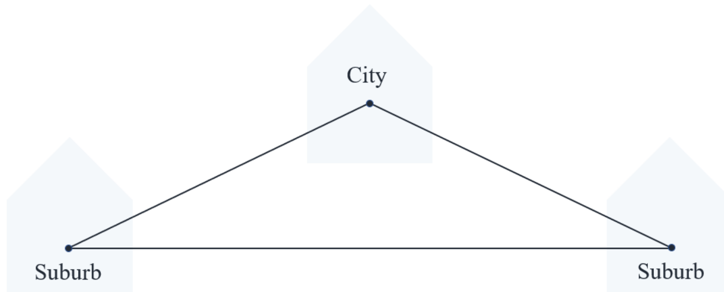
Wages w are higher for jobs that are close to other jobs in the same sector. Wages also depend on gender and relationship status g (single, man in couple or woman in couple). Overall, wage is a function $w(j, T, g)$ depending on job location, sector, gender and relationship status, hours and a random draw. Non-monetary benefit ξ_0 is an idiosyncratic random draw.[28]

I fit the model to match average location, commuting and work patterns in metropolitan areas in the United States. Then I study how these patterns change if potential commutes increase

[27] 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.

[28] This allows the solution to be continuous in key parameters.

Figure 5: Spatial structure of the model metro-area

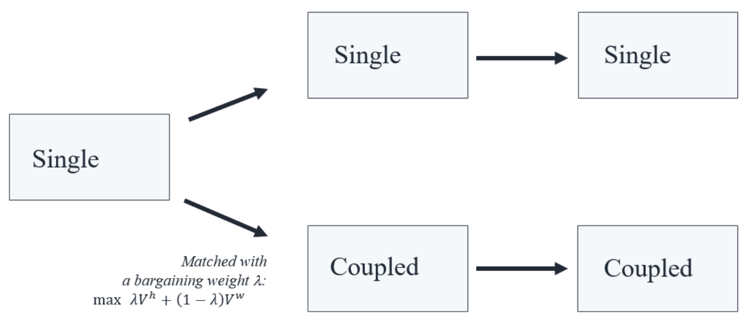


and what the implications are for the welfare of singles and couples.

3.1 Household choices and timing

There are two main types of households choosing where to live, work 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 decides whether to marry and stay married forever or whether to stay perpetually single.

Figure 6: Model timing: lifecycle



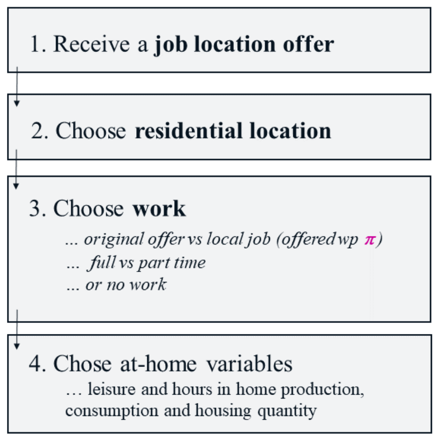
Couples differ from singles on three dimensions. First, couples have a more complex optimization problem. Whereas individuals maximize their own utility, couples maximize a weighted average of the utilities of the husband and the wife, where both live by definition in the same location. Second, couples derive more value from time 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.[29] Third, singles and couples have potentially different preferences over location amenities, with couples appreciating the suburbs more (for example, for better schools, less pollution 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 drawing a job offer and learning its location. With this information in hand (and taking residential rents as given) households choose where to live. Next, a share of households π learns about a local job. Everyone decides which job to take and whether to work part time or full time. After jobs are assigned, all households make decisions on time use at home,

[29] See figures A2 in the appendix.

consumption and housing quantity demanded. At the beginning of the next period, old job ties are severed, new offers ar presented, new jobs chosen and all variables re-optimized.

Figure 7: Model timing: within each stage of life



3.2 Job offers

Couples differ from singles by living in the same location but having to potentially commute to two different jobs. The collocation issue is exacerbated by men and women systematically working in different sectors of the economy and similar jobs clustering together in space. 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 $T \in \{1, 2\}$. Each sector has a hub in the city and in one of the suburbs. Figure 8 summarizes the spatial distribution of first job offers: with $f_T(i)$ denoting the probability a first offer in sector T comes from location i. Red and green distinguishes sectors 1 and 2, showing that the first suburb has more offers in sector 1. In every period each individual is assigned to one sector, and only draws job offers from that sector. Sector assignments are random with more men drawing from sector one $(T = 1)$.

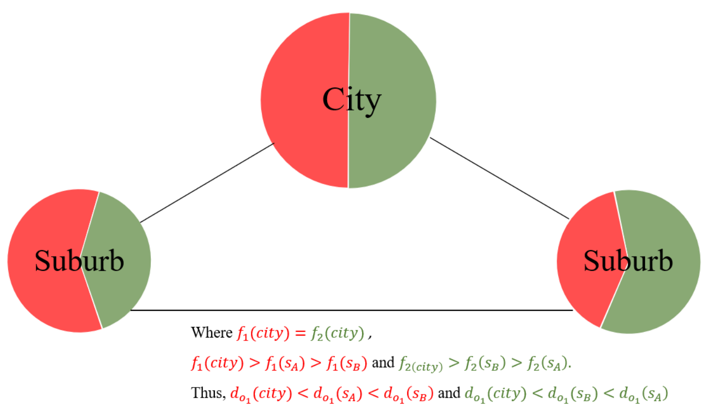
Jobs coming from locations where the sector is concentrated in come with higher wages. This way, the heterogeneity of jobs captures agglomeration effects: labor market sector hubs concentrate more productive and more innovative companies that provide their workers with better benefits.

Specifically, w is decreasing in $d_{o_T}(j)$, the distance in a location j to a random first job offer from a sector T. I use first offers which are exogenous, not the actual distribution of jobs which is endogenous, to avoid looking for a fixed point. Nonetheless, the spatial distribution of jobs and the distribution of first offers is closely linked.

There is a fixed gender pay gap for men and women in couples. There is no gender wage-gap for singles.[30] Overall, the wage function is defined as

$$w(j,T,g) = w_a \cdot e^{-w_{\bar{\Xi}} \cdot (b \cdot d_{o_T}(j) - b \cdot \bar{d}_{o_T}) + 1_{g==h} \cdot \frac{wgap}{2} - 1_{g==w} \frac{wgap}{2}}$$

Figure 8: 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. $d_{o_T}(j)$ is the implied distance in a location j to a random first job offer from a labor market sector T, that influences the benefits 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 – a fact that is not naturally reproducible with standard household incentives. What is required is a mechanism that allows men in couples to behave as if commuting was less costly for them than when they were single. I propose a functional form for the cost of commuting that rewards

[30] Including a smaller gender gap for singles would not change any principal conclusions of the paper. Gender gaps in couples are imposed on the model to properly capture the incentives for whether a wife or a husband, or both, participate in the labor market and work long hours. There is also a small endogenous component to the wage-gap. This paper does not aim to explain why wage gaps are much larger for people in couples.

specialization on this margin, and allows a model to quantitatively match the differences observed in the data. Specifically, I posit that working close to home has additional benefits to all households beyond the time saved. For singles, this is a simple fixed cost of working, that scales with time needed for a commute.

$$F(d) = \phi \cdot (b \cdot d) \tag{5}$$

Working close to home can be beneficial for many reasons, to be around in case of emergencies around the house, to accept deliveries, to walk the dog or to pick up a kid from a local school. Importantly, these kinds of benefits do 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 even very far away from home. This suggests that couples have an advantage over singles by sharing a household together, and that specialization of one member of the household working close to home is often the efficient choice. Equation 6 proposes a functional form that captures this intuition for couples

$$F^c(d^h, d^w) = \phi \cdot \min\Big\{b \cdot d^w, b \cdot d^h\Big\} \tag{6}$$

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

The principal reason to include this additional cost in the model is that even though there are several potential explanations for gender differences in commuting, none of them have quantitatively important implications for the gap in commuting between singles and couples. Next, I go through the potential explanations for gendered commuting behavior in more detail.

First, a gender gap in commuting could be rationalized by assigning men and women different preferences, as is sometimes implicitly or explicitly 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.

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, couples could prioritize job access of wives. This is the primary channel in Chiappori, de Palma and Picard (2018). 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 husband's sector, 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). Matching this moment in the data thus disqualifies a bargaining advantage as the primary factor explaining that women in couples have much shorter commutes.[31]

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 – women in couples do not systematically have better job access than men. Moreover, this mechanism would create a commuting gap among single men and women as well.

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. All of these are a feature of the model.

When both work, a wage gap 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 minimize the husband's commute to save his valuable time.

A gender gap in home productivity can motivate couples to prefer the wife's commute to be shorter than the husbands, as it makes her time more valuable. However, it does very little to allow husband's to accept longer commutes compared single men. This is because men perform very little housework both when single and when in a couple, so there is no substantial amount of time saved that would allow them to simply allocate it to commuting once in a couple.

Lastly, qualitatively part of the difference in commuting between husband and wives and between husbands and singles is rationalized by the fact that benefits to commuting in the model scale with hours. Since husbands work longer hours than other groups, their returns to commuting are in principle bigger. This mechanism is a part of the model and thus is accounted for, though

[31] 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.

are enough on its own, since the implicit returns to commuting that match the patterns observed in table 6 are not large enough.

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 has no potential in matching the gap between single men and husbands. Scaling of work benefits that trade off against commuting with hours (monetary and non-monetary) combined with a baseline wage gap and home productivity gap can generate a sizable gender gap in commuting within couples without costs of commuting being explicitly gendered.

3.4 Choices made at home

Equation 7 presents the optimization problem of a single person from sector T, after they have settled to a location i with rent $R(i)$ and a job characteristics $job = (j, l, T, \xi_0)$. The model abstracts from borrowing and lending, so each period a household spends all their income. As a result, the decision problem is static.

$$U^s(i, job) = \max_{c,L,H,x} u_c(c) + u_l(L) + u_H(H) + a^s(i) + u^s_x(X) - F^s(d_{i,j} \cdot (h > 0)) + \xi_0 \tag{7}$$

$$\begin{aligned} \text{s.t. } c &= l \cdot w - R(i)H \\ 1 &= L + \beta \cdot d_{i,j} \cdot (l > 0) + l + x \\ X &= P(x) \\ \text{where } w &= w(j, T, s) \end{aligned} \tag{8}$$

Utility is derived from consumption c, leisure L, housing quantity H, amenity $a^s(i)$ in a location i, a non-monetary benefit of a job ξ_0, time in home production x and additional costs of commuting. Time is constrained to sum up to 1: $1 = L + b \cdot d + x + l$ (where l stands for time spend at work, x for home production and $b \cdot d$ for commuting). Commuting time is given by $b \cdot d_{i,j*}$, where $d_{(.,.)}$ is the matrix of distances between neighborhoods.

A couple acts to maximize a weighted sum of the husband's and the wife's utility, with λ

representing the bargaining weight of the husband. The maximization problem of a couple within each period, given residential location i and job characteristics $job^g = (j^g, l^g, T^g, \xi_0^g)$ for $g \in \{h, w\}$ is presented in equation 9.

$$
\begin{aligned}
& U(i, job^h, job^w) = \qquad\qquad (9)\\
&= \max_{c^h, L^h, x^h, c^w, L^w, x^w, H} \{\ \lambda U^h(i, job^h, job^w) + (1-\lambda) U^w(i, job^h, job^w)\} \\
&\text{where } U^g(i, job^h, job^w) = \left[u_c(c^g) + u_l(L^g) + \xi_0^g + u_H(H/2) + a^c(i) + u_x^c(X) - F^c(d^h, d^w)\right] \\
&\text{s.t. } c^h + c^w = l^h \cdot w^h + l^w \cdot w^w - R(i)H \\
&\quad 1 = L^g + b \cdot d^g + l^g + x^g \\
&\quad X = P^c(x^h, x^w) \\
&\text{and } w^g = w(j^g, T^g, g),\ d^g = d_{i,j^h} \cdot (l^g > 0) \\
&\text{for } g \in \{h, w\}
\end{aligned}
$$

The value generated at home depends on times put in home production x^h and x^w.

3.5 Choosing a job

Equation 10 presents the optimization problem solved by a single person when choosing a job, given their industry T, residential location i and a first job offer location j. The person chooses how much (l) and where (k) to work. Each combination of l and k draws an idiosyncratic non-monetary job-match shock $\xi_0^{l,k}$ (with $\xi_0^{l,k} = 0$ if $l = 0$).

$$
\begin{aligned}
V_T^s(i, j) &= \pi \cdot E_{\xi_0^{l,j}}\left[\max_{l,\ k=j} U(i, job)\right] \qquad (10)\\
&+ (1-\pi) \cdot E_{\xi_0^{l,k}}\left[\max_{l,\ k\in\{i,j\}} U(i, job)\right] \\
&\text{where } job = (k, l, T, \xi_0^{l,k}) \text{ and } l \in \{0, \frac{1}{2} \cdot \bar{l}, \bar{l}\}
\end{aligned}
$$

A single person living in i knows the location j of their potential job. A share of the population learns about local jobs as well and can decide whether to take one instead. This would give a short commute which is weighed against the potential of a better match further away. Furthermore, individuals pick whether to work full time, part time or not at all. Denote $H^S_{i,j,T}$ to be the average quantity of hosing chosen by a single person in sector T with a first offer in j and living in i who has optimally selected their job.

The optimization problem of a couple choosing jobs is presented in equation 11. A couple knows its residential location i and the locations of their potential jobs j^h, j^w. A share of households learns about local jobs (located in i). This would give a short commute which is weighed against the potential of a better match. The couple collectively decides who works were and how much (full time, part time or not at all).

$$\begin{aligned} V^C_{T^h,T^w}(i, j^h, j^w) = \pi \cdot E_{\xi_0^{l^g,j^g}} \left[\max_{l^g,\ k^g = j^g} U(i, job^h, job^w) \right] \\ + (1-\pi) \cdot E_{\xi_0^{l^g,k^g}} \left[\max_{l^g,\ k^g \in \{i, j^g\}} U(i, job^h, job^w) \right] \\ \text{where } job^g = (k^g, l^g, T^g, \xi_0^{l^g,k^g}) \text{ and } l^g \in \{0, \frac{1}{2} \cdot \bar{l}, \bar{l}\} \text{ for } g \in \{h, w\} \end{aligned} \tag{11}$$

Denote $H^c_{i,(j^h,j^w),(T^h,T^w)}$ to be the average quantity of hosing chosen by a couple in sector (T^h,T^w) with first offers in (j^h,j^w) and living in i who have optimally selecteds their jobs. Similarly, denote $V^g_{T^h,T^w}(i, j^h, j^w)$ to be the average period utility of a person g in a couple in sector (T^h,T^w) with first offers in (j^h,j^w) and living in i. Notice we can write

$$V^C_{T^h,T^w}(i, j^h, j^w) = \lambda V^h_{T^h,T^w}(i, j^h, j^w) + (1-\lambda) V^w_{T^h,T^w}(i, j^h, j^w)$$

3.6 Choosing residential location and marriage

Each period every household first chooses where to live, either the city or one of the two suburbs. This is a standard discrete choice as in McFadden (1977), comparing systematic costs and benefits (access to current job offers, access to other potential jobs, amenity values and costs of housing) with idiosyncratic preferences per location ϵ_i. For singles:

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

For couples:

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

With ϵ_i following a Type-1 extreme value distribution, the choice probabilities ($P^s_{j,T}(i)$ and $P^c(i)_{(j^h,j^w),(T^h,T^w)}$) are solved in closed form.

The choice of whether to couple up for a man (h) and a woman (w) is done by comparing the expected value from remaining single and the expected value of being married for two periods (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

$$u^s+\theta_s = 2\cdot E_{T,j,\epsilon_i^*}\left(V^s_T(i^*,j)+\epsilon_i^*\right)+\theta_s$$

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

$$u^h(\lambda)+\theta_h = 2\cdot E_{T^g,j^g,\epsilon_i^*}\left(V^h_{T^h,T^w}(i^*,j^h,j^w)+\epsilon_i^*\right)+\Theta+\theta^h$$

$$u^w(\lambda)+\theta_w = 2\cdot E_{T^g,j^g,\epsilon_i^*}\left(V^w_{T^h,T^w}(i^*,j^h,j^w)+\epsilon_i^*\right)+\Theta+\theta^w$$

Expectations are taken over draws of job offer locations, the idiosyncratic location preference 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 unaccounted-for benefits to marriage (a constant Θ, identified to match the share of people staying single). I assumes full commitment and efficient risk sharing within the household. Moreover, to simplify assignment to a labor market sector T is randomly reshuffled after marriage (preserving the gender composition of each sector). This way with matching at random there is no differentiation in the incentive to marry by labor market sector T, preserving the internal logic of one common marriage market. As a result, the Pareto weight does not depend on the realizations of j or T.

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

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

3.7 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). 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 $\{f(j|T)\}_{T\in\{1,2\},j\in\{c,s_A,s_B\}}$. 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 across sectors $\{s^g(T)\}_{g\in\{h,w\},T\in\{1,2\}}$, and across locations of job offers $\{f(j|T)\}_{T\in\{1,2\},j\in\{c,s_A,s_B\}}$, 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, the choice probabilities to enter the marriage market $\{\boldsymbol{p^g}\}$ are equal for men and women*

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

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 $\{\boldsymbol{H^s_{i,j,T}}\}$ and $\{\boldsymbol{H^c_{i,(j^h,j^w),(T^h,T^w)}}\}$ are such that the housing markets clear

$$H_i = H_i^D(R,\lambda) = \sum_{sector\ T} \sum_{1st\ offer\ in\ j} N^s_{i,j,T} \cdot \boldsymbol{H^s_{i,j,T}}$$
$$+ \sum_{(T^h,T^w)} \sum_{(j^h,j^w)} N^c_{i,(j^h,j^w),(T^h,T^w)} \cdot \boldsymbol{H^c_{i,(j^h,j^w),(T^h,T^w)}}$$

where

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

Equilibrium prices $\{R(i)\}_{i=c,s_A,s_B}$ are to be interpreted as residential rents per unit of housing in each neighborhood. Section B.1 in the appendix presents details on how the model is solved.

3.8 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 an average metro-area in the United States, 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, the LODES jobs data, and the 2000 Census and 2006-2010 ACS IPUMS samples (Ruggles et al., 2019). Section C.1 in the appendix describes the details. Table C1 presents the list of targeted data moments $\bar{m}$ used in the estimation routine.

Overall, preferences are imposed to be the same for singles and couples, except for the value of home production and amenities. I set preferences over consumption and housing quantity as $\log(c) + \Omega_H \log(H)$. Thus λ is equal to the share of th couple's disposable income consumed by the husband and $\frac{\Omega_H}{1+\Omega_H}$ is equal to the share of expenditures spent on housing. Utility from leisure has the constant relative risk aversion functional form $u_L(L) = \Omega_L \cdot \frac{z^{1-\omega}}{1-\omega}$. Utility derived from home production has the same functional form, with $\Omega^s_x < \Omega^c_x$. Since childcare is part of producing value at home and couples are more likely to have young children in their household (see figures A2), it is likely that couples put a higher value on the products of home production time. Time endowment is set to one (but time variables are scaled in utility to be in the same scale as consumption).

The home production function is linear. Wives have a higher baseline productivity and time inputs of husband and wife are perfect substitutes (allowing for closed form solutions). Thus $P(x) = x$ and $P^c(x^h, x^w) = \kappa_w \cdot x^w + (1 - \kappa_w) \cdot x^h$.

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, the distribution of jobs and σ_{ϵ_i} is identified from distances between two random jobs (any and within the same labor market), share of jobs and of people close to city center, and distances to a random job and a job in your sector from a place of residence. Moreover, I target the average of $|d_o^w - d_o^h|$, the 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 time preference parameters ω and Ω_L and the distribution of stochastic match shocks ξ_0 helps to fit labor force participation of men and women in couples and average hours of singles, husbands and wives. Ω_x^s and Ω_x^c are pinned down by average home production hours of singles and couples. To identify the benefits (monetary and non-monetary) to working close to a sector hub, I include moments from tables 5 and 6 in the estimation. The share of income spent on housing from of Labor Statistics (2020), is used to calibrate Ω_H. 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 (mimicking the identification argument in Gayle and Shephard (2019)). Table C2 presents a complete list of parameters to be estimated. π (share of households with a second job offer) and ϕ (the scale of the costs of commuting rewarding specialization) is pinned down by the average commutes of singles and couples.

I estimate the model with a moment based procedure. There are ?26 parameters to be estimated 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 current guesses of other parameters combined with moments in the data. This partition decreases the number of parameters that are estimated via a global 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 constructed based on the inverse of the variance-covariance matrix of the data[32].

3.9 Fit of the model

Table 8 highlights that the model matches very well the commuting patterns of couples and singles, for men and women: the large difference between the commute of husbands and single men as well as the small difference for women. This difference is a combination of the couples moving to suburbs (thus further away from jobs in general) and men in couples being more willing to accept long commutes, wherever they live. Men in couples accept longer commutes, because couples are facing a collocation issue and because husbands have higher returns to commuting due to their longer hours, but especially because of the rewards to specialization on the commuting margin within households. Effectively, husbands have a lower cost of commuting compared to single men, because responsibilities around the house are already covered by the wife.[33]

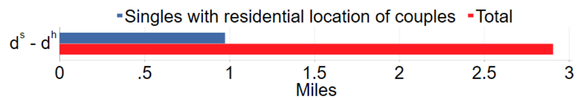
Couples are more likely to live in the suburbs, and suburbs have on average longer commutes. Still this alone cannot account for the difference in commuting between single men and men in couples in the model (as well as in the data). The bar graph in 8 illustrates this point, showing that if singles made the residential choices of couples, their commutes would increase by about a mile. 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

[32]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. Moreover, I increase the weight of the most crucial moments (see details in the appendix).

[33]**??** 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	9.036	8.667
$d^s_h - d^h$	**-2.918**	**-2.708**
$d^s_w - d^w$	0.226	-0.297



d^s is the average commuting distance of singles in miles. $d^s_h - d^h$ is the difference in commuting distance between single men and men in couples. $d^s_w - d^w$ 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.

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 quite well. 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). Table C1 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^h_j)	18.536	20.277
Distance to an average job in own labor market for a husband (d^h_o)	18.506	20.027
Distance between 2 random jobs	15.535	17.300
Distance between 2 random jobs of the husbands labor market	14.866	16.267
Distance between husbands and wifes actual jobs	10.040	9.740
$\|d^w_o - d^h_o\|$	2.250	1.862
$P(city\|couple) - P(city\|single)$	0.113	0.070
$d^s_o - d^h_o$	-1.288	-1.693
$d^s_j - d^h_j$	-1.257	-1.410
$d^w_o - d^h_o$	0.019	0.028
Share of jobs in city	0.563	0.498
Share of population in city	0.362	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 in fact 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 on commuting within couples allows husbands to accept long commutes, beyond how far away from jobs they move. Together tables 10 and 8 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 less than a mile of increase in actual commuting distance. The rest has to be accounted for by a change in behavior towards jobs. To sum up, the difference between couples and singles in the share of living in the suburbs is quite simply too small to explain the commuting differences.

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	**2.555**	**1.513**
	(.638)	
d^o	.207	0.651
	(.062)	
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 1. Here I present the fit on these non-targeted moments. In the data I regress a gender gap measure in a couple on binned distance of their residence 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 9 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 that gender gaps are more pronounced in the suburbs.

Lastly, I check whether the distribution of wages in the data with respect to how close a job is to the city center aligns with that in the model. Table 11 presents the results.

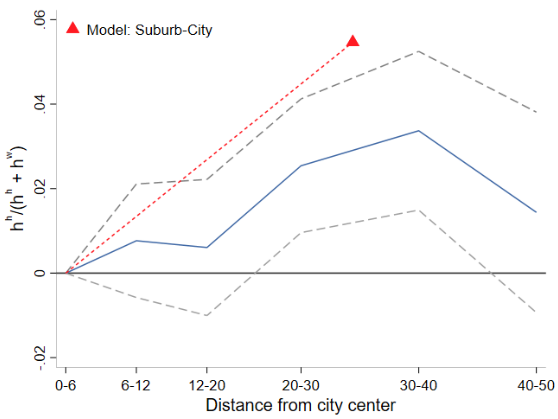
Table 11: Wage gradient by distance of the job to city center: data versus model

	Data	Model
$d_{\text{job to city}}$	-0.00387	-0.00518

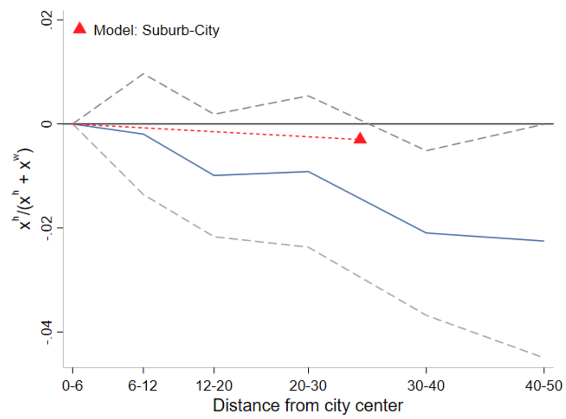
the first column is based on the PSID sample 18-50 years old with data available on the actual census tract of the job (waves 2013-2017). The coefficient presented comes from the following regression $\log(wage)_{it} = \beta d_{it}^{\text{job, city center}} + \gamma X_i + \alpha_{age} + \alpha_t + \alpha_{msa} + \epsilon_{it}$ where X_i includes race, gender, in couple, education, industry and education-cross-industry dummies.

Figure 9: Gender gaps within couples by distance of residential location from city center: data vs model

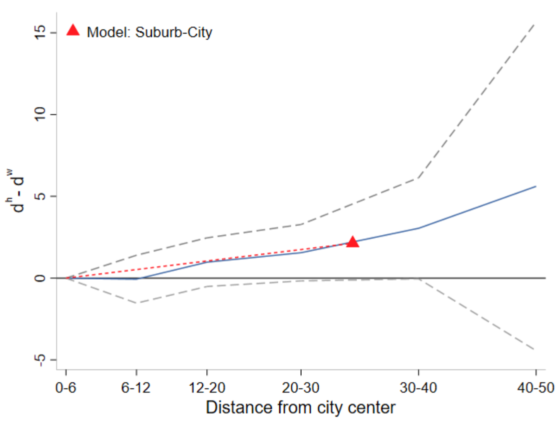
Share of market hours $\frac{h^h}{h^h+h^w}_{t,i}$



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



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

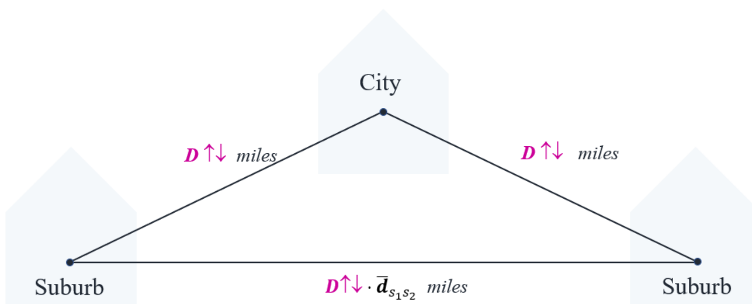


As in figure 1, I regress a gender gap measure in a couple on binned distance from city center in a metro area, controlling for dummies for age and education of both spouses, race of the head and number of children. $\frac{h^h}{h^h+h^w}_{t,i} = \sum_{j=2}^{N} \alpha_i^{\text{dist bin } j} + \alpha_i^{ah}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

4 Commuting and the value of marriage

Over the 20th century U.S. metropolitan areas have been sprawling out in space, increasing the necessary commutes one has to accept to work in a desirable job. In this section I mimic this trend by changing the geographic size of the model metro area. 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 stretched out in space, without any change in amenities or productivity (materialized as wages or non-monetary benefits) at work. Figure 10 summarizes this counter-factual. Lower values of D represent dense metro-areas with a short 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 10: Connectivity between suburbs and the city



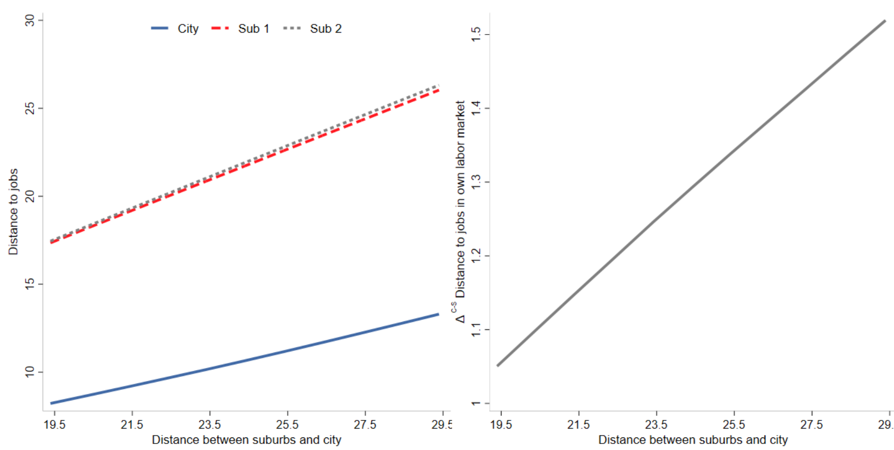
I study the effect on welfare of men and women and singles and couples, asking for whom commuting is ultimately most costly in a combined housing and marriage market equilibrium. All comparisons are between different steady states – alternative scenarios where the metro area would develop differently. I measure welfare for each subgroup (single and married men and women) as period utility averaged over the respective population: $W = \int_i u^*(i)$.[34] Moreover, I show how job access, gender gaps within couples, residential rents and sorting changes.

Overall, increasing D is a negative technology shock to the metro-area. All groups are hurt by it, on average. However, not everybody is affected the same way. Figure 11 presents the first set

[34]Since people decide whether to marry before all heterogeneity is revealed for the period, there is no difference in an average period utility of the original singles versus the new singles.

of results – the differential incidence of losing job access. 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 live in the suburbs, their job access deteriorates more compared to singles. In other words, the incidence of a policy that makes cities less easily accessible from the suburbs is higher on couples.

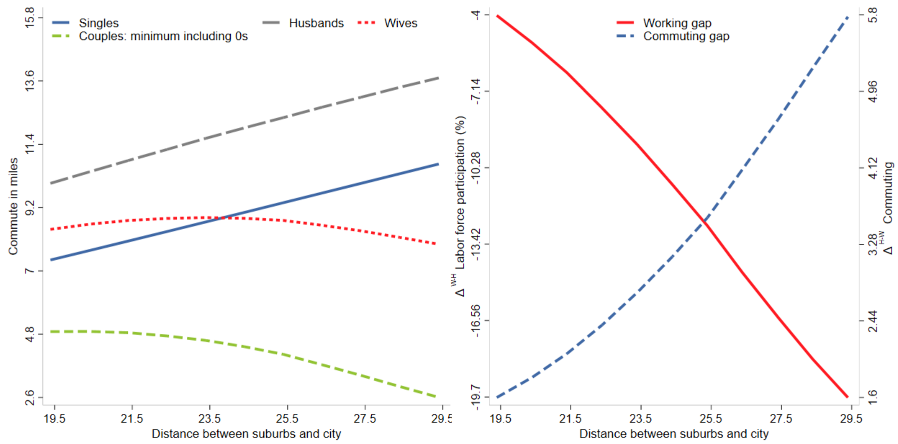
Figure 11: Job access when metro area grows in space



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

And yet, they are ultimately less affected in terms of welfare. This is because jobs are not taken randomly with respect to residential location. Households hustle to make their commutes short – by moving close to jobs and by taking jobs close to home. Moreover, couples specialize with one (more often the wife) taking a local job or no job at all 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 12 shows that husband's commute increases the most. Wives and singles also increase their commuting, but less so. The second figure shows that indeed within couples gender gaps increase, both in labor force participation and in commuting. Overall, women in couples are more sensitive in their labor market outcomes to long commutes than men. Figure 12 also shows how gender gaps help couples evade

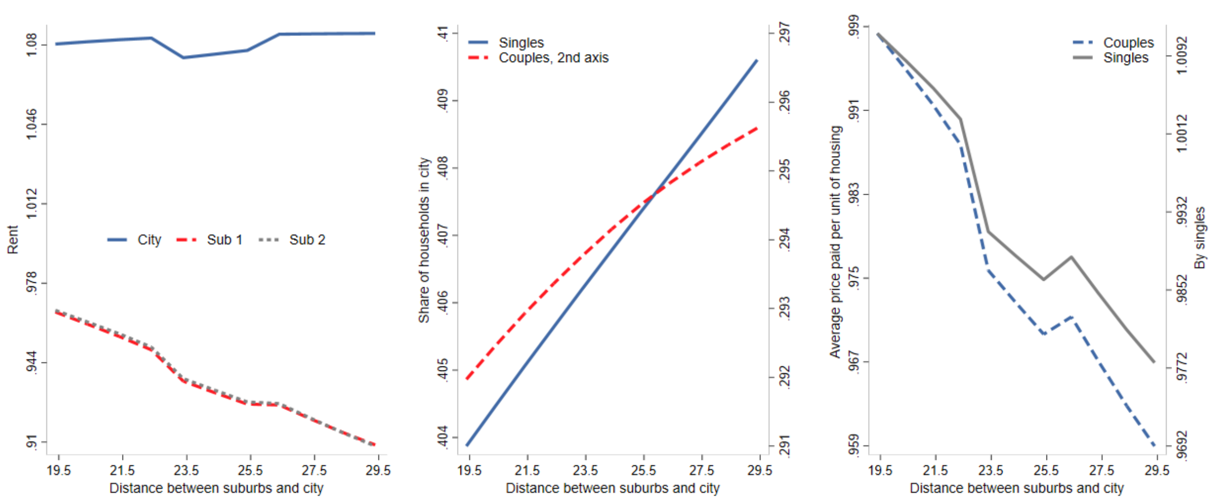
Figure 12: Commuting and gender gaps when metro area grows in space



Commuting of all subgroups. Gender gaps within couples.

part of the commuting costs. Even though all groups of people commute more on average, within couples at least one is often close by (assigning 0 commute to those who drop out of the labor force).

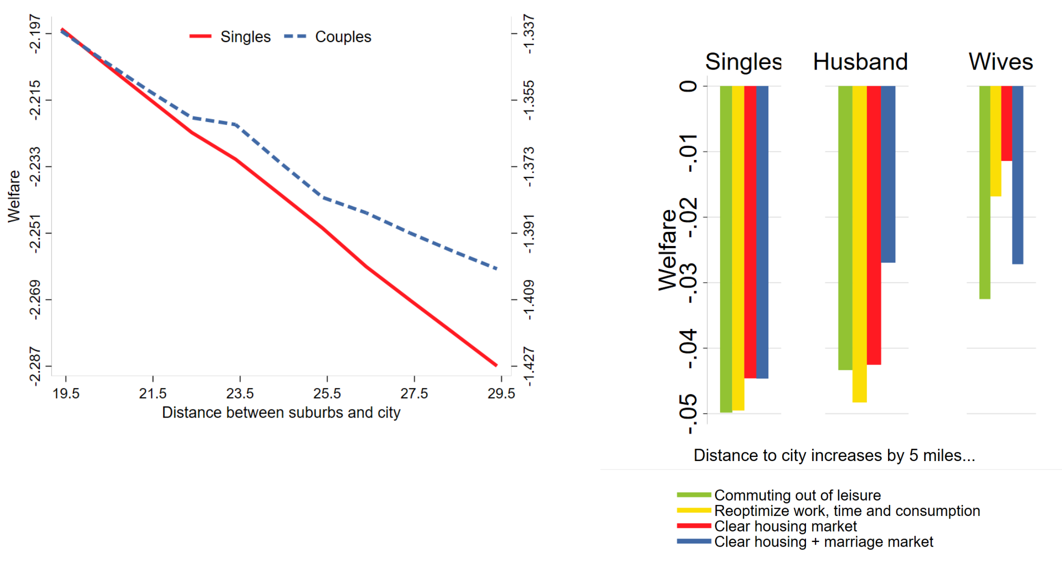
Figure 13: Housing when metro area grows in space



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

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 13 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 and they care less about suburban amenities. The spatial segregation of couples and singles within a 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.

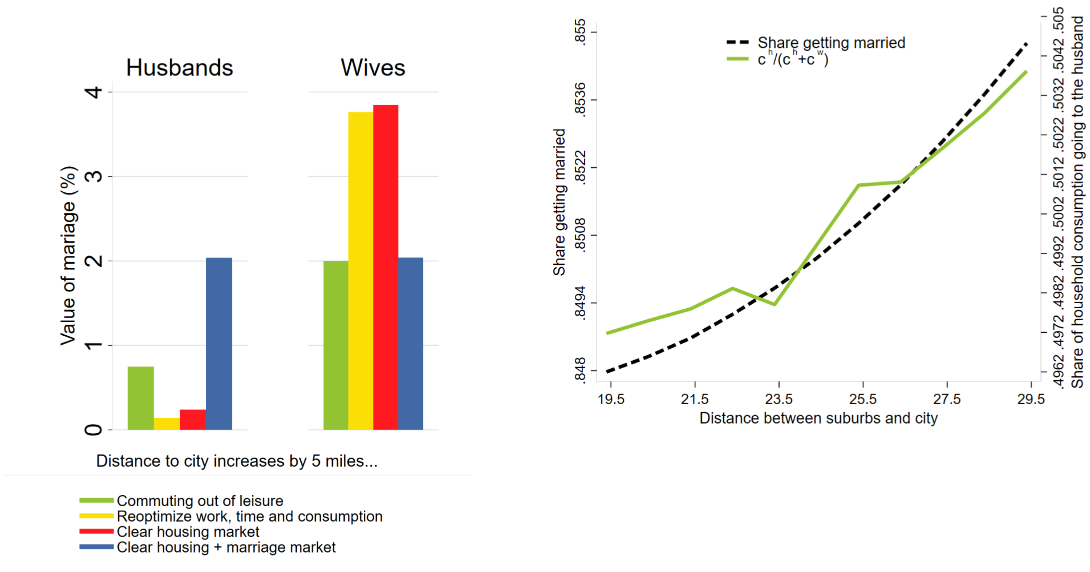
Figure 14: Welfare when metro area grows in space



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. 0.01 drop in welfare represents approximately a 1.5% decline in consumption.

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. Couples overall lose most job access. However, it is singles who lose the most when commutes are longer. Both husbands and wives change their behavior more than singles, but those large observable changes in behavior are in fact a sign that they have the added flexibility to do something about an inconvenient situation. Overall, couples benefit from evading commuting costs through specialization within the household, as housing prices adjust in the housing equilibrium and distribution

Figure 15: 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 position of husbands – determined by the price in the marriage market.

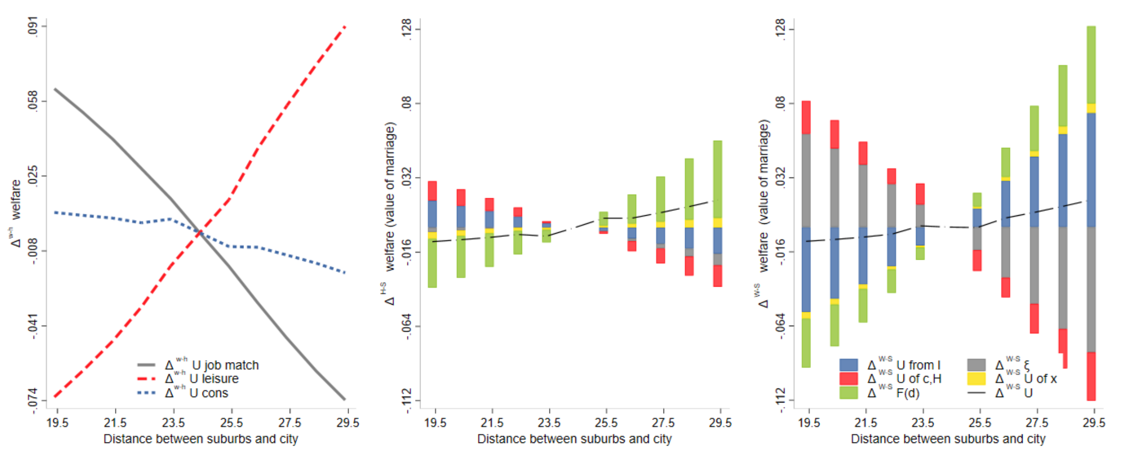
of tasks and resources within the couple adjusts in the marriage market equilibrium. Figure 14 presents this result. While welfare falls for everybody, it falls less for couples.

The endogenous responses of behavior and prices in the the joint housing and marriage market equilibrium only reinforce this result. Figure 14 presents the decline in welfare for singles, husbands and wives when the distance between suburb and cities increases by 5 miles. The green bar shows the effect when longer commutes simply subtract from leisure, without re-solving the housing and marriage market equilibrium. In this case, husbands loose markedly more than wives, precisely because they are the ones who are locked into the longest commutes. 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 more. This is precisely because they change their labor market behavior, 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 the household. Moreover, the gap between singles and couples widens, as specialization helps couples evade the commuting costs. The red bars shows the effect on welfare when the housing market re-clears. The blue bars show the final result within a full housing and marriage market equilibrium. The new prices help couples further (both husbands and wives), because they can now enjoy cheaper prices in the suburbs.

Figure 15 presents this explicitly, showing the effect of longer distances between suburbs and city on the value of marriage. The value of marriage increases for both men and women more after the new equilibrium is achieved. Couples save on housing, husbands keep their long commutes or opt for even better jobs, wives take local jobs or stay at home, but are ultimately compensated with more leisure within the household. This way couples evade part of the commuting costs. Figure 15 shows that the share of people marrying increases, while the bargaining weight of husbands (here presented as the share of couple consumption going to the husband) adjusts.

Figure 16 shows how the distribution of tasks and resources within couples is reorganized. The first figure shows that when metro-areas have long commutes, wives gain leisure 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 men and women. For both men and women, marriage becomes more valuable partially through home production and 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.

Figure 16: 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.

To summarize, the counter-factual simulation shows that if metro-areas spread out, couples gain compared to singles and marriage becomes more valuable for both men and women. This is facilitated through larger gender gaps in the labor market, more residential sorting and cheaper housing in the suburbs. While longer potential commutes are costly to all, single people have the most to lose.

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, Kolesnikova and Taylor (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

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

where i stands for an individual, m for a metro are, 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 12: Cross-metro area variation in work and commuting compared to model simulations

	Working	Commute (annualized)
$C_m\cdot$ (woman)	-0.0552	-0.239
	(0.0101)	(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.

Data

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.

	Working	Commute
	-0.422	-1.802

Implied by the D counter-factual.

Model simulations

Table 12 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.

Next, I repeat the exercise with commuting itself on the left hand side (and using a sample of working individuals), where d is a commute of an individual (measured in annualized hours).

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

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 more than wives' by an average of 0.24 hours. Qualitatively, this is exactly what happens in the model. Quantitatively, counter-factual exercises above imply a somewhat bigger effect on the gender gap in commuting.

Table 13: Cross-metro area variation in marriage compared to model simulations

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

SEs in parentheses, clustered at the MSA level. All data regressions include age, education, region, race dummies and MSA size polynomial.

Data

	(Ever married)·100	
C	0.0175	
$C_{husbands}$		0.0112

Implied by the D counter-factual.

Model simulations.

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.

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

$$\text{Ever in couple}_{im} = \gamma C_m + \gamma X_i + \delta X_m + \epsilon_{i,m}, \;\; \forall i : \text{age}_i \geq 30, \text{age}_i \leq 50$$

Ever in couple$_{im}$ is a dummy variable equal to 1 if the person is married, currently cohabiting with a partner or has ever been married. C_m, again, is the average annualized hours of commuting in a metro are m. Table D2 shows that, at least when metro-area-level controls X_m include religious participation and proxies for political affiliation, the estimate of γ is positive and statistically significant. 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 D2 show the result is robust to replacing C_m with the average commute among only married men, avoiding this type of selection.

Table 13 again compares the cross-metro area correlations to the equivalent change in marriage rates implied by the increase in distances between neighborhoods in the model simulations. 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 marriage more valuable by making living alone relatively more costly. This is despite the fact that long commutes hurt labor market prospects of married women, and couples lose more job access than singles.

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 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 collective 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. While long potential commutes increase the gap in labor market outcomes between married men and women, residential sorting of singles to the city and the rent differential between suburbs and the city, they also make marriages more valuable.

As metro-areas grow out in space while jobs concentrate in central cities, average commutes increase. I argue that there is an aspect of commuting costs that creates a wedge between singles and couples. In section **??** 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 (taking into account only the non-commuting aspect of working from home, without changing any benefits of the job). 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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COMMUTING AND THE VALUE OF MARRIAGE

Online Appendix—Not for Publication

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Deutsche Bundesbank

A Supplement to empirical observations

In this section I present supplementary empirical evidence. First, table A1 presents the kinds of commuting-related variables available in the PSID and the waves they are available in. Table A2 shows basic summary statistics of the main PSID sample used in the empirical section as well as in the estimation.

Table A1: Commuting variables available in the PSID

Variable	waves
Distance city center	1969-
Commuting distance	1970-1986 with gaps[35]
Commuting time annual	1970-1986 with gaps[36]
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)

Table A2: PSID sample summary statistics.

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

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 $Y - Y_{\text{first observed in a couple, or first year of marriage for original sample couples}}$.

Tables A3 and A4 show the differences in commuting between singles and couples, measured by directly comparing before and after outcomes (i.e. using person fixed effects). These differences are quantitatively smaller than the main analysis presented in section 2, primarily because only a limited number of individuals are observed in both states and the period they spent in being in a couple is very short. This is explicit in figures 2, showing event studies with person fixed effects, but pooling the comparison of before and after forming a couple with being in a couple for shorter and longer periods of time. The quantitatively large difference between singles and couples is robust to controlling for person fixed effects and emerges after about 5 years of being in a couple.

Table A5 shows the differences in commuting by gender and relationship status for two

Table A3: Commuting differences (distance) between singles and individuals in couples – person fixed effects

	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.

alternative measures of commuting in the psid: annualized hours of commuting (computed from an average daily commute report) and a distance from residence to work in miles (census tract to census tract). These are available in more recent waves of the survey, confirming this is a persistent pattern.

Tables A6 and A7 show the differences in commuting by gender and relationship status for the commuting variable available in the 2000 Census.

Table A4: Commuting differences (time) between singles and individuals in couples – person fixed effects

	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 A5: Alternative measures of commuting

	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 d^c		x		x
N	15215	15208	7922	7922
N clusters	171	170	160	160

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

All regressions include year, age, MSA fixed effects.

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

Table A6: Commuting differences by gender and relationship status in the 2000 Census.

	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.

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.

Table A7: Commuting differences by gender and relationship status in the 2000 Census.

	Commute (annualized)				
Man	4.085			40.38	3.000
	(0.978)			(1.893)	(0.949)
In couple	-12.35	20.82	-8.561		
	(2.247)	(1.218)	(2.370)		
Man in couple	35.85				
	(2.285)				
Sample:		men	women	couples	singles
N	2286363	1245988	1040375	1565336	721027

SEs statistics in parentheses, clustered at MSA level.

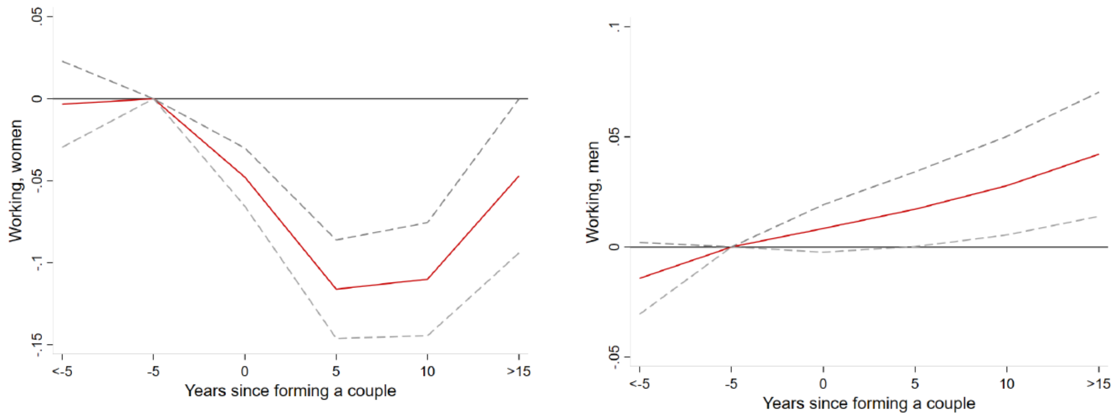
All samples include only people who are married or never married.

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

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.

Figures A1 present the well-known result that women are more likely to drop out of the labor force after forming a couple than men. Figures A2 show the concurrent increase in the number of children in the household.

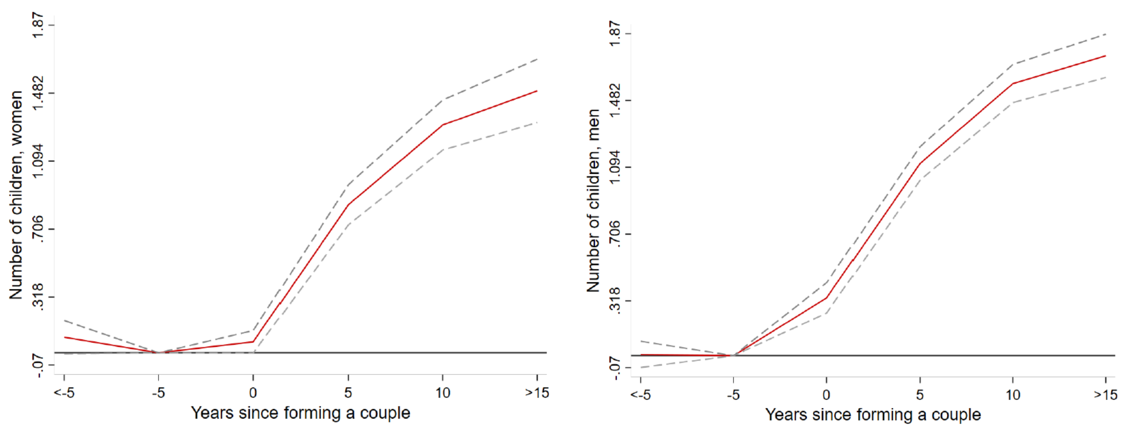
Figure A1: Employment with respect to time spend in a couple



women men

Source: PSID

Figure A2: Number of children living in the household with respect to number of years in a couple

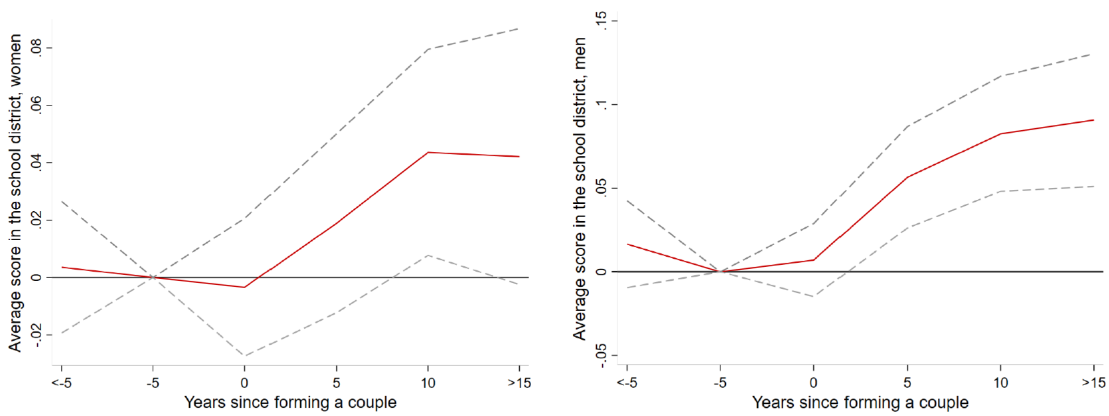


women men

Figure A3: Analogous regressions for figures 3. With distance to center d^c replaced with the number of children in the household.

As couples are more likely to have children bellow the age of 18 living with them in the household, 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 evolution of this proxy measure with respect to tenure in a couple (controlling for year and age dummies) is plotted in A4, showing that couples do move to better school districts after 5-10 years of being in a couple. It is noteworthy, that this measure of school quality correlates weakly with distance to center. Thus by this measure, suburbs have on average somewhat better schools. However, other measures of school quality (such as financing per pupil or the value-added measures produced by Reardon et al. (2021) fo not correlate systematical with distance to center).

Figure A4: Average test scores in the school district of residence with respect to time in a couple



women men

Figure A5: Analogous regressions for figures 3. 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).

In my model, I link the specialization on the commuting margin with specialization in time use in the household (as a source of the gendered nature of specialization, not the need for specialization in the first place). For the sake of simplicity, I do not distinguish between childcare and housework in my analysis. From the existing literature, we know that women perform more of both. In this paper I do not aim to uncover the root causes of this gendered specialization; I assume women are more productive in home production as a means to fit the observed patterns. Given the patterns in figures A2, it would be reasonable to hypothesize that the changes in commuting I observe after men and women form couples are somehow directly related to couples having children in the household, not to the nature of being in a couple alone. Table A9 shows, however that this is an especially difficult assertion to prove or disprove with this data, because the sample of individuals who ever end up in a couple, have information on commuting and are never observed in a household with a child living in it, is very small. In other words, almost all couples in the sample eventually end up having children, making it difficult to argue that any behavior in these couples is unrelated to future, present or past child-rearing.

Table A8: Commuting by relationship status, controlling for having children.

	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.

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

Still, the evidence in tables A8 and A9 suggests that specialization in commuting is not purely tied to children, but is more gendered when children are present. Table A8 shows that controlling for having a child under 18 in the household shrinks the increase in commuting for men after forming a couple marginally (by about half a mile). On the other hand, when controlling for having children women increase commuting after forming a couple by about 0.7 miles (up from the baseline increase of only 0.2 miles), though this difference between single and coupled women is not statistically significant. Correspondingly, table A8 shows that when a child is present, men commute more while women commute less. Overall, this suggests that child-rearing is related to the gendered nature of specialization in commuting and elsewhere. However, this evidence also suggests that the sizable increase in commuting after men form couples is not strongly tied to having children. In other words, the benefits to specializing on the commuting margin and thus the increased value of forming couples in long-commute environments come from the nature of sharing a household, not the presence of children. This is supported by the evidence in table A9. This table shows the increase in commuting for men after they form a couple with samples split by whether the person is ever observed having children in the household or not. While the sample of men who never end up having children is small, the increase in commuting is just as large as for those who end up having children.

Table A9: Commuting differences, separately by whether a person ever ends up in a couple living with a child or not.

	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.

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.

Table A10 repeats the analysis of hours within couples presented in table 6 showing in the second ling that within couples living far away from relevant jobs is associated with women's hours falling more compared to men's. The negative association between job access and hours for men is not robust to different sub-samples, but the gendered nature of the response is. Columns 1 and 2 limit the sample to waves when commuting distance and commuting time respectively are available. Columns 3 and 4 limit the analysis to a sample of waves when the alternative commuting measures, annualized hours and distance to work, are available. These are newer waves and only small samples. Table 5 shows that the result is robuts to using newer waves as long as a sufficient sample is used.

Table A10: Hours and potential commutes within couples – alternative samples

	Hours				
Distance to jobs (d^{opp})	3.675	5.101	-5.525	-7.118	-4.109
	(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.

Analogous analysis of hours spent working to table 6, except over samples when commuting variables are available, providing a more direct link to table 5. Using the backfilled d^{opp} from the first year available, typically 2002, in the first two columns.

B Model supplements

B.1 Model solution

The solution proceeds sequentially backwards from the choices made last to the choices made first within each period. First, given jobs and residential locations consumption, housing quantity and home production are solved in closed form:

$$Y^s = l^s \cdot w(j, T, s)$$

$$H^s = Y^s \frac{1}{\frac{R}{\Omega_H}^{1/\omega} + R}$$

$$c^s = Y^s \frac{\frac{R}{\Omega_H}^{1/\omega}}{\frac{R}{\Omega_H}^{1/\omega} + R}$$

With $\kappa^s = 1 - b \cdot (d^s - \bar{d})\kappa_d$

$$x^s = \kappa^s \cdot (1 - l^s - b \cdot d^s) \cdot \frac{(\Omega_x^s)^{1/\omega}}{(\Omega_x^s)^{1/\omega} + (\kappa^s)^{1-1/\omega} \cdot (\Omega_L)^{1/\omega}}$$

$$Y^c = h^c \cdot w(j^h, T^h, h) + h^w \cdot w(j^w, T^w, w)$$

$$H^c = Y^c \frac{1}{\frac{R}{\Omega_H}^{1/\omega} + R}$$

$$c^h = \lambda \cdot Y^c \frac{\frac{R}{\Omega_H}^{1/\omega}}{\frac{R}{\Omega_H}^{1/\omega} + R}$$

$$c^w = (1 - \lambda) \cdot Y^c \frac{\frac{R}{\Omega_H}^{1/\omega}}{\frac{R}{\Omega_H}^{1/\omega} + R}$$

For home production in couples, corner solutions are possible. If both do home production, the interior solutions are (with $\kappa^h = 1 - \kappa_w$ and $\kappa^w = \kappa_w$):

$$x^h_{int} = \frac{(1 - l^h - b \cdot d^h) \cdot [(\Omega_L)^{1/\omega}(1-\lambda)^{1/\omega}(\kappa^w)^{1-1/\omega} + (\Omega_x^c)^{1/\omega}] - (1 - l^w - b \cdot d^w) \cdot \lambda^{1/\omega}(\Omega_L)^{1/\omega}\frac{\kappa^w}{(\kappa^h)^{1/\omega}}}{(\Omega_L)^{1/\omega}[\lambda^{1/\omega}(\kappa^h)^{1-1/\omega} + (1-\lambda)^{1/\omega}(\kappa^w)^{1-1/\omega}] + (\Omega_x^c)^{1/\omega}}$$

$$x^w_{int} = \frac{(1 - l^w - b \cdot d^w) \cdot [(\Omega_L)^{1/\omega}(\lambda)^{1/\omega}(\kappa^h)^{1-1/\omega} + (\Omega^c_x)^{1/\omega}] - (1 - l^h - b \cdot d^h) \cdot (1-\lambda)^{1/\omega}(\Omega_L)^{1/\omega}\frac{\kappa^h}{(\kappa^w)^{1/\omega}}}{(\Omega_L)^{1/\omega}[\lambda^{1/\omega}(\kappa^h)^{1-1/\omega} + (1-\lambda)^{1/\omega}(\kappa^w)^{1-1/\omega}] + (\Omega^c_x)^{1/\omega}}$$

$$\begin{aligned} x^h =&(x^h_{int} \leq 0) \cdot 0 \\ &+(x^h_{int} > 0)(x^w_{int} > 0) \cdot x^h_{int} \\ &+(x^w_{int} \leq 0)(\kappa^h \cdot (1 - l^h - b \cdot d^h) \cdot \frac{(\Omega^c_x)^{1/\omega}}{(\Omega^c_x)^{1/\omega} + \lambda^{1/\omega}(\kappa^h)^{1-1/\omega} \cdot (\Omega_L)^{1/\omega}}) \end{aligned}$$

$$\begin{aligned} x^w =&(x^w_{int} \leq 0) \cdot 0 \\ &+(x^h_{int} > 0)(x^w_{int} > 0) \cdot x^w_{int} \\ &+(x^h_{int} \leq 0)(\kappa^w \cdot (1 - l^w - b \cdot d^w) \cdot \frac{(\Omega^c_x)^{1/\omega}}{(\Omega^c_x)^{1/\omega} + (1-\lambda)^{1/\omega}(\kappa^w)^{1-1/\omega} \cdot (\Omega_L)^{1/\omega}}) \end{aligned}$$

Plugging in the optimal choices at home, I solve for optimal job choices. This is a discrete choice. Singles choose either between 3 or 5 options (depending on whether they have a second local offer). The value of each option is $U^s(i, job)$ = the deterministic portion of period $+\xi_0^{l,j}$. Couples choose either between 9 or 25 options. The value of each option is $U(i, job^h, job^w) = +\lambda\xi_0^{l^h,j^h} + (1-\lambda)\xi_0^{l^w,j^w}$. ξ_0 are 0 if $l = 0$ and are drawn from an extreme-value-type-I distribution otherwise. I simulate a population and solve choice probabilities numerically, integrating also over the errors to get the proper conditional means, constructing $V^s_T(i,j)$ and $V^C_{T^h,T^w}(i,j^h,j^w)$. For each T, j combination for singles and T^h, T^w, j^h, j^w for couples, the choice probabilities for residential location are solved in closed form, given that idiosyncratic location preferences are distributed extreme-value-type-I (see McFadden (1977)). Equivalently for the choice to marry, the probabilities are solved in closed form (after numerically integrating over the idiosyncratic location preferences).

The equilibrium is a set of four equations and four prices, which is solved numerically.

$$m_{1-3}^{equilibrium} = H^i - H_i^D(R, \lambda)$$

$$m_4^{equilibrium} = p^h(R, \lambda) - p^w(R, \lambda)$$

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 C2 presents a complete list of parameters to be calibrated or estimated. I estimate the model with a moment based procedure. Table C1 presents the list of data moments $\bar{m}$ used in the estimation routine. Following Gayle and Shephard (2019) and Reynoso (2018), I add $m^{equilibrium}$ conditions to the list of moments and prices to the list of parameters. This way prices do not have to be solved at each iteration. 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.[37] This partition decreases the number of parameters that have to be searched for numerically, decreasing the computational burden in estimating the model. Letting $\alpha = [\alpha^1, \alpha^2, p, \lambda]$ denote the $Bx1$ parameter vector, the estimation problem may be formally described as

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

W is constructed based on the inverse of the variance-covariance matrix of the data. 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. Moreover, I increase the weight of the most crucial moments (commuting moments, price gradient, difference in hours within couples) and set the weight on market clearing conditions high.

C.1 Constructing moments

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

[37] α^1 inclued Θ and $A(1)$.

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. 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 observations who have been married (or in a couple as identified in the PSID) before and are now 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 (whichever available in each wave).

Average commute of singles d^s is an average commuting distance in miles for those identified as having never been in a couple. $d^s_h - d^h$ and $d^s_w - d^w$ 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 others) 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 away 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, to avoid unnecessary imputation. 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_b^a 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 14, 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, Stults and Xu, 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. Table C1 shows the list of moments as well as fit. h stands for annual hours of work, x for home production hour, d for commuting distance in miles, w for wage, d_j for distance between residence and a random job, d_o for distance between a residence and a random job in the person's mode industry and earnings segment, p for rent per unit of housing.

Moment	Model value	Data value	Directly used to fit a parameter	Group
Average commute of single d^s	9.0358	8.6669	0	1
$d^s_h - d^h$	-2.9184	-2.7085	0	1
$d^s_w - d^w$	0.2264	-0.2973	0	1
$h^h_{\text{both work}}$	2167.1102	2206.5421	0	2
$h^w_{\text{both work}} - h^h_{\text{both work}}$	-733.5813	-671.5465	0	2
$h^h_{\text{just husband works}} - h^h_{\text{both work}}$	172.8898	63.1028	0	2
h^s	1935.9913	1873.1261	0	2
$x^w_{\text{both work}}$	810.7029	973.9142	1	3
$x^w_{\text{just husband works}} - x^w_{\text{both work}}$	205.4922	683.0032	1	3
$x^h_{\text{both work}} - x^w_{\text{both work}}$	-774.8583	-604.5061	1	3
$x^h_{\text{just husband works}} - x^h_{\text{both work}}$	-35.8445	-50.5242	1	3
x^s	387.8715	495.3415	1	3
LFP of wives-husbands	-0.1114	-0.2207	0	2
LFP of husbands	0.9998	0.9738	0	2
$\log(\frac{w^w}{w^h})$	-0.2728	-0.2440	0	2
Share of population in city	0.3617	0.3919	0	4
Share of jobs in city	0.5630	0.4978	0	4

Distance to an average job for a couple (d_j^h)	18.5358	20.2769	0	4
Distance between 2 random jobs	15.5353	17.3000	0	4
Dist between 2 jobs of the husbands sector	14.8663	16.2667	0	4
$\|d_o^w - d_o^h\|$	2.2501	1.8622	0	5
Dist to a random job in own sector for husband (d_o^h)	18.5062	20.0266	0	4
$P(city\|couple) - P(city\|single)$	0.1127	0.0704	0	5
$\log(p)$ distance to jobs gradient	-0.0129	-0.0088	0	5
$\log(p)$ city over suburb	0.1436	0.0728	0	5
$d_o^s - d_o^h$	-1.2876	-1.6931	0	5
$d_j^s - d_j^h$	-1.2566	-1.4099	0	5
$d_o^w - d_o^h$	0.0188	0.0279	0	5
Distance between husbands and wives actual jobs	10.0403	9.7405	0	4
β_{wd}^{comm}	-0.1850	-0.1054	0	6
β_{wd}^{work}	-0.0128	-0.0016	0	6
β_{wd}^{hours+}	-2.1696	-2.4845	0	6
β_{wd}^{hours}	-22.4378	-5.1460	0	6
β_{wd}^{x}	1.9907	3.2846	0	6
β_{d}^{comm}	1.3656	0.7064	0	6
β_{d}^{work}	0.0025	-0.0019	0	6
β_{d}^{hours+}	-8.5531	-4.9347	0	6
β_{d}^{x}	-0.3465	-1.0640	0	6
$\beta_{wd}^{\log(w)}$	-0.0006	-0.0012	0	6
β_{d}^{hours}	-3.2614	-5.4621	0	6
$\beta_{d}^{\log(w)}$	-0.0034	0.0015	0	6
Share never married	0.1449	0.1449	1	3
$\hat{\lambda}_0$	0.4985	0.5360	0	3

Table C1: 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	Groups
ϕ	7.722	0	(9.568)	0.525	G1, G5, G6
$D(1,2) = D(1,3)$	24.393	0	(4.810)	5.071	G1, G5, G6
$D(3,2)/D(1,2)$	1.516	0	(0.874)	1.735	G1, G2, G5, G6
$(1\|.)/f(2\|.)$	4.288	0	(2.093)	2.049	G1, G5, G6
$f(2\|1)/f(3\|1)$	6.415	0	(12.959)	0.495	G5, G6
$A(1)$	0.727	1	(7.687)	0.108	G5, G6
$A^c(3) = A^c(2)$	1.550	0	(11.463)	0.135	G5, G6

σ_{ϵ_i}	3.161	0	(24.705)	0.142	G5, G6
Ω_l	1.754	0	(1.596)	1.099	G1, G5, G6
ω_l	1.890	0	(0.926)	2.041	G1, G5, G6
Ω_x	0.022	0	(0.057)	0.384	G1, G5, G6
$\bar{\kappa}_w$	0.586	0	(0.025)	23.895	G1, G5, G6
$\frac{\Omega_x^s}{\Omega_x}$	0.770	0	(0.223)	3.459	G1, G3, G5, G6
w_{gap}	-0.269	0	(0.024)	-11.405	G2
π	0.437	0	(0.086)	5.821	G1, G5, G6
μ_{ξ_0}	6.586	0	(7.036)	0.936	G1, G2, G5, G6
$\frac{\sigma_{\xi_0}}{\mu_{\xi_0}}$	0.119	0	(0.009)	14.465	G1, G2, G5, G6
w_{Ξ}	4.566	0	(2.055)	2.456	G5, G6
Θ	-0.579	1	(15.228)	-0.033	G5, G6
λ	0.494	0			
$R(c)$	1.074	1			
$R(s_A)$	0.931	0			
$R(s_B)$	0.933	0			
Ω_H	0.239	1			
w_a	24.383	1			
b	0.002	1			
$\bar{h}^U$	1.000	1			
σ_{θ_i}	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 C2: Model parameters. Baseline parameter values, when appropriate standard errors and t-statistics and groups of moments that the parameter is sensitive to (using the measure by Andrews, Gentzkow and Shapiro (2017) rescaled by the moments standard deviation and highlighting all groups with at least one moment with sensitivity of at least 10 percent of the maximum). Parameters in the lower part of the table are calibrated outside the estimation routine. Parameters in the upper part with 1 indicated in the third column are fitted directly within the estimation routine to satisfy a particular moment equation.

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).

While it is in any case identified practically within the model as a market clearing price, solving the marriage market equation given all the other parameters, it is useful to think about external sources of variation for this unobservable number (similarly to including moments about price differences within a metro-area to discipline the price gradient in the model). 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 14 presents a useful condition on the value of the bargaining weight (where u^h is the utility in marriage for a man)

$$\frac{\partial u^h(\lambda)}{\partial \lambda} = -\frac{(1-\lambda)}{\lambda}\frac{\partial u^w(\lambda)}{\partial \lambda} \tag{14}$$

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, Browning and Chiappori (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.[38]

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.[39] In this

[38] 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.

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

Table C3: Responsiveness of staying single long-term to sex-ratios across US metro areas.

	$\log\left(\frac{1}{s_k^g}-1\right)$
$\log(\frac{M}{F}_k)$	1.002
	(.317)
$\log(\frac{M}{F}_k)\cdot$ 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.

$s_k^g = 1 - \frac{\text{married or currently in couple}}{all}$ 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

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 within the model (using a numerical derivative with respect to $\frac{M}{F}$) resolving the housing and marriage market equilibrium, and collecting the implied changes in the share of single men and women) and use it in estimation. Since $\hat{\lambda}_0$ is now only one of the moment, I also take into account that it is just an imprecise estimate, weighting the associated uncertainty against that of other moments.

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.[40]

Identification of 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[41]. Congruently, in estimation I search over relative prices r_{s_A} and r_{s_B}, so that $R(c) = exp(r_{s_A}/2)$, $R(s_A) = exp(-r_{s_A}/2)$ and $R(s_B) = R(s_B) \cdot exp(r_{s_B})$, fixing the scale of prices to range around 1.

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).

Ω_H is set so that $\frac{\Omega_H}{1+\Omega_H} = 0.1927$, the expenditure share on housing from the 2019 Consumer Expenditures Report by the U.S. Bureau of Labor Statistics. σ_{θ_i} cannot be separately identified and is set to be equal to 1.[42][43]

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 independently from commuting behavior, so that parameters of commuting costs are identified. 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

[40] 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.

[41] Specifically, I utilize moments describing average hours, 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.

[42] 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.

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

(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 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 of amenity values for singles and couples A^c and A^s (6 parameters), as well as the dispersion (scale parameter) 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 $A(1)^s = A(1)^c = 0$. This leaves $A(1)$ as the difference for all between the amenity value of the city and suburbs and $A(2)^c = A^c(3)$ as the amenity differential for couples between suburbs and the city (on top of what is implied by $A(1)$). 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 making suburbs better for couples or cities better for singles. Lastly, a difference between the two suburbs would not be well identified as their difference comes from availability of male versus female jobs and the price effects of such differences in the data is not cleanly identified.[44] Amenity values are identified as residuals – after the value of access to opportunities is taken into account, amenities match the difference in the share of singles versus couples who live in the city, and the price gradient between city and suburbs. Specifically, $A^c(2) = A^c(3)$ matches $P(city|couple) - P(city|single)$ and $A(1)$

[44] $A^c(2) - A^c(3)$ could be identified also from moments describing $d_o^w - d_o^h$. However, this difference is small in the data and the model matches this moment without amenity differences well.

matches the price-distance-gradient moments. $A(1)$ is fit numerically within the estimation routine by closing the housing market clearing moments fixing the prices. This is practical as given prices (which are constrained in estimation by the observed price-distance gradients) and other guesses of parameters, the distribution of demand between suburbs and city can always be manipulated by this parameter, which does not influence any other decisions except for location. 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. Lastly, I include a share of overall population in the city as a moment in estimation.

There are 4 parameters governing preferences and technology for time, consumption and home production left (with Ω_H already calibrated): Ω_L, ω, Ω_x, $\frac{\Omega_x^s}{\Omega_x}$, κ_w and 5 parameters related to the distribution of jobs: w_{Ξ}, w_{gap}, μ_{ξ_0} and σ_{ξ_0}.

The location and scale parameters of the idiosyncratic job preferences (μ_{ξ_0} and σ_{ξ_0}) together with the time preference parameters Ω_L, ω are identified to match average hours moments (of singles and couples, men and women in couples, depending on if both work or just one) and labor force participation of men and women in couples.

Ω_x and $\frac{\Omega_x^s}{\Omega_x}$ are identified from average home production hours of couples and singles. κ_w fits the baseline difference in home production hours between men and women in couples.

w_{gap} is estimated to match the observed within-couple gender wage gap in the PSID sample. I include $\beta_{wd}^{\log(w)}$ and β_{wd}^{hours+}, coefficients estimate presented in table 6, measuring how much within couples a woman's wage and hours are more affected by the couple living far away from other jobs in the wife's labor market than a husband's wage would be to identify w_{Ξ}. 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 offers in her labor market, her wage and hours do fall more. To further help estimate the interlink between access to opportunities and labor market 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. Since w_{Ξ} effectively measures how returns to commuting scale with hours, they also affect the gender gap in commuting within couples.

The value of not commuting is governed by two aspects, the value of time (as governed by the preferences identified above) and the household value of being close to home. ϕ is than mainly identified from the difference in commuting between husbands and single men. 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.

Θ is a baseline shifter for the the value of marriage capturing returns to marriage not captured in the model 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). I fit this parameter directly within the estimation routine, matching the share choosing marriage exactly for the side that is closer. This way I also do not need to integrate over ϵ_i, as the conditional expectations only impact the value of marriage, not the marriage market clearing or other moments.

In the last column of table C1 I classify moments into broad groups: commuting, time use and marriage, distribution of jobs and people in space, location choices and sensitivity to opportunities within couples (βs). The last column of table C2, I compute the sensitivity of each parameter to the moments in the estimation using the measure proposed by Andrews, Gentzkow and Shapiro (2017). For each moment and each parameter I compute

$$|Sensitivity| = |-(G'WG)^{-1}G'W|$$

where W is the estimation weighting matrix and G is the numerical derivative of moments with respect to parameters evaluated at the estimated values. Given the scale of the moments is not always comparable, I multiply each element by the standard deviation of the moment (as recommended by Andrews, Gentzkow and Shapiro (2017)). For each parameter, I calculate the moment with maximum sensitivity, and consider any moment whose sensitivity is at least 10% of the maximal as being important. As I consider sets of moments, I describe a set as being important if at least one moment from that set is important according to this criterion.

D 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, Kolesnikova and Taylor (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

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

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_w is the coefficient of interest – it shows the differential impact of living in a place of long-commutes on men and women. Table D1, 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).

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

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

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

Table D1: The correlation of average commutes and differences in commuting by gender and relationship status across MSAs.

	Commute (annualized)			Working		
$C\cdot$ (in a couple)	0.0667	-0.170		0.0133	-0.0326	
	(0.006)	(0.036)		(0.0009)	(0.005)	
$C\cdot$ (woman)			-0.239			-0.0552
			(0.038)			(0.010)
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

SEs statistics in parentheses.

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

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.

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

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 D1 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.

Table D2: The correlation of average commutes and the probability of staying perpetually single across MSAs.

	(Ever married or cohabiting)·100			
C	0.00465 (.0097)	0.0158 (.0048)		
$C_{husbands}$			0.0114 (.0067)	0.0134 (.0031)
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:	$30 \leq \text{age} \leq 50$			

SEs statistics in parentheses.

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.

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 D2 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 D2 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.

Figures D1 visualizes the variation in average commuting across metro areas, with and without residualizing with respect to proxies for religious participation and political affiliation.

Figure D1: Average annualized commuting time, residualized.

Second figure residualizes also with respect to religion and politics proxies. As political affiliation 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).