The Spatial and Distributive Implications of Working-from-home: A General Equilibrium Model

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Abstract

In this paper, I look at the impact of the recent rise in remote work on households' consumption, wealth and housing decisions, and on wealth and income inequality in the short and long run. Using detailed UK property-level housing data, and an heterogeneous agents model with endogenous housing tenure and city geography, I show that work-from-home reshapes housing demand by increasing the taste for space and reducing worker's commuting costs. In the long run, work-from-home changes where people live inside the city and how much housing wealth they accumulate. Households are impacted differently depending on whether they can partake in remote work or not, and depending on their income and wealth. Work-from-home can be compared to a generalised gentrification shock, and while wealthy telecommuters buy larger houses in suburban areas, it crowds out the marginal owners and forces them into renting. In the long run, housing wealth and consumption inequality rise.

Keywords: Work-from-home, Housing Demand, City Structure, Inequality

JEL Classification: D31, E21, J81, R21, R23

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1 Introduction

In this paper I examine the impact of the recent shift to work-from-home on households' consumption, housing, and location decisions. I also explore how the rise in remote work affects consumption and wealth inequality in the short and long run. Work-from-home represents a sizable change in the way we organise labour and extended far beyond the period of the pandemic. In the UK for instance, 44% of workers still worked from home at least part time between September 2022 and January 2023 (ONS).

An important implication of this change in labour organisation is in its interaction with housing as remote work increases housing demand for space (Emmanuel and Harrington 2020, Mondragon and Wieland 2022). Moreover, work-from-home loosened the link between where people live and where people work. This shifted relative demand, as well as house prices and rents, inside and across cities (Bloom and Ramani 2022, Gupta, et al. 2021). However, the implications of these changes are little studied. How does work-from-home impact how and where people live? Should workers who cannot work-from-home care? Will this shift in working arrangement make our society more equal in the long run?

In this study, I exploit detailed UK property-level housing data, and an heterogeneous agents model with endogenous housing tenure and city geography to show that work-from-home reshapes housing demand by increasing the taste for space and reducing worker's commuting costs. In the long run, it changes where people live inside the city and how much housing wealth they accumulate. Households are impacted differently depending on whether they can partake in remote work or not, and on where they stand in the income and wealth distributions. Work-from-home can be compared to a generalised gentrification shock, and while wealthy telecommuters buy larger houses in suburban areas, it crowds out the marginal owners and forces them into renting. In the long run, housing wealth and consumption inequality rise.

I start by presenting motivational empirical evidence on the impact of working-from-home on London housing markets. To conduct this analysis I use real estate data at the property-level that provide a mapping between house prices and rents, and detailed dwelling characteristics. These data come from a merger of three datasets: His Majesty's Land Registry Price Paid data, the WhenFresh/Zoopla Rental data, and the Energy Performance Certificates. The resulting dataset encompasses the universe of all residential properties sold in the UK since 1995, and all properties listed for rent on the Zoopla website in the period 2012-2021 for England and Wales. First, in the raw data, I find that, larger properties and properties located further out from London's city center have appreciated the fastest since February 2020. This is true for house prices and for rents. For instance, between February 2020 and June 2022, the average price of large houses (5 rooms or more) increased by 20%, while that of small ones (studio or 1 room) dropped by 1%. Moreover, in the same period, the average price of properties located in London's very center (in a 5-kilometers radius of Bank of England) decreased by 1% while it rose by 13% on average for properties located in the periphery of London. Next, I estimate a hedonic pricing model for housing and examine whether there have been changes in the size premium and in the commuting discount following the work-from-home revolution. I find that since the pandemic, households' demand for space increased while the commuting penalty has declined.

I then explore the consequences of work-from-home on households though the lens of a novel theoretical framework. The model is a rich general equilibrium, heterogeneous agents model of remote work and housing tenure embedded in a spatial model of work and housing. The main components are the following. **The city**: the model has two locations - the Central Business District and the suburb - that differ in amenities, commuting cost and in housing supply elasticity. **The jobs**: some workers are employed in occupations where they can work from home. These workers allocate their working hours between the office (where they are more productive but have to commute) and their home (where they use some of their housing space in the production function). **The houses**: houses differ by their size, their location and their tenure (households decide if they want to own or rent). **Prices**: house prices and rents are determined in equilibrium in each location. With this framework, I aim at understanding who lives where, who owns real estate, and how this is changing with the spread of remote work. The heterogeneous agents feature enables me to think about housing affordability, and how the implications of remote work differ for households across occupations and along the income and wealth distributions.

Solving and parameterizing this complex model is challenging. I use a solution method which combines the Discrete-Continuous Endogenous Grid Method with taste shocks (DC-EGM) of Iskhakov and coauthors (2017) with the Nested Endogenous Grid Method algorithm (NEGM+) developed in Druedahl (2021). These methods extend the endogenous grid point method of Carroll (2006) to economies with non-convexities and exploit the nested structure of the problems. I then parameterize the model to be consistent with key features of the UK economy before the rise in remote work (2016-2019). Moreover, the model is successful in matching some important moments that were not explicitly targeted in the calibration. For instance the model reproduces the share of households who decide to live in the center - for the overall population, by occupation, and by income quintile.

To understand the impact of work-from-home on housing demand and households, I simulate a permanent shift in workers' taste for remote work. In the baseline economy, the taste for working from home is calibrated to match the share of total work supplied from home by workers employed in a telecommutable occupation in the first wave of the UK time Use Survey (15% of total work: UKTUS 2016 wave). I then solve for a post remote work economy where the work-from-home taste matches the high share of total work supplied from home by workers employed in a telecommutable occupation in the last wave of the UKTUS (2.5 days a week: UKTUS end of 2021 wave). The work-from-home's taste parameter goes from a negative value (aversion) to a positive one (fondness). Modeling the rise in work-from-home as a change in taste is motivated by the survey evidence from Barrero, Bloom, and Davis (2021). In their Survey of Working Arrangements and Attitudes (SWAA), the authors interview more than 30,000 Americans over multiple waves to investigate whether work-from-home will stick, and why. They find evidence of better-than-expected work-from-home experiences, and greatly diminished stigma associated with remote work.

Changes in the attitude towards work-from-home is of course not the only candidate to account for the recent shift in working arrangements. Another potential factor is that the productivity of work-from-home increased as workers got used to this new organisation, and technologies like Zoom or Microsoft Teams spread. This is the angle taken in Davis, Ghent, and Gregory (2023). However, I do not adopt this approach as my model adopts a macro take on the work-from-home issue with incomplete markets, non convexities, and rich multi-dimensional households choices. My focus is different from the urban papers on the topic. For this reason, I do not model the positive agglomerations externalities from working at the office. Consequently, in my context, modeling work-from-home's rise as the result of a pure positive productivity shock would likely overestimate the associated output gains as I abstract from the counterbalancing force (the decrease in the positive agglomerations at the office). Yet another hypothesis is that the adoption of work-from-home derives from multiple equilibria sources. This is the approach of Monte, Porcher, and Rossi-Hansberg (2023) who find that, following Covid-19, large US cities shifted to a high remote work equilibrium. The study of multiplicity of equilibria with incomplete markets is beyond the scope of this paper. I follow Deleventhal and Parkhomenko (2023) in modelling the work-from-home boom as a change in taste. Still, the qualitative implications coming from a shift in productivity and a shift in taste are similar.

I start by looking at the aggregate impact of the change in households' taste for remote work in the long run (comparing steady states), and find that aggregate output is 3% larger in the second steady state than in the baseline because of savings in commuting time. The reduction in time spent commuting comes from two channels. First, the direct channel: workers in telecommutable occupations largely increase the share of their labour that is supplied from home, commute less, and are therefore able to supply more working hours overall. Second, the indirect channel: working-from-home increases the relative attractiveness of the suburb for households employed in telecommutable occupations. These workers do move away from the center to enjoy larger and cheaper houses, and make the most out of the reduced commuting costs. Consequently, relative house prices and rents change across locations, and space in the center is freed up for some workers in non-telecommutable occupations. These workers now also enjoy reduced commuting time, and are also able to supply more working hours. The share of the center population employed in a non-telecommutable occupation rises by 3 points between the two steady states.

Beyond aggregate outcomes, remote work has heterogeneous implications across occupations. Workers employed in occupations in which work-from-home is possible constitute the winning category in the long run. These households' share of home-owners rises by 5 percentage points in the suburb and 3 points in the center, reflecting the shift in housing demand with the greater taste for space and the drop in commuting costs. These workers also benefit from an increase in income, consumption, and liquid wealth. On the other end of the spectrum, the share of home owners amongst households in non-telecommutable occupations decreases by 4 points in the long run (the drop is concentrated in the suburb). The mechanism at play is simple, the increased demand for suburban houses by telecommuting workers - who are on average high wealth and income households - leads the formerly cheap suburban properties to appreciate. The marginal homeowners are crowded out of home-ownership and forced into renting. This can be compared to a gentrification shock that hits the whole periphery at the same time. On top of this large drop in real estate wealth, non-telecommuters also record a reduction in mean consumption because of the higher house prices and rents. The average welfare of the non-telecommuters, computed as average utility, is 17% lower in the long run.[1]

Overall, the rise in work-from-home changes real estate wealth and consumption inequality in the long run. Housing wealth inequality measured by the ratio of average housing wealth of non-telecommuters over housing wealth of telecommuters significantly rises (the ratio drops from 50% in the first steady state to 40% in the second one). However housing wealth inequality amongst homeowners decreases because of two factors. On the one hand, there is a valuation effect. House prices and rents in the periphery appreciate more than in the center. As the wealthiest households were owning properties in the Central Business District before the spread of remote work, the value of their asset decreases relative to that of more modest homeowners who had settled in the suburb, lowering inequality. On the other hand, housing wealth inequality for homeowners drops because of a composition effect. The lowest income, lowest liquid wealth non-telecommuters have been crowded out of ownership and replaced by wealthier telecommuters. The group of homeowners is therefore richer and more homogeneous in the post work-from-home economy. Moreover, consumption inequality increases since the rise in working-from-home. For instance, the average consumption of non-telecommuters accounts for 69% of that of telecommuters in the baseline steady state, and only 65% in the post remote work one.

Finally, I compute transitions between the two steady states to study how the economy evolves in the short run. Most homeowners employed in a non-telecommutable occupation own houses in the suburb prior to the change in working arrangement. When remote work rises and suburban properties appreciate, a share of these households sell their houses and realize capital gains before moving to the center. However, despite these gains, they are not able to buy a property in the center because of the large difference in house prices across the two locations. These households become renters, and build up some liquid wealth. This has a direct consequence on the shape of the price paths in the two locations over the transition. House prices in the center adjust slowly to reach the new steady state value because the new movers to the neighborhood are these households whose housing demand

[1] We note here, that computing welfare as utility and comparing it across steady states would be an unfair exercise for the telecommuters' group. This is because these households had a change in a taste parameter. However, this issue does not apply to the workers employed in a non-telecommutable occupation as they cannot work from home. Therefore, their taste and parameters remained the same. The change in their utility is informative of their welfare evolution.

takes some time to materialise. On the other hand, suburban house prices jump right away to the new steady state value. Households moving to the suburb are telecommuters who seek to buy large properties to work from home. They are wealthy enough to purchase right away. The increase in demand for suburban properties is immediate, and prices rise to reflect it.

My work contributes to the strand of literature that investigates the impact of working-from-home on the housing market. First, it relates to studies that provide theoretical frameworks to understand how work-from-home changes housing demand and the city structure. These papers use urban economics models (Davis, et al. 2023, Delventhal and Parkhomenko 2023, Monte, et al. 2023, Delventhal, et al. 2022, Brueckner, et al. 2021) or a financial modelling approach (Gupta, et al. 2022). My study accompanies these papers as I incorporate endogenous housing tenure and household heterogeneity to the study of work-from-home and the city. Existing models have their focus elsewhere. On the one hand, the urban models developed in the literature do not model households' heterogeneity, nor wealth. On the other hand, the financial asset models are forward looking and fully transcribe the change in assets' value. However, they do not model the owners of the assets. This paper draws the direct link between the assets that are subject to demand and valuation changes, and the households who own these assets (or aspire to own them). This is important in order to understand how the changes in housing demand and city structure, impact the households living in it. In that respect, it is close to studies that, in a context outside remote work, look at cities' affordability and the welfare of their inhabitants (Favilukis and Van Nieuwerburgh 2021, Favilukis, Mabille, and Van Nieuwerburgh 2022).

Second, this paper is also linked to the literature that looks at the impact of working-from-home on housing from an empirical perspective. Such papers report a work-from-home induced rise in housing demand (Mondragon and Wieland 2022, Stanton and Tiwari 2021) as well as a demand shift from main US central business districts to suburban areas characterised by changes in relative house prices and rents as well as migration flows of households and businesses (Bloom and Ramani 2022, Gupta, et al. 2021, Liu and Su 2021). Bloom and Ramani label this phenomenon the “Donut Effect”, reflecting the hollowing out of city centers and the growth of suburban outer rings. An empirical contribution of my paper resides in providing novel evidence of a change in housing demand in the UK. Moreover, whilst the studies mentioned above exploit empirical evidence at some level of aggregation (using ZIP code or MSA level house price and rent indexes), I exploit data at the property-level to evaluate the relative prevalence of size and distance to city center in determining rents and house prices. Granular data is necessary to control for and study the importance of individual house characteristics.

Finally, my paper relates to the branch of work that investigates the impact of remote work on inequality. The main focus in this line of studies is workers' occupation. Dingel and Neiman (2020) provide data on the share of jobs that can be done from home and compute an occupation based Teleworkability index, illustrating that not all occupations are equal in front of remote work. In a similar vein, Chetty, et al. (2021), Althoff, et al. (2022), and Mongey, et al. (2021) indicate that employees in low work-from-home occupations are on average low education, low wage workers that suffered the most from pandemic induced job losses. De Fraja and coauthors (2020) provide a similar argument for the UK. This project complements this approach by interacting occupation with the housing dimension. Incorporating real estate in the study of remote work distributional implications is important because, beyond being one of the largest expense item in households' budget, housing is also the primary asset and primary liability in many households' savings portfolios (Causa, et al. 2020).

The remainder of the paper is structured as follows. Section 2 shows some empirical evidence for a change in housing demand within UK's largest metropolitan area: London. Section 3 presents the model. Section 4 describes the numerical implementation and the parameterization strategy. Finally, the experiment of the positive change in attitude towards work-from-home (with the long run analysis and the transitions) is found in Section 5. Section 6 concludes.

2 Empirical Evidence

2.1 Data

The real estate data used for this project are at the property-level, and provide a mapping between house prices and rents, and detailed dwelling characteristics. These innovative data come from three datasets. First, I use His Majesty's Land Registry Price Paid data that record the universe of all residential properties sold in the UK since 1995. From this dataset, I extract the detailed property address as well as sale date and transaction price. The land registry also displays a few characteristics of the dwellings sold like whether they are new, or the property type (detached or semi-detached house, flat or maisonette...).

Because this paper also looks at the impact of remote work on renters, I use the WhenFresh/Zoopla Rental data provided by the Consumer Data Research Centre. This proprietary dataset includes information on all properties listed for rent on the Zoopla website in the period 2012-2021 for England and Wales. Alongside the detailed address, we observe listed properties' rental price, listing date, as well as a small number of characteristics (e.g. type of property, number of bedrooms)

These two data sources provide detailed prices and rents associated with the exact address of the properties. However, information on the dwellings' characteristics is sparse. To bridge this gap I merge the Land Registry and the WhenFresh/Zoopla data with the Energy Performance Certificates dataset that contains a rich set of dwelling characteristics including exact address, type of property, size in square meters, number of rooms, energy rating, energy efficiency, or even window glazing. Since September 2008, properties need to have a valid EPC to be sold or let.[2] Therefore every land registry transaction and every Zoopla rental listing is associated with an EPC. The merging procedure follows Koster and Pinchbeck' s algorithm.[3]

2.2 Commuting Costs and Taste for Space: Evidence from Raw Data

This section starts by presenting some raw data on changes in London's real estate market since 2018. I am interested in analysing the effect of the rise in remote work on house prices and rents. remote work was very rare before March 2020 and soared at the onset of Covid-19. This change, however, went far beyond the period of the pandemic, and the shift to remote work is highly persistent. For instance in the UK, the ONS reports that 44% of the workforce still worked from home at least one day a week between September 2022 and January 2023. Similarly, Bloom and coauthors (2023) find that in the UK, around 20% of the flow of new jobs allow for at least one day of work-from-home a week in 2023.[4] Consequently, in the empirical section, I think of March 2020 (the onset of Covid-19) as the start of the rise in work-from-home.

In the empirical analysis, the geographical unit of observation is London's Travel To Work Area (TTWA). In the UK, TTWAs approximate self-contained labour markets. These are areas where most people both live and work implying that there are relatively few work commutes across TTWAs. These units are based on statistical analysis rather than administrative boundaries.[5] London's TTWA includes all areas within the boundary of Greater London, as well as some local authorities further out that are well connect to central London.

Table 1 provides some descriptive statistics from the merged housing dataset. The considered sample is from 2018 to 2021 for rents[6] and from January 2018 to June 2022 for house prices. There is a delay for the Land Registry to officially register a property transaction. This delay - referred to as the "registration gap" by British real estate lawyers - used to be six to eight months, and has been increasing since the Covid pandemic. For this reason, I restrict the analysis to transactions that occurred before 31st of June 2022. Still, I expect that not all the transactions that occurred in the first half of 2022 have been officially registered yet. This explains the relatively low number of observations for the first six months of 2022 compared to the previous years. Table 1 reports the number of

[2] An EPC is valid for 10 years.

[3] See Koster and Pinchbeck (2022) for detail. The merging identifier is the property address, consisting of the Primary Addressable Object Name (which identifies the building - e.g. house number, building name), the Secondary Addressable Object Name (which identifies the dwelling inside the building - e.g. flat number), the street, and the postcode.

[4] This number started at around 3% before the pandemic, and is on the rise since the end of the lock-downs.

[5] The TTWAs were produced by Newcastle University, using an algorithm to identify commuting patterns from the 2011 Census data.

[6] the Zoopla/Whenfresh data are available until end of 2021.

registered property transactions, the number of rental properties listed on Zoopla, as well as the average transaction price, weekly rent, and property size (in square meters). The number of transactions highlights that, after slowing down during the eye of the pandemic (2020), the real estate sale market was particularly dynamic in 2021.[7] We can also note an increase in the average price and average size of properties sold in London over the sample period. On the other hand, the number of observations for rental listings indicates a post Covid slowing down that persists throughout 2021. Between 2018 and 2021, the average weekly rent is stable, and the average size decreases slightly.

house prices	**2018**	**2019**	**2020**	**2021**	**2022**
# obs.	105,982	102,048	91,491	126,372	42,244
av. price	557,713	556,565	584,708	593,921	626,470
av. size (m^2)	85.52	85.90	87.36	88.93	89.39
rents					
# obs.	116,694	112,543	100,088	87,205	
av. wkeely rent	414	429	432	427	
av. size (m^2)	72.21	73.10	71.94	71.45	

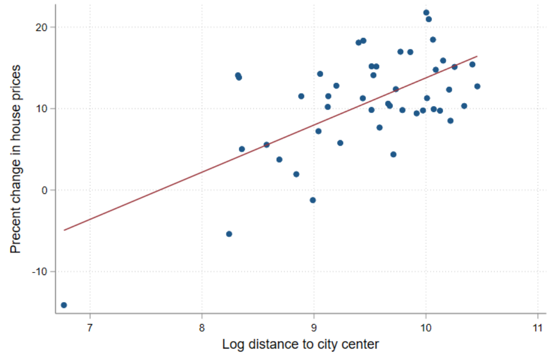
Table 1: Descriptive Statistics (London)

Appreciation of suburban properties: Figure 1 displays changes in house prices (panel a), and rents (panel b) as a function of distance to the city center. More precisely, each dot represents one of London's local authority (e.g. Camden, Hackney). The x-axis plots changes in average house prices and rents in each local authority between the year before Covid, and the last year of data available (July 2021 to June 2022 for house prices, and January to December 2021 for rents). The y-axis plots the logarithm of each local authority's average distance to the city center (in meters). Here, I assume that the center of London is Bank of England. A red fitted line is added to the plots.

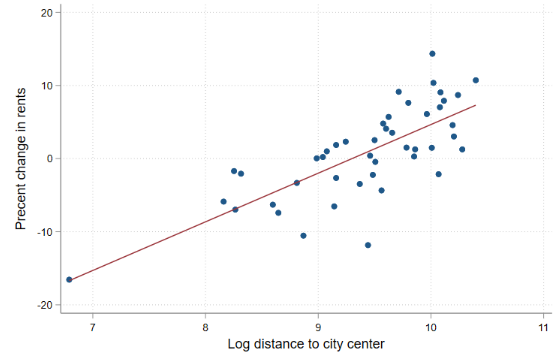
The two figures show a clear positive relationship between real estate appreciation and distance to the city center. In each panel, the outlier point at the bottom left corner is the City of London local authority. This is by far the smallest (and the most central) local authority, and records a drop of around 15% in house prices and rents over the period studied. As an additional test, I produce the same graphs plotting changes in house prices and rents between 2017 and 2018 on the log distance to the city center (the figures can be found in Appendix A1). These placebo tests show no positive relationship between properties' appreciation and distance to Bank of England.

The finding that properties located further out appreciated faster since the pandemic and the rise in remote work is not London specific. Bloom and Ramani (2021) document a

[7] Here I do not infer anything from the number of transactions for 2022 because of the aforementioned registration delay.



(a) House Prices



(b) Rents

Notes: Each dot represents one of London's local authority (e.g. Camden, Hackney). The x-axis plots changes in average house prices and rents between the year before Covid, and the last year of data available (July 2021 to June 2022 for house prices, and January to December 2021 for rents). The y-axis plots the logarithm of local authority's average distance to Bank of England (in meters). I exclude the top 1% in house prices, rents, and size (in square meters) in order to remove outliers.

Figure 1: Growth in Properties' Value as a Function of Distance to the Center (London)

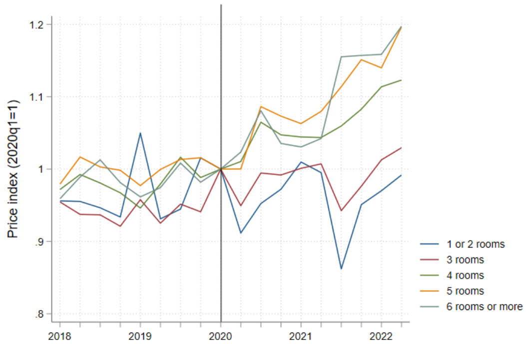
similar phenomenon for the 12 largest US metropolitan areas. The authors draw the link with working from home, and call this result the *Donut Effect*, referring to the hollowing out of the city centers and the rise in demand for peripheries.

Appreciation of larger properties: After location, I now look at another characteristic relevant to working-from-home: properties' sizes. Figure 2 displays house price (panel a), and rent indexes (panel b) by property size. The reference period is February 2020, right before the onset of the pandemic. Properties are split according to their number of rooms.[8] These evidence indicate that larger properties appreciated faster since the rise in remote work. For instance, between February 2020 and June 2022, the average price of large houses (5 rooms or more) increased by 20%, while that of small ones (studio or 1 room) dropped by 1%. Over the same period, rents of large properties (5 rooms or more) grew by 3%, and rents of small houses (studio or 1 room) dropped by 2%.

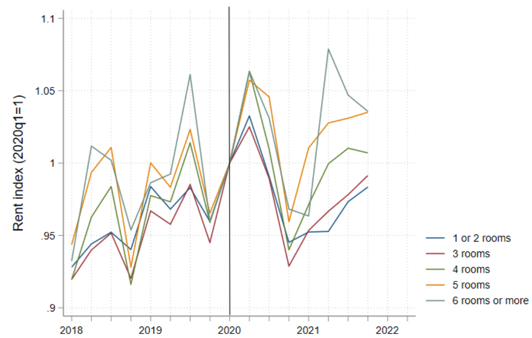
2.3 Hedonic Pricing Model

I now estimate the impact of property size and proximity to the city center on house prices and rents. Moreover, I look at whether the relative importance of these two key characteristics changed since the rise in remote work.

[8] Appendix A2 plots similar evidence but splits houses by quintile of size in m^2 instead of by number of rooms.



(a) House Price Index



(b) Rent Index

Notes: Properties are split by number of rooms. I exclude the top 1% in house prices, rents, and size (in square meters) in order to remove outliers.

Figure 2: House Prices and Rent by Size of Property (London)

To do so, I use a hedonic regression. The idea behind this method is that a house is made up of many characteristics, all of which may affect its value. Hedonic pricing models are used to estimate the marginal contribution of these characteristics. The property is valued through the value of its individual components and the regression estimates give the implicit prices of each characteristic. More specifically, I estimate with least squares:

$$ln(p_{ijt}) = \delta_P^{size}\ Post\ ln(size_i) + \delta_P^{dist}\ Post\ ln(dist_i) + \delta^{size} ln(size_i) + \delta^{dist} ln(dist_i) \\ + \beta X_i + \alpha_t + \eta_j + e_{ijt} \quad (1)$$

This equation is estimated for $ln(p_{ijt})$, property transaction price or listed rent for each property i, local authority j, and month t. α_t is a monthly fixed effect and η_j is a local authority fixed effect. The two characteristics of interest are the log of property's size (in square meters) and the log of distance to Bank of England. *Post* is a dummy variable equal to 1 for months after February 2020 and 0 otherwise. The non-interacted variable *Post* is captured by the time fixed effect. X_i is a set of property specific controls including the type of property (Bungalow, Flat, House, Maisonette), the energy rating, the energy efficiency, presence of a fireplace, and whether the property is new.[9] These controls account for housing quality heterogeneity. Finally, I restrict the regression sample to properties sold in the London TTWA between January 2018 and June 2022 and properties listed to rent on Zoopla between January 2018 and December 2021. I drop the top and bottom 1% of observations in prices, rents, and size to remove outliers. Standard errors are clustered at the local authority level.

[9] For the house prices equation only.

Table 2 reports the estimates of the impact of the log of size and the log of distance to the city center in determining the log of house prices (columns 1 and 3) and the log of rents (columns 2 and 4). Columns 1 and 2 correspond to the specification described above, while columns 3 and 4 conduct a placebo-type test. In these columns, I use data between January 2017 and December 2018. I take the year 2017 as pre-Covid, and 2018 as post-Covid. I expect the interaction term coefficients to be insignificant.

The coefficients associated with $log(size)$ are positive, implying that larger properties have higher prices and rents. These estimates can be interpreted as the percentage change in price or rent for a 1% larger property. For instance, Column 1 indicates that a property that is 1% larger will be 0.699% pricier. The coefficients associated with distance, on the other hand, are negative as properties further away from the city center tend to be cheaper. Column 1's $log(dist)$ coefficient indicates that if a property is 1% further away from the center, its price will be 0.264% lower. The distance gradient is negative.

The third coefficients of Table 2 show the interaction effects between size of property and the post Covid-19 period. It indicates how the importance of size in determining house prices and rents changed since the pandemic. In columns 1 and 2, these coefficients are positive meaning that size became even more important for house prices and rents than it was before the rise of working-from-home. Column 1 indicates that 1% of additional space increases properties' prices by 0.037% more since Covid. These positive interaction coefficients indicate a steepening of the size gradient. This implies that households' taste for space increased in the post-pandemic period.

In the non placebo specification, the interaction coefficients between post Covid and distance are negative. The penalty associated with properties located away from the city center decreased. Column 1 reports that being 1% further away from the city center decreases the properties' prices by 0.0159% less in the later part of the sample compared to before February 2020. This indicates a flattening of the distance gradient and therefore a decline in households' commuting costs. This result is in line with evidence from the US in which Gupta, et al. (2021) report a similar flattening of the distance gradient. We note that all the size and distance coefficients of columns 1 and 2 are statistically significant for house prices as well as for rents.

Finally, the interaction coefficients of the placebo specifications in columns 3 and 4 are not statistically significant.[10] Appendix A3 presents the results of an alternative specification, where I let the size and distance coefficients vary every month. The results also show a drop in commuting costs and an increase in the taste for space.

[10]Except the interaction of fake Covid with distance for rents, that is significant at the 10% level, but has a very small magnitude.

	(1)	(2)	(3)	(4)
	log_price	log_rent	log_price	log_rent
log_size	0.699***	0.497***	0.678***	0.486***
log_dist	-0.264***	-0.214***	-0.276***	-0.211***
log_size after WFH	0.0370***	0.0363***	0.007	0.004
log_dist after WFH	0.0159*	0.0473***	-0.001	0.004*
N	460240	415546	215121	221224
adj. R^2	0.589	0.607	0.525	0.595
Placebo	NO	NO	YES	YES
Monthly FE	YES	YES	YES	YES
LA FE	YES	YES	YES	YES
Property controls	YES	YES	YES	YES
SE	Clust. at LA	Clust. at LA	Clust. at LA	Clust. at LA

Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. This Table reports results from OLS regressions of Equation (1) using the log of house prices (columns 1 and 3) and the log of listed rents (columns 2 and 4) as dependent variables. Controls at the property-level: type of property, energy rating, energy efficiency, presence of a fireplace, and whether the property is new (for house prices equation only). Column 1 uses data between January 2018 and June 2022. Column 2 uses data between January 2018 and December 2021 (rent data availability). The placebo specification in columns 3 and 4 use data between January 2017 and December 2018.

Table 2: Impact of Size and Distance to City Center on House Prices and Rents

3 The Model

3.1 Households

The economy is populated by a measure 1 of households indexed by $i \in (0,1)$, living in a metro area with a Central Business District and a suburb. Households may be employed in an occupation where working-from-home is possible or not. I use $k = \{0,1\}$ to index occupations where $k = 0$ refers to non-telecommutable occupations and $k = 1$ to telecommutable occupations. A worker's occupation is predetermined and permanent. Time is discrete.

3.1.1 *Preferences*

Household i, with occupation type k, choosing to live in location j, in period t receives utility equal to:

$$U_{i,k,j,t} = \frac{\left[c_{i,k,j,t}^{\gamma}\tilde{h}_{i,k,j,t+1}^{(1-\gamma)}\right]^{(1-\sigma)} - 1}{1-\sigma} + \chi^{WFH}\eta_{i,k,j,t}^{H} + \overline{\epsilon_c} + \sigma_\epsilon \epsilon_{i,t}(j)$$

where c is consumption (the numeraire), $\tilde{h}$ is housing services, γ is the weight of non durable consumption in the utility function, and $1/\sigma$ is the coefficient of relative risk aversion. χ^{WFH} represents households' taste for working-from-home and is multiplied by the number of hours actually worked from home $\eta_{i,k,j,t}^{H}$. This term will vanish for households employed in a non-telecommutable occupation as, for them, $\eta_{i,k,j,t}^{H} = 0$. The taste parameter associated with work-from-home can be negative or positive. For instance, a negative parameter can be interpreted as the weight of social norms associating some stigma with remote work. On the other hand, a positive taste parameter can be viewed, for example, as workers' enjoyment for working in the comfort of their own house or spending their day with their partner or their pet.

3.1.2 *Locations*

The city is split between two locations: the center $j = C$ and the suburb $j = S$. All the jobs are assumed to be located in the center. Each location is associated with different commuting times to the office χ_j (commute is shorter in the center), land availability, housing supply elasticity, and amenities. Compared to the suburb, the center offers some extra amenities $\overline{\epsilon_c}$ to all households, reflecting its greater density of restaurants, bars, theaters, etc. In addition, each location j is associated with random choice-specific taste shifters $\sigma_\epsilon \epsilon(j)$, that are additively separable, i.i.d. and have an extreme value distribution with scale parameter σ_ϵ. These shocks are a smoothing device and can be interpreted as households' specific taste for amenities in each location or other considerations such as friends and family, schools, etc. Households decide in which area they want to buy or rent a house.

3.1.3 *Households' labour*

The labour specification relates to that of Davis, Ghent, and Gregory (2023). Each worker is endowed with one unit of time that needs to be split between hours spent working from home η^H, and hours spent working from the office η^O. Total time allocation follows:

$$1 = (1+\chi_j)\eta^O_{i,k,j,t} + \eta^H_{i,k,j,t}$$

where χ_j is the commuting cost in location j. Note here that the commuting is only paid for hours spent working at the office.

At the office, the worker produces efficient units of labour from the office, n^O, determined by:

$$n^O_{i,k,j,t} = A^O_t(\nu_{i,t}\eta^O_{i,k,j,t})^\theta$$

where A^O_t is a common productivity parameter for all workers at the office, ν is an idiosyncratic productivity shock assumed to follow a Markov process, and θ is the share of labour in the production process.[11]

Similarly, at home, the worker produces efficient units of labour from home, n^H, determined by:

$$n^H_{i,k,j,t} = A^H_{k,t}(h_{min})^{(1-\theta)}(\nu_{i,t}\eta^H_{i,k,j,t})^\theta$$

where $A^H_{k,t}$ is a common productivity parameter for all workers at home. It is occupation specific, and is equal to 0 for the occupation that cannot work from home. h_{min} is the amount of space that is necessary for a worker to be productive at home (think of it as a desk space or an office). Having a house that is much larger will not increase the worker's productivity. However, one cannot produce anything without this minimum amount of space.

Workers then combine efficient units of labour produced at home and at the office into an overall efficient unit of labour, n, determined by:

$$n_{i,k,j,t} = \left[(n^O_{i,k,j,t})^{(\frac{\rho-1}{\rho})} + (n^H_{i,k,j,t})^{(\frac{\rho-1}{\rho})}\right]^{\frac{\rho-1}{\rho}}$$

where ρ is the elasticity of substitution between work-from-home and work done at the office. I use a CES specification in order to be consistent with micro evidence finding that tasks done at home and tasks done at the office are imperfect substitutes.

Finally, households are paid w_t for each efficient unit of labour supplied. Labour income is given by: $n_{i,k,j,t}w_t$

[11] Here it is assumed that the space used in the production process at the office is 1.

3.1.4 *Housing*

The housing tenure part of the model is inspired by Kaplan, Mitman, and Violante (2020). Households have the option to rent or own their house. Houses are characterized by their size.

When they decide to rent, households pay rent $q_{j,t}$ that depends on the location j. Housing services $\tilde{h}$ that enter the renters' utility function follow:

$$\tilde{h}_{i,k,j,t+1} = (h_{i,k,j,t+1} - \alpha h_{min} \mathbb{1}_{WFH})$$

Where α is a discount for the space that is used to work from home (if the household does supply any hour of remote work). This relates to the idea that once you installed your desk chair and your monitors, some space becomes unavailable to enjoy for non work-related activities. Renters can adjust the size of their house without transaction costs.

For homeowners, house prices $p^h_{j,t}$ also depend on location. Housing services $\tilde{h}$ in the owners' utility function follow:

$$\tilde{h}_{i,k,j,t+1} = \omega(h_{i,k,j,t+1} - \alpha h_{min} \mathbb{1}_{WFH})$$

with $\omega > 1$ represents a utility bonus from home ownership. When they own, households have to pay a maintenance cost that fully offsets depreciation (δ) of the house :

$$\delta p^h_{j,t} h_{i,k,j,t}$$

Moreover, there are non-convex transaction costs $F^{sell} p^h_{j,t} h_{i,k,j,t}$ upon selling a house $h_{i,k,j,t}$. These transaction costs follow the specification of Grossman and Laroque (1990), and ensure to reproduce the lumpy pattern of housing adjustment.

3.1.5 *Other assets*

Households may save in one-period bonds $b_{i,k,j,t+1}$. Return from the bonds is the risk free rate r. Unsecured borrowing is not allowed. However, households who own a house (or buy a house) have access to collateralized debt $m_{i,k,j,t+1}$ with rate:

$$r_{m,t} = r(1 + \iota)$$

where ι is an intermediation wedge.

The issue of collateralized debt is subject to a loan to value constraint (LTV):

$$m_{i,k,j,t+1} \leq \lambda_m p^h_{j,t} h_{i,k,j,t+1}$$

where λ_m is the fraction of the house needed as a collateral and $h_{i,k,j,t+1}$ is the value of the house bought (or $h_{i,k,j,t} = h_{i,k,j,t+1}$ when households keep their house).

Therefore, when a household purchases a house, the minimum down-payment is:

$$p_{j,t}^{h} h_{i,k,j,t+1} - m_{i,k,j,t+1}$$

In a scenario where house prices would collapse, households with low savings and bad income realisations may not be able to repay their collateralized debt. In this case they would sell their house and incur a very large utility penalty. The large penalty ensures that defaulting is never a strategic choice for households.

3.2 Financial Sector

The supply side of the economy is close to that of Kaplan, Mitman, and Violante (2020). Following their strategy, I assume that collateralized debt and liquid assets are issued by foreign risk neutral agents with deep pockets. When households default, the foreign financial agents incur the losses.

3.3 Rental Sector in Location j

There exists a competitive rental sector in each location j that owns houses and rents them out. The rental companies operate only in one location and cannot change location. They can buy and sell houses frictionlessly. They incur depreciation costs (δ as for households homeowners) and a per period operating cost for each unit rented out (ψ). The rental companies are competitive. The rental rate in location j is determined by the following user cost formula:

$$q_{j,t} = \psi + p_{j,t}^{h} - (1-\delta)\frac{1}{1+r} E\left[p_{j,t+1}^{h}\right]$$

3.4 Final Good Producer

The final good producer is competitive and has constant returns to scale technology.

$$Y_t = N_t^c$$

where N_t^c is the quantity of efficient units of labour employed in the final good production sector.

The competitive wage is given by: $w_t = 1$.

3.5 Construction Sector in Location j

The construction sector in area j solves:

$$\max_{I_{j,t}^{h}} p_{j,t}^{h} I_{j,t}^{h} - w_t N_{j,t}^{h}$$

$$s.t \quad I_{j,t}^{h} = (N_{j,t}^{h})^{\alpha_j} (\overline{L_j})^{(1-\alpha_j)}$$

where $I^h_{j,t}$ is new housing investment in location j, $N^h_{j,t}$ is the quantity of efficient units of labour employed in the construction sector in location j, $\overline{L_j}$ are newly available land permits in location j, and α_j is the share of land in the construction function in location j. Labour is fully mobile across sectors, therefore $w_t = 1$ holds.

The equilibrium housing investment in location j is:

$$I^h_{j,t} = (\alpha_j p^h_{j,t})^{\frac{\alpha_j}{1-\alpha_j}} \overline{L_j}$$

3.6 Government

The government owns the land permits in each location j and therefore extracts all the profits from the construction sectors. I assume that the profits are used to provide a public good that does not impact households' marginal utility.

3.7 Recursive Formulation of the Problem

V^h is the value function of a household who owns a house at the beginning of the period. For brevity, the value function of a household who does not own a house at the beginning of the period is presented in Appendix A4.

$$V^h(b,h,m,\nu,k,j,\epsilon) = max\{v^h(b,h,m,\nu,k,j,C) + \sigma_\epsilon \epsilon(C), v^h(b,h,m,\nu,k,j,S) + \sigma_\epsilon \epsilon(S)\}$$

where $v^h(b,h,m,\nu,k,j,j'),\ j' \in \{C,S\}$ are *location choice-specific* value functions and $\sigma_\epsilon \epsilon(j')$ are random choice-specific taste shifters that are additively separable, i.i.d. and have an extreme value distribution with scale parameter σ_ϵ.

If $j = j'$:

$$v^n(b,h,m,\nu,k,j,j') = max\{v^{keep}(b,h,m,\nu,k,j,j'), v^{sell}(b^n,\nu,k,j,j')\}$$

$$s.t \quad b^n = b + (1-\delta - F^{sell})p^h_j h - (1+r_m)m$$

where v^{keep} is the *location j' choice-specific* value function of a household who decides to keep their house and v^{sell} is the *location j' choice-specific* value function of a household who decides to sell their house.

If $j \neq j'$:

$$v^n(b,h,m,\nu,k,j,j') = v^{sell}(b^n,\nu,k,j,j')$$

$$s.t \quad b^n = b + (1-\delta - F^{sell})p^h_j h - (1+r_m)m$$

When homeowners want to change location, they have to sell their house.

$$v^{keep}(b,h,m,\nu,k,j,j') = \max_{c,\eta^O,b',m'} u(c,\tilde{h}') + \beta E_\nu E_\epsilon \left[V^h(b',h',m',\nu',k,j',\epsilon')\right]$$

$$
\begin{aligned}
s.t \quad c + \delta p^h_{j'} h + b' + (1+r_m)m &\leq (1+r)b + wn + m' \\
n &= \left[n^{O(\frac{\rho-1}{\rho})} + n^{H(\frac{\rho-1}{\rho})}\right]^{\frac{\rho-1}{(\rho)}} \\
n^O &= A^O(\nu\eta^O)^\theta \\
n^H &= A^H(h_{min})^\theta(\nu\eta^H)^{(1-\theta)} \\
1 &= (1+\chi_{j'})\eta^O + \eta^H \\
\eta^H &= 0 \quad if \quad k=0 \\
\tilde{h}' &= \omega(h' - \alpha h_{min}\mathbb{1}_{\eta^H>0}) \\
h' &= h \\
j' &= j \\
b' &\geq 0 \\
m' &\leq \lambda_m p^h_{j'} h' \\
\nu' &\sim \Upsilon(\nu)
\end{aligned}
$$

where Υ is the distribution of ν' conditional on ν.

$$v^{sell}(b^n,\nu,k,j,j') = v^n(b^n,\nu,k,j,j')$$

4 Numerical Implementation, Parameterization, and Policy Functions

4.1 Numerical Implementation

I solve for the model's policy functions by combining the DC-EGM with taste shocks of Iskhakov and coauthors (2017) with the NEGM+ algorithm developed in Druedahl (2021). These methods extend the endogenous grid point method of Carroll (2006) to economies with non-convexities and exploit the nested structure of problems. An additional layer of optimisation is attained with an enhanced interpolation method. I solve for households' policies on 400-point grids for cash-in-hand and liquid assets, an 8-point grid for collateralized debt, and a 3-point grid for house sizes. Additionally, I discretize the autoregressive process for idiosyncratic productivity shocks into a seven states Markov process using the method proposed by Tauchen (1986). I iterate the value function until convergence using the absolute value of the largest difference as an error metric and a tolerance level of 1e-4. I solve the model in general equilibrium finding the two equilibrium prices - house prices in the center and in the suburb - with the Broyden algorithm.

4.2 Parameterization

I parameterize the model to be consistent with key features of the UK economy before the rise in remote work (2016-2019). One period in the model is 2 years. I use a mixed parameterization strategy. A subset of parameters is fixed using standard values and the literature. Another set of parameters is calibrated to match moments from the UK economy outside the model. The remaining parameters are jointly calibrated using the method of simulated moments inside the model. The parameter values are summarized in Table 3. Table 4 shows the targeted moments.

4.2.1 Households - general

The relative risk aversion parameter σ is set to 2 to get an elasticity of intertemporal substitution equal to 0.5. I assume Cobb-Douglas preferences for non-durable consumption and housing services as relevant evidence from micro data consistently finds support for an elasticity of substitution close to unity (Aguiar and Hurst 2013, Davis and Ortalo-Magne 2011, and Piazzesi, et al. 2007). I set the weight of non-housing consumption in the utility function, γ, to 0.76 following Davis and Ortalo-Magne (2011). The annual time-discount factor, $\beta = 0.9686$, is jointly calibrated to match the ratio of median net wealth to median income.

4.2.2 Households - locations

The city in the model is calibrated to match the city of London. The center corresponds to the boroughs defined by the ONS as Inner London,[12] which approximately corresponds to Zones 1 and 2 of the London Underground service. The suburb represents the boroughs that the ONS defines as Outer London,[13]. The parameter corresponding to the extra amenities available in center, $\epsilon_c = 0.0665$, targets the ratio of house prices[14] in the suburb and the center. The scale parameter for the location specific extreme value shocks is set to the standard value of 0.05.

[12] City of London, Camden, Hackney, Hammersmith and Fulham, Harringey, Islington, Kensington and Chelsea, Lambeth, Lewisham, Newham, Southwark, Tower Hamlets, Wandsworth, and Westminster.

[13] Barking and Dagenham, Barnet, Bexley, Brent, Bromley, Croydon, Ealing, Enfield, Greenwich, Harrow, Havering, Hillingdon, Hounslow, Merton, Redbridge, Richmond upon Thames, Sutton, and Waltham Forest.

[14] per square meter.

4.2.3 Households - labour

In the utility function, the taste parameter associated with remote work, $\chi^{WFH} = -0.3$, is chosen to replicate the share of total work done from home of 15% in 2016 for workers employed in a telecommutable occupation. The parameter value is negative, consistent with Barrero, Bloom, and Davis (2021)'s who argue that, prior to Covid-19, working-from-home was associated with a social stigma. For efficient units of labour (at home and from the office), the share of labour in production, $\theta = 0.82$, is fixed using evidence from Valentinyi and Herrendorf (2008). The minimum housing space needed to be productive from home is set to represent a $10m^2$ office, that roughly corresponds to the average size of a room in central London.[15] Productivity at the office is normalized to 1, while productivity from work done at home is set to 0.81. This is chosen in line with evidence from Gibbs, Mengel, and Siemroth (2023) who study IT professionals and estimate that their productivity fell by up to 19% when they switched to work-from-home during Covid. The elasticity of substitution between work-from-home and work done at the office is set to 4.4 in line with Delventhal and Parkhomenko (2023)'s estimates. Following Davis, Ghent, and Gregory (2023), the commuting time for workers in the center in set to 25.7 minutes one way versus 47.7 minutes in the suburb, and the share of workers employed in a telecommutable occupation is set to 46%. Finally, the stochastic productivity shock is modeled as an AR(1) process in logs with quarterly persistence of 0.97 and variance of 1% – both standard values in the literature (Storesletten, et al. 2004).

4.2.4 Households - assets

The utility bonus from owning a house, $\omega = 1.044$, is calibrated to match London's share of homeowners. Other parameters relating to wealth are chosen following Kaplan, Mitman, and Violante (2020). The depreciation rate of housing is 1.5% per annum, and the non-convex transaction cost when households want to sell their house amounts to 7% of the value of the property sold. I use a sparser version of the authors' house size grids. I set a risk free low return interest rate of 3% per annum and a collateralized borrowing intermediation wedge, τ, of 33% (Kaplan, Mitman, and Violante 2020). The collateralized debt's load to value constraint parameter, $\lambda = 0.85$, follows Greenwald (2018).

4.2.5 Construction and rental sectors

Elasticities of housing supply are set within the range estimated by Saiz (2010) for the US. I set α_s to 0.635 in the suburb (corresponding to a housing supply elasticity of 1.75 which is the average value of Saiz's estimates). I assume that the elasticity is lower in the center and set $\alpha_c = 0.6$ (housing supply elasticity of 1.5). The operating cost of the rental companies, $\phi = 0.008$, as well as the amount of total land permits available in the city

[15] Matching $10m^2$ to the size of the smallest houses owned in London ($43m^2$ for the 5th percentile of London houses' in the Land Registry).

follow Kaplan, Mitman, and Violante (2020). Inner London represents around 20% of the city's surface, therefore, 20% of these land permits are issued in the center, and 80% in the suburb.

Parameter	Value	Description	Target
Households - general			
β	0.9686	Discount factor	See Table 4
σ	2.00	Relative risk aversion	Standard value
γ	0.76	Weight of n.d.c. in utility	Davis, Ortalo-Magné 2011
σ_ϵ	0.05	Location taste shock scaling	Standard value
χ^{WFH}	-0.3	Taste for WFH	See Table 4
ϵ_c	0.0665	Extra amenities - center	See Table 4
Households - housing			
ω	1.044	Utility bonus from owning	See Table 4
F^{sell}	7%	Selling cost	Kaplan, Mitman, Violante 2020
δ	1.5%	Annual depreciation rate	Kaplan, Mitman, Violante 2020
$h_{gridOwn}$	$[1.92; 3.15; 5.15]$	Grid for houses - owned	Kaplan, Mitman, Violante 2020
$h_{gridRent}$	$[1.17; 1.92; 3.15]$	Grid for houses - rented	Kaplan, Mitman, Violante 2020
Households - labour			
θ	0.82	Labour share in eff. units of labour	Valentinyi, Herrendorf 2008
h_{min}	0.45	Housing used to WFH	$10m^2$ office space
A^O	1.0	Pty. work from office	Normalisation
A^H	0.81	Pty. work from home	Gibbs, Mengel, Siemroth 2023
ρ	4.4	EOS WFH and WFO	Delventhal Parkhomenko 2023
χ_c	0.0953	Commuting cost - center	Davis, Ghent, Gregory 2023
χ_s	0.1766	Commuting cost - suburb	Davis, Ghent, Gregory 2023
	46%	Share of workers in tele. occ.	Davis, Ghent, Gregory 2023
Construction sector			
α_c	0.6	h. supply elast. - center	Saiz 2010
α_s	0.637	h. supply elast. - suburb	Saiz 2010
$\overline{L}$	0.311	Land permits (whole city)	Kaplan, Mitman, Violante 2020
	20%	Share land permits - center	surface - Inner London
	80%	Share land permits - suburb	surface - Outer London
Rental sector			
ψ	0.008	Rental cies. operating cost	Kaplan, Mitman, Violante 2020
Financial sector			
r	0.03	Interest rate	Annual interest rate of 3%
ι	33%	Intermediation wedge	Kaplan, Mitman, Violante 2020
λ_m	0.85	Debt collat. constraint	Greenwald 2018

Notes: All values are reported for the yearly frequency of the model.

Table 3: Parameters

4.3 Non-targeted Moments

This subsection presents how the model's stochastic steady state fits some important moments that were not explicitly targeted in the calibration. Table 5 displays these cross-sectional moments in the model, and in the data.

First, the model can account for the location of households across geography even after

Moment	Model	Data	Parameter	Source
Median net wealth over median income	4.91	4.91	β	W&A survey
Share of work done from home (telec. occ)	0.15	0.15	χ^{WFH}	UKTUS
Share of renters (London)	0.49	0.49	ω	APS
Relative house price suburb/center	0.62	0.62	ϵ_c	Land Reg. - EPC

Notes: W&A survey refers to the Wealth and Assets survey, APS is the Annual Population Survey, UKTUS is the UK Time-Use Survey, and Land Reg. - EPC refers to the merged dataset of the EPC certificates and the land registry.

Table 4: Targeted Moments

conditioning on occupation. The share of households living in the center in the model (data) is 40% (41%) overall, 44% (44%) for telecommuters, and 38% (39%) for non-telecommuters. The model also matches where households live across the income distribution as it tracks well the share of households in the center for each labour income quintile. These features are particularly important as the model is used to understand who can live where inside the city, and the spatial re-allocations prompted by work-from-home.

As is common in this type of models, I do not capture the high degree of wealth concentration among the very rich (who own expensive properties in central London). Therefore, the share of homeowners in the center is a little underestimated in the model simulations: 27% versus 38% in the data.

Finally, the model reproduces well households wealth portfolios, and labour income by geography. The mean share of total wealth held as real estate is 37% in the model, and 36% in the Wealth and Assets survey. The model implied ratio of average labour income in the suburb over the center is 90%, against 88% in the data.

4.4 Decision Rules

To understand the mechanisms at play in the model, it is useful to look at households' decision rules. Figure 3 plots households' probability to choose to live in the center over the distribution of liquid wealth.[16]

Panel a displays this decision rule for a household that starts the period without owning any real estate.[17] We first notice that the probability to choose to live in the center is non-monotonic in liquid wealth. This is the case as this probability is obtained by comparing the expected value function in the center and in the suburb, and therefore interacts with the household's other location-specific decisions. The overall increasing pattern of the center probability over liquid wealth is expected. The center is on average the most attractive region because of the extra amenities and the lower commuting costs. These advantages are

[16] This is a probability because of the extreme value taste shocks on locations' amenities.

[17] More precisely, it is a household with median income, and employed in a telecommutable occupation.

Moment	Model	Data
Share of hhs. living in center	0.40	0.41
Share of telec. living in center	0.44	0.44
Share of non-telec. living in center	0.38	0.39
Share of bottom inc. quintile living in center	0.31	0.35
Share of 2nd inc. quintile living in center	0.37	0.38
Share of 3rd inc. quintile living in center	0.42	0.39
Share of 4th inc. quintile living in center	0.44	0.42
Share of top inc. quintile living in center	0.51	0.47
Share of owners in center	0.27	0.38
Mean share of wealth as housing	0.37	0.36
Labour income ratio suburb/center	0.90	0.88

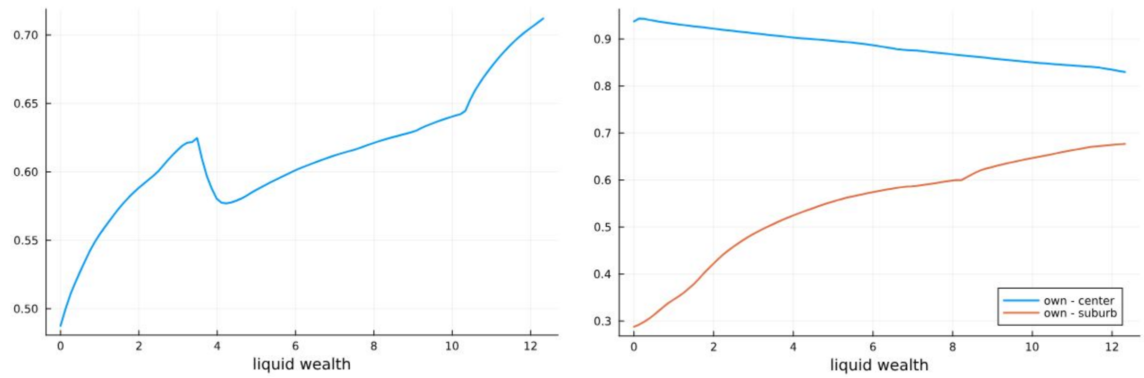
Notes: Telec. stands for telecommuters, non-telec. for non-telecommuters, and inc. for income.

Table 5: Non-targeted Moments

counterbalanced by higher house prices and rents. Therefore, when households get richer, they become more likely to pay the extra costs in order to enjoy the center's attractions. Note that the decision rule to live in the center has two kinks. Around a liquid wealth level of 4, the probability to choose the center drops. At this point, the household would actually be able to buy a house in the suburb, while they would remain a renter in the center. At the second kink (a wealth level a little bit above 10), the household would be able to be a homeowner in the center too. From this point on, the whole attractiveness of the center is restored, and the slope of the decision rule steepens.

Panel b, plots the same decision rule - the probability to live in the center - for two households, one that starts the period owning a house in the center (in blue), and one that starts the period owning a house in the suburb (in red).[18] First, we note that the probability to choose the city center is much higher for the household with the house in the center than for its suburban counterpart. This is the case as the owner in the suburb would need to sell their property in order to move. This is particularly costly because of the non-convex adjustment costs. Moreover, the gap between the probabilities of the two households narrows as liquid wealth increases. The reason for this is that the adjustment costs is particularly deterrent for lower levels of wealth, and loses some of its bite when households become richer. Finally, we note that the neighbourhood household specific taste shocks prevent the probability to choose the center to reach one. These mechanisms are intuitive and provide a sanity check for the model.

[18] More precisely, these are households with median income, median housing wealth, no collateralized debt, and employed in a telecommutable occupation.



(a) Non-homeowners (b) Homeowners

Notes: The households are employed in a telecommutable occupation, and have median income. The owners have median housing wealth, and no collateraized debt.

Figure 3: Decision Rules: Probability to Choose the Center

5 Results: the Work-from-home Experiment

5.1 Change in Taste

I now simulate the impact of a permanent shift in the taste parameter associated with remote work. In the baseline, the work-from-home taste parameter is calibrated to match the 15% of total work done from home by workers in telecommutable occupations prior to the pandemic (2016 wave of the UK Time Use Survey). In the latest wave of the UKTUS (2021), the share of total work done from home by workers in telecommutable occupations jumps to 53% (a little bit more than 2.5 days a week). The taste parameter associated with this amount of work-from-home is $\chi^{WFH} = 0.07$. Work-from-home's taste goes from a negative value (aversion) to a positive one (fondness). Intuitively, workers were forced into adopting remote work during the lock-downs, and many found a lot to like about it (e.g. working from the comfortable environment of their own home, spending more time with their partner or their pet...).

Modeling the rise in work-from-home as a change in taste is motivated by the survey evidence from Barrero, Bloom, and Davis (2021). In their Survey of Working Arrangements and Attitudes (SWAA), the authors interview more than 30,000 Americans over multiple waves to investigate whether work-from-home will stick, and why. They find evidence of better-than-expected work-from-home experiences, and greatly diminished stigma associated with remote work. For instance, around 60% of the respondents reported that they found themselves more productive than they expected to when working from home. Similarly, before Covid-19, working from home was often seen as a form of shirking. This changed as more than two thirds of the survey takers acknowledge an improved perception of work-from-home among the people they know. Finally, the authors report evidence of a strong taste for work-from-home *after* the pandemic, with nearly two-thirds of SWAA respondents valuing the option to work from home 2 to 3 days per week, and half on them seeing it as worth a pay rise of at least 5 percent.

A positive change in attitude towards work-from-home is not the only candidate to account for the recent shift in working arrangements. Another candidate is that the productivity of work-from-home increased as workers got used to this new organisation, and technologies like Zoom or Microsoft Teams spread. This is the angle taken in Davis, Ghent, and Gregory (2023). However, I do not adopt this approach for two reasons. First, my model adopts a macro take on the work-from-home issue with incomplete markets, non convexities, and rich multi-dimensional households choices. My focus is different from the urban papers on the topic. For this reason, I do not model the positive agglomerations externalities from working at the office. Consequently, in my context, modeling work-from-home's rise as the result of a pure productivity shock would likely overestimate the associated output gains as I abstract from the counterbalancing force (the decrease in the positive agglomerations at the office). Second, most of the technology needed to work from home (internet, videoconferencing, etc.) already existed in 2019. It did marginally improve, but it is hard to think about these changes as a technology revolution (or at least, as a large enough technical change to cause such a massive shift in workers' attitudes). Yet another hypothesis is that the adoption of work-from-home derives from multiple equilibria sources. This is the approach of Monte, Porcher, and Rossi-Hansberg (2023) who find that, following Covid-19, large US cities shifted to a high remote work equilibrium. The study of multiplicity of equilibria with incomplete markets is beyond the scope of this paper. I follow Deleventhal and Parkhomenko (2023) in modelling the work-from-home boom as a change in taste.

5.2 Long-run Analysis

First, I analyse the long term impact of remote work by computing the steady state consistent with the updated taste parameter, and comparing it to the baseline one. The new steady state is informative of how the economy will change in the long run.

Aggregate implications: remote work is associated with higher aggregate output (+3%) in the second steady state. This is because of complementarities between work-from-home and work at the office, and savings in commuting time. We note here, that this is the case even if working-from-home is relatively less productive that working at the office. This finding is consistent with Barrero, Bloom, and Davis' (2021) who state that "*the conventional approach* [to evaluate productivity gains] *ignores time spent commuting, which misses much of the gain associated with a shift to WFH* [work-from-home]".

The savings in commuting time come from two channels. First, the direct channel: workers in telecommutable occupations significantly increase the share of their labour that is supplied from home, and are therefore able to supply more working hours overall. Second, remote work also reduces commuting costs via an indirect channel. Working-from-home increases the relative attractiveness of the suburb for households employed in a telecommutable occupation. These workers do move away from the center to enjoy larger and cheaper houses, and make the most out of the reduced commuting costs. Consequently, relative house prices and rents change across the city, and space in the center is freed up for some workers in non-telecommutable occupations. These workers now also enjoy reduced commuting time, and are also able to supply more working hours. The share of the center population employed in a telecommutable occupation decreased by 3 points between the two steady states (going form 50% to 47%). Note here that I do not model leisure, therefore all the time that is not commuted is worked. However, my results are consistent with Barrero, et al.(2021) who repport that Americans devote around 95% of their savings in commuting time to work related activities.[19]

The output gains from remote work are consumed (aggregate consumption rises by 3% between the two steady states), and invested in real estate. In the post work-from-home steady state, households' housing wealth is 6% larger in aggregate, implying a higher overall housing demand, and an increased taste for space - as documented in the data. Following the change in housing demand, house prices increase in both locations, but the rise is larger in the suburb, where the benefits from the reduction in commuting costs are the largest. The ratio of house prices in the suburb versus the center goes from 62% in the first steady state to 63% in the later one. This change in relative prices is modest because in the long run, housing supply fully adjusts to the change in demand. Nonetheless, this modest change in equilibrium house prices is accompanied by a significant reallocation of households across the city. Moreover, the consequences of the rise in remote work are heterogeneous across occupations.

Wining category - The impact on households in a telecommutable occupation: Following the change in taste associated with work-from-home, telecommuters re-optimize their tenure and neighborhood decisions. The upper part of Table 6 displays telecommuters' tenure and location in the first steady state, and in the second steady state. The share of these households who own a house in the suburb rises by 5 percentage points in the long run, going from 41% to 46%. The share of homeowners in the center also rises by 3 percentage points, bringing overall telecommuters' home-ownership rate to 63%, against 55% in the baseline steady state. These changes in how much telecommuters own and where they live reflect the increased housing demand, and the drop in commuting costs. Moreover, the share of households employed in a telecommutable occupation that rent in the suburb shrinks by 20%. This indicates that the telecommuters are thriving in the new steady state because the suburban renters represent the most disadvantaged group in the economy, with mean consumption and liquid wealth less than 75% and 70% of the population averages.

Moreover, between the two steady states, telecommuters' average labour income rises

[19] 35% to their primary job, and 60% for other work related activities.

by 5%[20], consumption by 7%, liquid wealth by 5%, and real estate wealth by 16%. These gains span the whole population of telecommuters. For instance, panels a and b of Figure 4 plot telecommuters' consumption and housing wealth distributions. We note a rightward shift in both distributions between the first steady state (in blue), and in the second one (in orange).

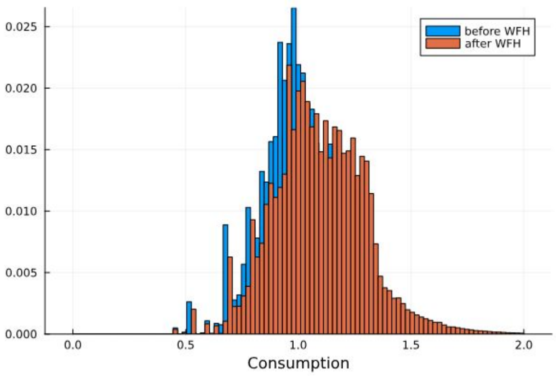
Share of households	Before WFH	After WFH	Change
Telecommutable occ.			
Own - Center	14%	17%	$+3pts$
Own - Suburb	41%	46%	$+5pts$
Rent - Center	30%	25%	$-5pts$
Rent - Suburb	15%	12%	$-3pts$
Non-telecommutable occ.			
Own - Center	8%	8%	–
Own - Suburb	39%	35%	$-4pts$
Rent - Center	30%	32%	$+2pts$
Rent - Suburb	23%	25%	$+2pts$

Table 6: Location and Tenure Allocations

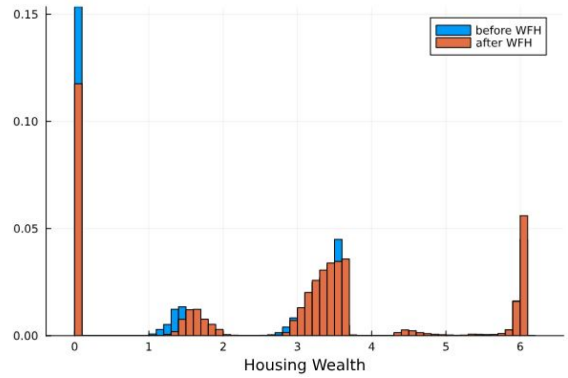
The impact on households in a non-telecommutable occupation: Like their telecommuting counterparts, households employed in a non-telecommutable occupation change their location and tenure decisions between the two steady states. The lower half of Table 6, shows a significant drop in the share of non-telecommuters who own a house in the suburb (4 percentage points, from 39% to 35%). If telecommuters increase their overall home-ownership rate between the two steady states, the opposite is true for the non-telecommutable occupation. The 4 percentage points drop in suburban home-ownership is paired with a 4 percentage points increase in the share of renters. The mechanism at play is simple. In the suburb, properties are cheaper (recall that in the baseline steady state, the house prices ratio in the suburb relative to the center is 0.62), therefore they are held by the least wealthy amongst homeowners. The increased demand for suburban houses by telecommuting workers - who are on average high wealth and income households - leads the formerly cheap suburban properties to appreciate. The marginal homeowners become unable to afford them, and are crowded out of home-ownership and forced into renting. Table 7 illustrates this point by displaying the location and tenure probability in the 2 steady states for the marginal non-telecommuter buyer in the baseline economy.[21] The

[20] Because of longer working hours and some degree of complementary between work-from-home and work at the office.

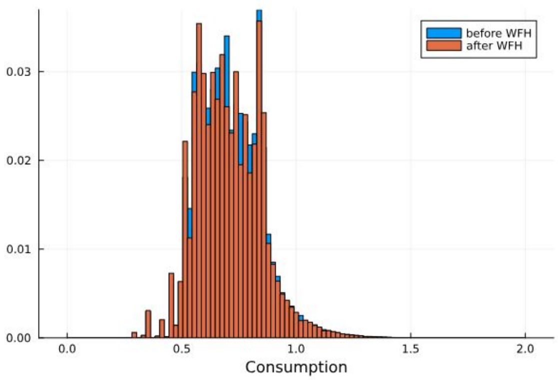
[21] More precisely, the marginal buyer amongst non-telecommuters is a non-telecommuter who will buy a house with positive probability, and who would not have done so with a lower level of liquid wealth or



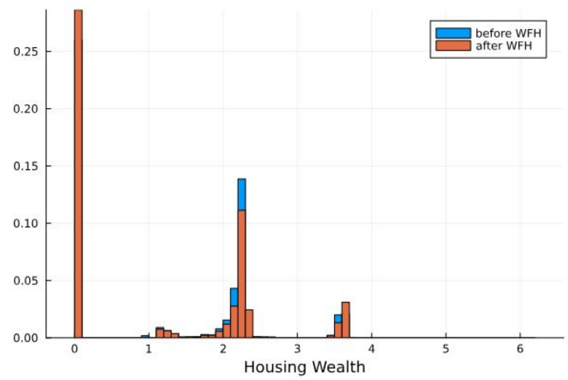
(a) Consumption (Telecommuters)



(b) Housing Wealth (Telecommuters)



(c) Consumption (Non-telecommuters)



(d) Housing Wealth (Non-telecommuters)

Notes: The discontinuous shape of the housing wealth distributions comes from the discrete grid for houses

Figure 4: Distributions in the Two Steady States

marginal non-telecommuter buyer is an household who starts the period without owning any real estate, whose liquid wealth equals the population's 60th percentile, and whose income is at the median. In the first steady state, this marginal buyer will purchase a house in the suburb with probability 0.49, and become a renter in the center with probability 0.51. In the new steady state, this same household is crowded out of the owner occupied housing market, rents in the suburb with probability 0.46, and rents in the center with probability 0.54. The increase in telecommuters' housing demand in the suburb and the pricing out of the least wealthy owners and buyers can be compared to a gentrification shock that hits the whole periphery at the same time.

Moreover, non-telecommuters' average income rises by 0.1% (because of the lower commuting for those who managed to reallocate to renting in the center), but their average

income.

Steady state	P.buy - center	P.buy - suburb	P.rent - center	P.rent - suburb
Before WFH	0.0	0.49	0.51	0.0
After WFH	0.0	0.0	0.54	0.46

Notes: The marginal non-telecommuter buyer is an household who starts the period without owning any real estate, whose liquid wealth equals the population's 60th percentile, and whose income is at the median. P. stands for probability.

Table 7: Decisions of the Marginal Non-telecommuter Buyer

housing wealth drops by 7% and their mean consumption by 0.4% (because of the increased house prices and rents). Once again, this is not only the case for average values, but holds along the distributions. Panels c and d of Figure 4 show a small leftward shift in non-telecommuters' consumption and housing wealth distributions. Overall, the average welfare of the non-telecommuters, computed as average utility, is 17% lower in the new steady state. Workers in a non-telecommutable occupation represent the losing category in the long run. We note here, that computing welfare as utility and comparing it across the two steady states would be an unfair exercise for the telecommuters' group. It is the case because these households had a change in a taste parameter between the two economies, making utility-based welfare comparisons uninformative. However, this issue does not apply to the workers employed in a non-telecommutable occupation as they cannot work from home. Therefore, their taste and parameters remained the same over the experiment. The change in their utility is informative of their welfare across the two steady states.

Long-run implications for inequality: The rise in remote work has strong implications on where households live and their tenure decisions in the long run. Consequently, it also has implications for consumption and real estate inequality. Table 8 reports several measures of housing wealth and consumption inequality in the two steady states.

First, we note that the median to 90th percentile ratio is lower in the post work-from-home economy, meaning lower housing wealth inequality amongst homeowners. This drop in the housing wealth discrepancy in the intensive margin is explained by two factors. On the one hand, there is a valuation effect. As the wealthiest households were owning properties in the Central Business District before the spread of remote work, the value of their asset decreased relative to that of more modest homeowners who had settled in the suburb, lowering inequality. On the other hand, housing wealth inequality for homeowners drops because of a composition effect. The lowest income, lowest liquid wealth telecommuters have been crowded out of ownership and replaced by wealthier telecommuters. The group of homeowners is therefore richer and more homogeneous in the post work-from-home economy. Moreover, housing wealth inequality measured by the ratio of average housing wealth of non-telecommuters over housing wealth of telecommuters significantly rises (the ratio drops from 50% in the first steady state to 40.0% in the second one).

Secondly, the lower part of Table 8 reports a rise in consumption inequality across 4 different measures. The 10th-to-90th and median-to-90th consumption percentile ratios fall. Similarly, the average consumption of non-telecommuters accounts for 69% of that of telecommuters in the baseline steady state, and only 65% in the post remote work one. Similarly, the ratio of mean consumption of renters to owners goes from 85% to 80% across the two economies. This rise in consumption inequality is driven by higher rents and house prices, as well as larger income for the part of the population able to telecommute.

Inequality Measure	Before WFH	After WFH
Housing wealth		
median/90th ptile	0.55	0.58
non-telec./telec.	0.50	0.40
Consumption		
10th/90th ptile	0.49	0.45
median/90th ptile	0.71	0.67
non-telec./telec.	0.69	0.65
renters/owners	0.85	0.80

Notes: Telec. stands for telecommuters, non-telec. for non-telecommuters, and ptile for percentile. The displayed inequality measures are: the 10th-to-90th percentile ratio, the median-to-90th percentile ratio, the average consumption (housing wealth) of the non-telecommuters over the average consumption (housing wealth) of the telecommuters, and the average consumption (housing wealth) of the renters over the average consumption (housing wealth) of the home-owners.

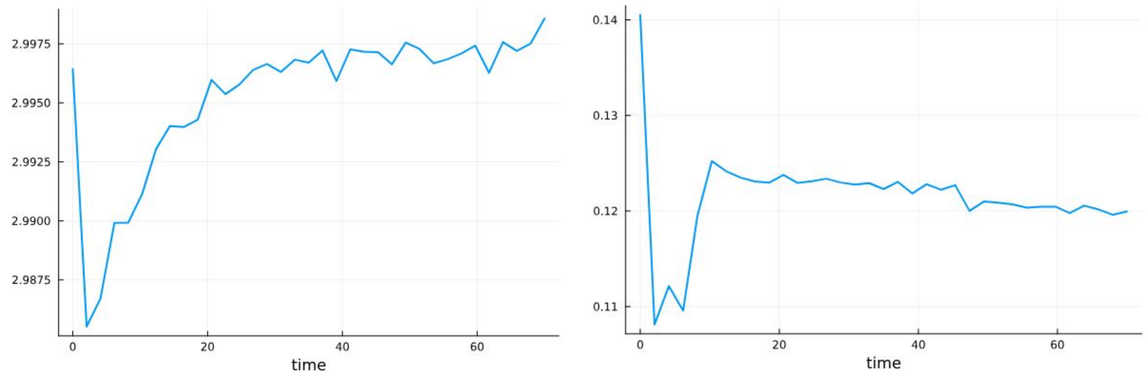
Table 8: Housing Wealth and Consumption Inequality

5.3 Transitions

The previous section identifies some winning and losing categories of households in the long run. However, across the distribution, the impact of the rise in remote work depends on accounting for transitional dynamics. Most homeowners employed in a non-telecommutable occupation own houses in the suburb prior to the change in working arrangement.[22] These households own the properties that appreciate the most with work-from-home. Therefore, we expect that these particular households benefit from the structural change. Here, I compute the transition paths between the two steady states non-linearly, solving for the equilibrium sequence of prices over the whole transition period.

Figure 5 plots the real estate wealth of the non-telecommuters over the transitions. Panel a displays houses owned by non-telecommuters that start the period with some real estate (this is analogous to the intensive margin of real estate wealth), while panel b shows

[22] Suburban homeowners represent 83% of the non-telecommuters with real estate.



(a) Intensive Margin (b) Extensive Margin

Notes: Panel a plots the housing wealth of non-telecommuters who started the period owning real estate (referred to as intensive margin). Panel b shows the housing wealth of non-telecommuters who started the period without owning any real estate (referred to as extensive margin).

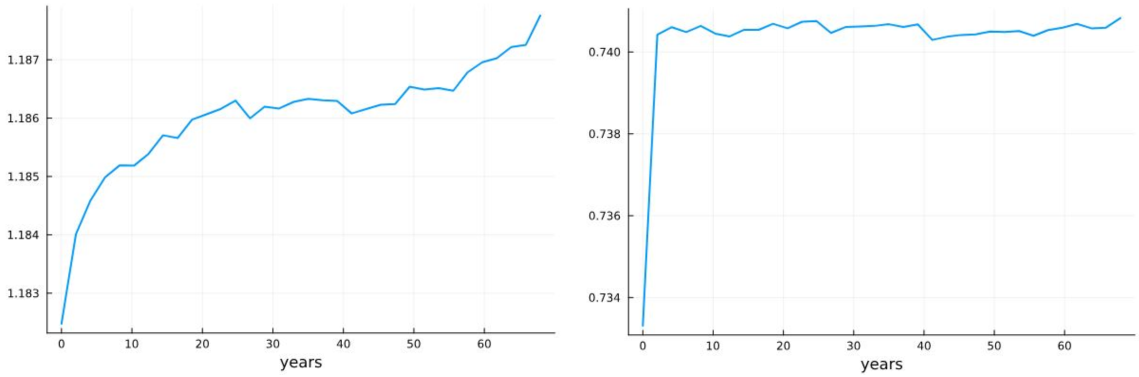
Figure 5: Non-telecommuters Housing Wealth over the Transition

houses bought by non-telecommuters who did not own any real estate at the start of the period (analogous to the extensive margin of real estate wealth).

On the intensive margin, we note that, when work-from-home rises, the housing wealth of the existing owners drops. A share of these owners indeed sell their houses in the suburb to respond to the increased demand coming from wealthy telecommuters. These sellers then move to the center. However, the capital gains from their sale does not allow them to directly buy in the center because of the large difference in house prices across the two locations. Therefore, they become renters in the center, and build up some liquid wealth. Conditional on good income shock realisations, a share of them will eventually access home-ownership in the center.

This has a direct consequence on the shape of the price paths in the two locations over the transition. Figure 6 plots house prices' path for the center in panel a, and the suburb in panel b. The house prices in the center adjust slowly over the transitional period. This is because the new movers to this area are the households who just sold their house to telecommuters, and whose housing demand materialises later in the transition. Therefore, house prices in the center take longer to rise. On the other hand, suburban house prices adjust very rapidly to the new steady state value. Households moving to the suburb are telecommuters who seek to buy large properties to work from home. These households are wealthy enough to buy right away. The increase in demand for suburban properties is immediate, and prices rise to reflect it.

Finally, Panel b of Figure 5 illustrates non-telecommuters' pricing out of the property market over the transition. Following the rise in house prices and rents, new houses bought by non-telecommuters drop straight away, and eventually stabilize at a lower level than in the baseline world. The pricing out of non-telecommuter buyers is immediate.



(a) Center

(b) Suburb

Figure 6: House Prices Paths over the Transition

Conclusion

This paper presents novel evidence on the impact of a structural change in the way we organise labour - the spread of working-from-home - on households' consumption, wealth, and housing decisions. It builds a new rich theoretical framework to understand how work-from-home shifted households' allocation inside the city, and explores the associated distributional implications. I show that work-from-home reshapes housing demand by increasing the taste for space and reducing worker's commuting costs. Households are impacted differently depending on whether they can partake in remote work or not, and on where they stand in the income and wealth distributions. In the long run, work-from-home can be compared to a generalised gentrification shock, and while wealthy telecommuters buy larger houses in suburban areas, it crowds out the marginal owners and forces them into renting. Long run, housing wealth and consumption inequality rise. In the short run however, the less wealthy homeowners own the properties in the suburb that just appreciated following the drop in commuting costs. Some of these households sell their houses and realise capital gains. Still in most cases, the gains are not large enough for the households to purchase a house in another neighborhood. The sellers end up renting closer to the city center, and slowly building up their liquid wealth. This has a direct consequence on the shape of the price paths over the transition. The house prices in the center are slow to reach the new steady state value as the new movers' housing demand takes some time to materialise. On the other hand, movers to the suburbs are households that are wealthy enough to buy right away. Consequently, suburban house prices adjust immediately to the new steady state value.

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A Appendix A: Additional Empirical Results

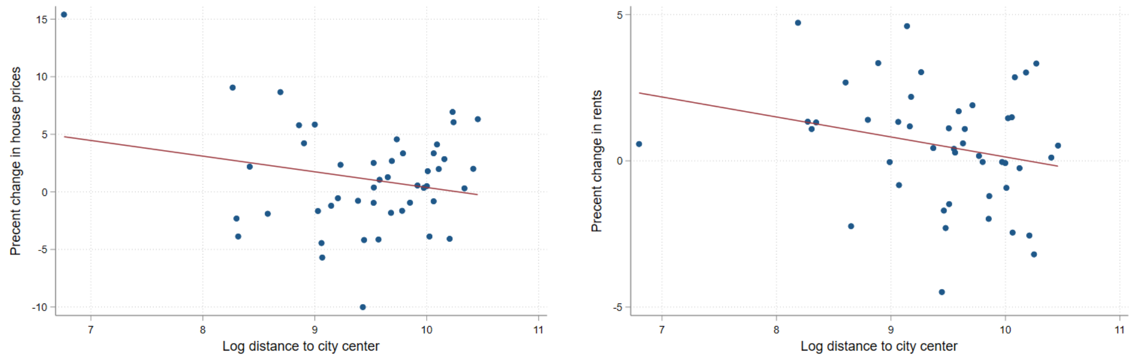
A.1 Raw data: Prices and Distance to the City Center

Figure 7 reproduces the plots in Figure 1 for a placebo period. I plot changes in house prices and rents between 2017 and 2018 on local authorities' average log distance to the city center. In this placebo specification, we do not observe the clear positive relationship emphasized during the Covid period.

Figure 8 provides additional evidence for the relative appreciation of properties located further out from the city center. The left panels plot house price indexes and the right panels plot rent indexes. The reference period is February 2020. In the top two panels, properties are split into two groups: the center properties that are within a 5km radius of BoE and the suburban properties that are located further out. In the bottom two panels, I plot properties by quintile of distance to the city center. In both specifications, since February 2020, properties located further away from the city center appreciated faster than more central ones.

A.2 Raw data: Prices and Size

Figure 9 reproduces the evidence displayed in Figure 2 - the relative appreciation of larger properties since February 2020 - splitting the data by quitile of size in m^2 (instead of by number of rooms). This plot is similar to the alternative specification of the main text.



(a) House Prices (b) Rents

Notes: Each dot represents one of London's local authority (e.g. Camden, Hackney). As this is the placebo specification, the x-axis plots changes in average house prices and rents between the year 2017 and 2018. The y-axis plots the logarithm of local authority's average distance to Bank of England (in meters). I exclude the top 1% in house prices, rents, and size (in square meters) in order to remove outliers.

Figure 7: Growth in Properties' Value as a Function of Distance to the Center (London - Placebo Specification)

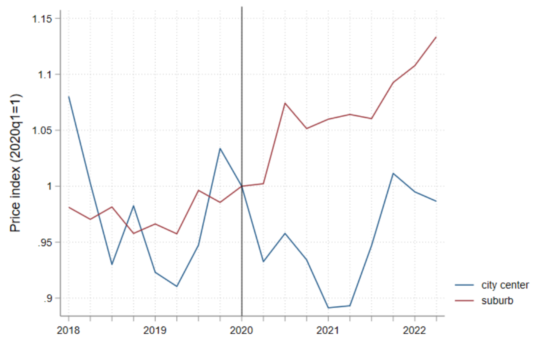
A.3 Alternative Hedonic Specification: Monthly Coefficients

Equation 1 in the main text evaluates the total change in the importance of size and distance in determining house prices and rents for the overall post pandemic period. Another interesting exercise is to look at the size and distance gradients in every month of our sample.

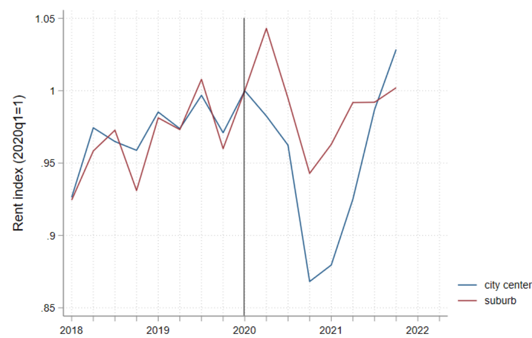
$$ln(p_{ijt}) = \delta_t^{size} ln(size_i) + \delta_t^{dist} ln(dist_i) + \beta X_i + \alpha_t + \eta_j + e_{ijt} \quad (2)$$

Equation 2 allows for the coefficients of log size and log distance to vary every month. They capture the effect of size and distance on the outcome variable in each month relative to the default period of February 2020. These month-specific coefficients allow to test for pre-trends.

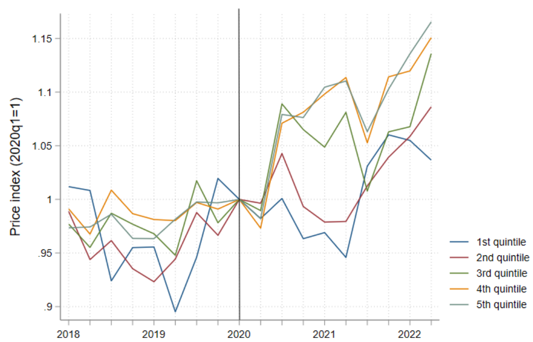
Figure 10 plots the size and distance monthly coefficients from Equation 2. The top 2 panels display δ_t^{size} for house prices (Panel a) and rents (Panel b). The bottom 2 panels display δ_t^{dist} for house prices (Panel c) and rents (Panel d). 95% confidence intervals are shown in green and the last period before Covid (February 2020) is highlighted with the vertical red dotted line. I regard this exercise as a test for the absence of pre-trend in the importance of size and distance in determining households' housing demand. Reassuringly, there is no clear trend before the pandemic: most pre-February 2020 effects are not significant. However, δ_t^{size} and δ_t^{dist} are positive and significant in the later part of the sample. This confirms the previous result that size became more important in determining house prices and rents while the penalty associated with distance from the city center decreased.



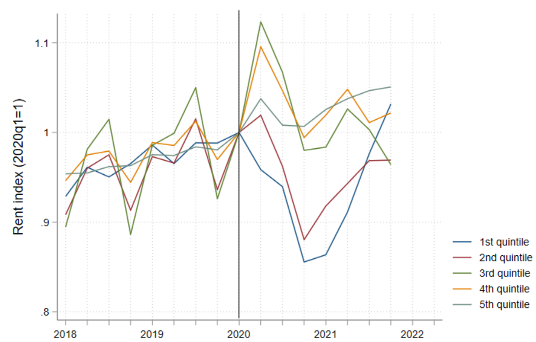
(a) House Price Index (Center/Suburb)



(b) Rent Index (Center/Suburb)



(c) House Price Index (Distance Quintiles)



(d) Rent Index (Distance Quintiles)

Notes: I exclude the top 1% in house prices, rents, and size (in square meters) in order to remove outliers.

Figure 8: House Prices and Rents by Distance to the City Center (London)

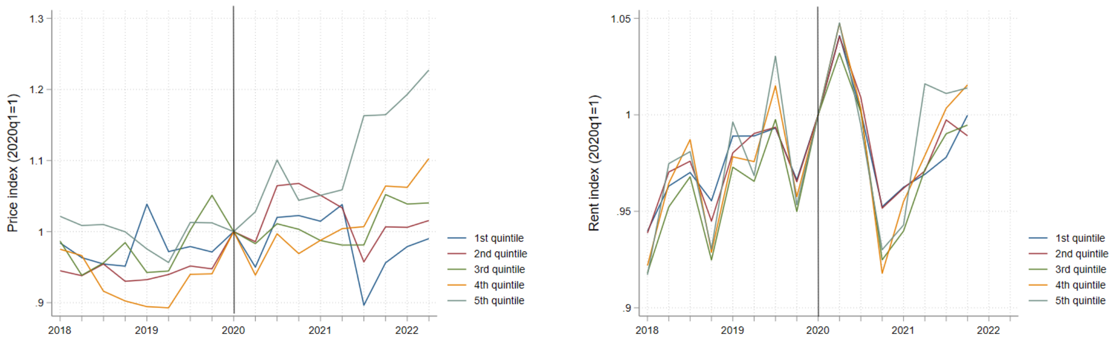
A.4 Recursive Formulation of the Problem: household who does not own a house at the beginning of the period

V^n is the value function of a household who does not own a house at the beginning of the period.

$$V^n(b,\nu,k,j,\epsilon) = max\{v^n(b,\nu,k,j,C) + \sigma_\epsilon \epsilon(C), v^n(b,\nu,k,j,S) + \sigma_\epsilon \epsilon(S)\}$$

where $v^n(b,\nu,k,j,j')$, $j' \in \{C,S\}$ are *location choice-specific* value functions and $\sigma_\epsilon \epsilon(j')$ are random choice-specific taste shifters that are additively separable, i.i.d. and have an extreme value distribution with scale parameter σ_ϵ.

$$v^n(b,\nu,k,j,j') = max\{v^{rent}(b,\nu,k,j,j'), v^{buy}(b,\nu,k,j,j')\}$$



(a) House Price Index (b) Rent Index

Notes: Properties are split by quintile of size in m^2. I exclude the top 1% in house prices, rents, and size (in square meters) in order to remove outliers.

Figure 9: House Prices and Rent by Size of Property (London)

where v^{rent} is the *location j' choice-specific* value function of a household who decides to rent and v^{buy} is the *location j' choice-specific* value function of a household who decides to buy.

$$v^{rent}(b, \nu, k, j, j') = \max_{c, h', \eta^O, b'} u(c, \tilde{h}') + \beta E_\nu E_\epsilon \left[V^n(b', \nu', k, j', \epsilon') \right]$$

$$s.t \quad c + q_{j'}h' + b' + \leq (1+r)b + wn$$

$$n = \left[n^{O\left(\frac{\rho-1}{\rho}\right)} + n^{H\left(\frac{\rho-1}{\rho}\right)} \right]^{\frac{\rho-1}{(\rho)}}$$

$$n^O = A^O(\nu\eta^O)^\theta$$

$$n^H = A^H(h_{min})^{(1-\theta)}(\nu\eta^H)^\theta$$

$$1 = (1 + \chi_{j'})\eta^O + \eta^H$$

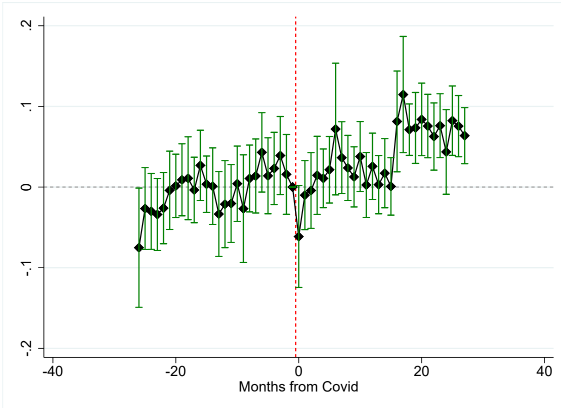
$$\eta^H = 0 \quad if \quad k = 0$$

$$\tilde{h}' = h' - \alpha h_{min} \mathbb{1}_{\eta^H > 0}$$

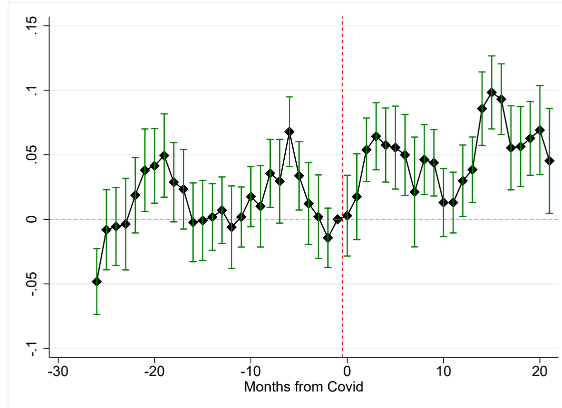
$$b' \geq 0$$

$$\nu' \sim \Upsilon(\nu)$$

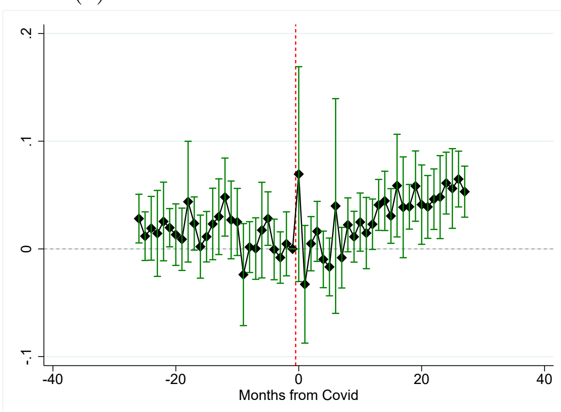
where Υ is the distribution of ν' conditional on ν.



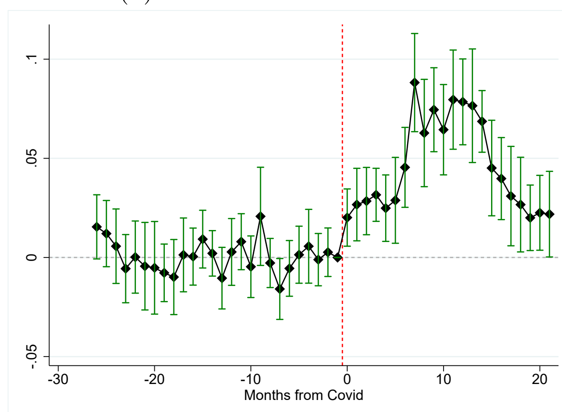
(a) Size Coefficients on House Prices



(b) Size Coefficients on Rents



(c) Distance Coefficients on House Prices



(d) Distance Coefficients on Rents

Notes: Standard errors are clustered at the local authority level. I exclude the top 1% in house prices, rents, and size (in square meters) in order to remove outliers.

Figure 10: Month-Specific Size and Distance Coefficients (London)

$$v^{buy}(b, \nu, k, j, j') = \max_{c,h',\eta^O,b',m'} u(c, \tilde{h}') + \beta E_\nu E_\epsilon \left[V^h(b', h', m', \nu', k, j', \epsilon') \right]$$

$$s.t \quad c + p^h_{j'} h' + b' \leq (1 + r)b + wn + m'$$

$$n = \left[n^{O(\frac{\rho-1}{\rho})} + n^{H(\frac{\rho-1}{\rho})} \right]^{\frac{\rho-1}{(\rho)}}$$

$$n^O = A^O (\nu\eta^O)^\theta$$

$$n^H = A^H (h_{min})^\theta (\nu\eta^H)^{(1-\theta)}$$

$$1 = (1 + \chi_{j'})\eta^{O} + \eta^{H}$$
$$\eta^{H} = 0 \quad if \quad k = 0$$
$$\tilde{h}' = \omega(h' - \alpha h_{min}\mathbb{1}_{\eta^{H}>0})$$
$$b' \geq 0$$
$$m' \leq \lambda_m p^{h}_{j'} h'$$
$$\nu' \sim \Upsilon(\nu)$$