Remote Work and Household Formation

Adam Ozimek, Eric Carlson

April 11, 2023

Abstract

If remote work has reduced the demand for living in big cities, then why have their rents gone up so much? In this paper, we argue that one key to this question lies in understanding the heterogeneous effects of remote work on housing demand. Consistent with the emerging literature, we show that remote work in expensive and dense places causes less housing demand through out-migration, which helps to explain why big cities have seen declining population and relatively weaker rents and house prices. However, we show that is counterbalanced by remote work also causing a surge in household formation. Methodologically, this paper adds to the growing body of remote work literature by being the first to use actual, post-pandemic remote work rates at a granular level as an instrumental variable. At the individual level, we utilize occupation and industry fixed-effect IVs, and at local housing market level we utilize a shift-share approach. The causal effect of remote work on housing markets is consistent with OLS, suggesting modestly larger effects for both individual and housing market models.

Keywords: Remote work, housing demand, household formation
JEL codes: R10, R21

1 Introduction

A growing body of research has documented a significant impact of remote work on where people want to live. This has generated an emerging consensus that demand for dense, high cost areas has decreased while demand for less dense, less expensive areas has increased, both within and between metro areas (Ramani and Bloom, 2021; Gupta et al., 2021; Delventhal and Parkhomenko, 2020; Brueckner et al., 2021; Liu and Su, 2021; Delventhal et al., 2022; Althoff et al., 2022; Ozimek, 2022b). However, less well understood is how these changes play out at the intensive and extensive margins of housing demand. In this analysis we expand the scope of the literature on remote work and housing markets by examining changes along these margins of demand. In addition, we look at these effects at both the individual level and the market level to demonstrate how individual choices aggregate regionally. Changes along these margins of demand help to explain important trends in the post-pandemic housing market. Importantly, they help explain why remote work led to housing price increases in initially densely-populated and expensive areas despite the out-migration of remote workers.

Our work builds on the growing body of literature on remote work and housing markets. Much of this burgeoning research focuses on the spatial reallocation of people and work. For example, Ramani and Bloom (2021) demonstrate a "donut-effect" of COVID-19 whereby demand for dense city centers decreased while demand for surrounding residential areas and suburbs increased.

Our paper is also related to a smaller body of remote work literature that goes beyond spatial reallocation and specifically examines the direct effect of remote work on housing demand. The study most closely related to ours is Stanton and Tiwari (2021). The authors use pre-pandemic microdata from the American Community Survey (ACS) to show that remote households have greater housing demand along the intensive margin relative to non-remote households. They find that households with remote workers consumed larger and more expensive housing compared to otherwise similar households without remote workers. In addition, our paper is also related to the work of Mondragon and Wieland (2022) who examine the effect of remote work on housing demand at the market level. They utilize 2020 ACS data on the remote work share at the Core-Based Statistical Area (CBSA) level and instrument for this using the 2015-2019 remote work share. In addition, they control for the impact of remote work on migration by including actual migration rates from credit panel data. In contrast to our work and the work of Stanton and Tiwari (2021), they focus exclusively on house prices and rents as measures of housing demand. Finally, our work is related to Howard et al. (2022) who decompose the demand for housing into both location-specific and overall changes in housing demand. However, this research does not focus on the effect of remote work on household formation.

For this analysis, we use microdata from the 2019 and 2021 waves of the ACS to run individual level regressions that examine how remote work affects demand for housing. We first look at the intensive margin of housing demand as measured by each household's total monthly spending on housing. We measure spending using both mortgage payments as well as rental payments at the household level. We find remote work has a positive and statistically and economically significant impact. Even after controlling for a variety of household characteristics and regional fixed effects, we find that remote households spend more on housing than otherwise comparable non-remote households. This is consistent with Stanton and Tiwari (2021)'s analysis of household-level pre-pandemic data and Mondragon and Wieland (2022)'s analysis of CBSA-level data.

In addition, we find that remote work is associated with households moving into new dwelling units. This is consistent with remote work changing housing demand through both the intensive and extensive margins. On the intensive margin, it could reflect households and families moving into new homes that are bigger, have more amenities, or have more outdoor space (rather than constructing additional rooms or floors to their existing residence). On the extensive margin, it could reflect changing preferences away from joint living arrangements in favor of of smaller households.

We next explore the impact of remote work on the extensive margin. Specifically, we find that remote work is associated with greater household formation. A household is defined as all individuals living in a housing unit, and a housing unit is any "house, an apartment, a group of rooms, or a single room intended for occupancy as separate living quarters".'[1] This is, we believe, the first evidence of remote work's affect on household formation. These results are robust to a variety of individual and local controls and are robust to the use of household and individual-level instrumental variables for remote work status as well as alternative measures of household formation.

To understand how individual behaviors aggregate to behaviors at the housing market level, we next examine the impact of remote work on Census Public Use Microdata Areas (PUMAs).[2] While Mondragon and Wieland (2022) show that remote work has had a positive effect on migration, we show that there is important heterogeneity with more expensive and dense places losing population as a result of higher rates of remote work. We find that remote work overall is associated with higher rents, higher home values, and a growing population, but in more dense and expensive places the effects of remote work is weaker or even negative. That is, in denser and more expensive PUMAs, remote work is more weakly associated with rents and home values as is negatively associated with population. However, in the most dense and expensive PUMAs, we find that remote work has a stronger positive effect on household formation. This growth in household formation helps to reconcile why even large urban areas that have suffered the most out-migration and loss of relative demand from remote work have nevertheless experienced relatively tight housing markets.

We expand on the literature though our use of data, our empirical strategy, and, importantly, our focus on the extensive margin of demand. We use post-pandemic ACS data, an instrumental

[1]https://www.census.gov/construction/bps/definitions.html

[2]PUMAs, or Public Use Microdata Areas, are Census Bureau provided geographic areas of at least 100,000 people that constitute a non-overlapping and exhaustive coverage of the U.S. For more see https://www.census.gov/programs-surveys/geography/guidance/geo-areas/pumas.html.

variable approach at both the individual and market level, and household formation as an extensive margin outcome. In doing so, this paper makes three main contributions to the literature.

First, we build on the existing research on remote work and housing demand by being the first study to use 2021 ACS data to examine the effects of remote work on individual level outcomes. The ACS is a large, nationally representative dataset that measures remote work directly and allows more geographic granularity than the CPS. The 2021 ACS data is also the first reliable post-pandemic ACS data, as the 2020 1-year ACS collection suffered from data collection disruptions that resulted in significant data quality issues.[3]

Second, we use use actual post-pandemic remote work rates to construct instrumental variables for working from home. At the individual level, our instrumental variable approach takes advantage of the ACS's large sample size to construct an instrument based on actual remote work rates at the detailed occupation and industry level. At the market level, we use a shift-share approach based on actual changes in national remote work exposure to instrument for remote work at the PUMA level. Dingel and Neiman (2020) created a widely-cited measure of whether occupations can theoretically be done remotely, and this measure has been validated by Howard et al. (2022) and Althoff et al. (2022) as predicting actual remote work. Similarly, Mondragon and Wieland (2022) instruments 2020 data on actual remote working at the CBSA level using pre-pandemic rates of remote working. However, our work is the first to use actual and reliable post-pandemic remote work rates to instrument for remote work. In both cases we show the instruments have sufficient first-stage significance, and in the shift-share case we argue that they satisfy the criteria offered by Goldsmith-Pinkham et al. (2020).

Third, our study extends the prior research by focusing on household formation as an important extensive margin of housing demand. Most prior research focuses on housing prices. For example, Stanton and Tiwari (2021) focus on the share of household income spent on rent and mortgage payments as well as price per room and home sizes as intensive margins of housing demand. Similarly, Mondragon and Wieland (2022) focuses on rents and prices with migration controls to measure housing demand holding location choice constant. It is important to understand whether demand is increasing because people desire more space or housing quality by itself, or actual formation of new households. For example, it is consequential whether the growth of work from home implies a demand for larger homes or for more homes altogether. Our results suggest that remote work has led to both.

2 Stylized Facts

There has been a rapid rise in real house prices and real rents after the pandemic. However, the spatial distribution of the changes in housing demand has been uneven. For example, remote workers have left large city centers and flocked to surrounding suburban areas. Nevertheless, housing markets have managed to tighten in city centers despite this out-migration. This

[3]https://usa.ipums.org/usa/acspumscovid19.shtml

tightening may be driven in part by the observed rise in household formation. In other words, the increase in the number of (smaller) households may have offset some of the effect of population loss.

Figure 1 illustrates the rapid post-pandemic rise in real house prices and rents. However, these gains are not evenly distributed. As Ramani and Bloom (2021); Howard et al. (2022); Brueckner et al. (2021); Gupta et al. (2021) and others have documented, growth in both rents and prices has been stronger in some places than others. Specifically, Ramani and Bloom (2021) coined the term "donut effect" to describe the weaker growth in housing demand in downtown large urban cores and stronger growth in ex-urban, suburban, and rural areas. These papers also illustrate that large urban metros and counties overall have seen weaker demand relative to less dense suburban housing markets.

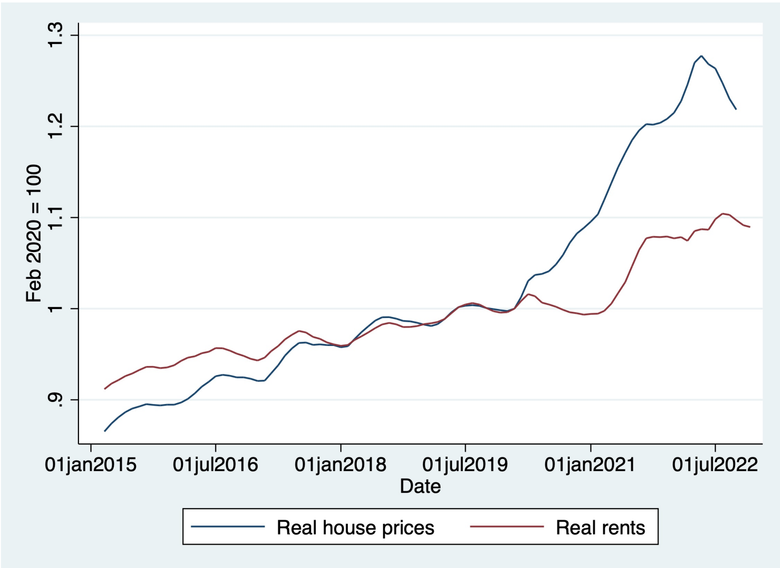


Figure 1: Real House Prices and Rents
Note: House prices measured using S&P/Case-Shiller U.S. National Home Price Index, rents measured using Zillow Observed Rent Index for all homes plus multifamily. Both series deflated by the CPI and indexed to February, 2020

Nevertheless, while large urban areas have experienced out-migration since the onset of the pandemic, housing markets have remained relatively strong in many of these areas. Indeed, as shown in Ramani and Bloom (2021), it is only with the city centers of the 12 most populous Metropolitan Statistical Areas (MSAs) where nominal home values haven't risen more than the 15% in overall US inflation since the onset of the pandemic. Even high density zipcodes within the top 12 MSAs and city center zipcodes in MSAs outside of the top 12 have seen real house prices rise more than the CPI.[4].

As an illustrative example, consider the housing market in New York City. As shown in Figure 2, despite losing 2.9% of its population from 2019 to 2021, real rents in the New York City metro area grew since the start of 2021. In addition, the apartment vacancy rate had

[4]See Ramani and Bloom (2021) Figure 5.

fallen to below pre-pandemic levels by the start of 2022.[5] Continued weakness in US Post Office moves data for New York City suggests the strong housing demand is not simply a matter of population returning.[6]

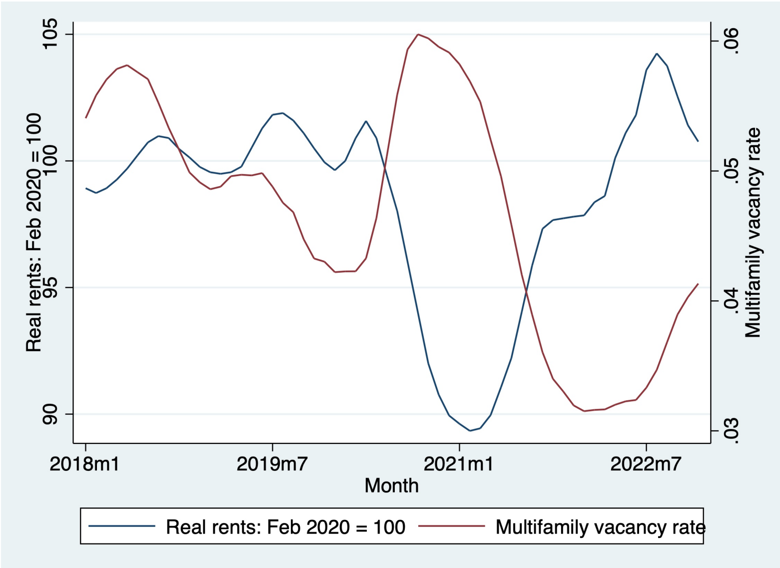


Figure 2: New York City Housing Market
Note: Real rents measured using Zillow Observed Rent Index for all homes plus multifamily deflated by CPI, vacancy rate from ApartmentList.com. Both series are for the New York City metro area.

This pattern of broadly strong housing demand is not limited to New York City, nor is it limited to places with positive population trends. Looking across all metro areas, 81% saw a decline in vacancy rates from 2019 to 2021 in ACS data. Weighted by population, 91% of the country in metro areas saw vacancy rates decline. Indeed, even among metro areas that lost population, 85% saw vacancy rates decline.

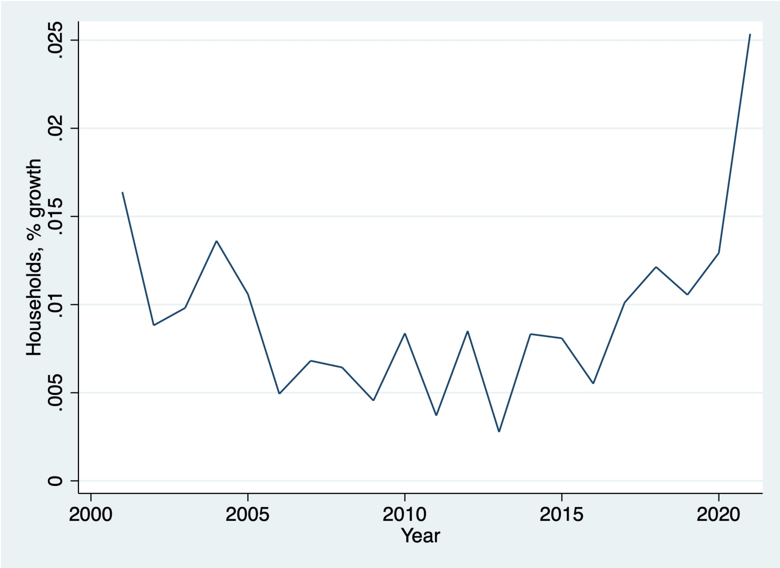
Another important basic fact of housing markets during the pandemic is that there was a rapid expansion of household formation. As Figure 3 shows, household formation surged 2.5% in 2021, more than double the fastest pace post Great Recession. Similarly, looking at the householder rate for individuals aged 16 and up, 2021 showed a drastic rebound and larger change than any within the post-2000 sample. Though more moderate, this pattern is qualitatively consistent with the results in García and Paciorek (2022), who show a strong recovery in householder rates in CPS data through the end of 2021.[7]

Importantly, this puts the experience of the US economy during the COVID shock in stark contrast with the experience of the Great Recession (Dyrda et al., 2012; Lee and Painter, 2013; Rogers and Winkler, 2014; Bitler and Hoynes, 2015). For example, during the Great Recession, the household formation rate declined as young people moved in with their parents after college

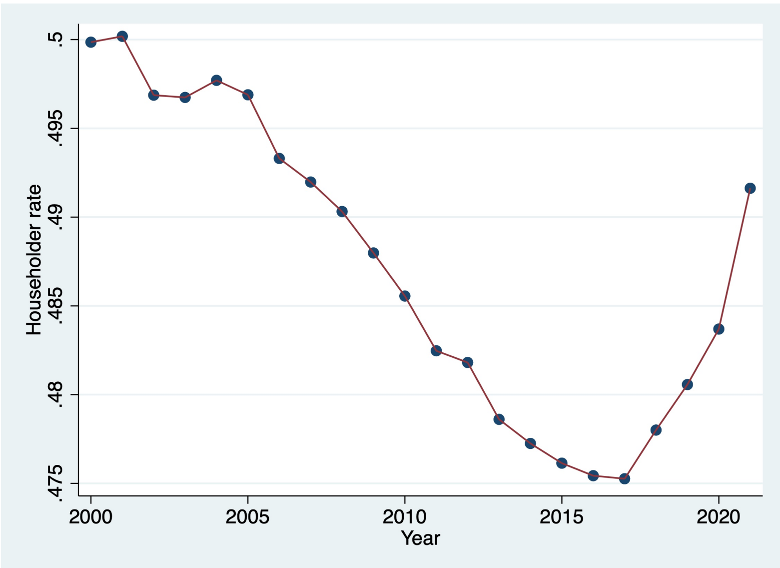
[5] Nominal rents deflated using U.S. CPI; however, the real rent growth would be even stronger using CPI from the New York City CBSA.

[6] See: https://www.thecity.nyc/2022/5/31/23145072/nycs-population-plummeted-during-peak-covid-and-its-still-likely-shrinking

[7] CPS suggests household formation rates have come down since, likely reflecting the impacts of interest rate hikes among other factors.



(a) Annual household formation



(b) Annual householder rate

Figure 3: Annual Household Formation and Annual Householder Rate (2002 – 2021)
Note: Panel (a): Annual percent growth in the number of non-group quarter households, Panel (b): Annual householder rate for population ages 16 and up. Both from American Community Survey data from 2000 to 2021. Data from IPUMS USA, University of Minnesota, www.ipums.org.

and people chose to live with roommates well into their late twenties and early thirties (Bitler and Hoynes, 2015). During the pandemic, on the other hand, remote work allowed many to hold onto their jobs. Many of these workers, including younger members of the workforce, chose to form households of their own. As we will argue, this growth in household formation is crucial to understanding why housing demand was strong even in places that were losing population.

3 Conceptual Framework

Our conceptual framework is based on the fact that remote work increases the salience of housing-related purchases in people's consumption bundles. In our model, budget-constrained consumers allocate their income between consumption goods and housing goods. In addition to being budget-constrained, consumers are also constrained by time in the sense that every hour spent working an office reduces the total number of hours available for home enjoyment. However, when consumers can work remotely, they spend more time experiencing their homes. As a result, housing-related goods become a larger component of their utility calculations. People who work from home will therefore allocate more of their budgets toward home goods.

There is both anecdotal and empirical evidence supporting a budget reallocation framework. For example, the early days of stay-at-home orders saw sales of home fitness gear surge as people's homes became their primary sites of fitness and leisure. With remote work becoming a fixture of the American economy, these at-home fitness purchases appear to be here to stay (Shaban, 2021).

Similarly, the lockdowns of 2020 saw an uptick of spending on home-improvement projects (Morris, 2020). Parents built playhouses for their kids and cohabiting partners needed more home office space. A recent survey of people undertaking home-improvement projects showed that newly-found time was the primary driving force behind these decisions (Porch Research, 2020). This flurry of home improvement activity led to an increase in demand for lumber, tools, and contractor services.

More direct evidence for these behavior changes can be seen in GDP data on home improvements, where private fixed investment in single-family residential structures grew 30% in real terms from 2019 to 2021.[8] Likewise, Home Depot—the nations largest home improvement retailer in the U.S.—saw 37% growth in sales from 2019 to 2021, noting in it's annual financial report that, "In fiscal 2021, we saw continued elevated home improvement demand, which began at the end of the first quarter of fiscal 2020, with strong performance across our departments as customers continued to focus on home improvement projects and repairs."[9]

[8]Bureau of Economic Analysis Table 5.4.6. Real Private Fixed Investment in Structures by Type, Chained Dollars

[9]Home Depot Annual Report, 2021

3.1 Baseline Model

To model the changing demand for home goods, we augment the standard consumer choice model to include both income and time constraints. The time constraint factors into the utility function by increasing or decreasing the salience of home goods in consumers' total utility. When the consumer can work from home, home goods contribute relatively more to her total utility than when she works at an office.

We assume that the consumer spends t hours every week working at a wage rate W and gains utility from buying both consumption goods C and housing goods H. Housing goods can include purchases of workout gear, furniture, and home improvement equipment. More closely related to our empirical work, these housing goods can also include new homes with more room or more amenities. The consumer spends a fraction $\theta \in [0, 1]$ of her work time in an office and a fraction $1 - \theta$ working from home. A fully remote work schedule implies $\theta = 0$ while hybrid work is represented by $0 < \theta < 1$.

$$U(C, H; \theta) = U\left(C, \left(\frac{T - \theta t}{T}\right) H\right) \tag{1}$$

where T is the total number of waking hours per week and $T - \theta t$ is total waking hours spent at home. We also assume that the consumer experiences diminishing marginal utility in consumption goods and housing. Formally, we assume that $\partial U/\partial C > 0$, $\partial U/\partial H > 0$, $\partial^2 U/\partial C^2 < 0$, and $\partial^2 U/\partial H^2 < 0$.

The consumer's budget constraint is given by $P_C C + P_H H \leq W \cdot t$ where P_C is the market price of consumption goods and P_H is the market price for housing goods. For simplicity, we also assume that the consumer is a price-taker in both the goods market and the labor market. In addition, we assume that weekly labor hours are set exogenously through a pre-existing labor contract between the consumer and her employer.

Optimizing consumers allocate their income between consumption goods and housing goods by equating their marginal utility per dollar of each input. The first-order condition is given by

$$\frac{U_H}{U_C} = \left(\frac{T}{T - \theta t}\right) \frac{P_H}{P_C} \tag{2}$$

where U_H is the marginal utility of consumption and U_H is the marginal utility of housing. In this case, the consumer explicitly considers the amount of time she spends at home (*i.e.*, the time spent experiencing her housing purchase). Equation (2) implies that more remote work (operationalized as a decrease in θ) leads to the optimality condition requiring a lower marginal utility of housing goods relative to consumption goods. Since marginal utility is decreasing in its inputs, this implies that for a given wage rate $H'/C' > H/C$ whenever $\theta' < \theta$. In other words, all else being equal, increasing remote work will lead the consumer to shift her consumption bundle toward more housing goods and away from consumption goods.

3.2 Adding Household Formation

In only considering spending as a margin of adjustment to remote work, the baseline model abstracts away from the fact that consumers may be members of households with multiple residents; however, many adults—especially those in their twenties—live with roommates. The experience of the Great Recession has shown that some workers adjust to economic conditions by joining existing households, either by living with their parents or living with roommates (Paciorek, 2016; Bitler and Hoynes, 2015). Thus, another way that a remote worker can increase their consumption of H may be to form a household of their own.

In this section, we extend the baseline model to explore the relationship between remote work and household formation. For tractability, we introduce more structure into the utility function of the consumer. Formally, preferences are given by

$$U(C,H;\theta)=\left(C^{\frac{\sigma-1}{\sigma}}+\left(\frac{T-\theta t}{T}\right)^{\frac{1}{\sigma}}H^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where the parameter σ is the elasticity of substitution.

In addition, rather than focusing on the behavior of a single consumer, we will aggregate over all consumers in the housing market. We will assume that all consumers share the same utility function and differ from each other only in terms of their income. Let the market size be given by M and let the income distribution be given by $F(W)=Pr[w<W]$.

We also complicate the housing market by introducing two types of living situations. A consumer can either live by herself or she can live with roommates. For example, consumers can rent a one-bedroom apartment alone or they can split a two-bedroom apartment with someone else. For simplicity, we assume that housing prices are offered on a continuum such that $P_H\in\mathcal{P}\equiv\left[\underline{\mathrm{P}},\overline{P}\right]$. Assume that prices are ordered such that there is a threshold price $\widetilde{P_H}\in\mathcal{P}$ such that consumers are paying for joint housing whenever $P_H<\widetilde{P_H}$ and are paying for their own place whenever $P_H\geq\widetilde{P_H}$. We assume that consumers always prefer living alone but cannot always afford it.

The functional form of the utility function implies that consumers facing the same set of prices will spend the same share of their income on housing regardless of income. Formally, maximizing behavior implies that the share of income spent on housing will be

$$\eta_H(\theta)=\frac{\left(\frac{T-\theta t}{T}\right)P_H^{1-\sigma}}{P_C^{1-\sigma}+\left(\frac{T-\theta t}{T}\right)P_H^{1-\sigma}}. \tag{4}$$

Similar to the baseline model, this function is decreasing in θ. Total spending by a consumer with a given income W and remote work parameter θ is given by $W\eta_H(\theta)$.

For simplicity, assume that $\theta\in\{0,1\}$ and let η_H^R be the income share devoted to housing for remote workers and let η_H^N bet the income share devoted to housing for non-remote workers. In addition, let the share of remote workers be given by ξ and the shrae of non-remote workers given by $1-\xi$. The wages of remote workers are distributed by a function $F_R(W)$ and the wages of non-remote workers are distributed by a function $F_N(W)$ such that $F_h(W) = Pr[w < W]$ for $h \in \{R, N\}$. Then total spending in the market Y_H is given by

$$Y_H = M\left(\xi \int_{\underline{W}}^{\overline{W}} W\eta_H^R dF_R(W) + (1-\xi)\int_{\underline{W}}^{\overline{W}} W\eta_H^N dF_N(W)\right) \tag{5}$$

A consumer i will live alone and form her own household as long as $\eta_H(\theta_i)W_i \geq \widetilde{P_H}$ or, equivalently, if $W_i \geq \frac{\widetilde{P_H}}{\eta_H(\theta_i)}$. The total number of consumers living alone is therefore

$$M_{ALONE} = M\left(\xi\left(1 - F_R\left(\frac{\widetilde{P_H}}{\eta_H^R}\right)\right) + (1-\xi)\left(1 - F_N\left(\frac{\widetilde{P_H}}{\eta_H^N}\right)\right)\right). \tag{6}$$

Likewise, the number of consumers living with roommates is

$$M_{JOINT} = \xi M F_R\left(\frac{\widetilde{P_H}}{\eta_H^R}\right) + (1-\xi)MF_N\left(\frac{\widetilde{P_H}}{\eta_H^N}\right). \tag{7}$$

Thus, the overall number of independent households depends on the distribution of income in the market.

Combining 6 and 7 along with the assumption that all joint arrangements consist of two consumers allows us to express the the household headship rate—the ratio of total households to total consumers. Letting HH represent the number of households, the headship rate HH/M in a housing market with threshold $\tilde{P}$ is given by $M_{ALONE}/M + \frac{1}{2}M_{JOINT}/M$ or

$$\frac{HH}{M} = 1 - \frac{1}{2}\left(\xi F_R\left(\frac{\tilde{P}}{\eta_H^R}\right) + (1-\xi)F_N\left(\frac{\tilde{P}}{\eta_H^N}\right)\right). \tag{8}$$

We can see from this equation that increasing the prevalence of remote work will increase the total number of households and the headship rate if it increases the optimal housing expenditure of consumers whose original spending was close to $\widetilde{P_H}$.

In this simple framework, remote work increases the share of income she allocates toward housing but does not change her income. If the worker is initially working full time in an office and has a housing expenditure just below $\tilde{P}$, remote work may push her over the threshold. In this way, remote work can lead people to form their own households. Assume, for example that no consumer works remotely in period 1 and all consumers work remotely in period 2. That is, $\xi_1 = 0$ and $\xi_2 = 1$. Then, as long as $\frac{\tilde{P}}{\eta_H^R} \in [\underline{W}, \overline{W}]$, the headship rate will unambiguously increase. Similarly, if a random subset of workers switch to remote work such that $F_R(W) = F_N(W) = F(W)$, then the headship rate will also unambiguously increase since $\tilde{P}/\eta_H^R < \tilde{P}/\eta_H^N$ implies $F(\tilde{P}/\eta_H^R) < F(\tilde{P}/\eta_H^N)$ for all values of $\tilde{P}$.

However, if only the highest-income or the lowest-income consumers switch to remote work, there will be no change in household formation. That is, the richest consumers already live in their own households and the poorest consumers will still not be able to afford their own place. In practice, therefore, the household formation rate will change the most if non-remote workers earning close to $\tilde{P}/\eta_H^N$ become remote workers. Thus, the overall effect of remote work on household formation remains an empirical matter.

3.3 Empirical Predictions

The model is not intended to generate specific estimating equations. Rather, it is a tool for systematizing the relationship between remote work and housing markets and for generating a set of testable hypotheses. The model yields predictions at two levels of aggregation. The baseline model generates predictions about individual behavior and the household formation model gives us predictions about market-level adjustments to remote work.

First, at the individual level, we expect remote work to lead to increased spending on housing all else being equal. This may be observed through increased spending on gross rents and mortgage payments. Second, at the market level, we expect this demand to aggregate to higher market prices for homes. This may be observed through higher median home values or higher median rents. Third, we expect remote work to lead to increases in the propensity to form households. This may be observed through increased household head designations as well as smaller average household sizes.

In addition, the theoretical models suggest why the impact of remote work may vary by geography. At an individual level, marginal increases in $\tilde{P}$ reduce the propensity to form a household, suggesting that geographic variation in the cost of housing may affect the extent of household formation that remote work causes. In addition, the impact of remote work on population, either by encouraging in-migration or out-migration, may either offset increases in house prices or exacerbate increases in prices caused by changes in the extensive and intensive margin of housing demand. Likewise, the housing supply is an important factor that can affect the extent to which increases in housing demand manifest as extensive or intensive margin increases. In completely inelastic housing supply markets with no vacancies, for example, the desire for individuals to form new households may be limited as increases in housing demand along an inelastic supply curve increase prices, and thus $\tilde{P}$. Finally, the decision of an individual who is a remote worker has spillovers on the decisions of others in the local housing market, including current roommates but also other potential buyers in the market. In short, local housing markets matter, and the way remote work impacts individual decisions may aggregate to different outcomes at the housing market local.

4 Empirical Strategy

Consistent with the model outlined above, we will estimate housing market outcomes at two different levels of aggregation. First, we will use microdata to look at outcomes at the level of the decision maker. These decision makers include both households and individuals. At the household level, we will look at the effect of remote work on gross monthly rental payments, monthly mortgage payments, and the propensity to move into new homes. At the person level, we will look at the propensity to head households. Next, we will examine how these individual decisions shape housing markets using data at the PUMA level. The aggregate outcomes we will examine are changes in rents, median home values, population, headship rates, and moves into new dwelling units.

4.1 Main Estimating Equations

At the micro level, the analytical strategy is to compare differences in engagement with the housing market between remote workers or households and workers or households who do not work remotely. At the household level, remote work will be measured in two ways. First, we will measure remote work as an indicator that equals 1 if the household head works remotely and 0 otherwise. Next, we will measure remote work as the share of household members over the age of 21 who work from home. At the individual level, remote work will be measured as an indicator that equals 1 if the respondent works from home and 0 otherwise.

The main estimating equation will be of the form

$$Y_{it} = \alpha + \beta WFH_{it} + \Gamma W_{it} + \delta_p + \varepsilon_{it} \tag{9}$$

where Y_{it} is the main outcome of interest, WFH is a measure of working from home, W is a vector of controls, and δ_p is a PUMA-level fixed effect. The index i denotes households for mortgage payments, rental payments, and propensity to move and denotes individuals for household formation. We include control variables that are likely to affect both an individual's propensity for working remotely as well as their engagement with the housing market. These controls include household income, whether the household head attended college, the age (and squared age) of the household head, sex of the household head, and the race of the household head.

We apply a few sample restrictions to the microdata regressions. First, we only include individuals between the ages of 16 and 64, inclusive who are not institutionalized. People outside of this group are unlikely to engage with the housing market and are unlikely to make choices about remote work. In addition, we only include employed individuals since we are interested in how the choice to work remotely affects housing market decisions and unemployed people are not making choices about working remotely. Finally, in regressions on rental payments and mortgage payments, we restrict the sample to only include people paying rent or paying mortgages, respectively. In addition, because we expect decisions to be mediated by population density and the average costs of available home, we also categorize PUMAs by their density and median home values. We interact the natural log of each PUMA's population density with the natural log of its median home value. We then take group PUMAs by deciles of this interaction.

At the market level, the analytical strategy for exploring the aggregate effects of remote work is to compare housing expenses and household formation across PUMAs with varying degrees of exposure to working from home. In this case the estimating equation is of the form

$$Y_{it} = \alpha + \sum_{j=1}^{10} \delta_j + \sum_{j=1}^{10} \beta_j \left(WFH_{it} \times \delta_j\right) + \Gamma W_{i,t} + \delta_s + \varepsilon_{it} \tag{10}$$

where Y_{it} is the the outcome variable in period t, WFH_{it} is the level of exposure to working from home[10], $W_{i,t-1}$ is a set of control variables, and δ_s is a state fixed effect. The dummy δ_j is a set of indicators showing a PUMA's decile of the density and home value interaction.

In the aggregate regressions, we restrict the sample to workers between the ages of 16 and 64 who or not institutionalized. In contrast with the individual level regressions, we include respondents who are unemployed. Each model includes a set of labor market controls and technology controls. Labor market controls include the unemployment rate and the share of workers in the manufacturing industry. Technology controls include the share of households with computers and the share of households with broadband connections. For each model, standard errors are clustered at the state level.

4.2 An Instrumental Variables Approach

Both the micro and market level regressions suffer from endogeneity. At the individual level, choices about how to engage with the housing market may affect a person's decisions about working from home. For example, there may be reverse causality if someone who plans to move regularly chooses remote work regardless of their occupation. At the aggregate level, the strategy is to capture regionally distinct exposures to a common remote work shock. However, idiosyncrasies may pollute the measure of the remote work share and distract from the common shock. We use national data on remote work to create an instrument for both sets of regressions. In each case, we will estimate the models using two-stage least squares (2SLS).

To address endogeneity at the micro level, we employ an instrumental variable technique in which a household or individual's remote work measure will be predicted based on the national remote work shares of their industry and occupation. This is given by

$$\widetilde{WFH}_{hk} = \sum_i WFH_i / E_{hk} \tag{11}$$

where WFH_i is the individual indicator for working from home and E_{hk} is total employment in occupation k in industry h. This instrument is essentially a measure of the probability that a given worker in occupation k in industry h works remotely.

We bring this measure to the household level in two ways. When the household's remote work status is dictated based on the household head, we simply use the work from home probability based on the occupation and industry of the household head. When the household's remote work status is based on the share of members over 21 who work from home, we use the average

[10] Overall exposure to working from home is measured as the share of workers in a PUMA who work remotely. This is measured in percentage points on a scale from 0 to 100.

remote work probability based on the occupations and industries of each household member over the age of 21. These measures are highly predictive of working from home. Regressions of each remote work measure against their respective instruments yield large F-statics and first-stage coefficients that are close to unity.

To address endogeneity at the market level, we use a shift-share approach in which we use changes in the remote work shares of occupations at the national weighted by local occupational employment shares. Similar to Autor and Dorn (2013), when we compute the national remote work shares at the occupation level for each PUMA, we exclude the state containing that PUMA. As Goldsmith-Pinkham et al. (2020) point out, a key assumption for this approach is the exogeneity of the national shock. We are confident that our instrument fits this criteria since it is primarily the result of governmental responses to the COVID crisis which was essentially a force majeure.

Formally, our instrumental variable for PUMA i at time t is given by

$$\widetilde{WFH}_{it} = \sum_{k} WFH_{kt}^{S_{-i}} \cdot \frac{E_{ik,t-1}}{E_{i,t-1}} \tag{12}$$

where $WFH_{kt}^{S_{-i}}$ is the change in the work from home share for occupation k at time t as measured using data from all states excluding the state containing PUMA i; $E_{ik,t-1}$ is the start of period employment in occupation k in PUMA i; and $E_{i,t-1}$ is the total start of period employment in PUMA i. Again, first-stage regressions show that this instrument is strong predictor of our main independent variable. The first-stage F-statistic is large and the estimated coefficient is positive and statistically significant.

5 Results

We first turn to the effect of remote work on the intensive margin of housing demand. The outcome of interest in this case is total monthly spending on housing. This is measured using both monthly mortgage payments as well as monthly gross rental payments. Mortgage and rental payments are both household level variables. [11] We find that remote work is positively associated with housing expenditures both in terms of mortgage payments and rent. This is consistent with the theoretical framework outlined above in which more time at home increases the salience of housing expenditure in consumption.

Table 1 shows the estimated effect of remote work on monthly mortgage payments. In panel A remote work is measured based on the household head and in panel B remote work is measured based on the share of household members older than 21 who work from home. The estimates using each method are consistent both in terms of magnitude and direction, so we will focus on the results based on the household head. We find that households headed by remote workers

[11] We use gross rent instead of contract rent because contracts are not easily comparable across individuals. For example, some contracts may include utilities while others don't.

spend more money on their mortgages relative to otherwise comparable households headed by non remote workers.

The OLS estimates shown in columns (1) and (2) show that, compared to households headed by non remote workers, having a household head who works remotely is associated with mortgage payments that were 9 percent larger in 2019 and 5 percent larger in 2021. The 2SLS estimates shown in columns (5) and (6) are consistent with the OLS results but larger, implying that having a household head work from home led to a 30 percent increase in mortgage payments in 2019 and a 10 percent increase in mortgage payments in 2021. To put these results in dollar terms, consider a household with a non remote head making $4,000 mortgage payments each month. Having the household head work remotely would have led to about a $1,300 per month increase in mortgage spending in 2019 and a $400 per month increase in mortgage spending in 2021.

Table 2 shows the estimate effect of remote work on monthly rent payments. Again, panel A shows the estimates when remote work is measured based on the household head and panel B shows the estimates when remote work is measured based on the share of adults who work from home. As with mortgage payments, households headed by remote workers also tend to spend more money on rent relative to otherwise comparable households whose heads do not work remotely.

The 2SLS coefficient estimates shown in columns (5) and (6) indicate that remote work led to about a 33 percent increase in monthly rental payments in 2019 and about a 20 percent increase in rental payments in 2021. This is an economically significant effect size. Consider a non remote household making $2,500 rental payments each month. Becoming a remote household would have led to about an $825 increase in monthly rent in 2019 and about a $500 increase in 2021.

Our estimates of the effect of remote work on housing demand are similar in magnitude to those in Stanton and Tiwari (2021). For example, they estimate that remote work increases home values by between 13 to 20 percent. Similarly, they find that remote work increases the share of income spent on rent by between about 7 to 14 percent. While these represent slightly different measures of the intensive margin of housing demand, taken together our results are consistent with remote work increasing the willingness to pay for housing by between 10 to 20 percent. The consistently larger effects from the IV approach suggest the importance of controlling for endogeneity in estimating the effects of remote work on housing demand.

We next turn to individual decisions at the extensive margin of housing demand. We operationalize the extensive margin as the decision to move into a new housing unit as well as the decision to head a household. Moving to a new housing unit is measured at the household level using an indicator that equals 1 if the household moved into their current dwelling within 12 months of the survey and 0 otherwise. Headship is measured at the person level using an indicator equal to 1 if the respondent is listed as a household head and 0 otherwise. In both cases, decisions are modeled using a linear probability. Overall, we find that remote work increased both the propensity to move and to head households.

Table 3 shows estimates of the effect of remote work on moving into a new home. The OLS

	A. Remote work measured based on household head					
	OLS		Reduced Form		2SLS	
	2019	2021	2019	2021	2019	2021
	(1)	(2)	(3)	(4)	(5)	(6)
Remote HH head	0.090***	0.045***			0.278***	0.105***
	(0.000)	(0.000)			(0.001)	(0.000)
Teleworkable HH head			0.307***	0.100***		
			(0.001)	(0.000)		
Demographic controls	✓	✓	✓	✓	✓	✓
PUMA fixed effects	✓	✓	✓	✓	✓	✓
Observations	35,392,375	35,810,998	35,392,375	35,810,998	35,392,375	35,810,998
Adjusted R^2	0.425	0.413	0.425	0.413	0.420	0.411

	B. Remote work measured based on share of household working remotely					
	OLS		Reduced Form		2SLS	
	2019	2021	2019	2021	2019	2021
	(1)	(2)	(3)	(4)	(5)	(6)
Remote share	0.120***	0.054***			0.346***	0.112***
	(0.000)	(0.000)			(0.001)	(0.001)
Avg. hh teleworkability			0.393***	0.114***		
			(0.001)	(0.001)		
Demographic controls	✓	✓	✓	✓	✓	✓
PUMA fixed effects	✓	✓	✓	✓	✓	✓
Observations	35,303,490	35,721,599	35,303,490	35,721,599	35,303,490	35,721,599
Adjusted R^2	0.425	0.413	0.425	0.413	0.421	0.412

Table 1: Relationship Between Remote Work and Monthly Mortgage Payments (Log Scale)
Note: The dependent variable is the natural log of monthly mortgage payments. Monthly mortgage payments are adjusted to 2021 USD using the Consumer Price Index from the Bureau of Labor Statistics. The sample is limited to non institutional households headed by employed people between the ages of 16 and 64. In Panel A, remote work is based on the work arrangements of the household head. In Panel B, remote work is based on the share of household members over the age of 21 who work from home. Columns (1) and (2) report OLS estimates using remote work as the independent variable, columns (3) and (4) report reduced form estimates using the instrument as an independent variable, and columns (5) and (6) report 2SLS estimates using remote work predicted by the instrumental variable as the independent variable. All models include demographic controls and PUMA fixed effects. All regressions use household level frequency weights and the listed observations are *implied* observations based on the ACS weighting scheme. All data come from ACS PUMS files downloaded from usa.ipums.org.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	A. Remote work measured based on household head					
	OLS		Reduced Form		2SLS	
	2019	2021	2019	2021	2019	2021
	(1)	(2)	(3)	(4)	(5)	(6)
Remote HH head	0.064***	0.058***			0.330***	0.183***
	(0.000)	(0.000)			(0.001)	(0.000)
Teleworkable HH head			0.274***	0.170***		
			(0.001)	(0.000)		
Demographic controls	✓	✓	✓	✓	✓	✓
PUMA fixed effects	✓	✓	✓	✓	✓	✓
Observations	28,016,858	27,132,921	28,016,858	27,132,921	28,016,858	27,132,921
Adjusted R^2	0.510	0.501	0.511	0.502	0.498	0.493
	B. Remote work measured based on share of household working remotely					
	OLS		Reduced Form		2SLS	
	2019	2021	2019	2021	2019	2021
	(1)	(2)	(3)	(4)	(5)	(6)
Remote share	0.081***	0.067***			0.390***	0.202***
	(0.000)	(0.000)			(0.001)	(0.001)
Avg. hh teleworkability			0.329***	0.193***		
			(0.001)	(0.000)		
Demographic controls	✓	✓	✓	✓	✓	✓
PUMA fixed effects	✓	✓	✓	✓	✓	✓
Observations	27,379,844	26,447,298	27,379,844	26,447,298	27,379,844	26,447,298
Adjusted R^2	0.512	0.501	0.512	0.502	0.500	0.494

Table 2: Relationship Between Remote Work and Monthly Rental Payments (Log Scale)
Note: The dependent variable is the natural log of gross monthly rental payments. Monthly rental payments are adjusted to 2021 USD using the Consumer Price Index from the Bureau of Labor Statistics. The sample is limited to non institutional households headed by employed people between the ages of 16 and 64. In Panel A, remote work is based on the work arrangements of the household head. In Panel B, remote work is based on the share of household members over the age of 21 who work from home. Columns (1) and (2) report OLS estimates using remote work as the independent variable, columns (3) and (4) report reduced form estimates using the instrument as an independent variable, and columns (5) and (6) report 2SLS estimates using remote work predicted by the instrumental variable as the independent variable. All models include demographic controls and PUMA fixed effects. All regressions use household level frequency weights and the listed observations are *implied* observations based on the ACS weighting scheme. All data come from ACS PUMS files downloaded from usa.ipums.org.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

estimates in columns (1) and (2) of panel A show that in both 2019 and 2021, households headed by remote workers were about 6 percentage points more likely to have moved within the last 12 months than households whose heads did not work remotely. The effect sizes of the 2SLS estimates are considerably larger and imply that working from home led to a 33 percentage point greater probability of moving in 2019 and a 20 percentage point greater probability of moving in 2021.

Table 4 shows the estimates of the effect of remote work on household headship. The OLS estimates in columns (1) and (2) show that remote workers were 3 percentage points more likely to head households in 2019 and 6 percentage points more likely to head households in 2021 than non-remote workers. The 2SLS estimates imply that switching to remote work increases the probability of heading a household by between 25 and 30 percentage points. In addition, Appendix Table A.10 shows that remote work has led to smaller household sizes, offering further support for the positive effect of remote work on household formation.

The results in tables 1 – 4 show that remote work increased the demand for housing at both the intensive and extensive margins. That is, working from home has led people to form new households and it has led people to be willing to spend more for housing. We now turn to regressions at the PUMA level to explore how these household and individual decisions are reflected in aggregate housing markets. As before, we focus on measures of housing expenditure and mobility. Remote work is measured in terms of changes in the share of workers who report working from home. Key to our analysis is the heterogeneity of remote work across regions. To capture this, we interact changes in remote work with decile indicators for high population density and home value interactions because, as demonstrated in prior literature, remote work has led people to look for housing outside of busy and expensive city centers. (Ramani and Bloom, 2021; Ozimek, 2022a,b; Howard et al., 2022; Althoff et al., 2022). The results of the PUMA level regressions are shown in Table 5

The data show that density and home values have a hand in mediating the effect of remote work on housing demand. In general, the interaction between the tenth decile indicator and the share of workers who work from home was statistically significant. For rent, home values, and population the estimated coefficient was lower for the interaction with the tenth decile than for interactions with other deciles. For household formation, the estimated coefficient much larger for the interaction with the tenth decile than for interactions with other deciles. In line with prior research, this suggests that remote work has had led to greater growth of suburban an exurban regions relative to dense city centers. However, this also suggests that working from home has led residents in dense and expensive regions to form their own households. This may help explain why remote work has led to a (small) increase in big city rents despite outmigration. This pattern in the coefficient estimates of the interaction terms from our OLS regressions are shown in Figure 4.

Column (1) of table 5 shows OLS estimates of the effect of remote work on gross median rents. The results show that at the tenth decile, a one percentage point increase in the share of people working from home leads to a 0.8 percent increase in rents. In contrast, at most other

	A. Remote work measured based on household head					
	OLS		Reduced Form		2SLS	
	2019	2021	2019	2021	2019	2021
	(1)	(2)	(3)	(4)	(5)	(6)
Remote HH head	0.007***	0.011***			0.034***	0.033***
	(0.000)	(0.000)			(0.001)	(0.000)
Teleworkable HH head			0.035***	0.030***		
			(0.001)	(0.000)		
Demographic controls	✓	✓	✓	✓	✓	✓
PUMA fixed effects	✓	✓	✓	✓	✓	✓
Observations	75,907,607	77,148,650	75,907,607	77,148,650	75,907,607	77,148,650
Adjusted R^2	0.131	0.137	0.131	0.138	0.130	0.137

	B. Remote work measured based on share of household working remotely					
	OLS		Reduced Form		2SLS	
	2019	2021	2019	2021	2019	2021
	(1)	(2)	(3)	(4)	(5)	(6)
Remote share	0.005***	0.013***			0.021***	0.035***
	(0.000)	(0.000)			(0.001)	(0.000)
Avg. hh teleworkability			0.022***	0.034***		
			(0.001)	(0.001)		
Demographic controls	✓	✓	✓	✓	✓	✓
PUMA fixed effects	✓	✓	✓	✓	✓	✓
Observations	75,084,943	76,264,651	75,084,943	76,264,651	75,084,943	76,264,651
Adjusted R^2	0.120	0.126	0.120	0.126	0.120	0.125

Table 3: Relationship Between Remote Work and Propensity to Move

Note: The dependent variable is an indicator that equals 1 if the household moved into their home within the past 12 months and 0 otherwise. The sample is limited to non institutional households headed by employed people between the ages of 16 and 64. In Panel A, remote work is based on the work arrangements of the household head. In Panel B, remote work is based on the share of household members over the age of 21 who work from home. Columns (1) and (2) report OLS estimates using remote work as the independent variable, columns (3) and (4) report reduced form estimates using the instrument as an independent variable, and columns (5) and (6) report 2SLS estimates using remote work predicted by the instrumental variable as the independent variable. All models include demographic controls and PUMA fixed effects. All regressions use household level frequency weights and the listed observations are *implied* observations based on the ACS weighting scheme. All data come from ACS PUMS files downloaded from usa.ipums.org.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	OLS		Reduced Form		2SLS	
	2019	2021	2019	2021	2019	2021
	(1)	(2)	(3)	(4)	(5)	(6)
WFH	0.030***	0.059***			0.260***	0.291***
	(0.000)	(0.000)			(0.001)	(0.000)
Teleworkable			0.244***	0.259***		
			(0.001)	(0.000)		
Demographic controls	✓	✓	✓	✓	✓	✓
PUMA fixed effects	✓	✓	✓	✓	✓	✓
Observations	146,255,704	144,016,084	146,255,704	144,016,084	146,255,704	144,016,084
Adjusted R^2	0.148	0.144	0.149	0.149	0.137	0.116

Table 4: Relationship Between Remote Work and Propensity to Head Household
Note: The dependent variable is an indicator that equals 1 if the respondent is listed as a household head and 0 otherwise. The sample is limited to employed people between the ages of 16 and 64 who are not institutionalized. Columns (1) and (2) report OLS estimates using remote work as the independent variable, columns (3) and (4) report reduced form estimates using the instrument as an independent variable, and columns (5) and (6) report 2SLS estimates using remote work predicted by the instrumental variable as the independent variable. All models include demographic controls and PUMA fixed effects. All regressions use household level frequency weights and the listed observations are *implied* observations based on the ACS weighting scheme. All data come from ACS PUMS files downloaded from usa.ipums.org.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

deciles the same increase in the share of people working from home leads to between a 1 and 1.3 percent increase in median gross rents. The 2SLS estimates shown in column (5) confirm these results. At the tenth decile, a one percentage point increase in the share of people working from home leads to a 1 percent increase in median gross rents. While at most other deciles, a one percentage point increase in the share of people working from home leads to about a 1.5 percent rent increase.

The effects of remote work mediated through population density and median home value are similar for homeowners as well. Column (2) of table 5 shows OLS estimates of the effect of remote work on median home values. At the tenth decile, a one percentage point increase in the share of people working from home leads to a 1.3 percent increase in median home values. In contrast, at most other deciles a one percentage point increase in the share of people working from home leads to between a 2.0 and 3.0 percent increase in median home values. Again, the 2SLS estimates confirm the OLS results. In the PUMAs with the highest density and home value interactions, we estimate that a one percentage point increase in the share of people working from home leads to a 1.1 percent increase in median home values. In most other PUMAs the same increase in the share of people working from home leads to a roughly 2 to 3 percent increase in median home values.

The results also show evidence that remote work led to population declines in the densest and most expensive PUMAs. Column (3) shows OLS estimates of the effect of remote work on

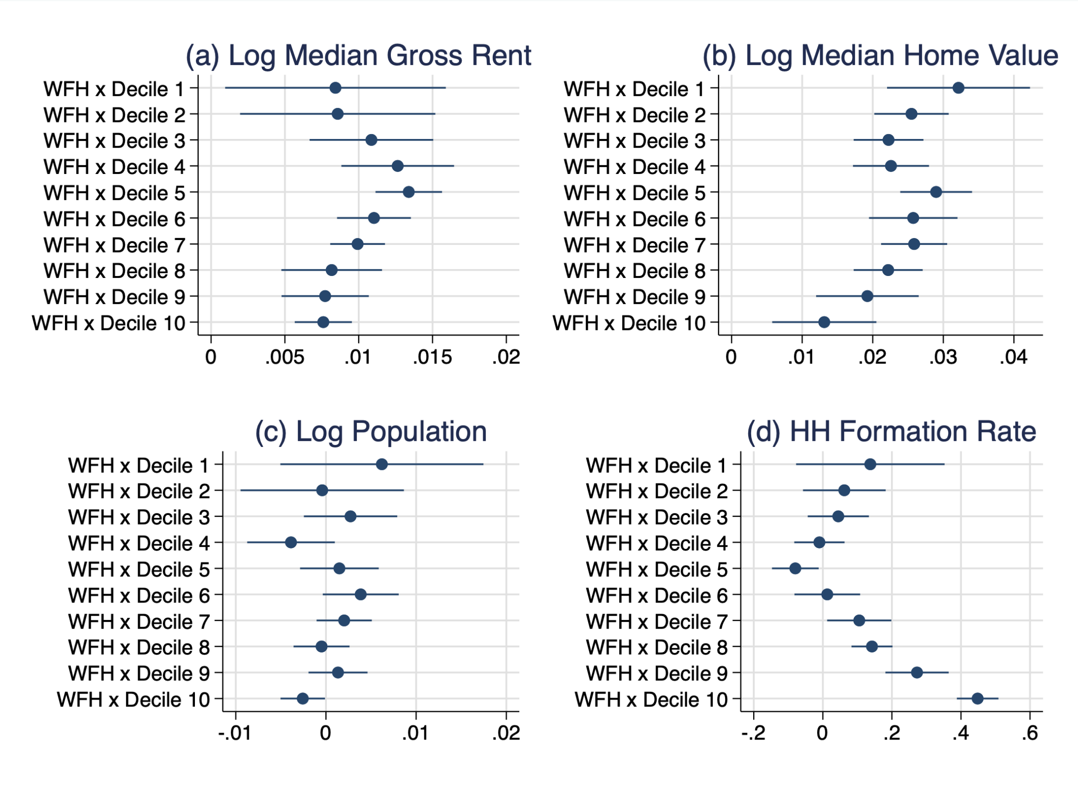


Figure 4: Coefficient Estimates for Density × Home Value Interactions

population while column (7) shows the 2SLS estimates. The OLS estimate for the tenth decile interaction shows that a one percentage point increase in the share of workers working remotely is associated with a 0.3 percent decline in population. The 2SLS estimate for the tenth decile interaction has the same magnitude but is not statistically significant.

At the same time, the results show that remote work has had a strong positive effect on the household headship rate of dense PUMAs. Column (4) shows OLS estimates of the effect of remote work on the headship rate. At the tenth decile, a one percentage point increase in the share of workers teleworking leads to a 0.45 percentage point increase in the share of the population heading their own household. A one percentage point increase in the share of people working from home leads to between a 0.14 and 0.30 percentage point increase in the household rate at other top deciles and there is no statistically significant relationship between working from home and household formation at lower deciles.

Column (8) shows 2SLS estimates of the effect of remote work on the headship rate. These estimates are consistent with the OLS estimates in column (4). At the tenth decile, a one percentage point increase in the share of workers teleworking leads to a 0.52 percentage point increase in the share of the population heading their own household. A one percentage point increase in the share of people working from home leads to between about a 0.18 and 0.32 percentage point increase in the household rate at other top deciles while there is no statistically significant relationship between working from home and household formation at lower deciles.

For PUMA level results, we see that the IV approach increases impacts across the board.

While OLS results are of a consistent order of magnitude and same sign, controlling for endogeneity suggests larger impacts. As an additional robustness test, we utilize a first-differences model in Table A.9 in the appendix, with results for variables measured in changes between 2019 and 2021. While PUMA level changes are noisy and therefore the models explanatory power is relatively low compared to levels, the results indicate the same relative impacts of work from home, with rents, house prices, and population having a weaker or negative relationship for the most dense and expensive places, and household formation being positive for the most dense and expensive places.

Taken together, these results are consistent with remote work generating increased demand for more space, more home-based amenities, and more privacy. Similarly, remote work led to increased demand for one's own space over living with roommates. This is shown in the increased household formation resulting from working from home. These finding are largely consistent with the established 'donut' effects of COVID-19 on dense city centers. However, our finding that remote work led to increases in household formation in the most dense and expensive PUMAs sheds light on why big city rents continued to increase despite overall outmigration to less dense regions.

6 Conclusion

In this paper we explore how remote work affected housing demand at both a micro level and an aggregate level. Methodologically, this paper adds to the growing body of remote work literature by being the first to use actual, post-pandemic remote work rates at a granular level as an instrumental variable. At the individual level, we utilize occupation and industry fixed-effect IVs, and at the local housing market level we utilize a shift-share approach. The causal effect of remote work on housing markets is consistent with OLS.

We find that remote work has increased the demand for housing at both the intensive and extensive margins for households and individuals. Remote households spent more on rent and mortgages than otherwise comparable non-remote households. In addition, remote households were more likely to have moved into their home within the last 12 months, and individuals who worked remotely were more likely to head their own households. All individual level effects are larger when using IV approaches.

In general, exposure to remote work led to increases in housing demand as shown, for example, through gross monthly rental payments and home values. However, this effect was smaller for PUMAs with high population densities and expensive housing markets. Indeed, we find a negative effect of remote work exposure on population growth the most dense and expensive PUMAs, suggesting that working from home led to some level of out-migration from these areas. However, in these dense and expensive PUMAs, the positive effect on the household formation helped offset the population loss. In short, one reason places that lost population nevertheless saw robust housing markets was that they had stronger household formation.

This paper makes three main contributions to the literature. First, we build on the existing literature by being the first study to use 2021 ACS data to examine the effects of remote work on individual level outcomes. Second, we use actual post-pandemic remote work rates to construct instrumental variables for working from home. Lastly, we extend the prior research by focusing on household formation as an important extensive margin of household demand.

This paper also opens up potential avenues for subsequent research into the economic geography of remote work and the future of cities. For example, our research has shown that remote work has changed the way that people live within dense and expensive urban areas. Working from home has led to both an out-migration from city centers as well as increased headship rates in those same areas. It remains an open question to estimate the magnitude of the effects of these changes on local economies and governments.

	OLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH × (Density × Home Value) Decile								
Decile 1	0.008**	0.032***	0.006	0.138	0.013*	0.021	0.007	0.134
	(0.004)	(0.005)	(0.006)	(0.107)	(0.007)	(0.014)	(0.025)	(0.249)
Decile 2	0.009**	0.025***	-0.000	0.062	0.020**	0.037***	-0.001	-0.042
	(0.003)	(0.003)	(0.005)	(0.060)	(0.008)	(0.006)	(0.007)	(0.164)
Decile 3	0.011***	0.022***	0.003	0.045	0.015***	0.021***	-0.003	0.116
	(0.002)	(0.002)	(0.003)	(0.044)	(0.003)	(0.004)	(0.006)	(0.087)
Decile 4	0.013***	0.023***	-0.004	-0.010	0.015***	0.016***	-0.011**	0.083
	(0.002)	(0.003)	(0.002)	(0.036)	(0.003)	(0.006)	(0.005)	(0.082)
Decile 5	0.013***	0.029***	0.001	-0.080**	0.013***	0.029***	0.001	0.004
	(0.001)	(0.003)	(0.002)	(0.034)	(0.002)	(0.004)	(0.003)	(0.048)
Decile 6	0.011***	0.026***	0.004*	0.013	0.012***	0.027***	-0.003	0.093*
	(0.001)	(0.003)	(0.002)	(0.047)	(0.002)	(0.003)	(0.004)	(0.050)
Decile 7	0.010***	0.026***	0.002	0.106**	0.012***	0.028***	-0.002	0.082
	(0.001)	(0.002)	(0.002)	(0.046)	(0.001)	(0.003)	(0.003)	(0.062)
Decile 8	0.008***	0.022***	-0.000	0.142***	0.010***	0.025***	-0.005**	0.184***
	(0.002)	(0.002)	(0.002)	(0.030)	(0.002)	(0.002)	(0.003)	(0.049)
Decile 9	0.008***	0.019***	0.001	0.273***	0.009***	0.026***	-0.001	0.316***
	(0.001)	(0.004)	(0.002)	(0.046)	(0.002)	(0.002)	(0.002)	(0.077)
Decile 10	0.008***	0.013***	-0.003**	0.448***	0.011***	0.011**	-0.003	0.517***
	(0.001)	(0.004)	(0.001)	(0.030)	(0.001)	(0.005)	(0.002)	(0.059)
Technology controls	✓	✓	✓	✓	✓	✓	✓	✓
Labor market controls	✓	✓	✓	✓	✓	✓	✓	✓
Density decile FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,344	2,345	2,345	2,345	2,344	2,345	2,345	2,345
Adjusted R^2	0.853	0.868	0.154	0.429	0.849	0.865	0.139	0.420

Table 5: Relationship Between Work From Home Share, Gross Monthly Rent, Home Values, Population, and Headship (Density × Home Value Interactions)

Note: Dependent variable in columns (1) and (5) is median gross rent. Dependent variable in columns (2) and (6) is median home value. Dependent variable in columns (3) and (7) is population. Dependent variable in columns (4) and (8) is household rate. Density × home value interaction based on product of log population density and log median home value. Median gross rent, median home value, and population are measured in logs. Household rate is measured in percentage points. Sample restricted to 2021 data. Standard errors clustered at the state level. Data on remote work, population, and headship come from the ACS PUMS downloaded from usa.ipums.org. Data on median gross monthly rent and median home values from ACS 1-year summary files. Data on population density uses square mileage measures from the Geographic Correspondence Engine maintained by the University of Missouri. All dollar values adjusted to 2021 USD using the Consumer Price Index from the Bureau of Labor Statistics.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	A. Density Interactions				B. Home Value Interactions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH × Decile								
Decile 1	0.008**	0.031***	0.003	0.180	0.010***	0.004*	-0.002	0.341***
	(0.003)	(0.004)	(0.005)	(0.115)	(0.003)	(0.002)	(0.004)	(0.074)
Decile 2	0.010***	0.024***	-0.002	0.055	0.010***	0.002*	0.002	0.253***
	(0.002)	(0.002)	(0.003)	(0.043)	(0.002)	(0.001)	(0.004)	(0.056)
Decile 3	0.013***	0.022***	0.004*	0.048	0.005***	0.001	0.002	0.191***
	(0.002)	(0.003)	(0.002)	(0.053)	(0.002)	(0.001)	(0.003)	(0.062)
Decile 4	0.013***	0.023***	-0.000	-0.042	0.004**	0.003***	-0.007**	0.253***
	(0.002)	(0.002)	(0.003)	(0.028)	(0.002)	(0.001)	(0.003)	(0.079)
Decile 5	0.013***	0.026***	-0.002	0.014	0.005**	0.002	-0.003	0.268***
	(0.001)	(0.003)	(0.002)	(0.060)	(0.002)	(0.001)	(0.003)	(0.059)
Decile 6	0.010***	0.025***	0.002	0.056*	0.007***	0.003**	-0.001	0.219***
	(0.001)	(0.003)	(0.002)	(0.031)	(0.002)	(0.001)	(0.002)	(0.069)
Decile 7	0.012***	0.028***	0.001	0.082	0.005***	0.003*	-0.000	0.249***
	(0.001)	(0.002)	(0.001)	(0.052)	(0.002)	(0.002)	(0.003)	(0.050)
Decile 8	0.009***	0.028***	0.001	0.197***	0.002	0.004***	-0.000	0.349***
	(0.001)	(0.002)	(0.001)	(0.044)	(0.002)	(0.001)	(0.002)	(0.070)
Decile 9	0.009***	0.023***	0.003**	0.289***	0.003***	0.003**	-0.002	0.403***
	(0.001)	(0.003)	(0.001)	(0.059)	(0.001)	(0.001)	(0.002)	(0.044)
Decile 10	0.008***	0.015***	-0.002	0.457***	0.007***	0.015***	-0.002	0.323***
	(0.001)	(0.003)	(0.001)	(0.030)	(0.001)	(0.004)	(0.001)	(0.033)
Technology controls	✓	✓	✓	✓	✓	✓	✓	✓
Labor market controls	✓	✓	✓	✓	✓	✓	✓	✓
Density decile FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2,344	2,345	2,345	2,345	2,344	2,345	2,345	2,345
Adjusted R^2	0.847	0.854	0.141	0.425	0.881	0.975	0.122	0.418

Table 6: Relationship Between Work From Home Share, Gross Monthly Rent, Home Values, Population, and Headship (Interactions)

Note: Dependent variable in columns (1) and (5) is median gross rent. Dependent variable in columns (2) and (6) is median home value. Dependent variable in columns (3) and (7) is population. Dependent variable in columns (4) and (8) is household rate. Median gross rent, median home value, and population are measured in logs. Household rate is measured in percentage points. Sample restricted to 2021 data. Standard errors clustered at the state level. Data on remote work, population, and headship come from the ACS PUMS downloaded from usa.ipums.org. Data on median gross monthly rent and median home values from ACS 1-year summary files. Data on population density uses square mileage measures from the Geographic Correspondence Engine maintained by the University of Missouri. All dollar values adjusted to 2021 USD using the Consumer Price Index from the Bureau of Labor Statistics.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References

Althoff, L., Eckert, F., Ganapati, S., and Walsh, C. (2022). The geography of remote work. *Regional Science and Urban Economics*, 93:103770.

Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American economic review*, 103(5):1553–1597.

Bitler, M. and Hoynes, H. (2015). Living arrangements, doubling up, and the great recession: Was this time different? *American Economic Review*, 105(5):166–170.

Brueckner, J., Kahn, M. E., and Lin, G. C. (2021). A new spatial hedonic equilibrium in the emerging work-from-home economy? Technical report, National Bureau of Economic Research.

Delventhal, M. and Parkhomenko, A. (2020). Spatial implications of telecommuting. *Available at SSRN 3746555*.

Delventhal, M. J., Kwon, E., and Parkhomenko, A. (2022). Jue insight: How do cities change when we work from home? *Journal of Urban Economics*, 127:103331.

Dingel, J. I. and Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics*, 189:104235.

Dyrda, S., Kaplan, G., and Ríos-Rull, J.-V. (2012). Business cycles and household formation: The micro vs the macro labor elasticity. Technical report, National Bureau of Economic Research.

García, D. and Paciorek, A. (2022). The remarkable recent rebound in household formation and the prospects for future housing demand.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Gupta, A., Mittal, V., Peeters, J., and Van Nieuwerburgh, S. (2021). Flattening the curve: pandemic-induced revaluation of urban real estate. *Journal of Financial Economics*.

Howard, G., Liebersohn, J., and Ozimek, A. (2022). The short- and long- run effects of remote work on u.s. housing markets. *Available at https://eig.org/wp-content/uploads/2022/11/The-Short-and-Long-Run-Effects-of-Remote-Work-on-U.S.-Housing-Markets.pdf*.

Lee, K. O. and Painter, G. (2013). What happens to household formation in a recession? *Journal of Urban Economics*, 76:93–109.

Liu, S. and Su, Y. (2021). The impact of the covid-19 pandemic on the demand for density: Evidence from the us housing market. *Economics letters*, 207:110010.

Mondragon, J. A. and Wieland, J. (2022). Housing demand and remote work. Technical report, National Bureau of Economic Research.

Morris, F. (2020). Why home improvement has surged and how it's changing america.

Ozimek, A. (2022a). How remote work is shifting population growth across the u.s. *Available at https://eig.org/how-remote-work-is-shifting-population-growth-across-the-u-s/*.

Ozimek, A. (2022b). The new geography of remote work. *Available at* `https://adamozimek.com/admin/pdf/EconReport_RemoteWorkersnotheMove2_Feb2022.pdf`.

Paciorek, A. (2016). The long and the short of household formation. *Real Estate Economics*, 44(1):7–40.

Porch Research (2020). Survey: Home improvement trends in the time of covid.

Ramani, A. and Bloom, N. (2021). The donut effect of covid-19 on cities. Technical report, National Bureau of Economic Research.

Rogers, W. H. and Winkler, A. E. (2014). How did the housing and labor market crises affect young adults' living arrangements?

Shaban, H. (2021). The pandemic's home-workout revolution may be here to stay.

Stanton, C. T. and Tiwari, P. (2021). Housing consumption and the cost of remote work. Technical report, National Bureau of Economic Research.

A Additional Tables

	(1)	(2)	(3)	(4)
ΔWFH × (Density × Home Value) Decile				
Decile 1	0.0006	0.0051***	0.0017**	0.0840
	(0.0010)	(0.0016)	(0.0008)	(0.0521)
Decile 2	0.0001	0.0041***	0.0016**	-0.0139
	(0.0010)	(0.0014)	(0.0007)	(0.0621)
Decile 3	0.0014	0.0018	0.0004	-0.0316
	(0.0014)	(0.0011)	(0.0007)	(0.0383)
Decile 4	0.0004	-0.0014	0.0001	-0.0712
	(0.0014)	(0.0012)	(0.0007)	(0.0458)
Decile 5	0.0002	-0.0014*	0.0002	-0.0472
	(0.0010)	(0.0007)	(0.0006)	(0.0323)
Decile 6	0.0005	-0.0020*	0.0003	-0.0543**
	(0.0011)	(0.0011)	(0.0007)	(0.0244)
Decile 7	0.0002	-0.0020*	0.0001	-0.0459**
	(0.0007)	(0.0010)	(0.0006)	(0.0187)
Decile 8	-0.0002	-0.0011	0.0006	-0.0137
	(0.0005)	(0.0007)	(0.0006)	(0.0208)
Decile 9	-0.0003	-0.0017**	-0.0008*	0.0148
	(0.0005)	(0.0008)	(0.0004)	(0.0195)
Decile 10	-0.0008***	-0.0020***	-0.0010**	0.0536**
	(0.0003)	(0.0004)	(0.0004)	(0.0209)
Technology controls	✓	✓	✓	✓
Housing market controls	✓	✓	✓	✓
Observations	2,346	2,347	2,347	2,347
Adjusted R^2	0.011	0.124	0.113	0.096

Table A.7: Relationship Between Changes in Work From Home Share and Changes in Gross Monthly Rent, Home Values, Population, and Headship (Density × Home Value Interactions)
Note: Dependent variable in column (1) is changes in median gross rent. Dependent variable in column (2) is changes in median home value. Dependent variable in column (3) is changes in population. Dependent variable in column (4) is changes in household rate. Interaction based on product of log population density and log median home value. Changes in median gross rent, median home value, and population are measured in log differences. Household rate is measured in percentage point changes. Sample restricted to changes between 2019 to 2021. Control variables measures as start-of-period levels. Standard errors clustered at the state level. Data on remote work, population, and headship come from the ACS PUMS downloaded from usa.ipums.org. Data on median gross monthly rent and median home values from ACS 1-year summary files. Data on population density uses square mileage measures from the Geographic Correspondence Engine maintained by the University of Missouri. All dollar values adjusted to 2021 USD using the Consumer Price Index from the Bureau of Labor Statistics.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
ΔWFH × Density Decile				
Decile 1	0.0006	0.0052***	0.0022***	0.0505
	(0.0012)	(0.0016)	(0.0008)	(0.0477)
Decile 2	0.0003	0.0035***	0.0001	-0.0054
	(0.0010)	(0.0012)	(0.0008)	(0.0544)
Decile 3	0.0018*	0.0017	0.0014**	-0.0153
	(0.0011)	(0.0012)	(0.0005)	(0.0393)
Decile 4	0.0010	-0.0019**	-0.0002	-0.0715*
	(0.0011)	(0.0008)	(0.0007)	(0.0378)
Decile 5	-0.0004	-0.0014	-0.0004	-0.0501*
	(0.0008)	(0.0008)	(0.0004)	(0.0250)
Decile 6	-0.0000	-0.0023**	-0.0002	-0.0274
	(0.0007)	(0.0010)	(0.0005)	(0.0234)
Decile 7	0.0001	-0.0011	-0.0005	-0.0146
	(0.0005)	(0.0009)	(0.0005)	(0.0211)
Decile 8	-0.0003	-0.0025***	0.0001	-0.0211
	(0.0005)	(0.0007)	(0.0006)	(0.0184)
Decile 9	-0.0007	-0.0011	-0.0001	0.0076
	(0.0007)	(0.0008)	(0.0005)	(0.0166)
Decile 10	-0.0006	-0.0029***	-0.0012***	0.0573**
	(0.0005)	(0.0005)	(0.0003)	(0.0221)
Technology controls	✓	✓	✓	✓
Labor market controls	✓	✓	✓	✓
Observations	2,346	2,347	2,347	2,347
Adjusted R^2	0.011	0.111	0.122	0.095

Table A.8: Relationship Between Changes in Work From Home Share and Changes in Gross Monthly Rent, Home Values, Population, and Headship (Density Interactions)

Note: Dependent variable in column (1) is change in median gross rent. Dependent variable in column (2) is change in median home value. Dependent variable in column (3) is change in population. Dependent variable in column (4) is change in household rate. Changes in median gross rent, median home value, and population are measured in log differences. Household rate is measured in percentage point changes. Sample restricted to changes between 2019 to 2021. Control variables measures as start-of-period levels. Standard errors clustered at the state level. Data on remote work, population, and headship come from the ACS PUMS downloaded from usa.ipums.org. Data on median gross monthly rent and median home values from ACS 1-year summary files. Data on population density uses square mileage measures from the Geographic Correspondence Engine maintained by the University of Missouri. All dollar values adjusted to 2021 USD using the Consumer Price Index from the Bureau of Labor Statistics.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
ΔWFH × Home Value Decile				
Decile 1	0.0026***	0.0067***	0.0003	0.0500
	(0.0008)	(0.0013)	(0.0006)	(0.0442)
Decile 2	0.0010	0.0045**	-0.0009*	0.0537
	(0.0010)	(0.0018)	(0.0005)	(0.0357)
Decile 3	0.0007	0.0018*	0.0006	-0.0037
	(0.0009)	(0.0011)	(0.0007)	(0.0491)
Decile 4	0.0006	0.0002	-0.0011*	0.0456
	(0.0008)	(0.0018)	(0.0006)	(0.0448)
Decile 5	-0.0004	-0.0010	-0.0015***	0.0012
	(0.0008)	(0.0011)	(0.0005)	(0.0510)
Decile 6	0.0013	-0.0020*	-0.0012***	0.0182
	(0.0011)	(0.0011)	(0.0004)	(0.0531)
Decile 7	-0.0001	-0.0013	-0.0004	0.0740**
	(0.0006)	(0.0012)	(0.0007)	(0.0314)
Decile 8	0.0001	-0.0012	-0.0003	0.0407*
	(0.0006)	(0.0009)	(0.0006)	(0.0229)
Decile 9	-0.0008	-0.0010	0.0002	0.0424
	(0.0005)	(0.0010)	(0.0008)	(0.0256)
Decile 10	-0.0006***	-0.0018**	-0.0009***	0.0322
	(0.0001)	(0.0008)	(0.0002)	(0.0209)
Technology controls	✓	✓	✓	✓
Housing market controls	✓	✓	✓	✓
Observations	2,346	2,347	2,347	2,347
Adjusted R^2	0.024	0.135	0.103	0.071

Table A.9: Relationship Between Changes in Work From Home Share and Changes in Gross Monthly Rent, Home Values, Population, and Headship (Home Value Interactions)

Note: Dependent variable in column (1) is change in median gross rent. Dependent variable in column (2) is change in median home value. Dependent variable in column (3) is change in population. Dependent variable in column (4) is change in household rate. Changes in median gross rent, median home value, and population are measured in log differences. Household rate is measured in percentage point changes. Sample restricted to changes between 2019 to 2021. Control variables measures as start-of-period levels. Standard errors clustered at the state level. Data on remote work, population, and headship come from the ACS PUMS downloaded from usa.ipums.org. Data on median gross monthly rent and median home values from ACS 1-year summary files. Data on population density uses square mileage measures from the Geographic Correspondence Engine maintained by the University of Missouri. All dollar values adjusted to 2021 USD using the Consumer Price Index from the Bureau of Labor Statistics.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.1 Comparison of Occupation-Based to Place-Based Components of Telework

The instrumental variable used in Table 5 is meant to capture each PUMA's exposure to the nation-wide increase in remote work. It is constructed to have a high value when a larger share of a PUMA's local workforce works in occupations with high degrees of remote work nationally. The observed local remote work share is generated from a combination of factors that are common to occupations as well as factors that are unique to the PUMA. That is, overall remote work has an occupation-based and a place-based component.

The residuals from a first stage regression of the observed remote share and the occupation-based instrument give us the place-based idiosyncratic component. In other words, it captures the remote work share due to features that are particular to each PUMA. Under this construction, PUMAs have high values if the occupation-based measure overpredicts remote work and lower values if the occupation-based measure underpredicts remote work.

A comparison of these instrumental variables, therefore, represents a decomposition of the effects of remote work on housing demand into an occupation-based effect and a place-based effect. We re-run the aggregate regressions in Table 5 using each of these instruments as independent variables. The results of these reduced-form regressions are shown in Table A.11.

In general, for regressions in levels, the coefficients on the occupation-based instrument were both statistically significant. Remote work, whether occupation-based or place-based, tended to increase housing demand and increase the household formation rate. In addition, for these regressions, the coefficient on the occupation-based instrument was larger in magnitude than the coefficient on the place-based instrument. This suggests that the national shock was more influential for outcomes than the idiosyncratic shock.

	A. Remote work measured based on household head					
	OLS		Reduced Form		2SLS	
	2019	2021	2019	2021	2019	2021
	(1)	(2)	(3)	(4)	(5)	(6)
Remote HH head	-0.017***	-0.044***			-0.107***	-0.262***
	(0.000)	(0.000)			(0.001)	(0.000)
Teleworkable HH head			-0.164***	-0.183***		
			(0.001)	(0.000)		
Demographic controls	✓	✓	✓	✓	✓	✓
PUMA fixed effects	✓	✓	✓	✓	✓	✓
Observations	75,907,607	77,148,650	75,907,607	77,148,650	75,907,607	77,148,650
Adjusted R^2	0.215	0.213	0.216	0.214	0.215	0.201

	B. Remote work measured based on share of household working remotely					
	OLS		Reduced Form		2SLS	
	2019	2021	2019	2021	2019	2021
	(1)	(2)	(3)	(4)	(5)	(6)
Remote share	-0.125***	-0.173***			-1.008***	-0.860***
	(0.000)	(0.000)			(0.001)	(0.001)
Avg. hh teleworkability			-0.961***	-0.749***		
			(0.001)	(0.001)		
Demographic controls	✓	✓	✓	✓	✓	✓
PUMA fixed effects	✓	✓	✓	✓	✓	✓
Observations	75,084,943	76,264,651	75,084,943	76,264,651	75,084,943	76,264,651
Adjusted R^2	0.206	0.205	0.211	0.220	0.155	0.123

Table A.10: Relationship Between Remote Work and Family Size

Note: The dependent variable is the number of adults living in the household. The sample is limited to non institutional households headed by employed people between the ages of 16 and 64. Columns (1) and (2) report OLS estimates using remote work as the independent variable, columns (3) and (4) report reduced form estimates using the instrument as an independent variable, and columns (5) and (6) report 2SLS estimates using remote work predicted by the instrumental variable as the independent variable. All models include demographic controls and PUMA fixed effects. All regressions use household level frequency weights and the listed observations are *implied* observations based on the ACS weighting scheme. All data come from ACS PUMS files downloaded from usa.ipums.org.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	Median Rent		Median Home Value		Population		HH Rate	
	Levels	Changes	Levels	Changes	Levels	Changes	Levels	Changes
WFH (occupation)	0.019***		0.029***		-0.009***		0.305***	
	(0.001)		(0.003)		(0.003)		(0.049)	
WFH (place)	0.010***		0.026***		0.001		0.198***	
	(0.001)		(0.003)		(0.001)		(0.037)	
Δ WFH (occupation)		0.0002		-0.0029***		-0.0006		0.0318
		(0.0007)		(0.0011)		(0.0006)		(0.0397)
Δ WFH (place)		-0.0001		-0.0021**		-0.0011***		0.0190
		(0.0003)		(0.0009)		(0.0003)		(0.0176)
Constant	3.311***	-0.100	7.972***	-0.282*	10.659***	-0.112	61.837***	-10.484***
	(0.195)	(0.071)	(0.331)	(0.159)	(0.244)	(0.113)	(7.683)	(3.036)
Technology controls	✓	✓	✓	✓	✓	✓	✓	✓
Labor market controls	✓	✓	✓	✓	✓	✓	✓	✓
State fixed effects	✓		✓		✓		✓	
Observations	2,344	2,346	2,345	2,347	2,345	2,347	2,345	2,347
Adjusted R^2	0.831	0.004	0.830	0.048	0.111	0.066	0.348	0.065

Table A.11: Comparison of Occupation-Based Instrument and Place-Based Instrument

Note: Sample restricted to 2021 data for regressions in levels. For regressions in changes, sample restricted to changes between 2019 to 2021 and control variables measures as start-of-period levels. Standard errors clustered at the state level. Median rent, median home value, and population measured in logs for regressions in levels and log changes for first-difference regressions. Household rate measured in percentage points for regressions in levels and as percentage point changes for first-difference regressions. Data on remote work, population, and headship come from the ACS PUMS downloaded from usa.ipums.org. Data on median gross monthly rent and median home values from ACS 1-year summary files. Data on population density uses square mileage measures from the Geographic Correspondence Engine maintained by the University of Missouri. All dollar values adjusted to 2021 USD using the Consumer Price Index from the Bureau of Labor Statistics.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$