NBER WORKING PAPER SERIES

HOUSING CONSUMPTION AND THE COST OF REMOTE WORK

Christopher T. Stanton
Pratyush Tiwari

Working Paper 28483
http://www.nber.org/papers/w28483

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2021

We thank Ed Glaeser, Bill Kerr, Nathan Seegert, and seminar participants in the HBS Entrepreneurial Management Unit for helpful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Housing Consumption and the Cost of Remote Work
Christopher T. Stanton and Pratyush Tiwari
NBER Working Paper No. 28483
February 2021
JEL No. J32,J81,J82,R21,R3,R40

ABSTRACT

This paper estimates housing choice differences between households with and without remote workers. Prior to the pandemic, the expenditure share on housing was more than seven percent higher for remote households compared to similar non-remote households in the same commuting zone. Remote households' higher housing expenditures arise from larger dwellings (more rooms) and a higher price per room. Pre-COVID, households with remote workers were actually located in areas with above-average housing costs, and sorting within-commuting zone to suburban or rural areas was not economically meaningful. Using the pre-COVID distribution of locations, we estimate how much additional pre-tax income would be necessary to compensate non-remote households for extra housing expenses arising from remote work in the absence of geographic mobility, and we compare this compensation to commercial office rents in major metro areas.

Christopher T. Stanton
210 Rock Center
Harvard University
Harvard Business School
Boston, MA 02163
and NBER
christopher.t.stanton@gmail.com

Pratyush Tiwari
Harvard University
ptiwari@hbs.edu

1 Introduction

The surge in remote work during COVID-19 has the potential to change residential real estate markets, yet very little prior research has examined the housing choices of remote versus non-remote households. At the time of our writing, projections about the location of remote workers across states or territories remain difficult due to the sheer size of the pandemic shock and questions about whether remote households will be free to relocate to new cities after the pandemic subsides. However, historical data on housing consumption of remote versus non-remote households is likely to be informative about differences in housing needs for remote workers. In this paper we ask whether remote households make different choices when facing the same housing market conditions. That is, do households with remote employees consume more housing? We also ask whether remote households sort to suburbs or rural parts of their respective commuting zones. These differences between remote and non-remote households are two crucial building blocks for understanding the general equilibrium implications of remote work (Behrens, Kichko, and Thisse, 2021).

We address these questions using American Community Survey data from 2013-2017. We split the analysis for households who rent versus own. When we hold fixed household income, education, and household structure (age, children, number of adults), we find that the average renting household with at least one adult who works remotely spent between 6.5 and 7.4 percent more of their income on housing compared to similar non-remote households in the same narrow 100,000 person Public Use Microdata Area (PUMA) or in the same broader Commuting Zone. Among owners, mortgage payments and property taxes as a share of household income were between 8.4 and 9.8 percent greater for remote households.

To understand why remote households were spending more of their income on housing, we first decompose the differences in housing expenses for remote and non-remote households into three components: differences in the size of the dwelling (measured by rooms, as square footage isn't available in the ACS data), differences in the price per room after holding fixed average prices in a PUMA, and differences in the average price of housing across PUMAs in the same commuting zone. The first channel captures demand for more space. The second channel captures either demand for higher quality housing or demand for larger rooms. The third channel captures sorting within a commuting zone to areas that are on average either more or less expensive.

Prior to the COVID pandemic, remote households consumed 0.3 to 0.4 more rooms per dwelling, which is between a 5% to 7% increase in space relative to non-remote households. Remote households also lived in higher quality housing, as measured by rent- or value-per-room, but these quality measures may also capture larger average room sizes for remote households. Remote households were thus consuming more space, and were possibly consuming higher-quality space.

There has been much recent discussion regarding how remote work might affect geographic sorting. When we conduct analysis within commuting zones (shutting down geographic sorting across disconnected areas but allowing sorting within the same markets, a la Rosenthal, Strange, et al. (2005)), remote households are actually found to have located in areas with slightly higher than average home prices compared to non-remote households. Further assessment of whether remote households are more or less suburban or rural depends on a number of factors, including educational attainment and whether the household was a "mixed" household containing both on-premises and remote workers. Unconditionally, mixed households are more likely to be suburban and less likely to be rural, but adult education appears to be explaining these location outcomes rather than remote status. Controlling for education, fully remote households are slightly more likely to live in rural areas rather than urban or suburban ones, but any differences in location sorting are small in magnitude. That is, location sorting within commuting zones, at least prior to the pandemic, did nothing to offset remote households greater housing expenditure share.

Our primary focus is on housing demand for remote households, and focusing at the commuting zone level is natural because it allows us to compare consumption differences for households that face similar prices. This analysis within commuting zone sidesteps a possible reshuffling across geographies, where remote households may flee to areas with cheaper or more elastic housing supply. Forecasting post-pandemic locations across commuting zones from the pre-pandemic location distribution is likely unwise, but our estimates are nonetheless useful for understanding historical patterns of where remote households located by commuting zone. Prior to the pandemic, remote households were not locating in the least expensive commuting zones; instead they were likely to be in places with some urban urban amenities. Reflecting this, we find that housing expenditure differences actually increase by about 40% for renters and 20% for owners when we omit commuting zone fixed effects.[1]

[1] In ongoing related work, we find that remote households were less likely to be located in the 10 most expensive commuting zones prior to the pandemic, but they were also less likely to locate outside of the 50 most expensive commuting zones.

Having established that the greater housing expenditure share among remote households is due to larger houses, we ask why remote work entails choosing more space. Two possibilities are: 1) Vehicles are complementary with commuting for non-remote households, and savings on vehicles allow remote households to consume more housing. 2) Additional space complements working at home, so remote households adjust housing consumption to accommodate home offices. After accounting for differences in the presence of vehicle for remote and non-remote households, we conclude that vehicles are insufficient to explain remote households' greater housing expenses. The most plausible explanation for larger homes is that additional space is needed to accommodate remote work.[2]

For firms, managers often speak colloquially of cost savings from remote work due to reductions in office space. But this neglects the fact that remote households need more space to accommodate working from home. As a result, remote work entails a transition from firms' financing of office space to household financing of home workspaces. To quantify how big a cost expanding remote work would be for the marginal household, we conduct a back-of-the envelope calculation to capture how much more non-remote households would need to earn to compensate for the additional housing expenses they would incur if moving to remote work (the remote premium).[3] The premium amount varies over the household income distribution due to differences in the average expenditure share on housing. We estimate that bottom decile households would require between a 10-15% earnings premium, while households between the 80th and 90th percentile of income would require about a 3% earnings premium, and households in the top decile would not require additional compensation to offset housing expenses. Across the income distribution, the expected premium is 3.8% of household income with no adjustments and is 2.4% when we adjust for vehicle expenses that may not be required with remote work. Using this latter number, if 10% of non-remote households became remote, the required compensation would total $15 billion annually at current housing prices.[4] Of course new demand for housing that can accommodate remote work may push up prices for larger dwellings, whereas sorting to cheaper areas or places with elastic housing supply may offset some of these costs (Ozimek, 2021). This analysis

[2] It is also possible that more space is simply complementary with time spent at home, but this explanation is unlikely to fully explain the results, as households where one spouse engages in home production (rather than working for pay outside the home), have only one-third the space increases associated with remote work.

[3] Our exercise assumes preference neutrality for remote versus in-office work, so our results are the documented non-pecuniary preferences for remote work arrangements Mas and Pallais (2017). Presumably those pushed into remote work by the pandemic will be less likely to have high willingness to pay for the remote work amenity compared to those who were previously observed in remote jobs.

[4] For analysis of how remote work is affecting prices, see Ramani and Nick Bloom (n.d.)

also says nothing about the incidence of potential productivity gains or losses from remote work.[5]

Our final piece of analysis examines housing cost differences for remote and non-remote households relative to office space expenses across major metropolitan areas. This analysis serves as a rough estimate of potential office cost savings in the event that there is limited sorting across geographies, i.e. where most remote households remain in the same commuting zone as their original offices. Using average commercial rents and assuming the average worker has about 150 square feet of office space suggests that increased housing expenditures from remote work would offset about one-third of any savings on office space. Despite having very expensive housing, the San Francisco Bay Area would still offer the highest savings in office rents, at about $6,000 per worker per year because of San Francisco's extremely high commercial rents. For other areas, some non-obvious patterns emerge. For example, the entire New York metro area had the third highest commercial rents nationwide as of 2020 but New York ranks sixth in terms of savings from remote work due to high local housing costs. Nashville had the twelfth most expensive office space, but low housing costs mean the $4,100 per-worker net savings from remote work ranks seventh nationally. The areas with the lowest estimated cost savings from remote work are Detroit, Michigan and Fort Worth, Texas, at $2,100 and $1,400 annually.

The combined findings are relevant for understanding an ever-expanding literature on remote work. Several important papers estimate the productivity effects of remote workers (Choudhury, Foroughi, and Larson, 2020; Nicholas Bloom et al., 2015) or the extent of remote work (Mas and Pallais, 2020). More recent papers document changes in remote work and time use during the pandemic (Barrero, Nicholas Bloom, and Davis, 2020a; Bick, Blandin, and Mertens, 20200; Brynjolfsson et al., 20200) or forecast the extent of remote work after pandemic health risks subside (Bartik et al., 2020). This paper fills a gap by seeking to understand how a shift to remote work might affect housing consumption and broader housing demand, with more general implications for understanding how information technology affects demand for space in cities (Gaspar and Glaeser, 1998) or the demand for suburbanization (Baum-Snow, 2007). While a general equilibrium model that might account for changing locations, the disutility of commuting, and other standard features in urban economics is beyond the scope of our empirical orientation in this paper, our findings corroborate some of the tenets of this general equilibrium model with remote work in Behrens,

[5] For evidence on the productivity implications of remote work, see Bartik et al. (2020); Barrero, Nicholas Bloom, and Davis (2020b); Ozimek (2020).

Kichko, and Thisse (2021).

2 A Framework

We consider the consumption choices of two types of households. Households with at least one remote worker are denoted by R and households with no remote workers by N. All households derive utility from consuming a bundle of non-housing goods denoted C and housing denoted H. The simplest way to model differences in housing expenditure is to formulate a utility function with differences across household types. As in Glaeser and Gottlieb (2009), we work with a simple Cobb-Douglas utility setup, but we allow the share parameters to vary by household type $k \in \{R, N\}$. We use this simple version to fix ideas, but when taking the model to the data, we will allow the parameters to vary flexibly by other household characteristics and by income, as housing expenses appear non-homothetic. In this simple model, households maximize

$$
\begin{aligned}
U_k(C_i, H_i) = C_i^{1-\alpha_k} H_i^{\alpha_k} \\
\text{subject to} \\
C_i + P_a H_i \leq W_i.
\end{aligned}
$$

In the budget constraint, W_i is the income of household i, the price of the consumption bundle C_i is normalized to 1, and the price of a unit of housing in area a is given by P_a. Solving for the consumption decisions yields the following for households of type $k \in \{R, N\}$:

$$
\begin{aligned}
C_k &= (1 - \alpha_k) W_i \\
H_k &= \alpha_k \frac{W_i}{P_a}
\end{aligned}
$$

When $\alpha_R > \alpha_N$, remote households place a higher value on additional units of housing, and their housing expenditures are given by $\alpha_R W_i > \alpha_N W_i$, as α_k is the expenditure share on housing for type k.

As we confront the possibility that many more households may move to remote work after the pandemic, it is useful to understand how compensation would need to change to equalize utility between remote and non-remote households. That is, how much additional income would be required for a remote household to be on the same indifference curve as a non-remote household under the parameters for non-remote households? The indirect utility function is used to calculate this differential, labeled β, setting equal the maximized utility as-if remote households had the same parameters as non-remote households.[6]

$$
\begin{aligned}
(1-\alpha_R)^{1-\alpha_N}\left(W(1+\beta)\right)^{1-\alpha_N}(H_R)^{\alpha_N} &= (1-\alpha_N)^{1-\alpha_N}W^{1-\alpha_N}(H_N)^{\alpha_N} \\
\implies \beta &= \frac{(1-\alpha_N)}{(1-\alpha_R)}\left(\frac{H_N}{H_R}\right)^{\alpha_R/(1-\alpha_N)} - 1
\end{aligned} \tag{1}
$$

In this formulation, β is the additional compensation required to make a household indifferent between remote and non-remote work due to the additional housing expense. When we estimate β empirically, we also account for sources of possible savings among remote households, like on vehicle expenses. This framework might also be adjusted to account for differences in labor supply and leisure time, but we find work hours vary little between remote and non-remote workers.

We note that this framework is likely most useful for understanding the expansion of remote work rather than as a commentary on the utility levels of remote versus non-remote households. In particular, we do not observe the counterfactual for households of either type. This is important because remote employees may be earning a premium relative to their non-remote option in order to finance additional housing expenses. While our empirical strategy conditions on W_i, it is possible that remote households are consuming more housing because their employers pay them more to do so. Assuming the incidence of who pays for office expenses remains similar, any differences would indicate that the shift to remote work will require a transfer from employers to workers to compensate for higher housing expenses.

3 Data and Summary Measures of Differences Between Remote and Non-Remote Households

We use data from the 2013-2017 1-year waves of the American Community Survey (ACS), an annual survey of 1% of the population conducted by the Census Bureau. From the ACS, we primarily use data on remote working status of individuals in the household, household income, home ownership status, monthly rent, the value of the house, the number of rooms, the number of children, adult education, and population density.

We define a household as a remote household if it has at least one member that works

[6] The indirect utility function is $v_k(P_a, W) = (1-\alpha_k)^{1-\alpha_k}\left(\frac{\alpha_k}{P_a}\right)^{\alpha_k} W$.

remotely. Our measure of an individual's remote working status originates form the IPUMS variable "TRANWORK", which is based on the question "How did this person usually get to work LASTWEEK? If this person usually used more than one method of transportation during the trip, mark (X) the box of the one used for most of the distance." Among the choices, respondents have the option to choose "Worked at home" and anyone making that choice is defined as a remote worker.

Our modeling approach requires comparing similar households except for their choices to work remotely. While households are heterogeneous along a number of dimensions, the most important one from the model's perspective is the household budget constraint. Budget constraints obviously vary with household income, but may also vary with household structure, as households with slightly older adults or with children may have different savings levels and propensities to consume out of savings. We deal with many of these issues via controls or matching: what is crucial is to compare remote and non-remote households with a similar budget constraint, meaning their income levels are similar today, their expected life-cycle earnings are similar (meaning we must control for age and education), and they face the same set of home and goods prices. To approximate the household budget constraint, we use pre-tax household income and then flexibly control for household structure and local area to account for different tax regimes. Pre-tax household income is computed based on the IPUMS variable "HHINCOME", which is defined as "total money income of all household members age 15+ during the previous year."[7] We incorporate household structure by examining the age of adults, the number of adults, and the number of children. We define any household member aged 21 or more as an adult and calculate the average adult age by taking the mean for all adults living in the household. The household (rather than the nuclear family) is our unit of analysis for this comparison, as multi-generational household structures may determine dwelling choices.

We also use several measures describing the price and characteristics of each housing unit. For renters, we use the IPUMS measure for the amount of the household's monthly contractual rent payment and multiply by 12 to annualize the measure. For home owners, we calculate home value from the survey question "About how much do you think this house and lot, apartment, or mobile home (and lot, if owned) would sell for if it were for sale?" To capture

[7] This amount in turn, equals the sum of all household members' individual incomes, as given by the individual income variable "INCTOT" and the ACS survey question that populates "INCTOT" is "What was this person's total income during the PAST 12 MONTHS? Add entries in questions 47a to 47h; subtract any losses. If net income was a loss, enter the amount and mark (X) the "Loss" box next to the dollar amount."

dwelling size, we use the number of rooms. Rent per room and value per room are each calculated by dividing rent and house value amounts by the number of rooms in the house.

To capture differences in non-housing aspects of consumption, we examine vehicles and time spent working (the complement of leisure). The ACS includes data on the number of vehicles available, and we capture leisure time as the inverse of hours worked plus time spent commuting.

We use Public Use Microdata Area (PUMA) and Commuting Zone (CZ) as the main geographic units of analysis. PUMAs are geographically contiguous units used for dissemination of Public Use Microdata samples. They are nested within states and for the years 2013-17, have a minimum population of 100,000. CZs are geographical units that most accurately reflect the local economy - where people live and work and we use them to identify local economies for our analysis, along the lines of much of the recent work on spatial differences across labor markets.[8]

Table 1 provides summary statistics for the main outcomes and controls, overall and by household type. The first row is informative for our empirical strategy and displays household income for different types of households. Average household income is $\$84,400$ in the overall sample, yet mean income for remote households is $\$42,500$ higher than non-remote households. Households with remote workers are also more likely to be owners than non-remote households, with 25% of remote households renting versus 34% of non-remote households.

Given our interest in understanding how the housing needs of remote and non-remote households differ, we focus on the characteristics of housing to quantify differences in demand for space. Using rooms as a measure of house size, remote households have 6.89 rooms per house on average compared to 5.95 rooms for non-remote households, implying a 16% difference in space. However, this is not an apples-to-apples comparison, as remote households may live in different areas and face different prices. Later our analysis will compare remote and non-remote households who face the same consumption opportunities and prices by using

[8] Commuting zones frequently contain multiple counties, although counties are sometimes contained in multiple commuting zones. We thus use commuting zones rather than counties because the ACS sampling frame is based on residence rather than workplace, and we want to capture features of local labor markets broadly. Sampling weights are constructed accounting for this probabilistic mapping by using the product of the ACS weights and the PUMA to Commuting Zone mapping. The sum of the resulting weights for an individual or household, across all the Commuting zones that the individual or household is mapped to, equals the original ACS sampling weight.

Commuting Zone or PUMA fixed effects. Similar issues plague simple analyses of the share of income spent on housing, as without adjusting for income differences and prices, remote households actually spend a lower share of household income (HHI) on rent. Yet when examining rent per room and the number of rooms, it is clear that remote households on average are spending more in rent in total, suggesting that accounting for income differences will be important. Among owners, remote households report average home values that are $121,000 greater than non-remote households, with part of this difference arising from a $13,700 average difference in value per room.

The next two rows display demographic information by household type. Remote households average 0.86 children (household members under 18) compared to 0.67 children for non-remote households, and mean adult average age in a remote household is 48 compared to 50.6 in non-remote households.

The next row is important to understand that not all remote households are equal, and may themselves face different constraints. The variable "Share of Mixed Remote HH" is an indicator that the remote household has at least one adult who is a non-remote worker. Fifty-six percent of the remote households in our sample are mixed households, where at least one adult is working outside the home. These households may need to locate closer to an urban core to accommodate commuting needs, whereas fully remote households may be able to more freely sort to areas with different amenities or cheaper prices per square foot.

The next two rows examine commuting and vehicle ownership patternsn. Remote households spend a smaller amount of time commuting per day, with remote households totalling 34 minutes of one-way commute time on average compared to 42 minutes for non-remote households.[9] Surprisingly, remote households have more vehicles, 2.14 compared to 1.84, likely reflecting income differences, households structure differences, and possibly location differences.

The next two rows capture potential location differences, defined by characteristics of different local areas. We adopt a classification by Molfino (2020) of whether a census tract is urban, suburban, or rural. We then aggregate these characteristics to the PUMA level using

[9] One may have thought that the total commute time among remote households would be less than half of the non-remote commute time, as 44% of remote households have no commuters. However, remote households are more likely to have multiple earners who enter the commute time calculation. Remote households are also less likely to be located in very sparse commuting zones where average commute times are lower. For more detail, see Figure A.2.

2010 Census Tract to 2010 PUMA relationship file from the Census Bureau. Sixty-eight percent of remote households live in PUMAs classified as suburban compared to 62 percent of non-remote households. While remote households are more likely to live in suburbs, they are less likely to locate in rural areas, with 18% of remote households in rural areas compared to 24% of non-remote households. Adding the rural and suburban share means that 14% of remote households were in urban areas prior to the pandemic, which is identical to the urban share among non-remote households. The overall summary statistics thus suggest remote households sort to the suburbs at the expense of rural areas, yet leave the urban share untouched. This may reflect some value placed on urban amenities or social opportunities for those who mostly work alone at home.

The last row of Table 1 shows that remote households actually work fewer hours, but work hours look more similar (especially for households with above-median incomes) after controlling for characteristics (see Figure A.3).

4 Housing Consumption Differences

It is obvious from Table 1 that remote households differ significantly from non-remote households - the average remote household earns more, consumes more housing, pays more per room, commutes less and has more vehicles than the average non-remote household. Comparison of household consumption thus may prove difficult because of non-overlap in the budget constraints faced by the different types of households. The ideal experiment to isolate how remote work influences consumption would be to randomly allocate some households to working remotely and then allow households to make housing choices with that knowledge in hand.

Of course remote work is not random, but for our purposes we need an approach that compares the choices households make when facing the same budget constraint, housing prices, and local consumption opportunities. To do so, we flexibly control for household income and household structure, which approximates households facing the same budget constraint. To provide flexibility in the specification, we classify households into deciles of the household income distribution, and allow for interactions of income decile dummies with household characteristics. We also let household income vary linearly within decile to capture differences in budget constraints locally.

To control for the same local prices, we use commuting zone and PUMA fixed effects. Although we present several specifications, they are all restricted versions of this general estimating equation:

$$y_{i,c,d,t} = \gamma_1 RH_{i,c,d,t} + X_{i,c,d,t}\gamma_2 + \tau_t + \eta_c + \delta_d + \delta_d HHI\gamma_3 + \delta_d AdultAge\gamma_4 + \varepsilon_{i,c,d,t} \qquad (2)$$

where $y_{i,c,d,t}$ is the outcome variable for household i, in commuting zone c, in income decile d and year t. The main parameter of interest is γ_1, the coefficient on $RH_{i,c,d,t}$, which is a dummy that takes the value 1 when i contains at least one adult who works remotely. The matrix $X_{i,c,d,t}$ is a set of controls that includes fixed effects for household structure (e.g. the number of children and the total number of household occupants) and may include adult education. τ, η and δ are year, geography (either commuting zone or commuting zone and PUMA) and income decile fixed effects, respectively. The coefficient γ_3 on the interaction of δ_d and household income allows the effect of household income to vary linearly within each income decile. Finally, γ_4 allows the effect of income deciles to vary linearly with average adult age, which may capture lifecycle changes in housing consumption beyond the presence of children. We subsequently run regressions varying the conditioning set to assess sensitivity to omitted variables.

Tables 2 contains the main results for various dependent variables that capture housing expenses and some other aspects of consumption. For analysis of housing expenditures, we split the sample between renters and owners to avoid confounding ownership and expenditure differences. Ultimately our results are similar for renters and owners, but evaluating renters separately is closer to the ideal experiment of allowing each type of household to optimize, as renters in most places have fewer frictions to changing or adjusting housing compared to owners.

The first set of regressions examines the log of the household expenditure share on rent, calculated as the log of annualized rent payments divided by the annual household pre-tax income. The coefficient estimate of 0.135 in Column 1 indicates that remote households spend about 13.5 percent more of their income (about 3.5 percentage points) on housing than non-remote with similar incomes. Column 2 interacts average adult age with income deciles, yielding a very similar estimate to Column 1. Adding fixed effect for household structure (number of children and size) does little to change the estimate.

The most substantial change arises from the addition of fixed effects for geography. The parameter estimate falls to 0.092 with the inclusion of commuting zone fixed effects. The change in the parameter indicates that remote households are actually locating in commuting zones with more expensive housing compared to non-remote households. At first glance this is surprising, but Stanton and Tiwari (2020) show that there is an inverted-U shaped pattern of remote work with respect to average commuting zone wages. Column 5 adds controls for adult education, and the coefficient remains at 0.71. Adding PUMA fixed effects in Column 6 allows more geographic granularity, allowing for sorting within a commuting zone. The coefficient indicates that within the same local area and facing the same local prices, remote households' spend about 7.8 percent more on rent, translating to a housing expenditure share that is 2.1 percentage points higher at the mean. The last column adds education and PUMA fixed effects, yielding a coefficient of 0.063.[10]

While the table examines the log expenditure share on rent, Figure 1 shows how the expenditure share in levels varies across the income distribution. This figure is constructed from separate regressions for each income decile after controlling for number of children, household size and commuting zone. Panel A shows that remote households spend a greater proportion of their income on rent across each decile, with the largest differences for lower income households. Later when we estimate utility differences between remote and non-remote households, we use the projected expenditure share for each decile and estimate how the implied compensation required to keep utility from remote work constant varies across the household income distribution.

The expenditure share for owners is a bit more difficult conceptually, as ownership is both a savings and consumption decision. We take several different approaches, all of which yield qualitatively similar answers to the analysis for renters. The second set of results in Table 2 shows that house values are between 21.5 and 15 percent higher for remote households, depending on whether geography and education fixed effects are present. We then examine the log of the expenditure share on flow housing costs, defined as the interest payments on a 30 year mortgage for the full value of the house plus depreciation and maintenance expenses (computed as home value divided by 40, capturing a 40 year useful life) and reported property taxes divided by households' pre-tax income. This measure captures something akin to what a new owner would need to pay in flow housing costs as a share of income. Estimates range from an 11.7-18 percent greater expenditure share. We also examine actual mortgage, property tax, and insurance payments as a share of income, which is closer to capturing the cash outlay on housing. The next row shows these expenditures are between 8 and 11.7

[10]Table A.2 in the Appendix also allows a comparison between these regression based adjustments and a nearest-neighbor matching approach.

percent higher for remote households.

Figure 1 Panel B describes how our preferred measure of expenditure shares for owners, the expenditure share on mortgage payments plus taxes, varies across the income distribution. We use these expenditure share estimates later when calculating compensation for remote households.

Regardless of the sample or the approach to estimating expenditures, remote households spend more of their budget on housing. The next rows of Table 2 shed light on different explanations for the greater housing expenses. Regressions of the number of rooms in the household show coefficients of about 0.32 to 0.44 relative to a sample mean of 5.99. Using the estimates of 0.37 with PUMA fixed effects implies that remote households are living in houses that are about 6.2% larger than non-remote households. Figure 1 Panel C shows differences in rooms across the income distribution. The next two sets of regression results also show that remote households are also spending more in rent per room and living in houses that have higher value per room, but it is not clear whether these measures capture housing quality or unobserved size differences, like bigger rooms. Thus the 6.2% increase in size for remote households is likely a lower bound on housing quantity demand.

To this point we have varied specifications with and without commuting zone and PUMA fixed effects. Differences in parameters provide a suggestive diagnostic on the extent of geographic sorting between different locations. The next specifications do more to address sorting directly. We examine average residual home prices in a PUMA Expensiveness Index after controlling for dwelling characteristics, to ask whether remote households are sorting to more or less expensive areas (see Table notes for details on index construction). Regressions of the PUMA expensiveness index yield positive coefficients on the remote dummy in all specifications. The coefficient in Column 3 roughly indicates that remote households are in PUMAs that are 0.068 standard deviations more expensive than the average PUMA in the United States. This specification does not contain commuting zone fixed effects, so this estimate is picking up both between commuting zone sorting and sorting within commuting zone. With commuting zone fixed effects in Column 4, the estimate remains positive and significant, but falls to 0.04. Comparing these estimates indicates that remote households are not locating to commuting zones with below average housing costs and they are not decamping to PUMAs with inexpensive housing within the commuting zones where they do choose to locate. Figure 1 Panel D shows this relationship over the income distribution. Unsurprisingly, there is little relationship with log density, as shown in the last sets of results.

Finally, why do remote households spend more? It is possible they need to spend less on other necessities for commuting, like vehicles or that time spent at home and larger dwellings are generally complementary. The last row of Table 2 examines vehicle ownership, and we find that on average, remote households own more vehicles unconditionally. After controlling for commuting zone and PUMA fixed effects, the coefficients turn negative, but they are small in magnitude. Vehicle expense reductions are thus unlikely to be large enough to explain increased housing expenses. However, it is possible that higher housing expenses arise from a time-use complementarity channel. Appendix Table A.3 re-estimates the model but looks at the effect of having a stay-at-home spouse (rather than a stay-at-home worker). When we regress rooms per household on the full suite of controls, we find positive coefficients of about .08 to .115 on the homemaker household dummy. By contrast, the estimates are three-times as large for the remote household dummy. Because we control for the household budget constraint and household structure, these differences are not arising because of different income levels or household composition, yielding support for the notion that extra space is complementary to the efficacy of working at home rather than space consumption arising due to general preference heterogeneity.

5 Geographic Sorting

With greater demands for space, will remote work reduce the demand for urban housing and encourage flight to the suburbs? To examine this question, we focus on the location choices of remote households. Table 3 displays estimates of three different regressions across the rows, where the dependent variables are a dummy for a rural PUMA, a dummy for an urban PUMA, and a dummy for a suburban Puma. By construction, the coefficients should sum to 0, as these estimates represent share differences for collectively exhaustive and mutually exclusive categories of places. The estimates are presented separately for fully remote households versus non-remote households and mixed-remote households, accounting for the possibility that fully remote households are more flexible in where they choose to live.

In columns without commuting zone fixed effects, both fully remote and mixed remote households are about 1.4-2.5 percentage points more likely to be suburban and are between .07 and 3.2 percentage points less likely to be rural. Mixed remote households are a bit less likely to be in urban PUMAs than fully remote households, possibly suggesting that fully remote households have a slight relative preference for urban consumption amenities compared to mixed households. However, much of this sorting appears to be between commuting zone.

When we add Commuting Zone fixed effects in Column 4, we find that coefficients fall across the board. We detect no differences in within-commuting zone locations for fully remote households: their location choices mirror non-remote households. Within commuting zones, mixed remote households are about 0.6 percentage points more likely to be suburban than other households and about 0.5 percentage points less likely to be rural. Because mixed households make up 56% of all remote households, this suggests a modest correlation between remote work and suburbanization within commuting zone, but overall evidence for the importance of sorting by geography is weaker than the evidence suggesting remote households need more space. We caution that these results from before the pandemic may look different in the face of an abrupt shock. After the COVID-19 pandemic, a large and persistent increase in the share of work done remotely may change these patterns, as suburban homes may be more or less readily available to meet the space requirements of an influx of new remote workers compared to the existing stock of urban dwellings.

6 What Compensation Would Non-Remote Households Require to Shift to Remote Work?

Given that remote households must spend more on housing, how much compensation would they require to offset other consumption losses? This section details estimates of β from equation (1), the percentage increase in household income required to compensate a non-remote household moving to remote work for their additional housing expenses. To that end, we need to estimate the parameters α_k and differences in housing quantity H_k, for $k \in \{N, R\}$. We estimate two βs, one using reported household income and one after adjusting household income for the cost of vehicle ownership. We adjust for the number of vehicles by multiplying the total vehicles present in a household by the yearly cost of owning a vehicle[11], and subtract the total from the household income. This latter approach is an implicit adjustment to income accounting for offsetting expenses by non-remote households.

We perform the estimation for renters and owners separately, then average within each decile. For renters, we estimate equation (2) with the share of income spent on rent and rooms per adult as the dependent variables, with the adjusted (unadjusted) income decile fixed effects. We then calculate the predicted values for both dependent variables using the regression estimates and then take the weighted mean of the predicted value by income decile and household type. For owners, we use the share of income spent on mortgage payments,

[11] We use an approximate annual cost of vehicle ownership as $\$10,000$

inclusive of property tax and insurance and repeat the process. Appendix Table A.1 displays the estimates of expenditure shares by income decile.

We find that lower income households would need substantial compensation to move to remote work. When using reported income in Figure 2 Panel A, households in the lowest decile of the income distribution require between 13 and 18 percent higher compensation to engage in remote work. The range in these estimates arises from differences in controls and whether geography fixed effects are included. Contrary to all other households, top decile households would move to remote work without any additional compensation. This is primarily due to these top-decile households spending a lower share of their income on housing than households in other deciles. When totaling across all households, we find an average β of 3.8% and a total required compensation dollar amount equal to $23.7 billion if 10% of the non-remote households (10.4 million households) moved to remote work.

Panel B presents the estimates after adjusting for vehicle ownership. Households in the lowest income decile require between 8 and 12 percent higher compensation to engage in remote work after adjusting for vehicle ownership differences in this decile. Patterns are similar (except in the second decile) across most of the income distribution. Totalling yields an overall estimate of 2.4%, which would mean that a shift of 10.4 million households to remote work would require $15 billion to keep non-housing consumption at the non-remote level.

Finally, Table 4 compares the additional cost required to compensate households for remote work to the potential per-employee savings in commercial office rents across different metro areas. We take data on commercial rents from JLL and assume that employees have 150 square feet of dedicated office space. We then compare the rent savings to metro-area level estimates of required compensation estimated via matching metro-by-metro. We caveat that this is surely an out-of-equilibrium analysis, but we believe it is a telling one nonetheless, allowing us to benchmark current commercial rental prices against housing compensation under the current spatial allocation of households. As a result, this analysis likely serves as a rough estimate of potential office cost savings in the event that there is limited sorting across geographies, i.e. where most remote households remain in the same commuting zone as their original offices and where office prices don't fall percipitously because of a large-scale move to remote work.[12]

[12]Large reductions in commercial office rents are likely to occur with a lag due to long-term contracts, but extreme rental price reductions may mean these estimates overstate potential savings from remote work.

Overall, Table 4 indicates that increased housing expenditures from remote work would offset about one-third of any savings on office space. Despite having very expensive housing, the San Francisco Bay Area would still offer the highest savings in office rents, at about $6,000 per worker per year because of San Francisco's extremely high commercial rents. New York is another interesting case given high rents and home prices. The entire New York metro area had the third highest commercial rents nationwide as of 2020 but New York ranks sixth in terms of savings from remote work due to high local housing costs. At a different place in the distribution, Nashville had the twelfth most expensive office space, but low housing costs mean the $4,100 per-worker net savings from remote work ranks seventh nationally. Finally, the areas with the lowest estimated cost savings from remote work are Detroit Michigan and Fort Worth, Texas, at $2,100 and $1,400 annually.

7 Conclusion

There has been much recent popular discussion about the potential for firms to save office space costs by allowing remote work. Our analysis shows that a the increased cost of housing needed to support remote working will offset a significant portion of any savings on commercial real estate from remote work. This is because households with remote workers spend more of their income on housing to live in larger dwellings to accommodate having a home office.

Assuming that the incidence of who bears expenses for home office and corporate space is similar, our findings indicate that nominal cost savings to firms are overstated by about 30% relative to hybrid remote work where workers stay in the same local areas. Cost savings will possibly be greater for firms if households are allowed to sort to lower cost areas, but it is yet to be determined whether frictions to mobility or preferences for places will limit this reallocation.

References

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis (2020a). "60 million fewer commuting hours per day: How Americans use time saved by working from home". *University of Chicago, Becker Friedman Institute for Economics Working Paper* 2020-132.

– (2020b). "Why Working From Home Will Stick". *University of Chicago, Becker Friedman Institute for Economics Working Paper* 2020-174.

Bartik, Alexander W et al. (2020). "What jobs are being done at home during the COVID-19 crisis? Evidence from firm-level surveys".

Baum-Snow, Nathaniel (2007). "Did highways cause suburbanization?" *The quarterly journal of economics* 122.2, pp. 775–805.

Behrens, Kristian, Sergey Kichko, and Jacques-François Thisse (2021). "Working from home: Too much of a good thing?"

Bick, Alexander, Adam Blandin, and Karel Mertens (2020). "Work from home after the COVID-19 Outbreak".

Bloom, Nicholas et al. (2015). "Does working from home work? Evidence from a Chinese experiment". *The Quarterly Journal of Economics* 130.1, pp. 165–218.

Brynjolfsson, Erik et al. (2020). "COVID-19 and remote work: an early look at US data".

Choudhury, Prithwiraj, Cirrus Foroughi, and Barbara Zepp Larson (2020). "Work-from-anywhere: The productivity effects of geographic flexibility". *Academy of Management Proceedings*. Vol. 2020. 1. Academy of Management Briarcliff Manor, NY 10510, p. 21199.

Dingel, Jonathan I and Brent Neiman (2020). *How many jobs can be done at home?* Tech. rep. National Bureau of Economic Research.

Dorn, David (Spetember 2009). "Essays on Inequality, Spatial Interaction, and the Demand for Skills. Dissertation". *University of St. Gallen no. 3613*.

Gaspar, Jess and Edward L Glaeser (1998). "Information technology and the future of cities". *Journal of urban economics* 43.1, pp. 136–156.

Glaeser, Edward L and Joshua D Gottlieb (2009). "The wealth of cities: Agglomeration economies and spatial equilibrium in the United States". *Journal of economic literature* 47.4, pp. 983–1028.

Mas, Alexandre and Amanda Pallais (2017). "Valuing alternative work arrangements". *American Economic Review* 107.12, pp. 3722–59.

– (2020). "Alternative work arrangements".

Molfino, Emily (2020). "The Urbanization Perceptions Small Area Index: An Application of Machine Learning and Small Area Estimation to Household Survey Data".

Ozimek, Adam (2020). "The future of remote work". *Available at SSRN 3638597*.

– (2021). "When Work Goes Remote". *Available at SSRN 3777324*.

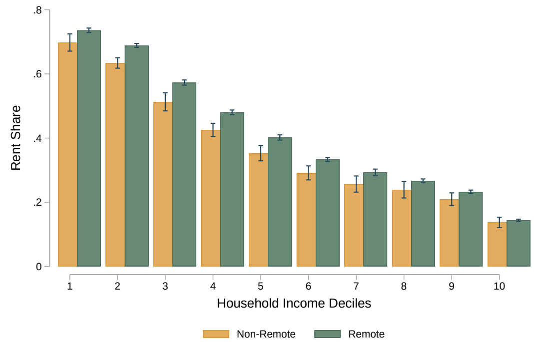
Ramani, Arjun and Nick Bloom (n.d.). "The donut effect: How COVID-19 shapes real estate" ().

Rosenthal, Stuart S, William C Strange, et al. (2005). "The geography of entrepreneurship in the New York metropolitan area". *Federal Reserve Bank of New York Economic Policy Review* 11.2, pp. 29–54.

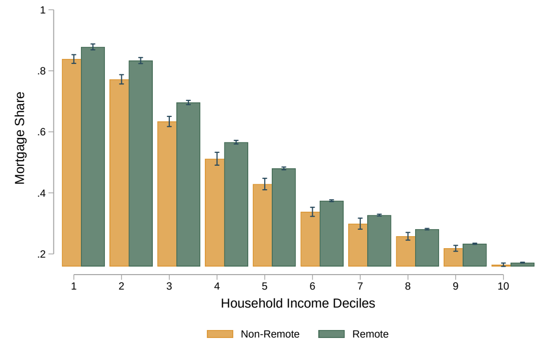
Ruggles, Steven et al. (2020). "IPUMS USA: Version 10.0 [dataset]".

Stanton, Christopher and Pratyush Tiwari (2020). “Remote Work Across Geographies and Occupations”.

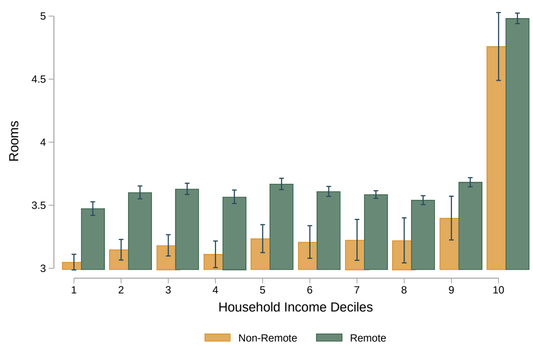
Figures and Tables



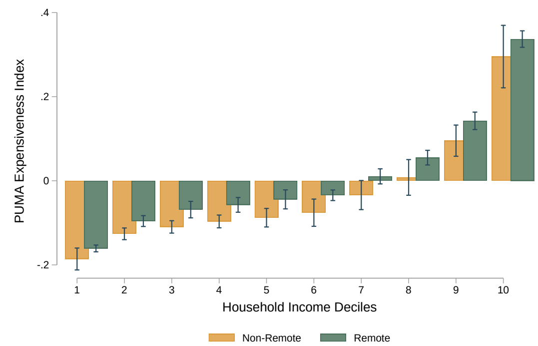
(a) Expenditure Share on Rent



(b) Expenditure Share on Mortgage + Taxes



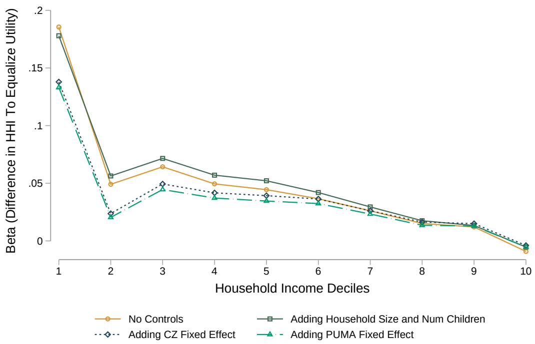
(c) Rooms Per Household



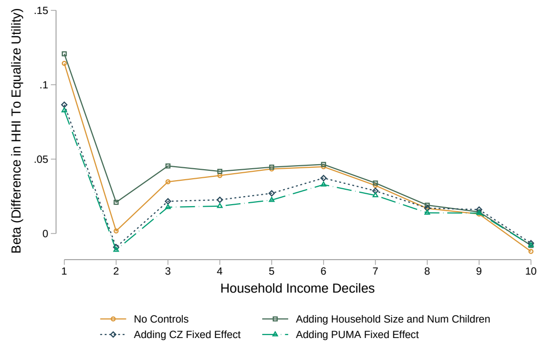
(d) PUMA Housing Expensiveness Index

Figure 1: Housing Consumption Measures Across the Household Income Distribution

Notes. Estimates of expenditure share on rent for renters, expenditure share on mortgage + property taxes for owners, rooms per household, and average PUMA expensiveness indices by household income decile. Household income deciles are calculated using pooled data from 2013-2017. The PUMA expensiveness index is a measure of residual prices calculated by regressing rent for renters (and value for owners) on number of rooms, age of structure, number of bedrooms and number of units in the building, taking the residual, standardising the residual to have mean 0 and standard deviation 1, and then averaging across ownership status in the PUMA using the sampling weights. All panels control for number of children, household size and commuting zone. Regressions to estimate cell averages are weighted using ACS sampling weights.



(a) Reported Income



(b) Adjusted Income

Figure 2: Estimates of Compensation Increase (Beta) Required Offset Utility Loss Due to Remote Work Housing Expenditure

Notes. Estimates of beta (the premium required to compensate households for remote work) are on the y-axis and household income deciles are on the x-axis. Calculations are done separately for renters and owners and then pooled and averaged together by decile. See text for calculation details. Households are weighted using ACS sampling weights. Reported income is raw income and adjusted income treats vehicles as a necessity by reducing household income in the budget constraint by $10,000 times the number of vehicles present.

Table 1: Summary Statistics

	Overall	Non-Remote	Remote	Difference
Household Income	84383.84	81917.39	128046.57	-42542.08***
	(86402.64)	(83719.68)	(116324.43)	(108.23)
Rooms per Household	6.00	5.95	6.89	-0.91***
	(2.40)	(2.37)	(2.69)	(0.00)
Proportion of Renters	0.34	0.34	0.25	0.07***
	(0.47)	(0.47)	(0.43)	(0.00)
Share HHI on Rent	0.28	0.28	0.26	0.02***
	(0.18)	(0.18)	(0.18)	(0.00)
Share HHI on Mortgage	0.27	0.27	0.25	0.01***
	(0.30)	(0.30)	(0.29)	(0.00)
Rent per Room	258.93	256.94	308.45	-48.40***
	(236.16)	(234.77)	(263.83)	(0.72)
Value of House	281001.46	272942.53	405968.93	-120640.54***
	(371169.74)	(360754.03)	(489243.14)	(485.78)
Value per Room	42751.46	41872.65	56378.92	-13689.21***
	(60390.73)	(59415.68)	(72531.48)	(77.52)
Number of Children	0.68	0.67	0.86	-0.22***
	(1.11)	(1.10)	(1.21)	(0.00)
Average Adult Age	50.45	50.59	48.02	3.40***
	(16.24)	(16.42)	(12.55)	(0.02)
Share of Mixed Remote HH	0.03	0.00	0.56	-0.55***
	(0.17)	(0.00)	(0.50)	(0.00)
Total HH Commute Time	41.90	42.22	34.10	7.84***
	(36.22)	(36.41)	(30.22)	(0.07)
Vehicles per HH	1.85	1.84	2.14	-0.36***
	(1.07)	(1.06)	(1.08)	(0.00)
Share Suburban HH	0.62	0.62	0.68	-0.06***
	(0.49)	(0.49)	(0.47)	(0.00)
Share Rural HH	0.23	0.24	0.18	0.07***
	(0.42)	(0.42)	(0.39)	(0.00)
Hours per Employed Member	40.09	40.16	39.25	0.52***
	(10.34)	(10.17)	(12.31)	(0.02)
Number of Observations	10943512	10392288	551224	
Implied Population	544222158	515123557	29098601	

Notes. Sample includes all households in the ACS 2013-17. HHI is an abbreviation for household (HH) income. For Rent per Room and Share HHI on Rent, the sample is restricted to only renters, while the sample is restricted to home owners for Value of House and Value per Room. A household is classified as remote if it has at least 1 member working from home. Mixed Remote HH are households that have at least one remote and one non-remote worker. Commute time is one-way travel time between home and work for all working adults. ACS household sampling weights are used for all calculations. Standard deviation (standard error in last column) in parentheses.

Table 2: Regression Results of Housing and Consumption Choices

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Expend. Share on Rent	0.1351***	0.1311***	0.1264***	0.0920***	0.0712***	0.0781***	0.0633***
	(0.0108)	(0.0109)	(0.0095)	(0.0040)	(0.0041)	(0.0033)	(0.0035)
	0.400	0.404	0.411	0.532	0.545	0.566	0.574
Log House Value	0.1916***	0.2061***	0.2150***	0.1822***	0.1566***	0.1499***	0.1316***
	(0.0071)	(0.0071)	(0.0072)	(0.0036)	(0.0037)	(0.0035)	(0.0035)
	0.194	0.202	0.213	0.328	0.334	0.367	0.374
Log Expend. Share on Flow Housing Costs	0.1645***	0.1770***	0.1806***	0.1576***	0.1355***	0.1335***	0.1172***
	(0.0057)	(0.0057)	(0.0059)	(0.0035)	(0.0037)	(0.0035)	(0.0034)
	0.165	0.173	0.181	0.258	0.270	0.290	0.298
Log Expend Share on Mortgage+Taxes	0.1154***	0.1170***	0.1162***	0.1067***	0.0935***	0.0896***	0.0802***
	(0.0046)	(0.0047)	(0.0048)	(0.0024)	(0.0025)	(0.0028)	(0.0028)
	0.367	0.370	0.380	0.455	0.463	0.478	0.483
Rooms per Household	0.4097***	0.4390***	0.3467***	0.3656***	0.3255***	0.3557***	0.3167***
	(0.0271)	(0.0268)	(0.0228)	(0.0130)	(0.0119)	(0.0105)	(0.0099)
	0.147	0.166	0.225	0.270	0.276	0.298	0.304
Log Rent per Room	0.0557***	0.0553***	0.0778***	0.0318***	0.0116**	0.0155***	0.0028
	(0.0163)	(0.0161)	(0.0131)	(0.0045)	(0.0048)	(0.0036)	(0.0039)
	0.122	0.125	0.178	0.380	0.391	0.431	0.437
Log Value per Room	0.1411***	0.1541***	0.1709***	0.1375***	0.1180***	0.1071***	0.0942***
	(0.0084)	(0.0084)	(0.0085)	(0.0043)	(0.0043)	(0.0039)	(0.0038)
	0.129	0.137	0.149	0.301	0.308	0.344	0.348
PUMA Expensiveness Index	0.0595***	0.0592***	0.0677***	0.0406***	0.0327***		
	(0.0138)	(0.0138)	(0.0135)	(0.0078)	(0.0066)		
	0.068	0.070	0.086	0.682	0.686		
Log PUMA Density	0.0304	0.0140	0.0329	-0.0195**	-0.0357***		
	(0.0260)	(0.0260)	(0.0218)	(0.0096)	(0.0091)		
	0.013	0.022	0.042	0.645	0.647		
Vehicles per Household	0.0669***	0.0593***	-0.0169**	-0.0205***	-0.0170***	-0.0148***	-0.0143***
	(0.0072)	(0.0080)	(0.0075)	(0.0043)	(0.0043)	(0.0046)	(0.0049)
	0.176	0.180	0.366	0.413	0.417	0.443	0.445
Household Income Decile*Household Income	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Income Decile*Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Household Structure Control	No	No	Yes	Yes	Yes	Yes	Yes
Commuting Zone Fixed Effect	No	No	No	Yes	Yes	Yes	Yes
State & PUMA Fixed Effect	No	No	No	No	No	Yes	Yes
Education Fixed Effect	No	No	No	No	Yes	No	Yes

Notes. Coefficients reported are for the remote household dummy. Dependent variable is displayed in the first column. The second row in each panel is the standard error and the third row is the R-squared. PUMA expensiveness is calculated by regressing rent/value (for renters/owners) on number of rooms, age of structure, number of bedrooms and number of units in the building, taking the residual, standardising the residual and then averaging across ownership status in the PUMA using sampling weights. ACS household sampling weights used for all calculations. Standard errors are clustered by commuting zone. The sample consists of 10,943,512 observations (households) in total, with 2,427,258 observations for renters and 8,252,533 observations for owners. These numbers change based on the availability of the particular variable of interest.

Table 3: Regression Results of Location Choices

Dependent Variable	(1)	(2)	(3)	(4)	(5)
	Panel A: Only Fully Remote Households				
Rural Dummy	-0.0187***	-0.0323***	-0.0207***	0.0033	0.0065***
	(0.0049)	(0.0051)	(0.0052)	(0.0020)	(0.0020)
	0.015	0.019	0.030	0.534	0.536
Urban Dummy	-0.0033	0.0103**	0.0062	0.0044	0.0026
	(0.0046)	(0.0048)	(0.0046)	(0.0037)	(0.0034)
	0.005	0.010	0.025	0.215	0.217
Sub-urban Dummy	0.0220***	0.0220***	0.0145**	-0.0077*	-0.0091**
	(0.0056)	(0.0062)	(0.0056)	(0.0041)	(0.0037)
	0.018	0.018	0.023	0.287	0.289
	Panel B: Only Mixed Remote Households				
Rural Dummy	-0.0147***	-0.0077*	-0.0215***	-0.0048***	-0.0003
	(0.0043)	(0.0040)	(0.0039)	(0.0016)	(0.0014)
	0.018	0.022	0.031	0.538	0.539
Urban Dummy	-0.0064	-0.0161***	-0.0035	-0.0013	-0.0022
	(0.0053)	(0.0061)	(0.0040)	(0.0027)	(0.0024)
	0.003	0.012	0.024	0.213	0.215
Sub-urban Dummy	0.0211***	0.0238***	0.0251***	0.0061**	0.0025
	(0.0046)	(0.0050)	(0.0041)	(0.0030)	(0.0027)
	0.020	0.021	0.025	0.299	0.300
Household Income Decile*Household Income	Yes	Yes	Yes	Yes	Yes
Household Income Decile*Age	No	Yes	Yes	Yes	Yes
Household Structure Control	No	No	Yes	Yes	Yes
Commuting Zone Fixed Effect	No	No	No	Yes	Yes
Education Fixed Effect	No	No	No	No	Yes

Notes. Reported estimates are coefficients on a dummy for remote household. The dependent variable is displayed in the first column. The second row contains the standard error and the third row the R-squared. The geographic area of analysis is a PUMA. We use the classification of census tracts from Molfino (2020) and aggregate to the PUMA level to determine whether each PUMA is rural, urban and suburban. For the sample in panel A, 15.5% of the households live in urban areas, 21.7% live in rural areas and the remaining 62.8% live in suburban areas. Of the households in each type of area, the share of households that are fully remote is 3.1%, 2.8% and 3.2% in rural, urban and suburban areas, respectively. For the sample in panel B, the share of households across areas is 14.7%, 23.4% and 61.9% for rural, urban and suburban areas, respectively. Of these households, 2.8%, 2.3% and 3.5% households are partially remote in rural, urban and suburban areas, respectively.

Table 4: Home-Office Real Estate Cost Difference-in-Difference

Commuting Zone	Office Cost	Housing Cost Difference	Net
San Francisco	8,845.80	2,815.48	6,030.32
Austin	7,489.50	2,082.63	5,406.87
Seattle-Bellevue	6,838.50	1,480.47	5,358.03
Washington, DC	6,394.50	1,492.20	4,902.30
Boston	6,609.00	1,724.19	4,884.81
New York	7,024.50	2,549.84	4,474.66
Nashville	5,073.00	928.15	4,144.85
Portland	5,041.50	1,145.40	3,896.10
Chicago	5,211.00	1,679.33	3,531.67
Los Angeles	6,138.00	2,681.04	3,456.96
San Diego	5,737.50	2,378.26	3,359.24
Houston	4,795.50	1,545.98	3,249.52
Denver	4,780.50	1,542.00	3,238.50
Orlando	3,837.00	710.97	3,126.03
Miami	6,003.00	2,916.43	3,086.57
Raleigh-Durham	4,288.50	1,323.77	2,964.73
Atlanta	4,402.50	1,460.08	2,942.42
New Jersey	4,356.00	1,416.28	2,939.72
Dallas	4,662.00	1,729.20	2,932.80
Phoenix	4,284.00	1,379.95	2,904.05
Minneapolis	4,411.50	1,594.67	2,816.83
San Antonio	4,063.50	1,445.12	2,618.38
Pittsburgh	3,903.00	1,368.08	2,534.92
Philadelphia	4,294.50	1,768.55	2,525.95
Salt Lake City	3,798.00	1,291.73	2,506.27
Stamford	5,617.50	3,129.53	2,487.97
Charlotte	4,911.00	2,468.06	2,442.94
Sacramento	3,943.50	1,703.31	2,240.19
Baltimore	3,976.50	1,780.71	2,195.79
Detroit	3,033.00	929.64	2,103.36
Fort Worth	3,717.00	2,305.64	1,411.36

Notes. The Office Cost column provides an estimate of the cost of providing in-office working space for each employee, based on marketed office rent per square foot taken from JLL (https://www.us.jll.com/en/trends-and-insights/research/office-market-statistics-trends) and scaled by an average per employee space consumption of 150 square feet. The Housing Cost Difference is an estimate of the dollar value difference in the yearly housing expenditure of remote households compared to their non-remote counterparts. This is calculated using matching estimates based on the main estimating equation. In particular, households are matched exactly on ownership status (renters versus owners), household income deciles, bins of average age of adults in the household, household structure and educational qualifications within each commuting zone. The last column provides the net difference between in-office versus at home yearly cost.

A Appendix Figures and Tables

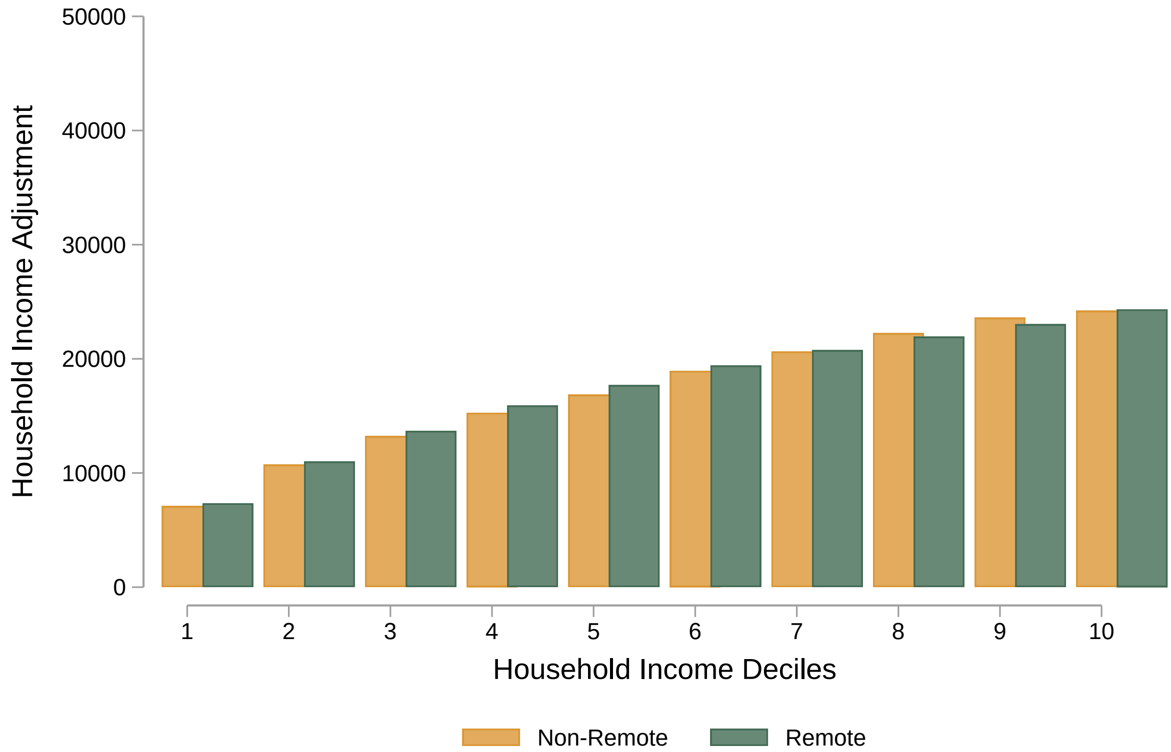
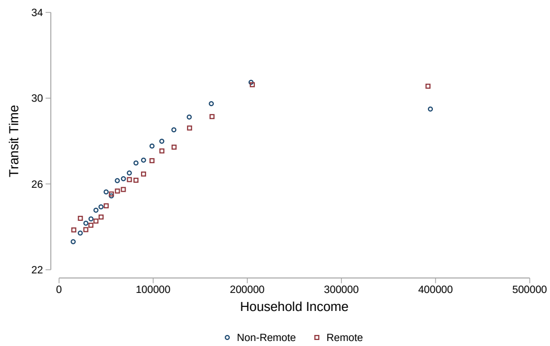
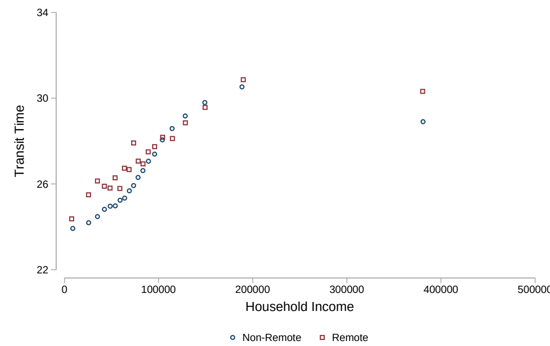


Figure A.1: Adjustment for Vehicles

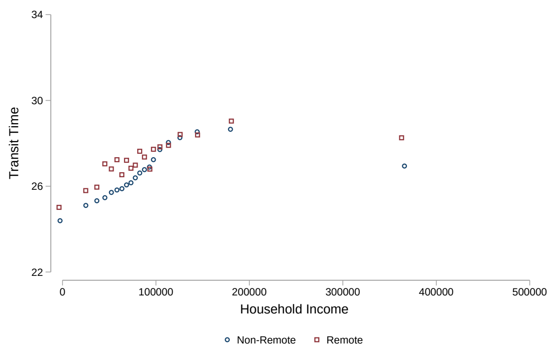
Notes. This figure displays the empirical distribution of adjustments to the household budget constraints for vehicle expenditures. We assume that each vehicle has a cost to the household of \$10,000, inclusive of driving expenses.



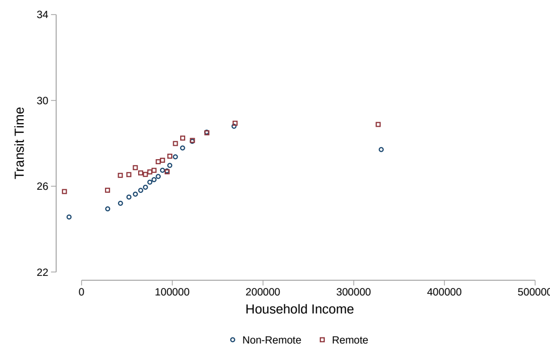
(a) No Controls



(b) Adding control for household structure



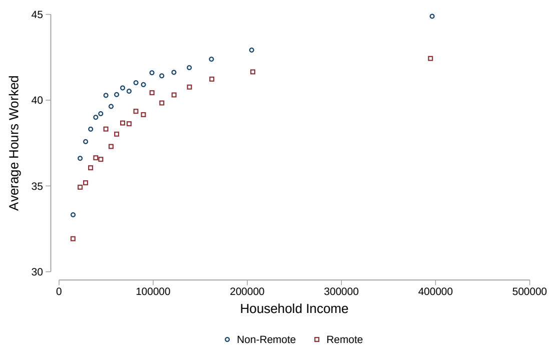
(c) Adding CZ FE



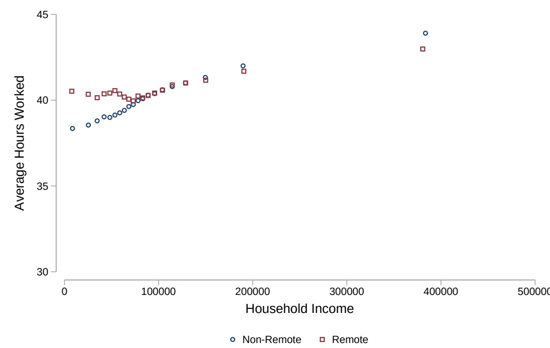
(d) Adding PUMA FE

Figure A.2: Average Commute Time versus Household Income

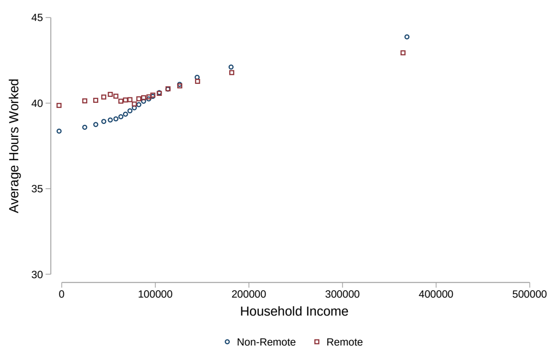
Notes. Average Commute time is on the y-axis and household income is on the x-axis. The sample consists of all the households in the ACS, from 2013 to 2017. Households are weighted using ACS sampling weights.



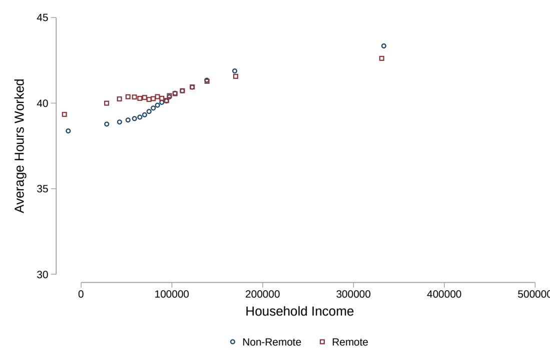
(a) No Controls



(b) Adding control for household structure



(c) Adding Commuting Zone FE



(d) Adding PUMA FE

Figure A.3: Hours Worked versus Income

Notes. Average number of hours worked by each employed individual in a household is on the y-axis and the household income is on the x-axis. The sample consists of all households in the ACS, from 2013 to 2018. Households are weighted using ACS sampling weights.

Table A.1: Estimates of Housing Expenditure Shares

	Unadjusted				Adjusted			
	Non-Remote		Remote		Non-Remote		Remote	
HHI Decile	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: Renters - Share on Rent								
1	0.480	0.481	0.558	0.520	0.512	0.513	0.578	0.546
2	0.391	0.390	0.465	0.442	0.485	0.485	0.536	0.520
3	0.320	0.321	0.391	0.382	0.430	0.430	0.487	0.475
4	0.273	0.273	0.333	0.326	0.374	0.373	0.434	0.419
5	0.240	0.240	0.292	0.287	0.321	0.321	0.379	0.367
6	0.214	0.214	0.260	0.259	0.276	0.276	0.329	0.322
7	0.194	0.194	0.229	0.229	0.240	0.240	0.280	0.276
8	0.174	0.174	0.201	0.200	0.206	0.205	0.236	0.232
9	0.156	0.157	0.172	0.173	0.177	0.178	0.194	0.193
10	0.128	0.126	0.142	0.141	0.140	0.139	0.156	0.153
Panel B: Owners - Share on Mortgage								
1	0.618	0.620	0.678	0.659	0.639	0.639	0.682	0.669
2	0.483	0.483	0.551	0.534	0.547	0.547	0.594	0.584
3	0.388	0.389	0.461	0.449	0.488	0.489	0.539	0.532
4	0.321	0.322	0.385	0.376	0.437	0.438	0.492	0.480
5	0.276	0.276	0.332	0.326	0.387	0.387	0.443	0.430
6	0.238	0.238	0.275	0.273	0.334	0.335	0.377	0.369
7	0.211	0.211	0.242	0.239	0.287	0.287	0.324	0.319
8	0.189	0.189	0.212	0.211	0.246	0.246	0.272	0.270
9	0.169	0.169	0.184	0.184	0.207	0.208	0.224	0.224
10	0.135	0.135	0.141	0.140	0.153	0.153	0.158	0.158

Notes. This table displays average projected expenditure shares on housing from regressions by deciles of household income. Unadjusted deciles use raw household income whereas adjusted deciles remove $10,000 times the number of vehicles for each household. Regressions are run separately for renters and owners. Columns numbered 1 have controls for household income, average household adult age and year, whereas columns numbered 2 additionally control for household structure and commuting zone fixed effects.

Table A.2: Regression and Matching Estimates of Housing Choices

Dependent Variable	Regression Estimate	Matching Estimate
Log Expend. Share on Rent	0.0712***	0.0644***
	(0.0041)	(0.0005)
Log House Value	0.1566***	0.1475***
	(0.0037)	(0.0004)
Log Expend. Share on Flow Housing Costs	0.1335***	0.1221***
	(0.0037)	(0.0004)
Log Expend Share on Mortgage+Taxes	0.0935***	0.0784***
	(0.0025)	(0.0003)
Rooms per Household	0.3255***	0.3269***
	(0.0119)	(0.0010)
Log Rent per Room	0.0116**	0.0103***
	(0.0048)	(0.0006)
Log Value per Room	0.1180***	0.1116***
	(0.0043)	(0.0004)
PUMA Expensiveness Index	0.0327***	0.0355***
	(0.0066)	(0.0001)
Log PUMA Density	-0.0357***	-0.1252***
	(0.0091)	(0.0004)
Vehicles per Household	-0.0170***	-0.0076***
	(0.0043)	(0.0003)
Household Income Decile*Household Income	Yes	Yes
Household Income Decile*Age	Yes	Yes
Household Structure Control	Yes	Yes
Commuting Zone Fixed Effect	Yes	Yes
Education Fixed Effect	Yes	Yes

Notes. Coefficients reported are for the remote household dummy. Dependent variable is displayed in the first column. The second row in each panel is the standard error. Households are matched exactly on commuting zone, ownership status (renters versus owners), household income decile, bins of average age of adults in the household, household structure and educational qualifications. The sample for matching estimates consists of 2,252,329 observations (households) in total, with 314,193 observations for renters and 1,600,757 observations for owners.

Table A.3: Remote Work versus Stay-at-Home Spouse Effects on Consumption of Space

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable: Rooms per Household						
Remote Household Dummy	0.4097***	0.4390***	0.3467***	0.3656***	0.3255***	0.3557***	0.3167***
	(0.0271)	(0.0268)	(0.0228)	(0.0130)	(0.0119)	(0.0105)	(0.0099)
	0.147	0.166	0.225	0.270	0.276	0.298	0.304
Homemaker Household Dummy	0.3426***	0.1374***	0.1127***	0.0846***	0.1148***	0.0844***	0.1101***
	(0.0203)	(0.0125)	(0.0150)	(0.0101)	(0.0097)	(0.0078)	(0.0077)
	0.129	0.137	0.166	0.219	0.228	0.248	0.256
Household Income Decile*Household Income	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Income Decile*Age	No	Yes	Yes	Yes	Yes	Yes	Yes
Household Structure Control	No	No	Yes	Yes	Yes	Yes	Yes
Commuting Zone Fixed Effect	No	No	No	Yes	Yes	Yes	Yes
State & PUMA Fixed Effect	No	No	No	No	No	Yes	Yes
Education Fixed Effect	No	No	No	No	Yes	No	Yes

Notes. The second row in each panel is the standard error and the third row is the R-squared. For the bottom panel, the sample consists of married households only. Homemaker Household Dummy is an indicator that switches on if one of the spouses is either not in the labor force or stays at home full time. ACS household sampling weights are used for all calculations. The sample consists of 10,943,512 observations (households) in total, with 2,427,258 observations for renters and 8,252,533 observations for owners. These numbers change based on the availability of the particular variable of interest.